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Comparing the economic value of lithium-ion battery technologies in the nine wholesale electricity markets in North America

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ABSTRACT
Lithium-ion batteries are becoming critical flexibility assets in future electric power systems. Batteries can arbitrage price differences in wholesale electricity markets to make a profit while at the same time reducing total system operating costs and improving renewable energy integration. However, lithium-ion batteries have a limited lifetime due to capacity degradation, and one battery pack can only make a limited profit before reaching its end-of-life. In this paper, we screen the profit potential of Lithium iron phosphate (LFP), nickel manganese cobalt (NMC), and lithium nickel cobalt aluminum oxides (NCA) batteries in all nine wholesale electricity markets in North America. We apply a systematic dynamic valuation framework that finds the highest revenue potential for the considered lithium-ion battery project subjecting to its degradation mechanism, while the degradation model used in the valuation is derived based on real lab test data over varying cycle conditions. The study found that battery valuation depends largely on battery technology and storage duration and varies across operational locations. Moreover, the study revealed that calendar life has a greater impact on battery valuation than cycle life for an 8-years calendar life scenario while cycle life shows greater impact for a 15-year calendar life scenario for all battery technologies. This impact is more pronounced in LFP than in NMC and NCA. The study recommends battery operators consider strategies that would maximize a longer cycle life or calendar life usage of a battery as this would accumulate higher profits over its lifetime.

KEYWORDS
Battery energy storage, degradation, power system economics.

Until a significant breakthrough is achieved in the cost of battery energy storage systems (BESS), efficient strategies that guarantee its economical operation in grid services remain the most viable option. In most regions of the world that have deregulated power systems, the participation of BESS in electricity markets is a must to accommodate heavy penetrations of intermittent renewable power generation and is more dominant than transmission investments[1]. Understanding the value of various BESS technologies through market participation is critical for investments and market planning.

In deregulated power systems, private entities deploy BESS to earn profits by strategically operating the battery in electricity markets[2,3]. Naturally, the cost of battery cells is the most compelling factor for planning a BESS project[4]. Yet, the cell cost becomes sunken after the BESS investment decision and should not be considered in the BESS operation[5]. Due to the absence of fuel cost, a BESS market operation strategy should consider the internal technology characteristics, including efficiencies and degradation rates, and the external market environment. Moreover, as it is in most deregulated states, investments risks on generation facilities are shifted to the suppliers rather than to the customers as in regulated systems because the regional transmission organizations (RTO) or the independent system operators (ISOs) use markets conditions to determine which generation plant is a better option at that point in time. Therefore, a storage participant who is an important supplier in such markets should understand the market-price determining condition and factors in the storage planning and operation.

While battery energy storage finds various applications in power systems, price arbitrage is becoming the predominant application, especially for future storage deployments. Other grid services, such as frequency regulation or operating reserves, have limited market capacity[6] and are not designed to balance renewable energy or reduce the cost of electricity. Hence based on market sizes and market objectives, future storage must participate in energy markets and provide price arbitrage in a decarbonizing power system. In the USA, arbitrage is becoming the primary application for storage. A recent report, EIA report[7], concluded that storage applications for price arbitrage had witnessed unprecedented growth. The report noted that out of the Unites States' 4600 MW capacity utility-scale battery in 2021, about 59% went into price arbitrage which was a 17% increase from the value in 2019 (Figure 1), and CAISO[8] mentioned that 80% of its battery capacity in 2021 alone went on arbitrage. This provides a good motivation for more research in arbitrage application for batteries especially as this is likely the main application for future battery deployments.

This paper conducts a forward-looking study on the valuation of three commercial lithium-ion battery technologies in conducting price arbitrage in nine wholesale electricity markets in North America. While there are ubiquitous models in the literature where the applications of BESS are specifically focused on energy markets[9–14], few have systematically investigated how technology characteristics and market environments would jointly impact the economic value of a BESS project, especially considering capacity degradation mechanisms in different BESS technologies. BESS has negligible immediate operating cost while the impact from capacity degradation is not apparent to observe but has a long-lasting

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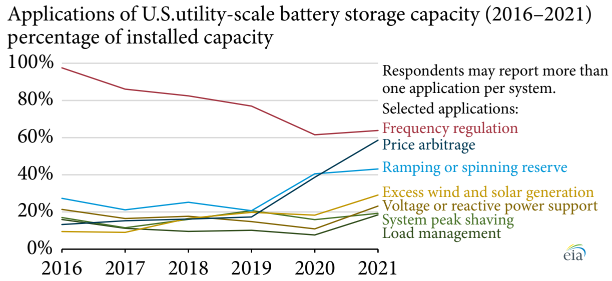


Fig. 1 Application of utility-scale battery storage capacity in United States 2016–2021 [7]**.**

impact over storage lifetime and future profit potentials. In this context, this paper employs a systematic valuation framework based on dynamic programming and compares three types of commercial lithium-ion battery technologies using real degradation test data and market price data. The results reveal the locational-specific economic value of various battery technologies which not only guide future BESS deployments but also provide insights into the development of potential long-duration storage technologies.

The remainder of this paper is organized as follows: Section 1 presents the previous related work from the literature, Section 2 describes the implemented battery valuation framework, Section 3 discusses the price data and battery data and their performance metrics. The simulation results are discussed in Section 4, and Section 5 concludes the paper.

1 Literature review

This section presents the characteristics of battery storage. We first discuss the different types of lithium-ion battery technologies and then review the types of models adopted for their valuation in electricity markets.

1.1 Battery storage technology

The major component of BESS is made of electrochemical cells, which work on converting chemical potential (when charging) to electrochemical potential (when discharging). There are many battery technologies with varying design and operating characteristics[15], and their usage depends largely on the application for which the battery will be used. Factors to be considered when selecting a battery technology for a particular purpose include cost, power density, energy density, longevity (calendar life), cell voltage, temperature tolerance, etc. Among the several available battery technologies, the lithium-ion (Li-ion) battery becomes the most popular battery technology for grid deployments in recent times. It has many advantages such as lightweight, high density, long cycle life, low self-discharge rate, and stable voltage curve compared to lead acid or nickel-based batteries[16]. Also, phosphate-based lithium batteries are considered the safest and offer a higher maximum discharge rate than nickel-based and lead-acid batteries[17].

Lithium iron phosphate (LFP), lithium nickel cobalt aluminum oxides (NCA), and nickel manganese cobalt (NMC) have emerged as the most commonly used[18] lithium-ion battery technologies. While these batteries have fully capable of providing a wide range of grid services, there is a serious concern about the limited lifetime of Li-ion batteries because of capacity degradation[19], which consequently limits the life-cycle value and revenue potentiality of a battery pack before its end-of-life. The end-of-life of lithium-ion batteries is usually defined as when a battery is degraded to 60% to 70% of its rated capacity. At this point, the battery will no longer be safe or economical to operate due to accelerated capacity loss and impedance increase[20]. Research is ongoing on how to develop new battery technologies, to improve the performance of existing ones and make them cheaper than they are now. Yet, in this paper, we focus on these three commercial Li-ion battery technologies: LFP, NMC, and NCA, with the scope to screen their economic value in North American wholesale electricity markets.

1.2 Lithium-ion battery models in electricity market studies

Battery valuation in power systems for energy arbitrage and ancillary services has been studied in the literature[21–24]. One such study[23] shows that the operational value of battery storage increases with an increase in renewable penetration in the energy market. Also, a similar study[21] determines the value of energy storage arbitrage across European markets and found that the value of energy storage becomes reduced as the market becomes more efficient with storage integration. Studies have also revealed that the economic value of battery storage could further be incentivized by analyzing and incorporating the historical prices of the energy market in the valuation process[25]. This means that there are yet many untapped values in the storage participating in the electricity markets and further research is needed to explore all possible options to earn higher economic values for the storage. Besides, studies are confirming that trade-offs between revenue and energy storage lifetime could be achieved by changing the operational pattern of the storage[11,26,27]. Specifically, increasing cycle life and calendar life of a battery has been found to critically affect the total revenue potential in the present worth[11]. Also, for bulk distribution storage deployed in the UK grid, times duration of 6 hours and 24 hours have proven to have a strong impact on both the system value and market value, respectively [28].

Researchers have employed models of various complexities to study the economic value of Li-ion batteries in grid applications[29,30]. To maximize the operational revenues or to economically optimize the sizing and placement decisions of Li-ion batteries in grid applications, optimization models include short-term and long-term operation of the batteries as well as certain constraints associated with market opportunities[31–36]. The simplest model for evaluating battery economic performance is the energy throughput[37], but has the limitation of not being able to accurately model capacity degradation caused by different cycle ranges or state-of-charge levels[38,39]. Prior studies that compare various degradation models have concluded that more accurate degradation models provide higher life-time revenue but also require significantly more computing power[38–41].

More importantly, the degradation effect also affects battery valuation, it limits the battery's value over its lifetime due to cycle and calendar degradation[20,39,42]. Strategic models as approximate models can significantly reduce the losses through co-optimization of degradation with storage arbitrage and ancillary services leading up to 36% profit improvement[42]. In contrast, studies[33,43,44] that consider more accurate operation scenarios and battery parameters often overlook the particular technology of lithium battery adopted and the associated complex degradation mechanisms. Clearly, there are limited works in the literature that have critically evaluated the values of lithium-ion batteries in the energy market, most especially considering battery technology parameters, market arbitrage price, and market locations. This study identifies and fills those gaps.

1.3 Contribution highlights

While many studies considered grid revenue services and revenue streams of storage in battery storage valuations, they ignore the revenue potential of storage in different wholesale markets, considering sizes of generation mix that significantly impact the operational modes of the storage. Moreover, the literature lacks studies that directly compare the valuation potential of the popular lithium battery technologies in wholesale markets while considering cycle degradation and calendar degradation. To this effect, the contribution in this study are highlighted as follows:

- The study implements a dynamic valuation framework that finds the highest revenue potential of battery energy storage in arbitrage applications considering storage duration.
- The proposed valuation framework is applied to three lithium battery technologies, LFP, NMC and NCA, and rigorously compares their relative performance.
- The framework is tested in all nine wholesale electricity markets in North America so that the performance of each battery technology is screened across all the locations using the historical real-time locational marginal price or zonal price.
- The framework considered cycle and calendar degradation of each battery technology to ensure the accuracy of the battery valuation results.
- The study quantitatively measures and compares the impact of a small increase in cycle life and calendar life separately in the marginal value of lifetime improvements in terms of increase in battery valuation for each technology.

2 Battery technology valuation framework

2.1 Dynamic valuation formulation

The study adopts a systematic dynamic valuation framework[45] (see Figure 2)that finds the maximum revenue potential of the lithium battery project when subjected to its degradation mechanism. The valuation framework adopts dynamic programming and records the opportunity value function of the battery state-of-health (SoH), which represents the expected revenue the battery could collect throughout the rest of its lifetime, after which the battery can no longer perform price arbitrage, given the current SoH. The strategy ensures that the battery is optimized according to the daily revenue income and cost of degradation. This valuation framework is recursively defined as follows

$$V_n(E_n) := \max_{\boldsymbol{p}_n \in P(E_{n+1})} O_n(\boldsymbol{p}_n) + \gamma V_{n+1}(E_{n+1}) \tag{1}$$

$$E_{n+1} = E_n - D_{\mathrm{cyc}}(\boldsymbol{p}_n) - D_{\mathrm{cal}} \tag{2}$$

in which V_n represents the economic opportunity value of the remaining battery capacity over day n, O_n represents the daily revenue, $\boldsymbol{p}_n$ is the battery operation profile over day n, and γ is the daily discount ratio. E_{n+1} is the remaining battery capacity (SoH) at the end of day n (also the start of day $n+1$). Constraint $\boldsymbol{p}_n \in P(E_{n+1})$ represents that the storage operation depends on the battery energy capacity E_{n+1} which we treat as a variable in this framework to model the impact of degradation. Eq. (2) models the degradation model, the energy capacity E_{n+1} at the beginning of day $n+1$ equals to the capacity E_n from day n minus the cycle degradation $D_{\mathrm{cyc}}(\boldsymbol{p}_n)$ which depends on the storage operation profile, and the calendar degradation D_{cal}. Appendix Al shows the complete formulation of the valuation framework used in this study.

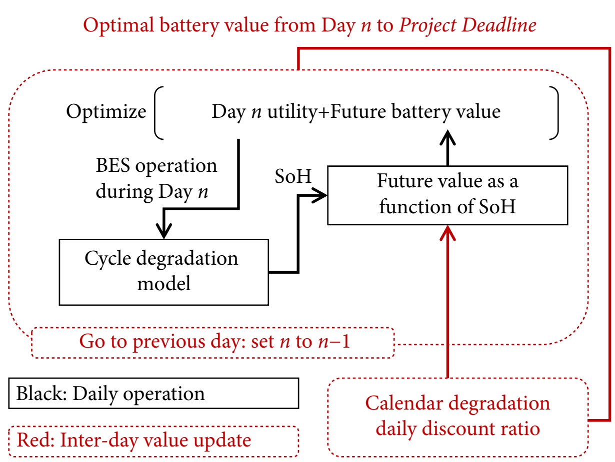


Fig. 2 The dynamic battery valuation framework. This framework works backward and keeps updating a value function to battery SoH. This function represents the value of the remaining battery SoH from the end of the current operating day till the project deadline, at which the battery has no more arbitrage value. On each operating day, the battery is optimized according to daily revenue income and the change in the battery SoH, based on a cycle degradation model. The result of this optimization is assembled into the new battery future value function, and this framework works recursively backward to evaluate the battery lifetime across the entire project duration.

2.2 Synthesis of battery economic value

We synthesize the economic value of batteries using historical electricity price data. We use D_{cyc} in Eq. (2) to model the cycle degradation mechanism of different battery technologies. $P(E_{n+1})$ models battery operation parameters such as efficiency and power ratings, and the electricity price data goes into O_n. We perform the valuation for each calendar year to capture the annual variation of battery value. Because batteries have a calendar life of around eight years and that one year of price data is not enough to capture the value of the full battery lifetime, we use a resampling approach in which we repeat the annual price profile to the same length of the battery calendar life. In this way, we calculate the full economic value of the battery lifetime, assuming electricity prices follow the same pattern in the target year. Therefore, we calculate a unique battery economic value for each combination of battery technology, energy duration, location, and calendar year. Appendix A3 describes the detailed battery value synthesis procedure, including a piece-wise linear approximation method to solve the dynamic programming storage valuation problem.

3 Data description

3.1 Electricity market data description

The major data used for the simulation in this study are the ISO energy price data collected across some of the locations or zones of all nine ISO/RTOs in North America, shown in Figure 3. We select zonal or locational price data based on the availability of the price data in different markets. Details about the data prices from each location are itemized below.

- **CAISO:** The California Independent System Operator (CAISO) has three locations. The locations include Walnut, Westlands, and Whitmore. All three locations have been selected for this study, and the duration of the price data is between 2016 and 2021.
- **AESO:** The Alberta Electric System Operator (AESO) provides a single system-wide price. The AESO price data duration is between 2010 and 2021.
- **IESO:** The Independent Electricity System Operator (IESO) maintains system-wise pricing like AESO. The data used is between 2011 and 2021.

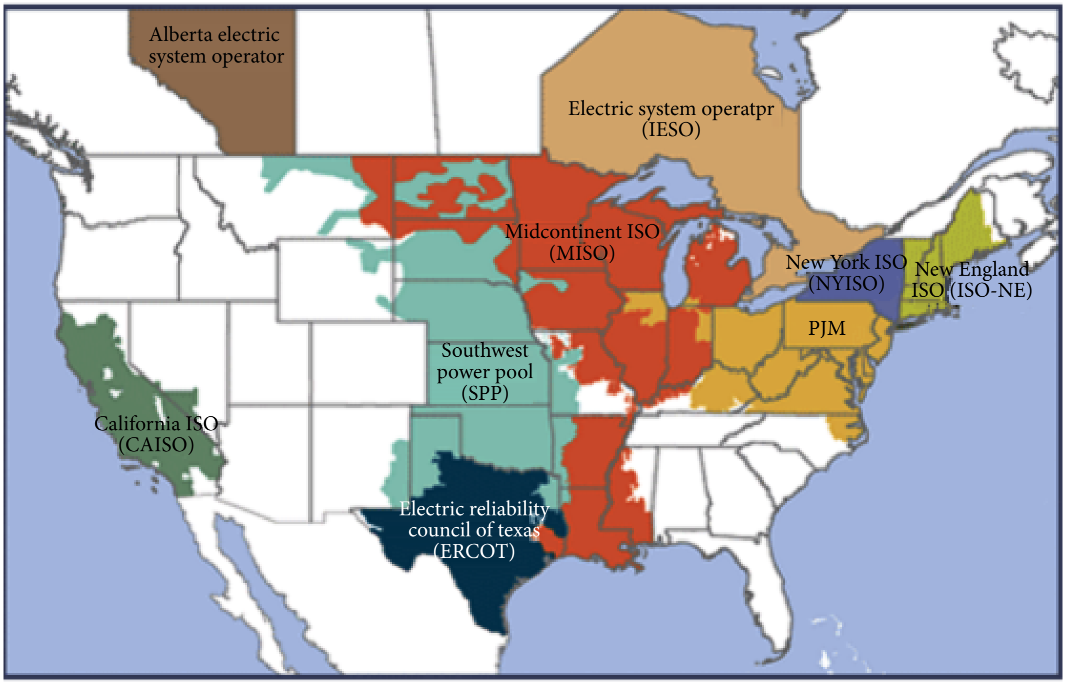


Fig. 3 Location of the nine ISO/RTOs in the United States.

- **ERCOT:** The Electric Reliability Council of Texas (ERCOT) provides East and West zonal price data. Both zones have been considered for this study with price data set ranges between 2013 to 2021.
- **NYISO:** Four price zones are chosen from the New York Independent System Operator (NYISO): LONGIL, NORTH, WEST, and NYC. All four zones have their price data range between 2010 to 2021.
- **SPP:** The South West Power Pool (SPP) provides North and South zonal prices. The range of the data used is between 2011 and 2021.
- **ISONE:** Only one zonal price node (Boston) is used for the Independent System Operator New England (ISO-NE) because of low congestion within the system. The considered data range from the year 2014 to 2021.
- **MISO:** The Mid-continent Independent System Operator (MISO) operates across 15 U.S. states and the Canadian province of Manitoba. Four price zones are included in this study: Illinois, Louisiana, Michigan and Minnesota. The data from MISO range from 2014 to 2021.
- **PJM:** The PJM stands for Pennsylvania, New Jersey, and Maryland. Price nodes in PJM are collected from PENELEC, JCPL, AECO, RTM and PEPCO from the year 2014 to 2021.

Furthermore, we present the percentage system energy generation by type for all nine ISOs in 2020 in Table 1. The table highlights the energy share by percentage of some selected generation types. There are other energy type such as geothermal, biomas/biogas, GAS-CC, etc which are not reported here because they are not peculiar to all nine ISOs. However, the report shows total generation reported at the end of year 2020, thus an increase/decrease within the previous or year after is not reflected.

3.2 Battery model and data description

3.2.1 *Cycle life*

Table 2 shows the equivalent full cycle (EFC) of LFP, NMC and NCA upon reaching 80% capacity under different cycling conditions from lab cell tests[46]. One EFC means the battery cumulatively charged and discharged energy equal to its rated energy capacity. The table shows that the cycle life of all three battery technologies decreases with wider cycle ranges. At all cycling conditions, LFP has significantly higher EFC than NMC or NCA.

3.2.2 *Power degradation*

Our study does not model the impact of storage power over battery degradation or the impact of degradation over the storage power rating. Our study solely focuses on grid-scale storage with a C-rate ranging from 0.25 (4-hour duration) to 1 (1-hour duration), while recent real-world deployment data shows most grid-scale battery storage projects are with 4-hour durations[8]. On the one hand, data from battery degradation experiments[46,47] have shown that power variation under low C-rates has negligible impacts on battery degradation rate. On the other hand, the low C-rate power will also not be impacted by power degradation.

3.2.3 *Round trip efficiency*

The round-trip efficiency (RTE) is the ratio of the discharge energy to the charge energy of the storage, which also reduces as

Table 1 Percentage system energy generation by fuel type in 2020

ISO	Energy type/percentage share					
	Wind	Solar	Hydro	Nuclear	NG/oil	Coal
CAISO	8	15	10	9	48	0
AESO	13	4	6	0	46	16
SPP	29	0	4	2	39	24
ERCOT	23	4	0	11	43	18
MISO	3	0	3	9	45	36
IESO	9	2	24	57	6	0
PJM	3	1	2	34	38	38
NYISO	5	1	23	29	43	0
ISONE	3	3	7	27	46	1

Table 2 EFC and RTE of three lithium battery technologies at different cycling conditions [46]

	Cycle range	EFC to 80% SoH	RTE (100% SoH)	RTE (80% SoH)
LFP	40%–60%	7795	97	97
	20%–80%	7192		
	0–100%	6369		
NMC	40%–60%	2056	95	95
	20%–80%	1554		
	0–100%	390		
NCA	40%–60%	1428	91	87
	20%–80%	605		
	0–100%	143		

the battery degrades [48,49]. The RTE of the three considered battery technologies when new and at the 80% SoH are included in Table 2. The LFP presents a higher RTE than NMC and NCA at all cycling conditions. Also, the LFP technology has its RTE unchanged when its capacity decreases from the initial value to 80%. The modeling of the change in the efficiency of the battery with respect to this study is described in Appendix A2.

3.2.4 Calendar life

The calendar life of a battery describes its degradation over time, while the cycle life describes the degradation of the battery due to charge/discharge action. The calendar life likely determines the lifetime of a battery cycled less frequently[11,50]. While our data source for cycle life and efficiency did not provide explicit data on the calendar life, we assume the battery technologies have a calendar life between eight years to fifteen years to reach 70% of remaining capacity at 25 Celsius, estimated based on relevant literature[51,52].

3.2.5 Storage duration

Another important battery metric is its storage duration. The storage duration is the time storage takes to fully discharge at its rated power capacity. For example, a 1 MW battery power capacity can provide 1 MW discharge power for 2 hours if its energy capacity is 2 MWh. It is necessary to consider the right storage duration for specific applications given high cost of battery cells[53]. In this study, we select one-, two-, and four- hour storage duration for each battery technology to study the impact of duration across all ISO locations or zones.

4 Results

This section presents the simulation results and compares battery economic values across location, duration, and technology.

4.1 Synthetic battery value results

We compare battery technology valuation results across the nine system operators. Figure 4 shows the valuation result for 4-hour, 2-hour and 1-hour batteries assuming eight or fifteen years of calendar life. Each bar represents the average battery value over all sampled years and locations from the same ISO/RTO, whiskers represent the minimum and maximum values across sampled years and locations from each ISO/RTO.

Figure 4 shows that the battery value varies significantly for different technologies in the same market and also for the same technology in different markets. For all battery technologies, AESO, ERCOT, CAISO, NYISO, and SPP recorded the top five valuations. These five ISO/RTOs also have higher shares of wind and solar generation compared to others. LFP yields the highest valuation due to having a significantly higher cycle life, while NMC produced higher values than the NCA. Given that the costs of all three battery technologies are similar[54], the results recommend LFP as the best technology for building grid-scale energy storage.

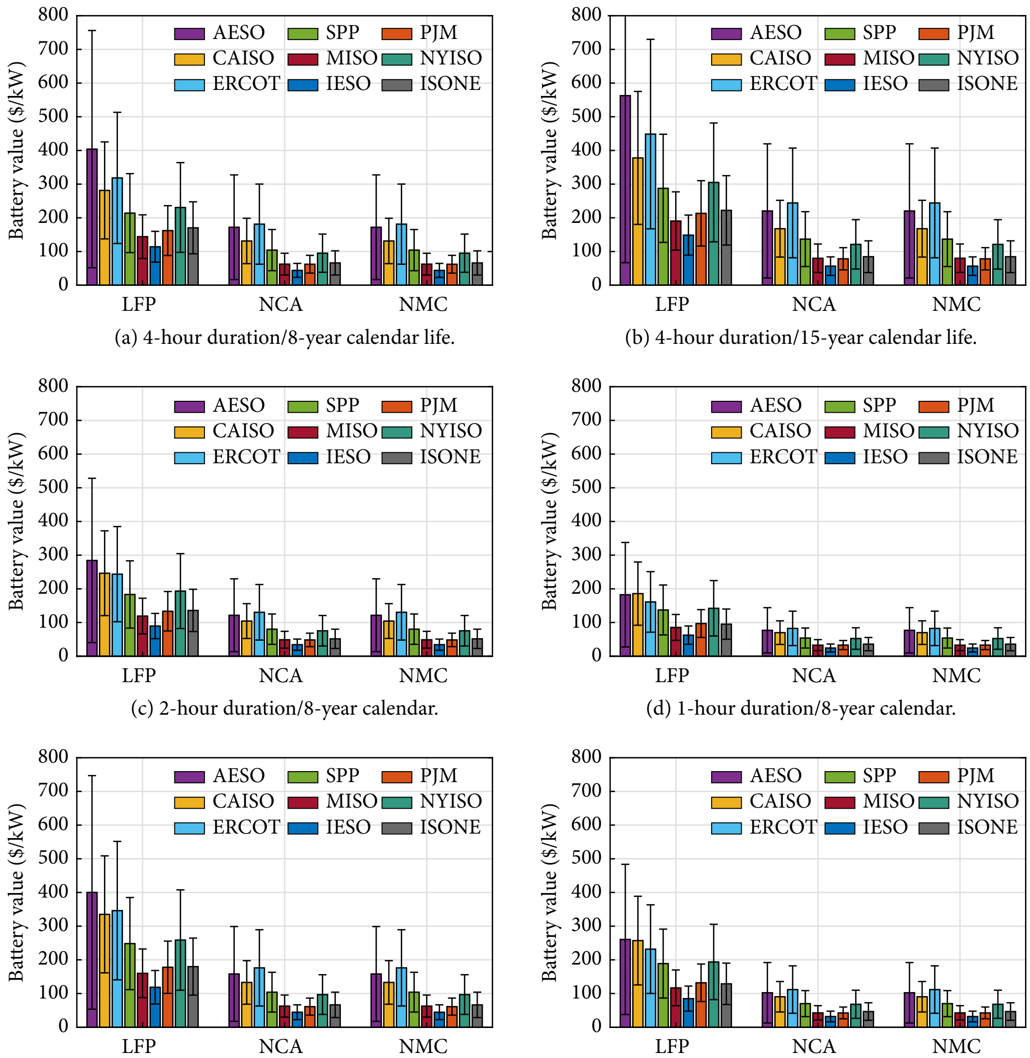
Conversely, NMC and NCA still achieved considerable value, around 50% compared to LFP, although their cycle life is only around 20% of LFP. This result suggests a saturation effect in storage cycle life that the value added from higher cycle life diminishes. The duration of energy storage shows a similar saturation effect. While a longer duration provides more storage value per kW of power capacity, the increments in value are not proportional to the duration increase.

We further compare Figures 4(a) and 4(b) to see the effect of range in battery calendar life on its valuation assuming 70% of the battery capacity remains between the calendar life of 8–15 years. By extending the calendar life of the batteries from eight years to fifteen years, there is about a 45% increase in storage value in LFP and about 30% each in NMC and NCA. Similar trend is observed for the 2-hour duration batteries (Figures 4(c) and 4(e)) as well as the 1-hour duration batteries (Figures 4(d) and 4(f)). However, this may not be the case if the battery is cycled more frequently in the fifteen years case than in the eight years case. Thus, we recommend that storage operators design their battery operational strategies in such a way that would guarantee longer life usage of the battery as this would accumulate higher profits over its lifetime.

Furthermore, Figure 4 shows that a trade-off option exists between calendar life and storage duration. For example, the valuation recorded in the 2-hour duration/15-year calendar life storage in Figure 4(e) is almost at par with the values recorded in the 4-hour duration/8-year calendar life storage in Figure 4(a). Also, the 2-hour/8-year calendar life case (Figure 4(c)) is almost at par with the 1-hour/15-year calendar life case (Figure 4(f)). Moreover, the valuations in the 2-hour/15-year calendar (Figure 4(e)) are about twice the valuation results in the 1-hour/8-year calendar life case, Figure 4(d). This shows that both storage duration and calendar life significantly contribute to battery valuation and it is possible to trade off one for the other for higher storage valuation. Finally, the value comparisons across markets are different across battery technologies and duration due to battery technologies having distinct cycle degradation mechanisms: the LFP battery has stable cycle life across all cycle depth ranges. In contrast, NMC and NCA batteries have significantly higher degradation rates at deep cycles, as shown in Table 2. These results suggest the importance of considering the unique combination of market price behaviors and storage degradation mechanisms in the storage valuation process.

4.2 Comparative analysis of battery duration

In Figure 5, we show the ratios of battery valuation between hour duration for all three battery technologies. We compare the performance of the batteries across all locations with respect to the duration of their operations. The trends in the figure depict valuations in the 1-hour duration exceed 55% of the valuations in the 4-hour duration for all three battery technologies and across zones except for LFP and AESO where it is about 42%. Similarly, valuations recorded in the 2-hour duration are in the average of 80% of the values recorded in the 4-hours duration for all zones except for AESO, which has about 72%. A cross-comparison between the 1-hour and 2-hour duration valuation to the 4-hour duration shows that there is a 25% gain in profits by increasing the time of participation of any of the batteries from 1-hour to 2-hour. We further analyze that, irrespective of the zones of operation,



(a) 4-hour duration/8-year calendar life.
(b) 4-hour duration/15-year calendar life.
(c) 2-hour duration/8-year calendar.
(d) 1-hour duration/8-year calendar.
(e) 2-hour duration/15-year calendar life.
(f) 1-hour duration/15-year calendar life.

Fig. 4 Synthesis of battery value estimation per kW battery storage capacity assuming: (a) 4-hour duration/8-year calendar life, **(b)** 4-hour duration/15-year calendar life, and **(c)** 2-hour duration/8-year calendar life, **(d)** 1-hour duration/8-year calendar life, (e) 2-hour duration/15-year calendar life, **(f)** 1-hour duration/15-year calendar life.

there are no significant valuation benefits based on time duration differences if an operator switches from one battery technology to another.

4.3 Marginal value of lifetime improvements

We study the impact of an increase in the battery lifetime on the battery value. In the simulation, we increase the battery lifetime in two ways:

- Increase the cycle life, the number of cycles the battery can perform over its entire life.
- Increase the calendar life, the period after which the battery has reached its end-of-life.

We increase the cycle life and the calendar life of the battery by 1% of its nominal characteristics and re-calculate the value for each technology. We then calculate the percentage increase of the battery valuation due to the change in the cycle life and calendar life. This is performed for the four areas belonging to the NYISO operator (NYC., LONGIL, WEST, NORTH) and all battery technologies; see Appendix A5.

The average increase across the four locations of the NYISO for the three battery technologies is depicted in Figures 6(a) and 6(b) for 8 years of calendar life and 15 years of calendar life, respectively. Figure 6(a) shows that, for an 8 years calendar life, an increase in calendar life has a greater effect on battery valuation than cycle life with the same percentage increase in both. Indeed, a 1% increase in calendar life resulted in nearly 0.45% for NCA and above 0.50% for LFP. Besides, due to a 1% increase in cycle life, an approximate 0.40% is observed for NMC and NCA, and only about 0.38% increase is observed in LFP. The performance of LFP is observed to surpass other technologies here with a greater impact due to calendar life than cycle life compared with NCA and NMC. Figure 6(b) revealed that the impact of cycle life becomes more significant for a battery of longer calendar life. The impact of cycle life is more than 50% greater than the impact of calendar life on battery value for the 15 years calendar life case in LFP and NMC, and it is about 20% in NCA. Without loss of generality, we could imagine what would be the difference in battery valuation if the increased margin were to be around 10%, 50%, or 100%. According to Table 2, each battery technology has a full cycle capacity limit based on cycling conditions. This means that, for optimal operation of the batteries, there is a limitation to what extent the cycle life could be ranged[46]. Based on this observation,

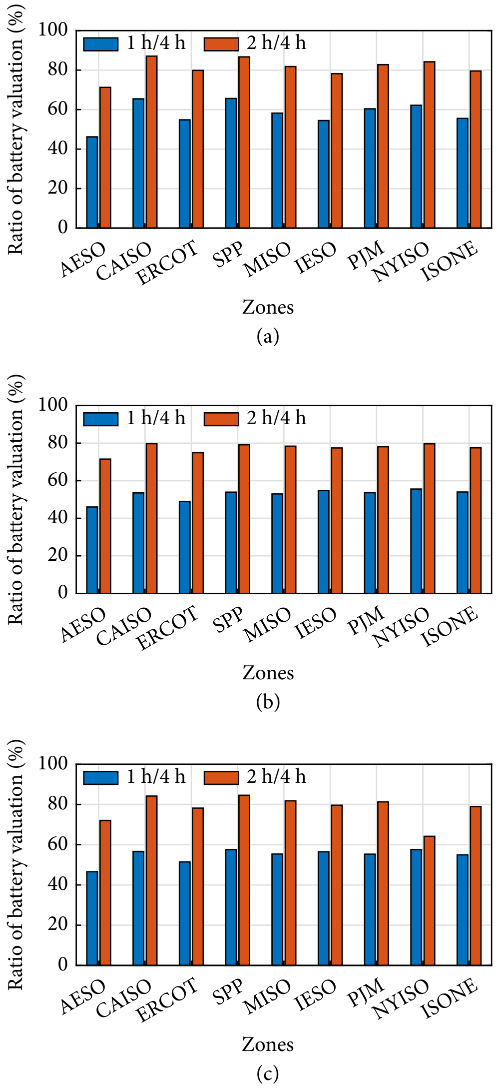


Fig. 5 Ratio of average battery valuations between hour duration for each technology for all zones (a) LFP, **(b)** NCA, and **(c)** NMC.

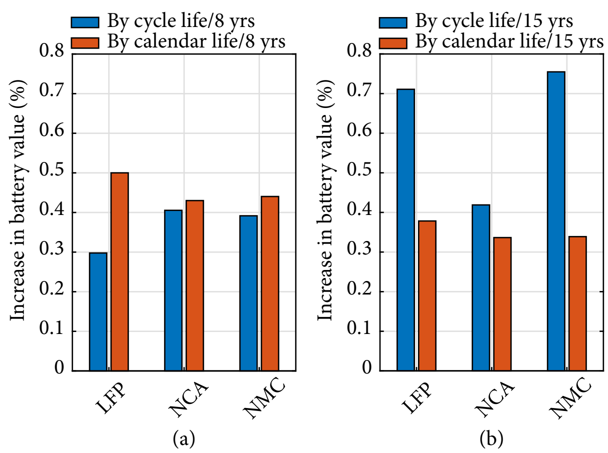


Fig. 6 Influence of 1% increase in cycle life and calendar life of the battery over its rated value in % across the locations in NYISO for (a) 8 years calendar life and **(b)** 15 years calendar life.

we conclude that increasing the calendar life of the battery has more impact on the battery value than increasing the cycle life within a certain calendar life. Beyond this value of calendar life, the cycle degradation becomes more significant than calendar degradation, provided the increase is by the same percent. In addition, an improvement of the battery value also depends on the technology: increasing the calendar life has more impact on LFP value than it is on NCA and NMC at lower calendar life, and an increase in cycle life has more impact than an increase in calendar life on both LFP and NMC than in NCA.

5 Conclusions

In this study, we investigated the economic value of three commercial lithium battery technologies (LFP, NCA, and NMC) across all nine wholesale electricity markets in North America. We adopted a systematic dynamic valuation framework that finds the highest revenue potential of each battery technology subjecting to its unique degradation mechanisms for different storage energy duration. We further examined the impact of increased cycle and calendar life on battery valuation and then quantitatively measured the differences across the three battery technologies. We found that valuation results highly depend on battery technology, operational location, and storage capacity. We also observed clear diminishing effects in battery cycle life and calendar life increments, in which the marginal benefit of increasing storage lifetime reduces.

The study confirms that LFP produces the highest economic value and surpasses the other two technologies by significant margins. When assuming 15 years of calendar life, the average LFP valuation results at AESO and ERCOT surpassed ＄400/kW, followed by CAISO, which falls slightly below ＄400/kW. Given that the current system cost for building 4-hour LFP utility-scale battery storage is around ＄400/kW[54], our result suggests that LFP battery projects provide positive investment return only through energy markets in these three markets, and the profit potential will likely to increase in the future as renewable penetration deepens. While we may not generalize the findings from this study, we believe it can help battery operators and investors participating in North American electricity markets make future economic decisions on which battery technology is most appropriate for a particular market, given the storage capacity and project lifetime. Another important recommendation from this work is that, because storage can potentially maximize profit from the price arbitrage market, it is expected that more storage would participate in the future market. Flexible policies should be on the way to ease the participation of storage in price arbitrage and increase the grants on research for storage-related studies to better improve the performance of the current technology".

Appendix

A1 Valuation formulation

The battery valuation formulation follows a dynamic programming approach which is recursively defined. The dynamic programming formulation uses a piece-wise linear value function approximation approach to model the value function of storage SoH. The valuation problem has the following indexes:

- $n \in \{1, \ldots, N\}$ is the index of the valuation days. For example, a 10-year valuation duration equals to $N = 3650$ days.
- $t \in \{1 \ldots, T\}$ is the index of the operation intervals same as the energy market clearing frequency, which is one hour in this study ($T = 24$).
- $i \in \{1, \ldots, I\}$ is the index of the piece-wise linear degradation value function approximation segments. In this paper, we

assume the battery reaches end-of-life at 70% remaining capacity and samples the value function every 1%, hence $I=31$.

- $j \in \{1\ldots,J\}$ is the index of the piece-wise linear degradation model approximation segments. All degradation models in this paper have three segments ($J=3$).

Parameters in the valuation problem include

- $\lambda_{n,t}$ is the electricity price over time period t on day n, unit in \$/MWh.
- γ is the daily discount ratio.
- $v^{s}_{i,n}$ is the opportunity value of the battery at the end of day n and SoH segment i, unit in \$.
- E^{s}_{i} is the storage capacity in MWh of the SoH segment i.
- P is the storage power rating, defined as the maximum energy that can be charged or discharged over one time period, unit in MWh.
- σ^{d}_{j} is the normalized cycle depth range over segment j.
- δ^{d}_{j} is the degradation rate in unit MWh/MWh (MWh of capacity loss per MWh of discharge power) over segment j.
- $\eta(E^{s}_{i})$ is the charge and discharge efficiency. We model the efficiency as a parameter dependent on the storage state of health E^{s}_{i}.
- D_{cal} is the capacity loss due to calendar degradation per day, unit in MWh.

Variables in the valuation problem include

- $p_{n,t}$ is the storage discharge power over time period t on day n, unit in MWh.
- $q_{n,t}$ is the storage charge power over time period t on day n, unit in MWh.
- $u_{n,t}$ is a binary variable, $u_{n,t}=1$ means storage is in discharge mode over time period t on day n.
- $p^{d}_{n,t,j}$ is the segment discharge power for cycle depth segment j, unit in MWh.
- $q^{d}_{n,t,j}$ is the segment charge power for cycle depth segment j, unit in MWh.
- $e^{d}_{n,t,j}$ is the energy stored in cycle depth segment j, unit in MWh.
- E is the storage energy capacity at the end of the operating day, unit in MWh. It is a variable because the energy capacity is updated based on the degradation model.
- v is the opportunity value of the remaining storage capacity, unit in \$. It is a variable used in the piece-wise linear value function approximation model.

Note the superscript s represents symbols are auxiliary parameters or variables for the piece-wise linear dynamic programming value function approximation model; the superscript d represents symbols are auxiliary parameters or variables for the piece-wise linear cycle degradation model.

The valuation framework follows a recursive dynamic programming formulation with the following objective function

$$v^{s}_{i,n-1} := \max \sum_{t=1}^{T} \lambda_{n,t}(p_{n,t}-q_{n,t}) + \gamma v \tag{A1}$$

The objective function maximizes the daily value of the storage, including arbitrage revenue (first term of the objective function) and the opportunity value of the remaining battery capacity v throughout day $n+1$ to the end of the project. The maximized objective value represents the opportunity value of the storage and is stored in $v^{s}_{i,n-1}$. Note that because we sample the storage opportunity value for all SoH segments and days, the objective function is defined for all $i\in\{1,\ldots,I\}$, $n\in\{1,\ldots,N\}$.

We discretize the storage SoH into segments indexed by i and sample the storage capacity opportunity value for each segment. The following constraint defines the piece-wise linear value function approximation based on pairwise SoH samples E^{s}_{i} and the corresponding storage opportunity value $v^{s}_{i,n}$

$$v \leqslant v^{s}_{i,n} + (v^{s}_{i,n} - v^{s}_{i+1,n})\frac{E-E^{s}_{i}}{E^{s}_{i}-E^{s}_{i+1}} \tag{A2}$$

The storage charge and discharge power are limited by the storage power rating P, $u_{n,t}$ enforces the storage cannot charge and discharge at the same time

$$0 \leqslant p_{n,t} \leqslant P u_{n,t} \tag{A3}$$

$$0 \leqslant q_{n,t} \leqslant P(1-u_{n,t}) \tag{A4}$$

The following constraint models the cycle-based battery degradation model and its impact on the capacity fade.

$$E = E^{s}_{i} - \sum_{t=1}^{T}\sum_{j=1}^{J}\delta^{d}_{j} p^{d}_{n,t,j} - D_{\mathrm{cal}} \tag{A5}$$

$$e^{d}_{n,t,j} = e^{d}_{n,t-1,j} + q^{d}_{n,t,j}\eta_t(E^{s}_{i}) - p^{d}_{n,t,j}/\eta_t(E^{s}_{i}) \tag{A6}$$

$$0 \leqslant e^{d}_{n,t,j} \leqslant \sigma_j E \tag{A7}$$

$$p_{n,t} = \sum_{j=1}^{J} p^{d}_{n,t,j},\ p^{d}_{n,t,j} \geqslant 0 \tag{A8}$$

$$q_{n,t} = \sum_{j=1}^{J} q^{d}_{n,t,j},\ q^{d}_{n,t,j} \geqslant 0 \tag{A9}$$

We employ a piece-wise linear degradation model to approximate the nonlinear cycle degradation rate[55]. Eq. (A5) models the daily storage capacity degradation, in which the storage capacity at the end of the day E is calculated based on the sampled storage capacity at the start of the day E^{s}_{i} minus the cycle degradation component, which is the sum of the degradation rate from all cycle depth segments and all period; and the calendar degradation component, which is a constant. Eq. (A6) models the energy evolution in each cycle depth segment. The storage efficiency $\eta(E^{s}_{i})$ is dependent on the storage state of health E^{s}_{i}, which we model as a look-up table at the beginning of each operating day. Eq. (A7) models the lower and upper cycle depth segment energy limit, note that the upper limit is defined based on the storage final capacity E. Eq. (A8) and Eq. (A9) model that the storage charge or discharge power is the sum of all segments.

A2 Efficiency variation

Since the RTE, η^{R} changes during the cycling operation of the battery, the RTE of the current cycle condition differs from the previous value. To model the current RTE, we interpolate between the RTE at 0% and 100% efficiencies (η^{R}_{0} and η^{R}_{100}). So that the current RTE (η^{R}_{t}) is calculated at the current cycle depth, Ds_t as in Eq. (A10). Since η^{R}_{0}, η^{R}_{100}, Ds_0 and Ds_{100} are known, we can interpolate to calculate η^{R}_{t} corresponding to Ds_t. So after every complete cycle, we calculate the new η^{R}_{t}, we then calculate the single trip efficiency, η_t using Eq. (A11). This would now be the efficiency input in Eq. (A6).

$$\eta_t^R = \eta_{100} - \frac{(\eta_{100}^R - \eta_{80}^R)(Ds_t - Ds_0)}{(Ds_{100} - Ds_0)} \tag{A10}$$

$$\eta_t = \left(\frac{\eta_t^R}{100}\right)^{\frac{1}{2}} \tag{A11}$$

A3 Battery value synthesis

We derive the battery value using location-specific price data and technology-specific battery degradation models. Since we assume an eight or fifteen-year calendar life of the batteries, we need sufficiently long price profiles to fully capture the total opportunity value of the battery capacity. To capture the annual variations and provide a range of historical battery values, we employ a price resample approach in which we repeat a single-year price data eight/fifteen times to generate an eight/fifteen-year price profile that meets the battery calendar life. Then we use this profile to perform battery valuation to obtain the battery value resulting from the considered year. We repeat the valuation for all considered storage technologies, arbitrage locations, and duration settings. The valuation framework has the following procedure.

1. **Update degradation model.** Pick a battery technology (LFP, NMC, or NCA), update δ_j^d using the following equation[55]:

$$\delta_j^d = \begin{cases} \frac{1}{\eta\sigma_j}\left(\frac{0.3}{M_j} - \frac{0.3}{M_{j-1}}\right) & \text{if} \quad j > 1 \\ \frac{1}{\eta\sigma_j}\left(\frac{0.3}{M_j}\right) & \text{otherwise} \end{cases} \tag{A12}$$

Based on the degradation cycle test data, we use three cycle depth segment with $\sigma_1 = 0.2$, $\sigma_2 = 0.4$, $\sigma_3 = 0.4$, representing cycle ranges 0 to 20%, 20% to 60%, and 60% to 100%, respectively. M_j represents the number of equivalent full cycles the battery can perform before reaching end-of-life. We place 0.3 in the numerator representing the capacity loss to the end-of-life SoH of 0.7. Hence $\frac{0.3}{M_j}$ represents the capacity loss per equivalent full cycle.

2. **Update price data.** Pick one year of price data over a location and year, repeat the yearly price profile eight/fifteen times to generate an eight/fifteen-year profile that outlives the storage calendar life.

3. **Update storage duration.** Pick a storage duration and update P accordingly.

4. We start from the final day of the valuation horizon, initialize $n \leftarrow N$, $E_i^s = 0.69 + (0.01)i$ (since this is a price-taker valuation, we normalize storage capacity to 1 MWh), and $v_{i,n}^s = 0$ for all $i \in \{1, \ldots, I\}$.

5. Sample the storage opportunity value over day n

(a) Set $i \leftarrow 1$;

(b) Solve the optimization problem (3) to (11), record $v_{i,n-1}^s$, update $i \leftarrow i+1$;

(c) If i equals I, exit; otherwise go to Step (a).

6. Update $n \leftarrow n-1$;

7. If n equals 0, go to Step 1 and repeat with new input data; otherwise, go to Step 2.

In the result, the pairs E_i^s and $v_{i,n}^s$ therefore represent the storage opportunity value over day n with a remaining capacity of E_i^s. Moreover, $v_{31,1}^s$ represents the value of a new battery at the start of the valuation period, which is used in the battery value synthesis. We repeat each year's price to perform the valuation based on the valuation function in (1) and the associated constraints. For the valuation results in each zone, we obtained the bar graphs with whiskers shown in Figures 4(a) and 4(b). The whiskers tell how spread the valuations are from the average values. The whiskers are calculated from the mean valuation, $\overline{V}_z^{\tau^*,\beta}$, maximum and minimum values of $V_z^{\tau^*,\beta}$ to obtain what we call the error-high ($\zeta_{z,H}^{\tau,\beta}$) and error-low ($\zeta_{z,L}^{\tau,\beta}$) for each zone as given in (15) and (16) respectively. The quantities $V_z^{\tau^*,\beta}$, $\zeta_{z,L}^{\tau,\beta}$ and $\zeta_{z,H}^{\tau,\beta}$ are then used to obtain the error bars presented in Section 4.1.

$$\zeta_{z,H}^{\tau,\beta} = \overline{V}_z^{\tau^*,\beta} - min.(V_z^{\tau^*,\beta}) \tag{A13}$$

$$\zeta_{z,L}^{\tau,\beta} = max.(V_z^{\tau^*,\beta}) - \overline{V}_z^{\tau^*,\beta} \tag{A14}$$

A4 Comparative analysis

In this section, we describe the method adopted to compare the performance of the battery technologies across all nine zones as presented in Section 4.2. To broaden our comparative analysis, we adopt a ratio strategy to compare battery valuations between technologies and their respective storage capacities in all zones. In this strategy, we expressed the ratios between storage duration, 1-hour to 4-hour duration, and also, the 2-hour duration to 4-hour duration. These steps are performed across all nine zones.

With reference to Eq.(1), the valuation function is repeated for each zone, z, duration, τ, and battery technology β so that the value, $V_{n,z}^{\tau^*,\beta}$ is obtained for all zones, $\mathbb{Z}$ (where $z \in \mathbb{Z}$) for the operating days n from their common terminal end to the beginning period of each project for the respective zones. Where $\beta \supset$ {LFP, NCA, NMC} and $\tau = [1, 2, 4]$. We compute the ratios $\frac{V_{n,z}^{1^*,\beta}}{V_{n,z}^{4^*,\beta}}$ and $\frac{V_{n,z}^{2^*,\beta}}{V_{n,z}^{4^*,\beta}}$ as percentage, where τ^* represents time duration condition. The quantity $V_{n,z}^{4^*,\beta}$ is always $>$ ($V_{n,z}^{1^*,\beta}$ or $V_{n,z}^{2^*,\beta}$); $\forall \beta$, $\forall z \in \mathbb{Z}$ so, each ratio is $<$ 100% as noted in Figurere 5(a)–5(c).

A5 Marginal value improvement analysis

The marginal value analysis of the batteries is done to investigate the impact of increasing cycle life and calendar life on the battery valuation. Here, we discussed how we arrived at the results presented in Section 4.3. The battery valuation function in (1) is computed for each of the four locations l, belonging to NYISO ($l \in \mathbb{L}_{NY}$). The four operators in NYISO include NYC., LONGIL, WEST and NORTH. Each battery valuation $V_{n,l}$ is computed after increasing the cycle life or calendar life of each battery technology by 1%. Assuming each valuation $V_{n,l}^{\beta}$ for each battery technology before and after the increment are $V_{n,l}^{b,\beta}$ and $V_{n,l}^{a,\beta}$, then the marginal value, $V_{n,l}^{m,\beta}$ for l location is defined in (17).

$$V_{n,l}^{m,\beta} = V_{n,l}^{a,\beta} - V_{n,l}^{b,\beta}; \forall \beta \tag{A15}$$

$$V_{L_{NY}}^{m,\beta} = \frac{1}{L_{NY}} \sum_{l=1}^{L} \frac{V_{n,l}^{m,\beta}}{V_{n,l}^{b,\beta}} * 100\%; \forall \beta \tag{A16}$$

Where $V_{n,l}^{a,\beta}$ results from running the simulation of the objective function (1) after increasing by 1%, the parameter N_{cyc} (for cycle life increase) and Y_{cal} (for calendar life increase). The percentage marginal valuation for the zone is then expressed as the average marginal values across all L_{NY} as in (18), where $L_{NY} = 4$. The quantity $V_{L_{NY}}^{m,\beta}$ is computed separately for cycle life and for calendar life increased conditions.

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Additional information

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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