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An intertemporal decision framework for electrochemical energy storage management

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Dispatchable energy storage is necessary to enable renewable-based power systems that have zero or very low carbon emissions. The inherent degradation behaviour of electrochemical energy storage (EES) is a major concern for both EES operational decisions and EES economic assessments. Here, we propose a decision framework that addresses the intertemporal trade-offs in terms of EES degradation by deriving, implementing and optimizing two metrics: the marginal benefit of usage and the average benefit of usage. These metrics are independent of the capital cost of the EES system, and, as such, separate the value of EES use from the initial cost, which provides a different perspective on storage valuation and operation. Our framework is proved to produce the optimal solution for EES life-cycle profit maximization. We show that the proposed framework offers effective ways to assess the economic values of EES, to make investment decisions for various applications and to inform related subsidy policies.

Energy storage will play a critical role in providing flexibility to future power systems that rely on high penetrations of renewable energy[1–4]. Unlike typical generating resources that have long and, essentially, guaranteed lifetimes, electrochemical energy storage (EES) suffers from a range of degradation issues that vary as a function of EES type and application[5,6]. Although several studies have explored ways to account for the degradation cost in investment and operational decisions for applications such as electric vehicle charging/vehicle to grid[7,8], microgrid management[9,10], energy arbitrage/peak shaving[6,11–15], frequency regulation[11,14–16], multiservice[6,11–15] and so on, a comprehensive and rigorous approach that optimally valuates and manages EES degradation over different decision horizons is still, to our knowledge, undocumented. Developing such an approach is imperative to mitigate the risk of making operational decisions that greatly deviate from the optimal case in terms of profit maximization based on inappropriate consideration for EES degradation. Additionally, the economic valuation of EES could be highly inaccurate if the profitability of EES is underestimated given these suboptimal operational decisions.

To take advantage of short-term forecasting information with reduced uncertainty, energy storage systems need to make short-term scheduling decisions much like those for traditional generators. Day-ahead hourly bids may be offered to decentralized electricity markets or some short-term scheduling in coordination with other resources may be applied in the case of a microgrid[17,18]. Such a framework works well for traditional generators, as they have explicit short-term operating costs that are independent from past and future scheduling decisions. However, the marginal operating costs of EES systems are near zero, and, more importantly, the unavoidable degradation caused by their usage brings several intertemporal requirements for their operation. First, EES owners/operators need to determine short-term usage rates according to different short-term benefit opportunities, so as to maximize the benefit per unit of degradation in the long term (life cycle), for example, to schedule a deeper cycle when the daily peak–valley price difference is larger, and to interrupt operation when the price difference is too small. Second, EES operators need to make a trade-off between short-term benefits and the value of lost battery life such that the total life-cycle benefit can be maximized[6,14], as larger short-term benefits imply higher EES usage rates and, in turn, shorter EES functional lifetimes. These trade-offs imply that when the benefit opportunity is comparatively low, the EES operators should limit or hold their operation to minimize degradation and wait for a better opportunity. However, because of the calendar degradation associated with most common types of EES[19,20] (especially lithium ion), the EES should not always keep waiting for the best short-term profit opportunity.

Two common existing methods incorporate EES degradation in short-term operational problems: the levelized cost of degradation (LCOD) method and the degradation constraint method. The LCOD method implements the amortized capital cost[7–9,13,16] or replacement cost[10–12] of EES into EES short-term operational decisions as the variable operating cost. The main weakness of the LCOD method is that it averages the depreciation cost over a long-term window, instead of considering a short-term marginal cost per unit of degradation, and implementing long-term average cost distorts the economic optimality of short-term schedules. In the degradation constraint method, constraints are set on the short-term usage of EES to limit degradation[6]. This method usually fails to determine reasonably the value of the degradation limit and how it should vary across time. Mathematically, the optimization models of LCOD and degradation constraint methods can be transformed into each other equivalently[21]. Some other studies did attempt to develop models that optimize a life-cycle objective to manage short-term EES usage[14,15]. However, assumptions that are oversimplified[14] (Supplementary Note 1) or without legitimate economic sense[15] are made on the objectives, and the time preference of EES owners on revenues earned over different periods are not addressed appropriately. Although the aforementioned studies are imperfect in some respects, they did contribute to EES degradation modelling

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and proved that to consider degradation is critical as it remarkably affects the decisions and the economic benefits of EES, in contrast to some related studies that did not consider degradation at all[22–24].

In this work, we develop an intertemporal (integrated from short- to long-term timescales) framework that incorporates incremental EES degradation in both operating and planning problems and is generally applicable to most EES applications and chemistries that exhibit degradation as a function of use or time. We propose two metrics for operating and planning, namely the marginal benefit of usage (MBU) and the average benefit of usage (ABU). For operating decisions, we present how MBU should be determined and implemented through short- to long-term timescales to maximize the total life-cycle benefit of EES within the life-cycle degradation limit. Specifically, the MBU brings long-term information to short-term decisions and is proved to guarantee that the life-cycle benefit is maximized when short-term decisions are made. For planning and valuation, we present how ABU can be utilized to assess the economics of different EES applications and to estimate the required subsidies to make EES economically viable. Through case studies, we demonstrate the effectiveness of our framework and its favourable performance compared to the common LCOD method. Our framework aims to facilitate EES owners to make better operational decisions with higher total life-cycle benefits, and help investors and policymakers assess the values of EES more accurately in investment and policy decisions.

The existing LCOD method

The LCOD method is the most commonly used method to monetize the EES degradation cost in short-term scheduling. It assumes an amortized proportion of initial capital cost[7–9,13,16] or future replacement cost[10–12] to represent the degradation cost, and that any degradation in the short term will incur a degradation cost proportional to the amount of degradation (equation (1) along with an example in Methods).

There are three drawbacks to the LCOD method. First, using the average capital/replacement cost per unit of usage/degradation to determine the short-term marginal cost is counterintuitive in economics (average cost and marginal cost are different conceptually[25] and, usually, numerically), and will almost certainly deviate from the optimal decision in terms of benefit maximization.

Second, decisions based on any 'sunk' (decided and incurred) cost, which cannot be recovered practically, are suboptimal. The LCOD derived from the capital cost is not only an average cost but also a sunk one, and should, thus, not affect any operational decisions. The future replacement cost that will not occur during the operational decision horizon, moreover, should not affect the operational decisions of the current EES system if the revenue streams of the current system are independent of the potential new EES system. This is because the objective of operational decisions should be to maximize the total benefits over the life cycle of the current system, whereas the future replacement decision is another planning problem.

Third, it does not reflect the time preference of the EES owner on benefits earned in different scheduling periods using the time-invariant LCOD as the marginal cost per unit of degradation. It is preferable to earn the same amount of money sooner than later, and, therefore, if the total available system energy throughput before the EES life ends is fixed, it is desirable to utilize the EES sooner than later. With a marginal operational cost invariant over the EES life, however, the operational decision criteria—characterized by setting the marginal revenues equal to the marginal operational cost to maximize benefit—do not change over time. Hence, there is no time preference in EES utilization in the LCOD method.

An intertemporal decision framework

The cost associated with degradation is literally an opportunity cost that results from the loss of future benefit opportunities. Based on classic intertemporal choice theory in microeconomics[25], we propose an intertemporal decision framework, which, first, coordinates short-term, mid-term and long-term EES scheduling to optimize the life-cycle benefit considering EES degradation, and, second, uses the estimated operational revenue to facilitate investment and subsidy decisions at the planning stage (Fig. 1). For simplicity, we assume that the EES earns benefits from electricity markets and is a price taker, which implies that the actions of the EES have little impact on the market prices. The benefits of EES can also include generation-cost saving, social welfare, risk premium and so on, and also the bidding strategy of EES can affect market prices when implementing the proposed framework. The optimality proof of the framework in terms of life-cycle benefit and detailed formulations are presented in Methods.

In the short term, typically the day-ahead horizon, the EES operator determines the optimal short-term outputs and bids accordingly in various markets to maximize the short-term/daily benefits, based on the discounted MBU (DMBU) determined in the mid term and the forecasted short-term market prices, as shown in Fig. 1a. The DMBU determines the marginal benefit per unit of usage for the optimal EES scheduling strategy, and thus plays the role of short-term marginal cost, but it is independent of the capital or replacement cost.

For the mid term, typically a time frame between a month and a year, the EES operator calculates the DMBU as the product of a discounting factor and the life-cycle MBU, which is determined in the long term.

For the long term, the EES operator determines the optimal life-cycle MBU to maximize the life-cycle benefit, which is the sum of the discounted short-/mid-term benefits in each year, subject to EES degradation constraints over the EES life.

For the planning stage, dividing both the life-cycle revenue and the initial capital cost by the life-cycle energy throughput defines the ABU and the average cost of degradation (ACD), respectively. Investment and replacement decisions and subsidy policies can be informed by comparing the ABU with the ACD.

When practicing the framework, the planning, long-term and short-term decisions should be made sequentially. Investors should first decide whether to invest on and construct an EES system based on cost–benefit analysis. After the EES is constructed, the operational decisions begin. The EES operator should first determine the long-term optimal life-cycle MBU, and then update the DMBU. Last, the EES outputs for each short-term scheduling periods should be determined.

The preceding decisions require the simulations of later decisions. Therefore, the simulation order is inverse to the decision order. To make a long-term decision (determining the life-cycle MBU), the EES operator should simulate short-term operation for all the values of MBU in a reasonable set based on future price projections and aggregate the maximum short-/mid-term benefits of each period to compute the life-cycle benefit, as shown in Fig. 1b. These short-/mid-term benefits do not have to be equal to the actual benefits earned in each period—they are just simulated values that reflect the expected future benefit opportunities to facilitate long-term decisions. After the optimal life-cycle MBU and corresponding maximum life-cycle benefit are determined, the ABU can be calculated, and the planning decision can be made.

The major assumption in this framework is that EES degradation is a Markov process throughout its lifetime—the degradation incurred during a certain period only depends on the state of EES at the beginning of the period and the operational decisions made in this period—which implies that we can linearly aggregate the degradations over different periods to compute the total degradation. This assumption is generally valid in electrochemistry and is also adopted in other methods used to consider EES degradation, for example, the LCOD method.

The required information in the framework includes the short-term price forecasts over the EES life. At present, perfect price

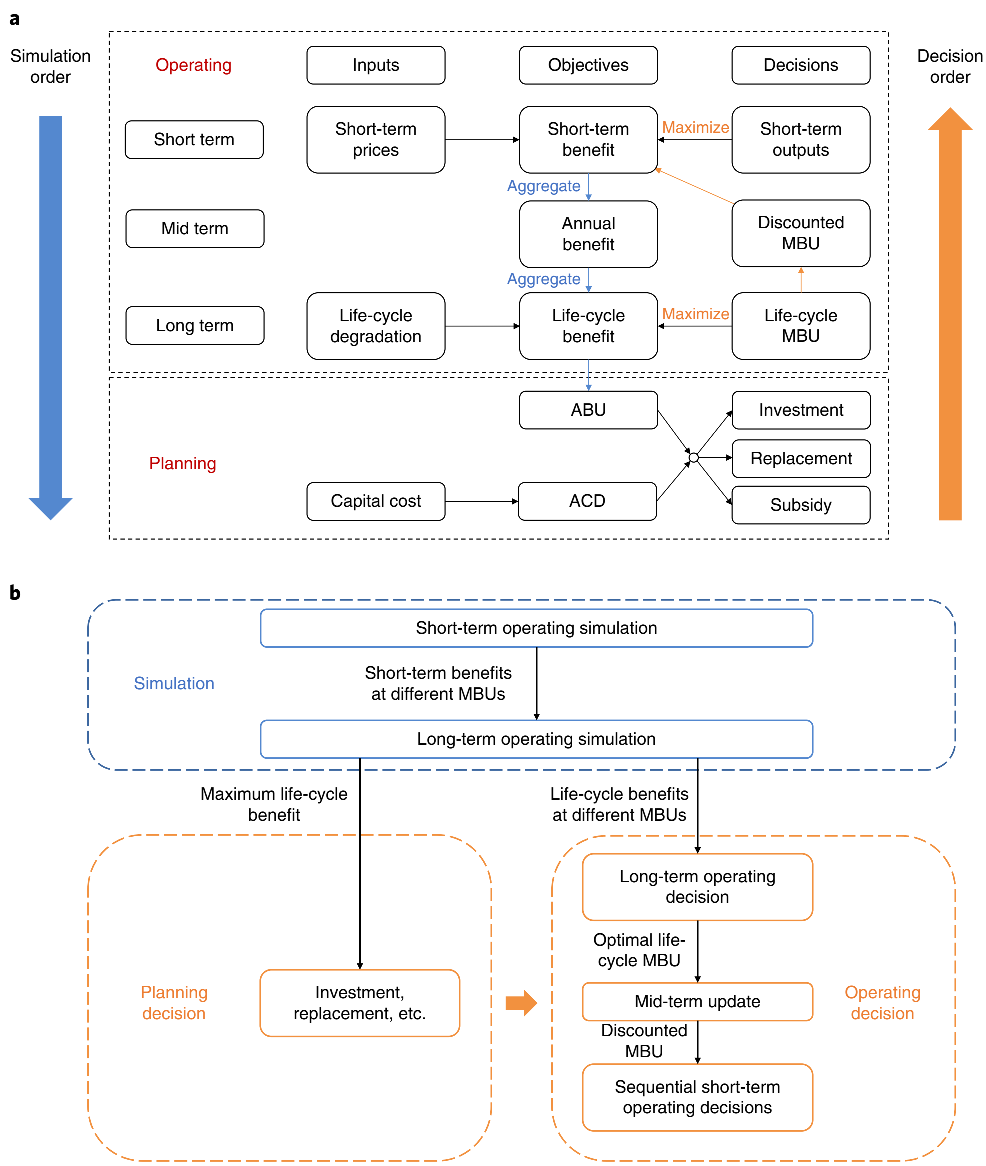

Fig. 1 | Schematic of the intertemporal decision framework for EES degradation management. a, Decision variables, objectives and key inputs for each decision and their relations. **b**, The data-flow diagram shows the necessary procedures of simulations and decisions to practice the framework and the data flow from each procedure to the next. MBU, marginal benefit of usage; ABU, average benefit of usage; ACD, average cost of degradation.

forecasts are impossible in any markets, and imperfect forecasts inevitably cause errors on the revenue estimation results presented in this paper. We have not conducted price forecasts to ascertain quantitatively the effect, as it is beyond the focus of this paper. The forecasting error, however, only affects our method by the mean forecasting error; this can, in turn, be relatively small, depending on the forecasting tool[26,27]. The projected life-cycle revenue and corresponding MBU will change as our expectations on the future electricity market prices change—similar to the fluctuations of stock market values. Our framework aims to produce the optimal decisions in terms of the maximization of life-cycle benefit under both degradation estimation and price forecasting uncertainties. In Supplementary Note 2, we prove that price uncertainty has little effect on the comparative advantage of our proposed framework over existing methods in terms of the maximization of the expected life-cycle revenue.

Application of energy arbitrage

A power system with a high solar penetration creates significant arbitrage opportunities for EES systems, characterized by pilot and scaled installations in California and South Australia[28]. The EES charges/buys energy when the sun shines and load demand is low, and then it discharges and sells energy when the sun goes down. Here we examine our MBU method and compare it with the LCOD method in an energy-arbitrage application.

We optimize the operating strategies and calculate the market revenues of a lithium-ion EES system in California that is rated at 50 MW/200 MWh. We use energy throughput (charging plus discharging) in megawatt hours as the measure of EES utilization and degradation, converted into full-cycle equivalent (Methods, equation (16)). The more energy throughput the EES processes, the more degradation the EES goes through[29–32]. As the degradation mechanism is complex and stochastic, there is uncertainty in the degradation estimation. To analyse the impact of this uncertainty, we evaluate three cases with zero, positive and negative degradation estimation biases. We use day-ahead energy market prices of 2016 from the California Independent System Operator (CAISO) as representative price scenarios.

Figure 2 depicts how the revenues and degradations of the EES vary with the MBU, from the long-term perspective, and

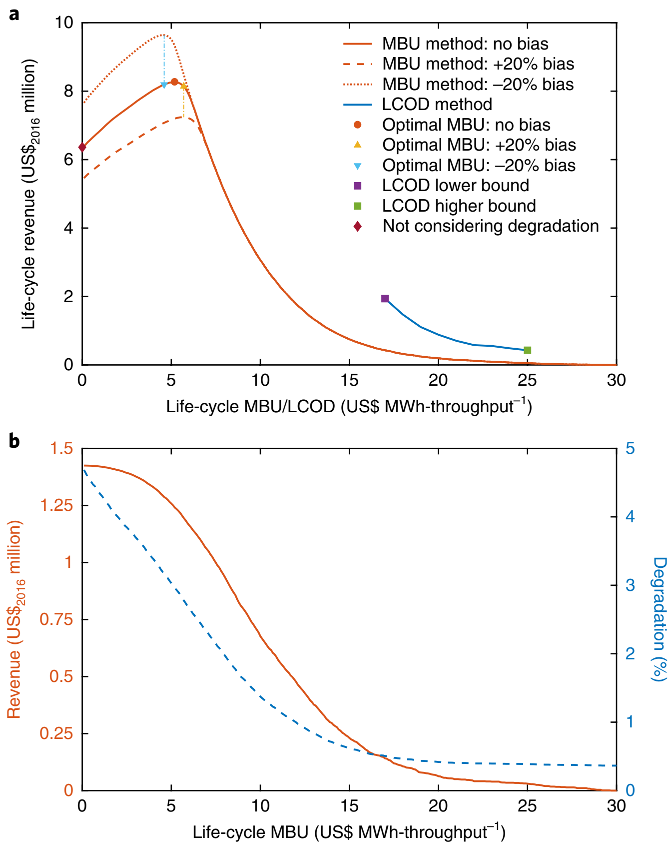

Fig. 2 | Results of a lithium-ion EES for energy arbitrage in CAISO using MBU and LCOD methods. a, Life-cycle revenue changes with the life-cycle MBU for cases with and without a degradation estimation bias using the MBU method, and the life-cycle revenues using the LCOD method. The optimal life-cycle MBU corresponds to the life-cycle revenue maximum. **b**, Changes in the annual revenue and the annual degradation (loss of capacity expressed as a percentage) with the life-cycle MBU in the first year of operation using the MBU method.

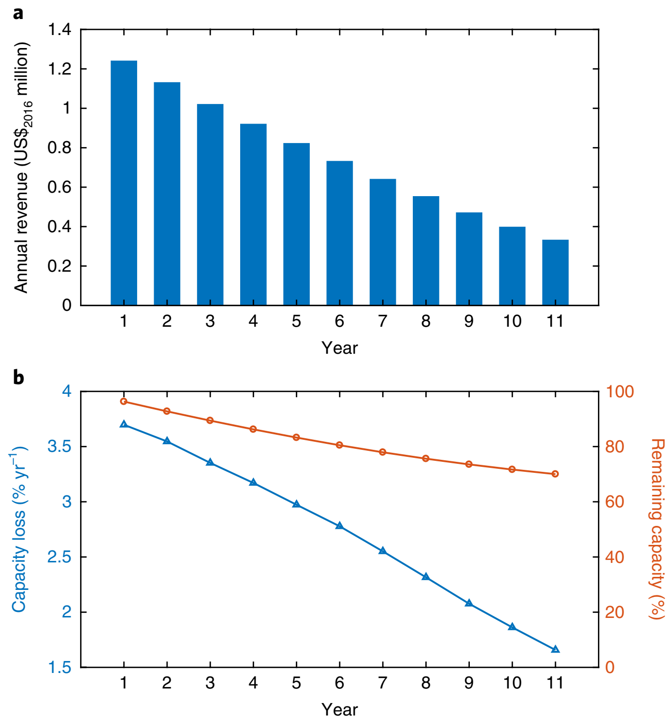

Fig. 3 | Annual revenues and degradations of a lithium-ion EES for energy arbitrage in CAISO. a, Annual revenues over the EES life. **b**, Annual capacity losses (triangles) and remaining capacities (circles) of each year over the EES life.

how the optimal life-cycle MBU is determined as the long-term decision. In the case of no degradation estimation bias (the estimation error mean is zero), the life-cycle revenue reaches the maximum, US$8.3 million, at a MBU of US$5 per MWh throughput (US$5 MWh throughput^{-1}), as shown in Fig. 2a. This implies that, in the real operation, we should set the short-term marginal revenue per unit degradation (energy throughput) in the first year at approximately US$5 MWh throughput^{-1} and adjust it by a discounting factor in the following years to achieve the maximum life-cycle revenue. As the life-cycle MBU increases, we utilize the EES less every year, so the total revenue in a single year decreases and the annual degradation also decreases, as shown in Fig. 2b, which indicates that the EES life increases. In this sense, varying MBU reflects a trade-off between short-term benefits and the EES lifetime. In some circumstances, for example, when the peak–valley price difference is small, the EES should save its life and wait for a better benefit opportunity, whereas in some cases its capacity should be utilized fully to capture the opportunity. The criterion to identify benefit opportunity is the long-term optimized and discounted MBU.

The unit-capacity capital cost of the lithium-ion EES system could range from US$200 kWh^{-1} to US$300 kWh^{-1} at the utility level, according to future price projections[33,34]. Assuming also that degradation is uniformly allocated throughout its 15-year lifetime and that the ratio of total depreciation to capital cost is 30% (equal to the capacity loss at the end of the EES lifetime), then the EES LCOD ranges between US$17 and US$25 MWh throughput^{-1}. If we use this range as the marginal degradation cost to make EES operational decisions, however, the life-cycle revenue will be no more than US$1.9 million, barely 23% of the maximum (Fig. 2a). The significant revenue loss is because the LCOD method does not maximize the life-cycle revenue. Instead, it requires the EES to operate only when the potential marginal benefit is high enough to compensate fully for the average unit degradation cost, and to halt operation and wait for a better benefit opportunity otherwise, ignoring that the EES has a calendar life—you cannot wait for a great opportunity indefinitely, for example, a century from now.

Setting the MBU to 0—no constraint for degradation/usage—is equivalent to not considering EES degradation in short-term operational decisions. Besides the remarkable revenue loss in this case of not considering degradation compared to the MBU method, we can also see from Fig. 2a that the life-cycle revenues produced by the LCOD method are even lower, which implies that a problematic modelling of degradation can be worse than doing nothing.

If the degradation estimator is biased, which means the estimation error has a positive/negative mean, then the life-cycle revenues and corresponding life-cycle MBUs produced by the MBU method are as shown by the yellow and blue triangles in Fig. 2a. The life-cycle MBUs we choose will deviate a bit from the optimal because of our estimation bias. If the bias is positive, the EES will degrade slower than we expect, so the estimated life-cycle revenue will be lower than the actual (lower dashed line in Fig. 2a), and vice versa. We can see that there are negative impacts on the life-cycle revenues from the biased degradation estimation, but they are very small compared to the losses from not considering the degradation or from using the LCOD method, even if the bias (estimation error mean) is as high as 20% of the true value.

When the MBU increases, there are less qualified benefit opportunities (which have a marginal benefit higher than the MBU) for

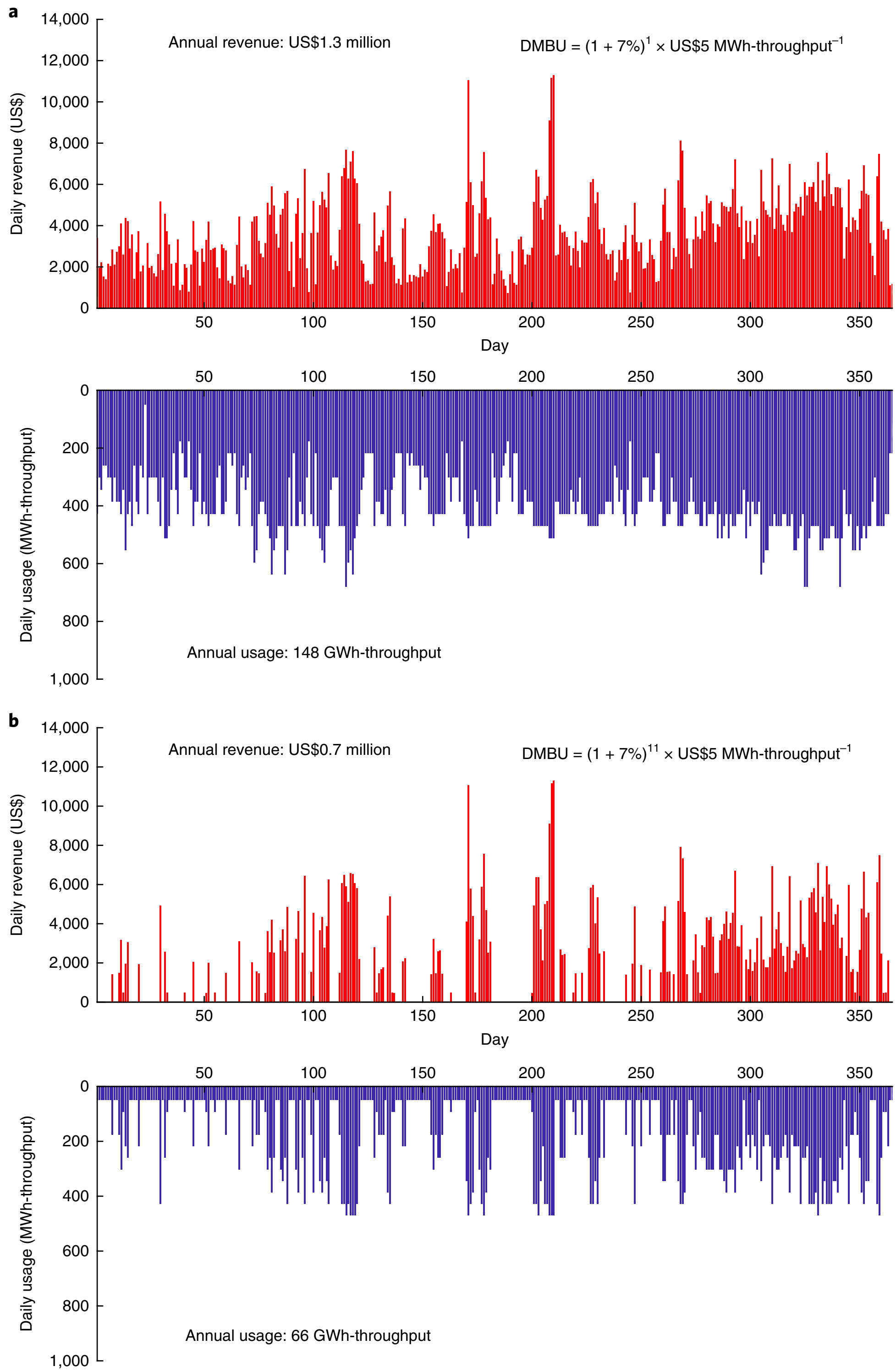

Fig. 4 | Optimal daily revenues and usages for energy arbitrage based on CAISO 2016 price scenarios. a, Year 1 with a lower DMBU. **b**, Year 11 with a higher DMBU.

an EES in a year, so the EES operates less frequently. As the short-term scheduling applies a DMBU, which increases every year, the annual degradation and revenues decrease from year 1 to year 11 (the end of the EES lifetime), as shown in Fig. 3. The time preference of the EES owner/operator, which is to utilize the EES and earn revenues sooner than later, ignored by the LCOD method, is indicated in this outcome of decreasing annual EES utilization and revenues.

Figure 4 illustrates the aforementioned time preference by comparing the optimal short-term (daily) schedules between year 1 and year 11. Though the daily prices are assumed to be the same for the two years, year 1 earns almost twice the revenues and processes more than twice the energy of year 11, because its DMBU is much lower. The implication is that the EES should be used more frequently (more days in operating status) and intensively (deeper cycle) in the early years of its lifetime, and vice versa.

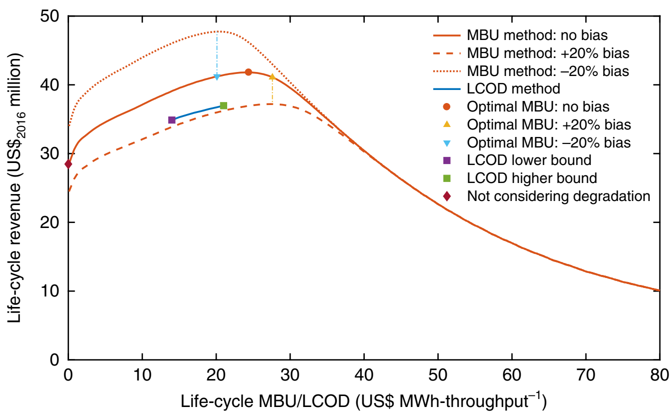

Fig. 5 | Life-cycle revenues of a lithium-ion EES for energy arbitrage and frequency regulation.

The ABU in this case is approximately US$7 MWh throughput^{-1}, much lower than the lower-bound ACD of US$33 MWh throughput^{-1} (US$200 kWh^{-1} capital cost). This indicates that if there is no subsidy and the peak–valley price difference does not increase dramatically, EES arbitraging in California will not be an economically feasible application. The break-even capital cost is approximately US$40 kWh^{-1}, and the minimum required subsidy to make EES economically viable in this case is US$26 MWh throughput^{-1}, the difference between ACD and ABU.

Application of energy arbitrage and frequency regulation

Combining different applications, if enabled by policy, can enrich the value stream of EES and enhance the economic viability substantially[3]. The proposed decision framework can also be applied readily to such combined applications with multiple revenue streams. Here we examine a combined application of energy arbitrage and frequency regulation, which is a common type of ancillary service in power systems, for the same lithium-ion EES. In addition to energy market prices, we use regulation capacity and mileage prices and real-time regulation mileages from CAISO in 2016 in the simulation.

The optimal MBU is US$25 MWh throughput^{-1} for this combined application, as shown in Fig. 5. This optimal MBU is much higher than that in the single application of energy arbitrage, because the benefit opportunity in the frequency regulation market is much greater, despite the market size being comparatively small. We should expect every unit of degradation to make more benefit through setting a higher MBU. The life-cycle revenue is also greater in this case, and with an ABU of US$35 MWh throughput^{-1}, no subsidy is required for the EES to be economically viable. The outcomes of the LCOD method are dominated by that of the MBU method, with a 12% revenue loss at minimum. The life-cycle revenue loss due to the degradation estimation bias (20% of the true value) is also comparatively small in this case.

Discussion

A valid decision framework is critical to estimating accurately and maximizing the values of EES, and therefore to allowing the EES greater potential to play a more significant role in decarbonizing energy sector at a limited cost. In this work, we propose an intertemporal framework that implements the MBU to coordinate EES degradation through short- to long-term timescales. This approach achieves the maximum life-cycle revenue of EES given valid price projections. Regardless of the EES investment viability (that is, whether or not a subsidy policy should be in place), the comparison outcomes of both single and combined applications indicate that our MBU method substantially outperforms the existing LCOD method in terms of revenue maximization or subsidy minimization. We conclude that it is not optimal to use the sunk capital cost or the future replacement cost, both of which are average cost rather than marginal cost, to determine short-term operational decisions directly.

The framework could be the foundation for decision-making in EES operation for all potential applications with either explicit (for example, market revenue) or implicit (for example, social welfare) benefits. It informs the industry that a marginal value should be used as the short-term variable cost to determine EES schedules and it provides an effective way to incorporate into scheduling decisions the time preference of the EES owner on revenues. As the framework can be applied not only to new EESs, but also to existing EESs that have been operating for some years, the projected ABU for the remaining lifetime of an EES could be a critical value indicator for EES ownership trading.

The framework can identify the true investment attractiveness and relative competitiveness of various EES chemistries in diverse applications for policymakers and investors, which is also part of our ongoing work. The unit usage/degradation metrics, ABU and ACD, proposed in the framework provide a different perspective for EES technology learning studies, in addition to the commonly used unit-capacity metrics[33,35].

Based on the analysis made possible by our framework, subsidy policy can be designed to compensate the difference in the optimal MBUs between the cases that consider environmental externality and those that do not. Moreover, the framework can be applied to analyse which EES characteristics are the most critical and how to make trade-offs among them for certain EES applications to indicate the research and development path.

Methods

LCOD method. Similar to the levelized cost of electricity calculation, the degradation cost in the LCOD method is given by equation (1):

$$\mathrm{DC}_t = \mathrm{LCOD} \times d_t = \frac{\gamma \times \mathrm{CAPEX}}{\sum_t \delta_t d_t} d_t \qquad (1)$$

where DC_t is the degradation cost at time t (US$), d_t is the EES degradation during time t (MWh throughput or capacity loss (%)), CAPEX is the initial capital cost of the EES (US$), γ is the ratio of the total degradation/depreciation cost to the total capital cost and δ_t is the discounting factor for time t. In the case study of this paper, the discounting factor takes the form of a typical exponential discounting, $\delta_t = (1+s)^{-t}$, where s is the discount rate. The degradation d_t is usually projected on an annual timescale assuming a uniform annual degradation rate over the EES life cycle.

For example, if the total degradation/depreciation cost of an EES is US$1 million, and the EES can do 3,000 full cycles in 15 years, then the short-term degradation cost for 1 full cycle of charging and discharging is about US$550, given a discount rate of 7%. As such, in this case, the EES owner/operator aims to optimize the short-term schedule by comparing the direct and/or indirect benefits brought by the full cycle to US$550 in each scheduling period or, put simply, assumes that the short-term marginal cost equals US$550 per cycle.

The intuition behind this method is to assume that every unit of degradation incurs a corresponding degradation cost, whose present value is equal to a fraction of the capital cost. The objective in the short-term scheduling problem is to maximize the benefits minus the degradation cost.

MBU method. The objective is to maximize the present value of the EES life-cycle benefit as the sum of the present values of all short-term benefits over the EES lifetime, subject to degradation constraints, as described in equations (2)–(4):

$$\mathrm{LB}_{\max} = \max_{d_t} \quad \mathrm{LB} = \max_{d_t} \sum_{t \le T} \delta_t \mathrm{SB}_t(d_t, \boldsymbol{\lambda}_t) \qquad (2)$$

$$\text{subject to} \quad \sum_{t \le T} d_t \le D \qquad (3)$$

$$d_t \ge C_t \qquad (4)$$

where LB represents the life-cycle benefit of EES (US$); SB_t is the maximum short-term benefit at time t (US$) as a function of the EES degradation and market prices (or other benefit rates, usually US\$ MWh^{-1} or US\$ MW^{-1}) at time t, denoted by d_t and $\boldsymbol{\lambda}_t$, respectively; the degradation d_t could be estimated based on the direct usage of EES in energy services, for example, energy arbitrage and/or the expected usage in capacity services, such as reserve and frequency regulation; D is the degradation (MWh throughput or capacity loss (%)) limit over the EES lifetime or the remaining energy throughput for an old EES; T is the length of the EES lifetime (year) determined by the EES degradation rates d_t and the degradation limit D; C_t is the calendar degradation rate at time t (MWh throughput or capacity loss (%) per unit of time). Calendar degradation comprises all degradation processes that are independent of EES cycling or usage and is dependent on temperature and the state of charge (SOC) of the EES[20,36–38].

Given price projections $\boldsymbol{\lambda}_t$, the decision variable of the long-term optimization model (2)–(4) is d_t, the EES degradation at each time t. Equation (2) describes the problem objective mentioned earlier. Equation (3) expresses that the total energy throughput over the EES life has a limit, determined by some certain end-of-life criterion. Equation (4) counts in the calendar degradation of the EES system.

The Lagrangian function of the long-term optimization model (2)–(4) is:

$$L=\sum_{t\leq T}\delta_t\mathrm{SB}_t(d_t,\boldsymbol{\lambda}_t)+\mu\left(D-\sum_{t\leq T}d_t\right)+\sum_{t\leq T}\alpha_t(d_t-C_t) \tag{5}$$

where μ and α_t are Lagrangian multipliers. If $\mathrm{SB}_t(d_t,\boldsymbol{\lambda}_t)$ is differentiable and concave over $d_t\geq C_t$, then the first-order Karush–Kuhn–Tucker (KKT) conditions are equations (3), (4) and (6)–(10):

$$\begin{aligned}\frac{\partial L}{\partial d_t}=\ &\delta_t\frac{\partial \mathrm{SB}_t(d_t,\boldsymbol{\lambda}_t)}{\partial d_t}-\mu+\alpha_t=0\\ \Leftrightarrow\ &\frac{\partial \mathrm{SB}_t(d_t,\boldsymbol{\lambda}_t)}{\partial d_t}=\frac{\mu-\alpha_t}{\delta_t}\end{aligned} \tag{6}$$

$$\alpha_t(d_t-C_t)=0 \tag{7}$$

$$\mu\left(D-\sum_{t\leq T}d_t\right)=0 \tag{8}$$

$$\alpha_t\geq 0 \tag{9}$$

$$\mu\geq 0 \tag{10}$$

From equations (6) and (7), we can observe that if $d_t>C_t$, which indicates the EES is operating at time t, we have:

$$\frac{\partial \mathrm{SB}_t(d_t,\boldsymbol{\lambda}_t)}{\partial d_t}=\frac{\mu}{\delta_t} \tag{11}$$

We designate μ as the life-cycle MBU (US\$ MWh throughput^{-1}), and $\frac{\mu}{\delta_t}$ as the DMBU. In the following we describe the decision procedures in our proposed framework, as shown in Fig. 1.

Short-term decision. We determine the charge/discharge schedules of EES given a DMBU by solving the optimization model of equation set (12):

$$\begin{aligned}&\mathrm{SB}_t(\mu,\boldsymbol{\lambda}_t)=\max_{\mathbf{P}_t\in\mathbf{F}}\quad r_t(\mathbf{P}_t,\boldsymbol{\lambda}_t)\\ &\text{subject to}\quad \frac{\partial \mathrm{SB}_t(\mu,\boldsymbol{\lambda}_t)}{\partial d_t(\mathbf{P}_t)}=\frac{\mu}{\delta_t}\\ &\qquad d_t(\mathbf{P}_t)>C_t\end{aligned} \tag{12}$$

where $r_t(\mathbf{P}_t,\boldsymbol{\lambda}_t)$ is the short-term benefit at time t (US\$) as a function of the charge/discharge schedules at time t (denoted as $\mathbf{P}_t$ (MW)) and the market prices; $\mathbf{F}$ is the feasible operating set of the EES, typically convex, and usually consists of the physical operational constraints of the EES. The EES degradation at time t, d_t, can also be expressed as a function of the charge/discharge schedules $\mathbf{P}_t$. If there exists no feasible solution to equation (12), the short-term decision and the corresponding degradation and revenue are:

$$\begin{cases}\mathbf{P}_t=\mathbf{0}\\ d_t=C_t\\ \mathrm{SB}_t=0\end{cases} \tag{13}$$

Mid-term update. We calculate DMBU, $\frac{\mu}{\delta_t}$, given a life-cycle MBU.

Long-term decision. We determine the value of the life-cycle MBU, μ, based on price projections by solving the optimization problem described by the equation set (14):

$$\begin{aligned}&\max_{\mu}\quad \mathrm{LB}=\max_{\mu}\sum_{t\leq T}\delta_t\mathrm{SB}_t(\mu,\boldsymbol{\lambda}_t)\\ &\text{subject to}\quad \sum_{t\leq T}d_t(\mu)\leq D\\ &\qquad d_t(\mu)\geq C_t\end{aligned} \tag{14}$$

The KKT conditions indicate that as long as $r_t(\mathbf{P}_t,\boldsymbol{\lambda}_t)-\frac{\mu}{\delta_t}d_t(\mathbf{P}_t)$ is concave (a subgradient method can be applied if this expression is not differentiable), we can achieve the maximum life-cycle benefit by following the above decision procedures[21]. $r_t(\mathbf{P}_t,\boldsymbol{\lambda}_t)$ is usually concave, if not linear, whereas $d_t(\mathbf{P}_t)$ is convex when the total cycle number of the EES, N_{DOD}, is a convex function of the depth of discharge (DOD):

$$N_{\mathrm{DOD}}=g(\mathrm{DOD}) \tag{15}$$

The function g is usually a power function[7,14,17,20,32]:

$$N_{\mathrm{DOD}}=N_0\mathrm{DOD}^k \tag{16}$$

where N_0 is the total cycle number at 100% DOD and k is a parameter related to the EES chemistry. The DOD is determined by the power outputs of the EES, usually in a form of linear combinations of the elements of $\mathbf{P}_t$. Therefore, $k\leq -1$ is a sufficient optimality condition in terms of EES life-cycle benefit. In the case studies of this paper, we set $k=-1$ for the studied lithium-ion EES[32]. This function is also used to convert the energy throughput of partial cycles into the equivalent throughput of full cycles.

Both the short-term and long-term decision models are convex in general, for which a global optimal solution could be achieved with common solving methods or commercial solvers. The MBU brings little additional computational complexity to the short-term optimization model, whatever form the model takes and algorithm it is solved by. Supplementary Note 3 contains more discussion of the computational complexity.

ABU method. The ABU (US\$ MWh throughput^{-1}) and the ACD (US\$ MWh throughput^{-1}) are calculated by equations (17) and (18):

$$\mathrm{ABU}=\frac{\mathrm{LB}_{\max}}{D} \tag{17}$$

$$\mathrm{ACD}=\frac{\mathrm{CAPEX}}{D} \tag{18}$$

Energy arbitrage. In the application of energy arbitrage, the short-term decision problem is described as equation set (19)–(24):

$$\mathrm{SB}_t=\max_{P_h^{\mathrm{dis}},P_h^{\mathrm{cha}}}\sum_{h\in(t,t+\Delta t)}\lambda_h^{\mathrm{e}}(P_h^{\mathrm{dis}}-P_h^{\mathrm{cha}})\Delta h-c_{\mathrm{fix}} \tag{19}$$

$$\text{subject to}\quad \frac{\partial \mathrm{SB}_t}{\partial d_t}=\frac{\mu}{\delta_t}\quad \text{if}\quad d_t>C_t \tag{20}$$

$$d_t=\sum_{\mathrm{DOD}}2E_t^{\max}n_{t,\mathrm{DOD}}\mathrm{DOD}^k+C_t \tag{21}$$

$$E_h=(1-\rho)E_{h-1}+P_h^{\mathrm{cha}}\eta_t\Delta h-\frac{P_h^{\mathrm{dis}}\Delta h}{\eta_t} \tag{22}$$

$$0\leq P_h^{\mathrm{dis}},P_h^{\mathrm{cha}}\leq P_t^{\max} \tag{23}$$

$$0\leq E_h\leq E_t^{\max} \tag{24}$$

The objective function, as in equation (19), is the sum of revenues at each hour h within the time interval $(t,t+\Delta t)$, minus the fixed operating and maintenance

(O&M) costs c_{fix} (US$). Δh denotes the time interval, which is 1 h in this paper. $n_{t,\mathrm{DOD}}$ denotes the number of cycles at a certain DOD during $(t, t+\Delta t)$, and is determined by the discharging and charging schedules, P_h^{dis} and P_h^{cha} (MW). Equation (21) estimates the EES degradation based on the cycle numbers at each DOD and calendar degradation[12,16], where $E_t^{\max}$ is the EES energy capacity during time t (MWh), and $2E_t^{\max}$ represents the energy throughput of a full cycle, which includes both charging and discharging. By assuming the temperature and the average SOC of the EES are constant, the calendar degradation rate can be regarded as a constant. For energy arbitrage, EES typically takes one or two cycles per day, and thus we can estimate the degradation by setting $n_{t,\mathrm{DOD}} = 1$ and $\mathrm{DOD} = \sum_{h\in(t,t+\Delta t)} \frac{P_h^{\mathrm{dis}} + P_h^{\mathrm{cha}}}{2E_t^{\max}}$.

Equation (22) describes the charging/discharging process of the EES as a function of its SOC, where E_h is the SOC at hour h (MWh), ρ is the self-discharge rate (%) and η_t is the charge/discharge efficiency during time t (%). Equations (23) and (24) indicate the physical constraints of the power output and the SOC of the EES, where $P_t^{\max}$ is the EES power capacity (MW) during time t. Equations (21)–(24) form the feasible set **F** in this application of energy arbitrage.

As described in Fig. 1, the planning decision should be made first by comparing the ABU and the ACD calculated by equations (17) and (18), and it requires both long-term and short-term simulations that solve equations (14) and (19)–(24). Then, the long-term decision is made by solving equations (14) and (19)–(24), based on projections on the future market prices. Finally, the short-term decisions are made rollingly by solving equations (19)–(24) repeatedly given the DMBU.

In the case study, we assume that the charge/discharge efficiency is 90% (ref. [39]), and the remaining capacity decreases to 70% of the originally available (when bought and installed) after 3,000 charge–discharge cycles at the maximum DOD. For this EES system, 3,000 full cycles are equivalent to a throughput of 1.2 TWh if the system does not degrade. Moreover, assuming the life of EES ends when the capacity has decreased to 70% of the initial, 1.2 TWh of processed energy corresponds to a 30% capacity loss. Note that the energy throughput here and in the following is measured at full (100% DOD) cycles, and the throughputs of other partial cycles are converted equivalently into that of full cycles[14,20]. The calendar degradation of the EES, which represents the degradation independent of the number of cycles, is assumed to be equivalent to processing at 50 MWh throughput per day (about 0.5% capacity loss per year)[36–38]. A discount rate of 7%, as a typical value for private investment recommended by the Office of Management and Budget of the United States[40], is applied for all results in this article. We do not account for taxation, salvage value and other lesser fixed O&M costs in the results, but these are easy to include for any additional analysis. The EES owner/operator is assumed to be a price taker with perfect price information.

Energy arbitrage and frequency regulation. The short-term scheduling model for the combined application of energy arbitrage and frequency regulation is described by the equation set (25)–(31):

$$\mathrm{SB}_t = \max_{P_h^{\mathrm{dis}},P_h^{\mathrm{cha}},P_h^{\mathrm{ru}},P_h^{\mathrm{rd}}} \sum_{h\in(t,t+\Delta t)} [\lambda_h^{\mathrm{e}}(P_h^{\mathrm{dis}} - P_h^{\mathrm{cha}})\Delta h + \lambda_h^{\mathrm{ru}} P_h^{\mathrm{ru}} \Delta h + \lambda_h^{\mathrm{rd}} P_h^{\mathrm{rd}} \Delta h)] - c_{\mathrm{fix}} \tag{25}$$

$$\text{subject to} \quad \frac{\partial \mathrm{SB}_t}{\partial d_t} = \frac{\mu}{\delta_t} \quad \text{if} \quad d_t > C_t \tag{26}$$

$$d_t = \sum_{\mathrm{DOD}} 2E_t^{\max} n_{t,\mathrm{DOD}} \mathrm{DOD}^k + C_t \tag{27}$$

$$E_h = (1-\rho)E_{h-1} + (P_h^{\mathrm{cha}}\Delta h + \sigma_h^{\mathrm{rd}} P_h^{\mathrm{rd}})\eta_t - \frac{P_h^{\mathrm{dis}}\Delta h + \sigma_h^{\mathrm{ru}} P_h^{\mathrm{ru}}}{\eta_t} \tag{28}$$

$$0 \le P_h^{\mathrm{dis}} + P_h^{\mathrm{ru}} \le P_t^{\max} \tag{29}$$

$$0 \le P_h^{\mathrm{dis}} + P_h^{\mathrm{rd}} \le P_t^{\max} \tag{30}$$

$$0 \le E_h \le E_t^{\max} \tag{31}$$

In equation (25), λ_h^{ru} and λ_h^{rd} represent the revenues per unit of power capacity (US$ MWh^{-1}) in regulation-up and -down markets at hour h, after accounting for regulation capacity and mileage prices, mileage and performance score; and P_h^{ru} and P_h^{rd} represent the power capacities (MW) committed in regulation-up and -down markets, respectively. In equation (28), σ_h^{ru} and σ_h^{rd} are the expected net energy per unit of power capacity (MWh MW^{-1}) for providing regulation-up and -down services. Equations (28)–(31) describe the constraints that the EES must hold enough power and energy capacities, in addition to energy arbitrage, to provide regulation services in response to the orders from the power-system operator. Equations (27)–(31) form the feasible set F in this combined application. To estimate the number of cycles at each DOD in this case, we referred to an existing cycle-number calculation method designed for frequency-regulation application[14,41], in which the cycle number is statistically estimated as a function of the committed capacities in energy and regulation markets (P_h^{dis},P_h^{cha}, P_h^{ru} and P_h^{rd}) based on historical regulation signals. The solving procedures are similar to those for the single application of energy arbitrage.

Data availability. The energy and regulation market price data of CAISO in 2016 are available from the CAISO Open Access Same-time Information System (OASIS) site (http://oasis.caiso.com/mrioasis/logon.do).

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Author contributions
G.H., J.F.W. and Q.C. conceived and designed the research. G.H. developed the decision framework. G.H. and J.F.W. carried out the simulations and analyses. All authors contributed to writing the article.

Competing interests
The authors declare no competing interests.

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