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Utility-Scale and Distributed Storage in Integrated Resource Plans: A Comparison of Plans for Indiana and Other States

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# Utility-Scale and Distributed Storage in Integrated Resource Plans

## A Comparison of Plans for Indiana and Other States

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This technical brief compares utility assumptions and methodologies for incorporating utility-scale and distributed energy storage in integrated resource plans (IRPs) filed by three utilities serving Indiana and five utilities serving other states. The brief also identifies opportunities to improve storage modeling. Berkeley Lab conducted the research for Indiana Utility Regulatory Commission Staff under the Economic Valuation of Energy Resources project funded by the U.S. Department of Energy.

### Introduction

Indiana Utility Regulatory Commission (IURC) Staff requested technical assistance from Berkeley Lab on economic valuation and assessment of utility-scale and distributed energy storage in the context of integrated resource plans (IRPs). Berkeley Lab identified six topics to guide research on modeling storage in IRPs:

1. Storage technology types
2. Utility-scale and distributed storage inputs and methodologies
3. Cost assumptions
4. Grid services
5. Model assumptions
6. Storage adoption outcomes

Research questions for each topic guided identification of key assumptions and methodologies for modeling storage in IRPs, listed in Appendix A. We applied our research questions to three Indiana utility IRPs prioritized by IURC staff—Hoosier Energy, IPL (now AES Indiana), and Vectren. We selected five additional utilities that included storage in their most recent IRP preferred portfolio: Arizona Public Service (APS), Duke Energy Carolinas (DEC), Puget Sound Energy (PSE), Sacramento Municipal Utility District (SMUD), and Xcel Energy (Xcel) in Minnesota. Hereafter, we refer to these collectively as “utilities” and “reviewed IRPs.” Appendix B is a list of IRPs reviewed, including the state(s) served, the duration of the planning period, and a link to each plan.

The next section of this brief is organized around the six topics listed above. We summarize the assumptions and approaches used by each utility, by topic. We conclude the brief with opportunities to improve modeling of energy storage in IRPs. Appendices provide additional information.

## Storage technology types

Energy storage technologies can be categorized into three broad categories: electrochemical, mechanical, and thermal. Electrochemical storage includes chemical-based systems, such as lithium-ion (Li-ion), lead-acid, and flow batteries. Mechanical storage holds energy through mechanical processes (e.g., compressed air, pumped hydro, and flywheels). Thermal storage holds energy through temperature gradients (e.g., water heaters, building insulation, molten-salt batteries, and ice storage). Table 1 provides a general list of categories of storage and technologies that exist today.

**Table 1. Energy storage technologies (DOE 2021)**

Category	Existing Technologies (some in R&D)
Electrochemical	<ul style="list-style-type: none"> <li>• Li-ion</li> <li>• Na-ion and Na metal</li> <li>• Lead Acid</li> <li>• Zinc</li> <li>• Other metals (Mg, Al)</li> <li>• Redox Flow</li> <li>• Capacitors</li> </ul>
Mechanical	<ul style="list-style-type: none"> <li>• Pumped hydro</li> <li>• Compressed air</li> <li>• Flywheels</li> <li>• Geomechanical</li> <li>• Gravitational</li> </ul>
Thermal	<ul style="list-style-type: none"> <li>• High-temperature sensible heat</li> <li>• Low-temperature storage</li> <li>• Phase change materials</li> <li>• Thermo-photovoltaic</li> <li>• Thermochemical</li> </ul>
Chemical	<ul style="list-style-type: none"> <li>• Hydrogen</li> <li>• Ammonia</li> <li>• Other chemical carriers</li> </ul>

The utilities estimated the potential for four storage technologies in the reviewed IRPs: Li-ion batteries, flow batteries, compressed air storage, and pumped storage (Table 2). These technologies can operate as standalone systems or as hybrid systems (i.e., paired with variable renewable energy such as solar or wind).

All of the utilities estimated the potential of utility-scale Li-ion batteries. Of the Indiana utilities, Vectren also estimated the potential of utility-scale flow batteries and hybrid storage systems paired with solar and wind. APS, DEC, PSE, SMUD and Xcel <sup>1</sup> included distributed batteries in their IRP analysis.

<sup>1</sup> Xcel's IRP does not explicitly include storage. The utility's preferred portfolio includes generic firm peaking resources that include a mix of storage and demand response.

The utilities excluded some storage technologies as less mature or posing higher risks of cost and operational uncertainty. For example, APS cited the need for more demonstration projects before hybrid systems (e.g., storage paired with solar and wind) are considered “seamless and reliable.”

**Table 2. Storage technology types considered in reviewed IRPs**

	Hoosier	IPL	Vectren	APS	DEC	PSE	SMUD	Xcel
<b>Utility-scale energy storage</b>								
Electrochemical								
Li-ion battery	X	X	X	X	X	X	X	X
Flow battery			X	X		X		
Mechanical								
Compressed air storage				X				
Pumped storage				X		X		
Hybrid								
Solar + Li-ion battery	X		X	X	X	X		X
Wind + Li-ion battery			X			X		X
<b>Distributed energy storage</b>								
Battery*				X	X	X	X	X

\*Utilities did not specify DER battery chemistry.

## Utility-scale and distributed storage inputs and methodologies

All of the reviewed IRPs modeled utility-scale storage as a potential resource in capacity expansion and production cost models. The Hoosier, Vectren, APS, Duke, PSE, SMUD, and Xcel IRPs also modeled hybrid storage systems as potential resources. Generally, utilities developed a selection of scenarios with various energy storage procurement levels based on different priorities and assumptions (e.g., renewables procurement goals, carbon policies, economic conditions, and power plant retirements). Each scenario was independently modeled as part of the process to select a preferred portfolio. Utilities also developed additional sensitivities (e.g., load growth levels, technology costs, and gas prices) to understand risks associated with each scenario. Table 3 describes how each utility considered utility-scale storage.

**Table 3. Utility-scale storage in IRP models**

Utility	Standalone Storage Range	Hybrid System Range	Duration Range	Number of Scenarios	Scenarios Modeled
Hoosier	0-250 MW	Not included	Not provided	6	Base case, stagnating economy, US economy decarbonizes, customers in control, challenged gas economy, flat gas
IPL	380-1,040 MW	Not included	4-hour	5	Reference case, scenario A: carbon tax, scenario B: carbon tax + high gas, scenario C: carbon tax + low gas, scenario D: tax + high gas
Vectren	0-152 MW	0-126 MW (solar), 0-340 MW (wind)	4-, 6-, and 8-hour	5	Base case, low regulation, high regulation, high technology, 80% CO2 reduction by 2050
APS	852-10,140 MW	Not included	4-hour	4	Bridge, shift, accelerate, and technology agnostic
DEC	1,050 MW-7,400 MW (includes standalone and hybrid)		4- and 6- hour	6	Base case, base case with carbon policy, earliest coal retirements, 70% carbon reduction: high wind, 70% carbon reduction: high small modular resources, no new gas generation
PSE	Modeled in 25 MW blocks, range not provided	Not included	2-, 4-, 6-, and 8- hour	3	Base, low, and high
SMUD	246-661 MW	Not included	4-hour	3	Adopted scenario (2030 GHG emissions goal), multiple GHG targets, absolute zero scenario
Xcel	0-400 MW	0-600 MW (solar), 0-900 MW (wind)	4-hour	15	Base, early coal retirements (3 scenarios), early nuclear retirements (4 scenarios), nuclear extension (7 scenarios)

In Indiana, Hoosier, IPL, and Vectren did not model distributed storage. The other reviewed IRPs model adoption of distributed battery storage as behind-the-meter customer-sited systems. APS, DEC, SMUD, and Xcel treat distributed battery storage as an exogenous parameter for capacity expansion and production cost models, incorporating it as a load forecast adjustment. In contrast, PSE modeled distributed storage as an endogenous variable that the capacity expansion model could

select as a resource, available as utility-owned 25 MW blocks intended for installation at the substation. Table 4 describes how each utility considered distributed storage.

**Table 4. Distributed storage in IRP load forecasts**

Utility	Distributed Storage Type	Load Forecast Adjustment?	Ownership	Quantity
Hoosier	None	No	None specified	None
IPL	None	No	None specified	None
Vectren	None	No	None specified	None
APS	Distributed storage included as part of demand-side management programs*	Yes	Customer	Unknown
DEC	Load shifting from Bring-Your-Own Battery program	Yes	Customer	Unknown
PSE	PSE does not include distributed storage in the load forecast. Instead, battery storage is included in resource optimization for non-wires alternative applications to meet a subset of distribution system needs.	No	Utility	25 MW blocks
SMUD	Load forecast includes distributed storage through customer adoption and utility procurement (80% battery, 20% thermal energy storage)	Yes	Utility procurement of customer storage	At least 9 MW
Xcel	Customer-sited storage	Yes	Customer	See Table 5

\*APS discussed thermal storage water-heater programs in their IRPs.

Aside from SMUD and Xcel, it was not clear how much storage the utilities included in customer adoption forecasts. SMUD included 9 MW of Li-ion and thermal distributed storage procurement by 2020 in its preferred plan. The utility assumed an 80%/20% split between residential and commercial, but did not identify if the storage systems are standalone or hybrid. The customer adoption forecast also included future procurements based on the estimated success of storage programs (potentially up to 12 MW), but the exact amount was not provided.

Xcel created low, mid, and high distributed storage customer adoption forecasts based on current adoption levels and interconnection applications combined with third-party data. For the low customer adoption forecast, Xcel extrapolated the historical average growth rate of interconnection applications from 2017-2019 through 2029. Table 5 shows Xcel’s adoption forecast. Xcel applied high and medium adoption growth levels to data on completed storage installations in its service territory from 2017-2019.



DEC included a Bring Your Own Battery program, which uses storage for “load shift/demand response.” They did not describe how the program impacts the utility’s load forecast. APS discussed a pilot program exploring integrating customer-sited storage into grid operations, but it is not included in its load forecast.<sup>2</sup>

**Table 5. Xcel’s distributed energy storage forecast**

	Cumulative MW		
	Low	Medium	High
2025	1	2	3
2030	2	5	12
2034	3	12	45

## Cost assumptions

The energy storage industry has gone through a rapid transformation over the last decade, which has led to improvements in technology, continually declining costs, and more future cost uncertainty than other potential resources (NREL 2020). The reviewed IRPs generally separated cost into three components: capital cost, fixed O&M (\$/year), and variable O&M (\$/kWh).

The utilities employed a combination of public, third-party, and internal price data to develop cost curve assumptions for energy storage. Utilities used a combination of publicly available data and internal cost data for storage cost projections. Most utilities used NREL data, and Xcel switched from using internal storage capital costs to using NREL data for its most recent IRP.

Table 6 summarizes data sources for storage cost assumptions by utility. Following are the publicly available sources used:

- [NREL’s Annual Technology Baseline](#): annual report containing detailed cost and performance data for renewable and conventional technologies
- [Lazard’s Levelized Cost of Storage](#): annual report of levelized storage costs for different applications
- [EIA’s Battery Storage in the United States: An Update on Market Trends](#): 2020 report on battery storage capacity addition trends with accompanying data
- [PNNL’s Energy Storage Technology and Cost Characterization Report](#): 2019 report that defines and evaluates cost and performance parameters for six electrochemical storage technologies and four other types of storage technologies

<sup>2</sup> APS’s Storage Rewards pilot program provides a battery system to the customer that the utility owns and operates.

**Table 6. Data sources for energy storage costs by utility**

	NREL	Lazard	EIA	PNNL	IHS	Wood Mackenzie	Bloomberg	Internal Data*
Hoosier			X					X
IPL	X	X			X	X	X	X
Vectren	X							X
APS						X		X
DEC	X	X		X				X
PSE	X							X
SMUD	X	X						X
Xcel	X							X

\*Includes data from resource solicitations, known interconnection costs, previous consulting work, and other undisclosed information.

In the reviewed IRPs, costs were reported based on technology type and year of installation. Some utilities applied cost sensitivities based on scenarios modeled (e.g., high vs. moderate technology advancements).

Results show wide disparity in the utility-scale Li-ion battery reference case capital costs assessed by utilities, ranging from a low of \$954/kW to a high of \$3,436/kW (Table 7). This is significant because technology reference case costs are typically the point of comparison for other technologies in IRPs and technologies with a relatively lower cost are more likely to be selected. Improving the accuracy of emerging technology costs will help utilities to conduct robust analysis and selection of low-cost technologies in long-term planning.

The utilities used similar cost curves, with costs decreasing 25% to 50% by 2040 depending on the utility and scenario. Table 7 presents reference case capital costs and cost curve scenarios by utility for utility-scale Li-ion batteries. Comparison of reference case capital costs between utilities is difficult because of variation in assumptions, such as interconnection and engineering costs. Where noted, Berkeley Lab estimated reference case capital costs using levelized cost, book life, and after-tax weighted average cost of capital (WACC). Appendix D provides additional details on WACC and levelized costs.



**Table 7. Summary of reference case capital costs and cost curve scenarios for utility-scale Li-ion batteries**

Utility	Reference Case Capital Cost (2020 \$/kW)	Scenario
Hoosier	Redacted	Redacted
IPL	954	Five curves designed to reach +/- 25% and +/-50% of reference case costs in 2038.
Vectren	1,498	Three curves designed as base, lower, and higher. Base cost in 2030 is 70% of 2020 cost; in 2039 it is approximately 56% of 2020 cost.
APS	1,417*	Not provided
DEC	Not provided	Scenarios and cost curve not shared. Capital cost declines by 49% in 2030.
PSE	2,100	“Mid Technology Cost” scenario from NREL cost data, where capital cost declines by 50% by 2050.
SMUD	1,899*	Single cost curve where levelized cost declines by 30% by 2030.
Xcel	3,436*	Three cost curves designed as base, lower, and higher. Base cost in 2030 is 78% of 2020 cost; in 2040 it is 83% of 2020 cost (the cost curve increases after 2030).

\*Estimated reference cost capital cost

## Grid services

For utilities, storage can provide value through services that can be broadly grouped into four categories: energy price (or cost) arbitrage (charging in lower cost periods and discharging in higher cost periods), ancillary services, capacity, and resilience (Table 8). Appendix E provides a detailed mapping of demand-side strategies to grid services and key characteristics.

**Table 8. Battery value to utilities (Berkeley Lab 2021)<sup>3</sup>**

<b>Energy price (cost) arbitrage</b>	Traditional energy price arbitrage
	Day-ahead and real-time price (cost) arbitrage
	Congestion management
	Renewable energy integration
<b>Ancillary services</b>	Frequency regulation
	Operating reserves
<b>Capacity</b>	System resource adequacy
	Local resource adequacy
	Distribution
	Transmission
<b>Reliability and resilience</b>	Backup generation

<sup>3</sup> The term “costs” in Table 8 refers to unit costs and includes prices in ISO/RTO markets, where relevant. The examples are illustrative and not all inclusive.

Table 9 summarizes the grid services each utility modeled in its IRP. All utilities modeled storage for capacity, and several modeled flexibility and co-location with renewables.

**Table 9. Grid services modeled for energy storage**

	Generation: Energy	Generation: Capacity	Ancillary Services	Flexibility	Co-location With Renewables
Hoosier		X			X
IPL	X	X	X		
Vectren		X			X
APS		X			
DEC		X			
PSE		X		X	
SMUD		X			
Xcel		X			

All utility IRPs modeled storage for capacity. IPL also optimized storage for energy arbitrage and Hoosier and Vectren co-located storage with variable renewable energy resources.<sup>4</sup> Vectren and IPL discussed application of storage for flexibility, but did not define flexibility services or explicitly say that it is modeled. IPL used its existing storage system for primary frequency response and “other reliability services” but did not model these technical features and value streams.

Similar to Indiana, the other utility IRPs reviewed discussed other potential uses of storage, but did not explicitly say how storage would be dispatched. For example, Xcel Energy discussed using storage for black start and frequency response, but it is unclear if and how the utility evaluated these grid services in the IRP. While ancillary services (e.g., frequency regulation, operating reserves) could improve the economics of storage, the utilities did not explicitly discuss if these services are modeled for storage.

PSE modeled storage for flexibility by simulating load and generation at 5-minute intervals and simulating market participation at an hourly interval. The utility modeled 2-hour and 4-hour Li-ion batteries as well as 4-hour and 6-hour flow batteries. PSE found that a 4-hour Li-ion battery can provide system savings of \$7.89/kW-yr while a 4-hour flow system can provide system savings of \$1.53/kW-yr (compared to combined-cycle combustion turbine savings of \$0.03/kW-yr) due to avoided ramping up and down of thermal plants. PSE did not explain the difference in savings for systems with identical durations. We believe that it may be influenced by a lower roundtrip efficiency of 73% for flow systems compared to a roundtrip efficiency of 87% for 4-hour Li-ion batteries.

<sup>4</sup> For more information, see Wiser et al. 2020.

It is not clear in the IRPs reviewed if the identified value streams for energy storage were dependent on the amount deployed, or what value streams the utilities included when they modeled hybrid storage systems (e.g., storage plus solar, storage plus wind). The IRPs reviewed did not calculate benefits of other value streams for storage.

A key component of the IRP process is resource adequacy analysis to ensure that the utility procures enough resources to satisfy forecasted future loads. A resource's contribution to resource adequacy is determined by the fraction of its rated capacity that can reliably provide firm generation. To determine the capacity credit of variable resources like wind, solar and storage, utilities can calculate the effective load carrying capacity (ELCC) using probabilistic modeling.<sup>5</sup> The ELCC is dependent on operating conditions, system configuration, and penetration level of other variable resources. The storage ELCC decreases as more storage capacity is added (e.g., the first 500 MW of storage installed having higher ELCC compared to the second 500 MW of storage installed). However, the ELCC of storage increases with higher-duration storage (e.g., a 4-hour system has a lower ELCC than a 6-hour system). or with greater The ELCC of storage also increases with greater renewable penetration. In other words, storage contributes more to resource adequacy with increased battery duration or increased renewable penetration.

The IRPs reviewed did not use a uniform approach to determine capacity credit for energy storage. Among Indiana utilities, Hoosier and IPL did not provide capacity credit values, while Vectren used a fixed value of 95%. IPL stated is considering incorporating dynamic storage ELCCs in future IRPs.

Other IRPs assigned a capacity value to storage as follows:

- DEC calculated a dynamic ELCC dependent on the storage duration, total capacity installed, and solar penetration level (base and high scenarios). The utility also applied three operational modes with varying levels of dispatch commitment for reliability events and economic optimization to compare ELCC values. Values range from 100% to 70% depending on these conditions.
- PSE calculated a dynamic ELCC using its probabilistic Resource Adequacy Model. The model calculates how much capacity with a 100% capacity credit can be replaced by a storage resource while maintaining the same expected unserved energy factor.<sup>6</sup> The ratio of capacities determines the ELCC. PSE's ELCC values are notably lower than DEC, ranging from 12.4% to 35.6% for Li-ion and flow batteries. This is somewhat influenced by PSE having a longer system peak period than is typical of utilities.
- Xcel Energy used a flat ELCC of 100%, noting that a more dynamic ELCC will be explored in future studies.
- SMUD and APS did not provide ELCC values for storage, despite calculating the ELCC for solar and wind.

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<sup>5</sup> Because the ELCC is dependent on how a resource is operated, the calculation is computationally intensive. While there are [multiple methods](#), generally ELCC is calculated by comparing the loss of load expected (LOLE) for a system with and without the storage resource. Load is added to the system with the storage resource until the LOLE is equal to the LOLE of the system without the storage resource. Finally, that load is divided by the storage resource capacity to calculate the ELCC.

<sup>6</sup> "The EUE is the summation of the expected number of megawatt hours of demand that will not be served in a given time period as a result of demand exceeding the available capacity across all hours. EUE is an energy-centric metric that considers the magnitude and duration for all hours of the time period, calculated in megawatt hours (MWh)." [North American Electric Reliability Corporation, 2018, Probabilistic Adequacy and Measures: Technical Reference Report Final.](#)

Of the IRPs reviewed, only DEC and PSE adjusted the ELCC based on storage penetration, storage duration, or the amount of solar penetration.

## Model assumptions

Storage is a relatively new resource modeled in utility IRPs. Models use different built-in assumptions and methodologies for integrating it with other resources. The model a utility chooses affects the outcome of resource optimization.

The reviewed IRPs used several industry-standard capacity expansion and production cost models.<sup>7</sup> Hoosier and Vectren both used AURORA, while IPL used PowerSimm. APS, PSE, and SMUD used both AURORA and PLEXOS, both from Energy Exemplar. AURORA, EnCompass, PLEXOS, and PowerSimm use a stochastic approach. Several of the utilities (IPL, Vectren, APS, PSE, and SMUD) employed both capacity expansion and production cost models (often using the same tool) to address different aspects of planning.

Production cost models can operate at sub-hourly intervals, but that requires additional time and data. Modeling battery dispatch using sub-hourly intervals can potentially capture additional storage benefits, such as fast ramping and energy arbitrage within hours. APS and PSE used sub-hourly modeling. PSE discussed using sub-hourly for modeling storage flexibility and APS applied 5-minute renewable forecasting and dispatch, but they did not discuss in detail how sub-hourly intervals improved storage modeling. All other IRPs reviewed used hourly intervals. Table 10 summarizes modeling approaches for each IRP.

**Table 10. Power system models used in utility IRPs**

Utility	Production Cost Model	Sub-hourly Modeling	Capacity Expansion Model(s)
Hoosier	AURORA	No	AURORA
IPL	PowerSimm	No	PowerSimm
Vectren	AURORA	No	AURORA
APS	AURORA	Yes	Strategist
DEC	SERVM	No	none
PSE	AURORA	Yes	AURORA
SMUD	PLEXOS	No	RESOLVE
Xcel	None	No	EnCompass and Strategist

<sup>7</sup> Capacity expansion models typically use a selection of typical days or weeks per year for optimizing resources for long-term planning. In contrast, production cost models use chronological dispatch at user-defined intervals (e.g., 1 hour, 5 minutes) to model reliability and ancillary services.

As discussed earlier, only PSE considered utility-owned distributed storage as a selectable resource in capacity expansion modeling—specifically, as a substation-level non-wires alternative. The utility did not consider customer-sited, behind-the-meter storage. Other utilities included distributed storage in the planning process through load forecast models, where resource penetration is based on customer adoption. Greater integration of distribution system planning and bulk power system planning would improve valuation of distributed storage.<sup>8</sup>

## Storage adoption outcomes in reviewed IRPs

All of the utilities—except Xcel—included incremental energy storage in their preferred plan and plan to procure more storage in later years (e.g., 2030-2040) when costs are expected to be lower than today. Drivers for adding storage capacity varied for each utility. Carbon tax scenarios drove incremental storage adoption for all of the reviewed Indiana IRPs. Early coal plant retirement scenarios for Hoosier and IPL also resulted in additional storage deployment. Vectren added storage capacity to meet reserve margin requirements and reduce their exposure to potentially volatile market prices.

SMUD's preferred plan included storage procurement in 2030 when it is expected to be cost-competitive with market capacity purchases. Due to cost uncertainty, Xcel did not commit specifically to storage. Instead, the utility plans to procure firm peaking resources from a mix of energy storage, demand response, hydrogen, and other alternatives. PSE and Vectren included both Li-ion and flow batteries in their preferred plans. The utilities distinguished between storage technologies by modeling flow batteries using longer durations (6 and 8 hours) and Li-ion batteries using shorter durations (2 and 4 hours). Table 11 summarizes storage resources included in the IRP preferred portfolios.

The utilities estimated the potential of other storage types (e.g., flow, compressed-air, and pumped storage), but did not include them in their analysis due to cost or commercial infeasibility in most cases. Only Vectren and PSE included technologies beyond Li-ion batteries.

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<sup>8</sup> State and Local Energy Efficiency Action Network 2020.



**Table 11. Energy storage included in utility IRP preferred portfolios**

	Preferred Portfolio	Primary Drivers
Hoosier	25 MW of generic storage added annually in 2035, 2037, and 2039	Meeting summer peak capacity and reliability goals with renewables; 2023 coal plant retirement
IPL	440 MW of 4-hour storage added from 2023-2039, growing in installments annually	Presence of a carbon tax, high natural gas prices, and early retirement of coal plants
Vectren	126 MW of paired 4-hour storage added in 2023 and 50 MW in 2030	Reduced market exposure risk, cost of carbon taxes, reserve margin, and reliability
APS	Three portfolios, each adding 752 MW of storage by 2024 and between 4.1 GW and 9.8 GW of additional storage by 2035	GHG emissions reduction targets and reliance on new renewable generation in place of merchant PPAs
DEC	No preferred portfolio. Storage ranging from 1.05 GW to 7.4 GW by 2035 for a combination of 4-hour and 6-hour standalone and hybrid resources	Adopted carbon taxes, 70% GHG reduction goal, and prohibiting new gas generation
PSE	A combination of Li-ion and flow batteries; 75 MW of storage by 2025, an additional 125 MW by 2030, and an additional 550 MW by 2045.	Improving flexibility with DER penetration, social cost of carbon and carbon taxes, electrification, and 2026 coal plant retirement
SMUD	246 MW of 4-hour storage added in 2030	Competitive costs with capacity market purchases and GHG reduction levels
Xcel	2.6 GW of cumulative firm peaking resources added between 2030 and 2034, agnostic to resource type (e.g., storage, DR, hydrogen)	Retirement of coal plants, carbon reduction goals, and resource adequacy

## Opportunities to improve storage modeling

Based on our review of eight IRPs—three for Indiana and five for other states—Berkeley Lab identified the following opportunities to improve energy storage modeling in IRPs by Indiana utilities. These opportunities also have potential to improve the accuracy and robustness of modeling for other types of resources.

- *Consistency and Transparency.* Use a standard, transparent approach and reporting template to document energy storage cost, adoption, and modeling assumptions in IRP filings. The reporting template could include:
  - Cost component values (e.g., battery module, inverter, balance of system, engineering, procurement, and construction) with sufficient detail to enable IURC staff or stakeholders to reproduce capital cost calculations
  - Description of the logic used to select cost assumptions and evolution of costs over time (e.g., more or less aggressive cost reduction curves)



- Financial benefits—by individual grid service if available—used to determine the economic feasibility of storage (e.g., system reliability and capacity reserve requirements)
- Description of how storage capacity is dispatched for competing grid services (e.g., capacity and balancing reserves)
- If multiple storage technologies are modeled (e.g., lithium-ion and flow batteries), documentation of how modeling approaches capture technical (i.e., non-cost) differences
- *Quantifying Storage Benefits.* Apply additional tools (e.g., sub-hourly production cost models, effective load carrying capacity studies, and resource adequacy models) to more accurately capture resource benefits from storage (e.g., flexibility, ancillary services, and effective load carrying capacity) and other electricity resources, rather than simply use assumed values in capacity expansion models, or omit them entirely. The results of these models could improve the cost-effectiveness of the utility's preferred portfolios by providing a more accurate calculation of value streams and storage dispatch. These additional tools also can be used for improved assessment of resource adequacy and representation of renewable energy sources.
- *Modeling Inputs.* Explicitly model utility and non-utility owned behind-the-meter storage as an input to the IRP model – specifically, adoption levels and operational strategy. The utility should explain in detail the adoption forecast model employed to predict behind-the-meter storage penetration and the model(s) employed to simulate the operational modes. The utility should explain how it aggregates the operational profile of behind-the-meter storage and its impact on net customer load. That includes demonstrating that there is no double-counting of storage capacity in (1) net load forecasts and then as (2) resources.
- *Storage as a selectable resource.* In addition to utility owned storage, integrate customer and third party-owned behind-the meter storage into capacity planning models. Rather than simply reflecting current levels of customer adoption. Treat distributed storage as a resource option in utility capacity planning models to evaluate the economic value of grid services (e.g., frequency support, regulation, peaking capacity) that battery storage can provide under various control strategies.<sup>9</sup> These model results can serve as the basis for related activities, including aligning customer program incentives and rate designs with their economic value to utilities).

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<sup>9</sup> State and Local Energy Efficiency Action Network 2020.

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## Appendix A. Research questions addressed

Berkeley Lab developed a list of questions, organized into six topics, for reviewing the IRPs. Some IRPs did not have sufficient information to address all of these questions.

### Storage resource types

- What types of storage are included, both for utility-scale and distributed applications? What types of storage ownership are included?
- Are hybrid resources (e.g., storage plus solar, storage plus wind, storage plus natural gas) considered? If so, how?
- Is there a screening process for storage technologies in the IRP? If so, what are the basic arguments?

### Utility-scale and distribution inputs and methodologies

- What information and assumptions are used to create forecasts of storage adoption?
- What inputs or methods are used for modeling storage?

### Cost assumptions

- What information, assumptions, and methodologies are used to forecast the cost of battery storage?
- Are costs adjusted based on use case factors (e.g., location, system technology/chemistry, dispatch assumptions)?

### Grid services

- What value streams/grid services are included (e.g., capacity, peak shifting, T&D upgrade deferral, renewable integration, flexibility, volt/var support, reliability, resilience)?
- How are the value streams for each grid service determined?
- Are distribution system benefits considered (e.g., reducing average and marginal line losses)?
- Are value streams adjusted with increasing storage deployment?
- How does the capacity credit of storage change with the size of the storage reservoir?
- Does the capacity credit of storage change with increasing storage deployment?
- How does the capacity credit vary based on the configuration of the hybrid resource?

### Model assumptions

- What dispatch assumptions are applied for storage systems capable of providing multiple grid services?
- How are control and visibility constraints factored into the model?
- How is storage modeled as a competing resource against traditional generation sources of capacity?
- What simulation or optimization approach is used to model storage?
- Are there modeling constraints that are only placed on storage deployed on the utility's distribution system?
- Does the IRP include scenarios with varying levels of distributed or utility-scale renewable energy? If so, how does it affect the quantity of storage selected?
- What factors influence scenarios that include distributed storage compared to those without?
- Are production cost models used in tandem with the capacity expansion model?

## Appendix B. Integrated resource plans reviewed

State	Utility	Analysis Years	Title and Link
Indiana	Hoosier Energy	2021-2040	<a href="#">Hoosier Energy 2020 Integrated Resource Plan – Public Version Volume I: Main Report</a>
Indiana	Indianapolis Power and Light	2020-2039	<a href="#">Indianapolis Power and Light Company 2019 Integrated Resource Plan</a>
Indiana	Vectren	2021-2039	<a href="#">2019/2020 Integrated Resource Plan</a>
Arizona	Arizona Public Service	2020-2035	<a href="#">2020 Integrated Resource Plan</a>
North Carolina and South Carolina	Duke Energy	2021-2035	<a href="#">Duke Energy’s 2020 Integrated Resource Plan</a>
Washington	Puget Sound Energy	2022-2045	<a href="#">2021 PSE Integrated Resource Plan</a>
California	Sacramento Municipal Utility District	2020-2030	<a href="#">Resource Planning Report</a>
Minnesota	Xcel	2020-2034	<a href="#">Upper Midwest Integrated Resource Plan 2020-2034, Supplement</a>



## Appendix C. Additional IRP review notes

### Modeling scenarios by utility

- Hoosier designed scenarios based on the timing of retiring a 900 MW coal-plant and replacing it with a combination of solar, wind, and natural gas.
- IPL's five scenarios combined three factors: the presence of a carbon tax, potential natural gas prices, forecasted load growth, and the amount of DSM programs.
- Vectren modeled five scenarios with many differences, such as regulatory barriers, technology costs, efficiency improvements, electrification, and carbon taxes.
- APS modeled four scenarios with increasing reliance on renewables, storage, and demand-side management for meeting capacity and reliability requirements.
- SMUD modeled three scenarios, primarily testing the various GHG emissions reduction targets.
- DEC modeled six scenarios that varied by presence of carbon policy, timing of coal plant retirements, GHG reduction targets, and primary type of new generation.
- Xcel modeled 15 scenarios categorized broadly as "Early Coal Family," "Early Nuclear Family," and "Nuclear Extension Family." Within these categories, Xcel further applied assumptions for carbon costs, technology costs, electrification levels, load forecasts, power prices, and distributed solar penetrations.
- PSE modeled multiple scenarios based on sensitivities such as gas prices, demand forecasts, electric prices, transmission constraints, carbon costs, emissions reduction goals, and distributed energy resources.

### Base cost and cost curve scenario development by utility

- Hoosier redacted costs and used one cost curve scenario.
- IPL used a blend of sources to determine storage capital and operating costs. The IRP provides a graph that shows capital cost estimates are lower than NREL's 2019 estimates and decline at a faster rate. IPL applied five cost curves based on case assumptions. Cost adjustments are relatively simple, where the curves are based on reaching +/- 25% and +/-50% of reference case costs in 2038.
- Vectren used an average of capital cost data from NREL, Pace, and Burns and McDonnell. The utility adjusted future capital costs using bid price data from its all-source request for proposals. Five scenarios tested low regulation and base case scenarios (using base technology costs) and high technology innovation, high regulation, and 80% CO<sub>2</sub> reduction scenarios (using lower costs). Separate cost curves tested standalone storage and combined solar plus storage.
- DEC used a combination of public and internal capital cost data. The IRP did not include the cost curve used, but stated that storage costs would decline by 49% through 2030.
- PSE used the "Mid Technology Cost" scenario from NREL's cost data. This cost curve represents capital costs for standalone storage declining by approximately 50% in 2050. The cost decline is less for solar plus storage, approximately 30%.
- SMUD used a single cost curve from the consulting firm E3. The levelized installed cost declines by approximately 30% by 2030.



- Xcel developed three cost curves based on NREL data, using lower and higher price forecasts. Base levelized cost is 78% of 2020 in 2030 and 83% in 2040, where the cost curve increases after 2030.
- APS did not include cost curve data.

## Utility IRP modeling approaches

- Hoosier modeled hourly dispatch of scenarios using AURORA's stochastic module to generate multiple probabilistic outcomes and determine portfolio risk. The utility modeled blocks of 25 MW energy storage units. The IRP did not state the duration of the storage modeled. Hoosier did not provide details about how storage is integrated into AURORA.
- IPL used PowerSimm for stochastic capacity expansion and production cost modeling. PowerSimm uses a battery module (BatterySimm) to model hourly storage dispatch optimization separately and then integrate the results into the full resource portfolio. While sub-hourly dispatch is available, IPL did not use it. The utility modeled 20 MW, 4-hour blocks of storage.
- Vectren used AURORA for capacity expansion and hourly dispatch modeling, using stochastic modeling in addition to deterministic modeling of scenarios. The utility did not provide details about how storage is integrated into AURORA.
- APS used Strategist for capacity expansion modeling and AURORA for production cost modeling. While other utilities used AURORA, APS's IRP is the only one we reviewed that used sub-hourly capabilities by re-dispatching storage for energy arbitrage every 10 minutes.
- DEC used SERVM for production cost modeling. SERVM can model storage resources in three modes: reliability dispatch only, mixed reliability and economic arbitrage, and third-party ownership with economic optimization only.
- PSE used AURORA for capacity expansion and hourly dispatch modeling. PSE also utilized PLEXOS for modeling sub-hourly capabilities of storage flexibility. Sub-hourly modeling demonstrated the additional value of storage and, thus, the importance of modeling storage at sub-hourly intervals to capture its full value.
- SMUD used RESOLVE for preliminary capacity expansion modeling and PLEXOS for production cost modeling.
- Xcel used both Strategist and EnCompass for capacity expansion modeling. Strategist uses a load duration curve for selecting resources, while EnCompass uses hourly dispatch using a simplified dispatch approach compared to production cost models. While Strategist prioritizes resource adequacy, EnCompass better captures resource flexibility and yields a more diverse set of preferred resources, including energy storage.

## Appendix D. Summary of storage costs for utility-scale Li-ion batteries

The table shows storage costs reported in the utility IRPs reviewed. SMUD and Xcel only reported levelized cost. Berkeley Lab estimated SMUD’s and Xcel’s reference cases for capital costs by using the utility’s reported book life and after-tax weighted average cost of capital (WACC) for energy storage.

### Summary of reported storage costs

Utility	Reference Case Capital Cost (2020 \$/kW)	Levelized Cost (\$/kW)*	WACC
Hoosier	Redacted	Redacted	Not used
IPL	954	—	Not used
Vectren	1,498	—	Not used
APS	1,417*	—	7.57%
DEC	Not provided	Not provided	Not used
PSE	2,100	—	Not used
SMUD <sup>10</sup>	1,899	210/year**	9.13%
Xcel	3,436	20.04/month**	6.47%

\*Estimated from reported value of \$1,225, where APS represented costs in year-2022 dollars.

\*\*Levelized over 20-year book life

<sup>10</sup> SMUD did not report WACC and book life values, so reported values from the California Public Utilities Commission’s [2019-2020 IRP](#) were used.

## Appendix E. Mapping demand-side management strategies to grid services

Demand-Side Management Strategies	Grid Services	Description of Building Change	Key Characteristics		
			Typical duration	Load change	
<b>Efficiency</b>	Generation: Energy Generation: Capacity T&D: Non-Wires Solutions	Persistent reduction in load. Interval data may be needed for measurement and verification purposes. This is not a dispatchable service.	Typical duration	Continuous	
			Load change	Long-term decrease	
			Response time	N/A	
			Event frequency	Lifetime of equipment	
<b>Shed Load</b>	Contingency Reserves	Load reduction for a short time to make up for a shortfall in generation.	Typical duration	Up to 1 hr	
			Load change	Short-term decrease	
			Response time	<15 min	
	Generation: Energy Generation: Capacity T&D: Non-Wires Solutions	Load reduction during peak periods in response to grid constraints or based on TOU pricing structures.	Event frequency	20 times per year	
			Typical duration	30 mins to 4 hrs	
			Load change	Short-term decrease	
Response time	30 min to 2 hrs				
Event frequency	<100 hrs per yr/seasonal				
<b>Shift Load</b>	Generation: Capacity T&D: Non-Wires Solutions	Load shifting from peak to off-peak periods in response to grid constraints or based on TOU pricing structures.	Typical duration	30 mins to 4 hrs	
			Load change	Short-term shift	
			Response time	<1 hour	
			Event frequency	<100 hrs per yr/seasonal	
	Contingency Reserves	Load shift for a short time to make up for a shortfall in generation.	Typical duration	Up to 1 hr	
			Load change	Short-term shift	
			Response time	<15 min	
	Avoid Renewable Curtailment	Load shifting to increase energy consumption at times of excess renewable generation output. This is not a dispatchable service but can be reflected through TOU pricing.	Event frequency	20 times per year	
			Typical duration	2 to 4 hrs	
<b>Modulate Load</b>	Frequency Regulation	Load modulation in real time to closely follow grid signals. Advanced telemetry is required for output signal transmission to grid operator; must also be able to receive automatic control signal.	Load change	Short-term shift	
			Response time	N/A	
			Event frequency	Daily	
	Voltage Support		Load modulation to offset short-term variable renewable generation output changes.	Typical duration	Seconds to minutes
				Load change	Rapid increase/decrease
				Response time	<1 min
	Ramping		Distributed generation of electricity to dispatch to the grid in response to grid signals. This requires a generator or battery and controls.	Event frequency	Continuous
				Typical duration	Subseconds to seconds
				Load change	Rapid increase/decrease
Response time	Subseconds to seconds				
Event frequency	Continuous				
<b>Generate</b>	Ramping	Distributed generation of electricity to dispatch to the grid in response to grid signals. This requires a generator or battery and controls.	Typical duration	Seconds to minutes	
			Load change	Rapid dispatch	
			Response time	Seconds to minutes	
	Generation: Energy Generation: Capacity T&D: Non-Wires Solutions		Distributed generation of electricity for use on-site and, when available, feeding excess electricity to the grid. This is not a dispatchable service, though metered data is needed.	Event frequency	Daily
				Typical duration	30 mins to 4 hrs
				Load change	Dispatch/negative load
	Response time		<1 hour		
	Event frequency		<100 hrs per yr/seasonal		
	Generation: Energy Generation: Capacity T&D: Non-Wires Solutions		Distributed generation of electricity for use on-site and, when available, feeding excess electricity to the grid. This is not a dispatchable service, though metered data is needed.	Typical duration	Entire generation period
Load change		Reduction/negative load			
Response time		N/A			
Event frequency	Daily				

Source: Table 2. Neukomm, M., V. Nubbe, and R. Fares. 2019. Grid-interactive Efficient Buildings Technical Report Series: Overview of Research Challenges and Gaps. U.S. Department of Energy. <https://www1.eere.energy.gov/buildings/pdfs/75470.pdf>