Energy Conversion and Management: X 21 (2024) 100519

Contents lists available at ScienceDirect

Energy Conversion and Management: X

journal homepage: www.sciencedirect.com/journal/energy-conversion-and-management-x

Smart and optimization-based operation scheduling strategies for maximizing battery profitability and longevity in grid-connected application

Masoume Shabani [a,*], Mohadeseh Shabani [b], Fredrik Wallin [a], Erik Dahlquist [a], Jinyue Yan [a,c]

[a] School of Business, Society & Engineering, Department of Sustainable Energy Systems, Mälardalen University, Sweden
[b] Department of Industrial Engineering, Azad University, Lahijan, Iran
[c] Department of Building Environment and Energy Engineering, Hong Kong Polytechnic University, Hong Kong

ARTICLE INFO

Keywords:
Day-ahead optimization-based battery operation scheduling
Price arbitrage within real-time electricity price tariff
Sustained profitability optimization
Degradation cost minimization
Revenue maximization
Residential-grid connected battery application

ABSTRACT

Lithium-ion battery storage has emerged as a promising solution for various energy systems. However, complex degradation behavior, relatively short lifetime, high capital, and operational costs, and electricity market volatility are critical factors that challenge its practical viability. Thus, to ensure sustained profitability of Lithium-ion batteries in real-life applications, a smart and optimal management strategy considering key influencing factors is imperative for achieving efficient battery utilization.

This study proposes two day-ahead battery-behavior-aware operation scheduling strategies to maximize profitability and longevity in residential grid-connected applications with dynamic electricity pricing. Each scenario employs unique approaches to make optimal decisions for optimal battery utilization. The first scenario optimizes short-term profitability by prioritizing revenue gains under three charge/discharge rates (high, moderate, low), considering daily charge and discharge timings as decision variables. Conversely, the second scenario proposes a smart strategy capable of making intelligent decisions on a wide range of variables to simultaneously maximize revenue and minimize degradation costs, ensuring short-term and long-term profitability. Decision variables include the cycle frequency for each specific day, timings as well as durations for charging and discharging per cycle. To ensure effective long-term assessment, both scenarios accurately estimate battery performance, calendric and cyclic capacity degradations, remaining-useful-lifetime, and internal states under real operational conditions until battery reaches its end-of-life criteria. The scenarios are assessed economically using various indicators. Furthermore, the impact of battery price and size on optimization outcomes are examined.

The key findings indicate that, among the first set of scenarios, the strategy with low charge/discharge rate extends the battery lifetime most efficiently, estimated at 14.8 years. However, it proved to be the least profitable, resulting in negative profit of −3€/kWh/yr. On the other hand, strategies with high and moderate charge/discharge rates resulted in positive profit of 8.3 €/kWh/year and 9.2 €/kWh/year, despite having shorter battery lifetimes, estimated at 10.1 years and 13.6 years, respectively. Furthermore, from a payback perspective, the strategy with fast charge/discharge capability led to 1.5 years shorter payback period than that of the moderate rate strategy. The findings highlight that the first set of scenarios limits the strategy's flexibility in achieving both sustainability and profitability. In contrast, the second scenario achieves impressive profit (18 €/kWh/yr), shortest payback period (7.5 year), a commendable lifespan (12.5 years), contrasting revenue-focused scenarios, emphasizing the importance of striking optimal balance between revenue gain and degradation costs for charging/discharging actions, ensuring sustained profitability. The findings offer valuable insights for decision-makers, enabling informed strategic choices and effective solutions.

* Corresponding author.
E-mail address: masoume.shabani@mdu.se (M. Shabani).

https://doi.org/10.1016/j.ecmx.2023.100519
Received 19 September 2023; Received in revised form 30 November 2023; Accepted 17 December 2023
Available online 21 December 2023

Nomenclature

Abbreviations

AIP Ageing influence parameter
BOL Beginning of life
DOC Depth of cycle of battery
EOL End of life
FEC Full equivalent cycle of a battery
$ICC_{battery}$ Initial investment cost of a battery
LF Battery lifetime
LFP/C Lithium-iron phosphate ($LiFePO_4$/C)
OCV Open circuit voltage
RTP Real-time price
SOC Battery state of charge
SOH Battery state of health
TMS Thermal management system

Symbols

C_{batt} Battery capacity
C_{fade,cal_t} Calendric capacity fade at time t (%)
C_{fade,cyc_t} Cyclic capacity fade at time t (%)
C_{fade,tot_t} Total capacity fade at time t (%)
$Cost_{\deg,battery}$ Battery degradation cost (€)
d Charge/discharge duration (h)
$I_{ch(dch),\ i}$ Battery charge (discharge) current at time t
$El_{w,t}$ Wholesale electricity price at time t
$El_{r,t}$ Retail electricity price at time t
m Number of days over project life; m = 1, …, project life
NOC Number of cycles per day
MA_{RTP_m} Moving average of RTP at time t of day m
opt optimal
$P_{batt,t}$ Battery power at time t
$P^{ch}_{min,t}$ Maximal charge power at time t
$P^{dch}_{max,i}$ Maximal discharge power at time t
$P_{batt-load,t}$ Transferred power from the battery to the load at time t
$P_{batt-grid,t}$ Exported power from the battery to the grid at time t
$P_{grid-batt,t}$ Imported power from the grid to the battery at time t
$P_{grid-load,t}$ Imported power from the grid to the load at time t
PI Profitability Index (%)
PPEI Averarge yearly profitability per energy installed (€/kWh/yr)
PV Present value
$R_{ch(dch),\ i}$ Battery internal resistance at time t
T Temperature (K)
time Passed time since the BOL (Sec)
$t_{ch,start,m}$ Start time indicator for charging the battery at day m
$t_{dch,start,m}$ Start time indicator for discharging the battery at day m
$V_{ch(dch),\ i}$ Battery terminal voltage during charging (discharging) at time t
X Decision variable in scenario B
Y Decision variable in scenario A

Greek Symbols

$\delta_{Replace}$ Battery replacement indicator

Introduction

Battery storage systems have emerged as a critical component in enabling a sustainable, efficient, and resilient energy system [1–3]. The growing demand for renewable energy sources, coupled with the need for a reliable and stable electricity grid, has highlighted the potential benefits of battery storage systems in providing a wide range of energy services for residential, commercial, and industrial sectors [4–8]. The flexibility and adaptability of batteries makes batteries a dominant and viable storage technology, supporting efficient and sustainable energy management [9–11]. Battery storage holds significant potential to participate in the arbitrage market, thanks to its flexibility and fast response time [12–14]. The idea behind price arbitrage strategy involves generating revenue by leveraging the fluctuating behavior of electricity prices. This is achieved by charging the battery when electricity prices are low and using the stored electricity when the electricity prices are higher, taking advantage of electricity price differentials [15–17].

Exploiting price arbitrage can alleviate the load on the grid during peak hours, thereby enhancing grid stability and reliability. Furthermore, shifting energy consumption from on-peak to off-peak hours can result in reduced electricity bills for customers [18], empowering them to manage energy consumption effectively and decrease peak demand in a cost-effective manner [19,20]. However, the practical viability of implementing batteries for price arbitrage faces challenges due to several key factors such as high investment costs, high operational costs, complex degradation behavior, relatively short lifetime, and electricity market volatility. In many cases, studies showed that the generated revenue from price arbitrage within battery system is often insufficient to overcome these challenges, yielding a negative profit [21–26]. Hence, a central question remains on how to enhance the viability of batteries for price arbitrage applications within the current electricity market. A key consideration revolves around the effective price arbitrage strategies to efficiently utilize and manage battery systems in practical applications. The methods employed for charge and discharge actions to capitalize on price differential within electricity market can significantly influence several factors such as degradation rate improvement, lifetime extension, operational cost reduction, increased revenue gains, replacement cost reduction, and emission implication. These factors collectively contribute to the overall profitability of batteries in the application [26,27]. Consequently, the development of an effective operation scheduling and management strategy for price arbitrage is a necessity to make informed decisions on how a battery system is efficiently controlled, maintained, and operated over its lifespan to maximize overall profit. Numerous studies shed light upon evaluating the economic viability of implementing batteries for price arbitrage in the electricity market. Each study employed specific constraints, assumption, simplifications to formulate price arbitrage strategy using battery storage in energy systems. However, as detailed in this section, there are notable hurdles in existing price arbitrage strategies that need to be addressed properly.

One of the main considerations in devising price arbitrage strategies lies in determining the pricing scheme under which the strategy will be developed. One of the common pricing schemes is real-time pricing (RTP) [28,29]. The RTP scheme implements fully dynamic rates, tracking wholesale market prices that vary hourly and daily, providing users with the flexibility to adjust their energy consumption based on real-time electricity prices [30]. However, the critical challenge lies in determining the optimal times to charge and discharge batteries to attain the maximum profit. One of the most straightforward and widely employed price arbitrage strategies involves charging and discharging batteries during "fixed and pre-set hours" such as those recent studies [21–23]. For instance, low-price hours may be designated between certain hours from midnight to 8 a.m., while high-price hours could span from 8 a.m. to 8p.m. This method assumes that the low- price hours and high-price hours for potential charging and discharging remain same across all days of the year [22], or in some cases there is assumption that these hours vary seasonally, or even between weekdays versus weekend [21]. In this approach, the peak and off-peak electricity price hours are usually provided by the power exchange company, or they can be determined by analyzing historical electricity price data [18,22,24]. However, this strategy has limitations in fully capturing the price arbitrage potential, especially under volatile RTP electricity scheme, where "optimal" price differential may occur at different periods than those originally set. Accordingly, setting fixed and pre-set hours may not be an optimal option as different selections of charge and discharge timings lead to different operation profits [22]. Addressing this limitation, several studies focused on enhancing the flexibility of price arbitrage strategy in capturing the maximum revenue potential. These studies employed various methods to identify and adjust profitable charge and discharge timings based on dynamic electricity price conditions. For instance, an approach relying on historical data was employed by several studies such as those in [22,24,31]. The implemented method involves finding the historical daily lowest and highest prices to determine the best times for charging and discharging each day. However, the results of these studies showed that the generated revenue under the evaluated strategy could not compensate the investment cost and was unprofitable under the market condition at the time of studies (year: 2021 [24], 2022 [22], and 2014 [31]). In contrast, a study by [32] employed a moving-average calculation method to determine the optimal daily charge and discharge timings, aiming to maximize daily profit under a specific RTP profile. Additionally, another study conducted by [26], took a different route evaluating all possible combinations of maximum and minimum RTPs per day. The optimal charge and discharge times were then determined by selecting the combination with the widest gap, aiming to maximize revenue under RTP scheme for a specific day. In the aforementioned studies, the effectiveness of price arbitrage strategy in maximizing revenue has been enhanced by identifying profitable times for charging and discharging actions. However, it is important to note that this improvement alone may not be sufficient for optimizing overall performance. One limiting factor in their investigation was the imposition of a "fixed charge and discharge duration" set at one hour. The charge and discharge durations, also known as charge/discharge C-rate, represent the ratio that determines the maximum hours a battery can deliver or accept its usable capacity, playing a vital role in capturing higher price differentials. The impact of various fixed charge and discharge C-rates (e.g, 0.1C,0.2C, 0.3C, …,1C), on revenue generation for arbitrage purposes has been evaluated by [24].The results showed that the total income increase as the C-rate increases. This was because batteries with higher C-rates can charge and discharge more quickly, resulting in less exposure to market price fluctuations. Another limiting factor identified is that most price arbitrage strategies restricted the battery system to one cycle per day, while, allowing for more cycles per day could enhance the strategy's flexibility to capture multiple significant price differentials within a day [33].

Another important factor which highly impacts the profitability of price arbitrage strategy with batteries is battery degradation. Battery degradation is a complex mechanism and is influenced by several factors [34–36]. Consequently, a comprehensive understanding of battery degradation mechanisms and the key influencing factors is crucial for the development of optimal battery management strategies [34]. However, literature studies on price arbitrage strategies have not thoroughly addressed the impact of degradation on battery operation scheduling. Many studies in the field completely ignored degradation [22,23,26,31,32,37–43]. In Some studies [18,44–48], battery ageing is calculated post-optimization, meaning that the strategy does not consider the impact of degradation on operational decisions. In these studies, two methods have commonly been employed to assess degradation: the Ah throughput method and the method based on cycle life in relation to the depth of discharge (DOD). In the Ah throughput method, the assumption is that a specific amount of energy can be cycled through a battery before reaching its end-of-life, regardless of the DOD. In contrast, the second method assumes an inverse relationship between the number of cycles a battery can complete and the battery DOD. In some study such as [22,49], only a fixed annual capacity loss rate has been considered to incorporate its effects when calculating yearly net present values. Some studies such as [32], the profit optimization objective function included a cost per cycle associated with the battery. This cost per cycle was determined by considering the initial investment cost and the total number of cycles that battery could perform at a specific DOD. It's important to note that the aforementioned study assumed that the battery capacity remained constant, and the impact of degradation was not factored into the calculations. In [50] a mathematical tool for cumulative degradation is introduced as a means to control battery aging. However, the focus remained on short-to-medium term system operation. A study conducted by [51], investigated the impact of battery ageing on energy arbitrage revenue related to grid-level energy storage. The authors emphasized the significance of incorporating degradation cost penalty into the assessment of battery profitability, enabling a better evaluation of the cost-effectiveness of battery storage implementation. However, the modeling of battery capacity fade, and degradation cost were assumed to be a linear function of energy throughput and further investigation is required to determine the optimal value for the degradation penalty cost, considering the battery's operational condition.

For more illustration, in real-life applications, particularly in applications where batteries are implemented to capture potential price differentials under RTP electricity scheme, the battery system operates under dynamic operational conditions, and battery degradation has non-linear behavior highly dependent on real operational conditions. For more illustration, batteries undergo two forms of aging: cyclic aging during use and calendric aging during storage. The influential factors in cyclic degradation include temperature, depth of cycle (DOC), current rate (C-rate), SOC level, and cycle frequency. For calendric aging, temperature, storage SOC, and elapsed time since the beginning of life are key factors [36,52,53]. Comprehensive overview of different battery degradation and lifetime models can be found in literature [54,55].

Overlooking or simplifying key aging influencing factors can impact decisions related to system operational efficiency, technical considerations, and economic assessments [54]. When designing a price arbitrage strategy, focusing solely on revenue gain without considering degradation can be problematic as degradation can significantly reduce the battery's capability to store and deliver energy, affecting projections of earned revenue. Furthermore, it impacts battery lifetime, potentially leading to increased replacement costs.

Objectives and contributions of the present study

Through the extensive review of the existing literature, it has been found that the viability of implementing batteries for capturing profit potential under RTP electricity schemes hinges on crucial factors such as (i) daily cycle frequency, (ii) charge and discharge timings within each cycle, and (iii) the duration of charge and discharge per cycle. These factors profoundly affect both revenue generation and battery degradation. However, existing price arbitrage strategies often rely on assumptions and objective functions that overlook the simultaneous consideration of all influencing factors on all key aspects including revenue gains, capacity degradation, operation-dependent lifetime, and their interconnected effects. This gap underscores the critical need to evaluate how overlooking or simplifying these factors as well as objectives can affect the system economic viability. Furthermore, this recognition highlights the urgent need for developing a robust and advanced price arbitrage strategy capable of making intelligent decisions on these factors concurrently, ensuring not only maximized profitability but also the longevity of the battery system.

The significance of factors (i)-(iii) and their interconnected impacts on revenue gain and degradation can be elucidated as follows: increasing the number of cycles per day can potentially increase revenue but simultaneously accelerate battery degradation. Conversely, opting for fewer cycles can extend the battery's lifespan but may gain lower revenue in the long run. For instance, sometimes increasing the number

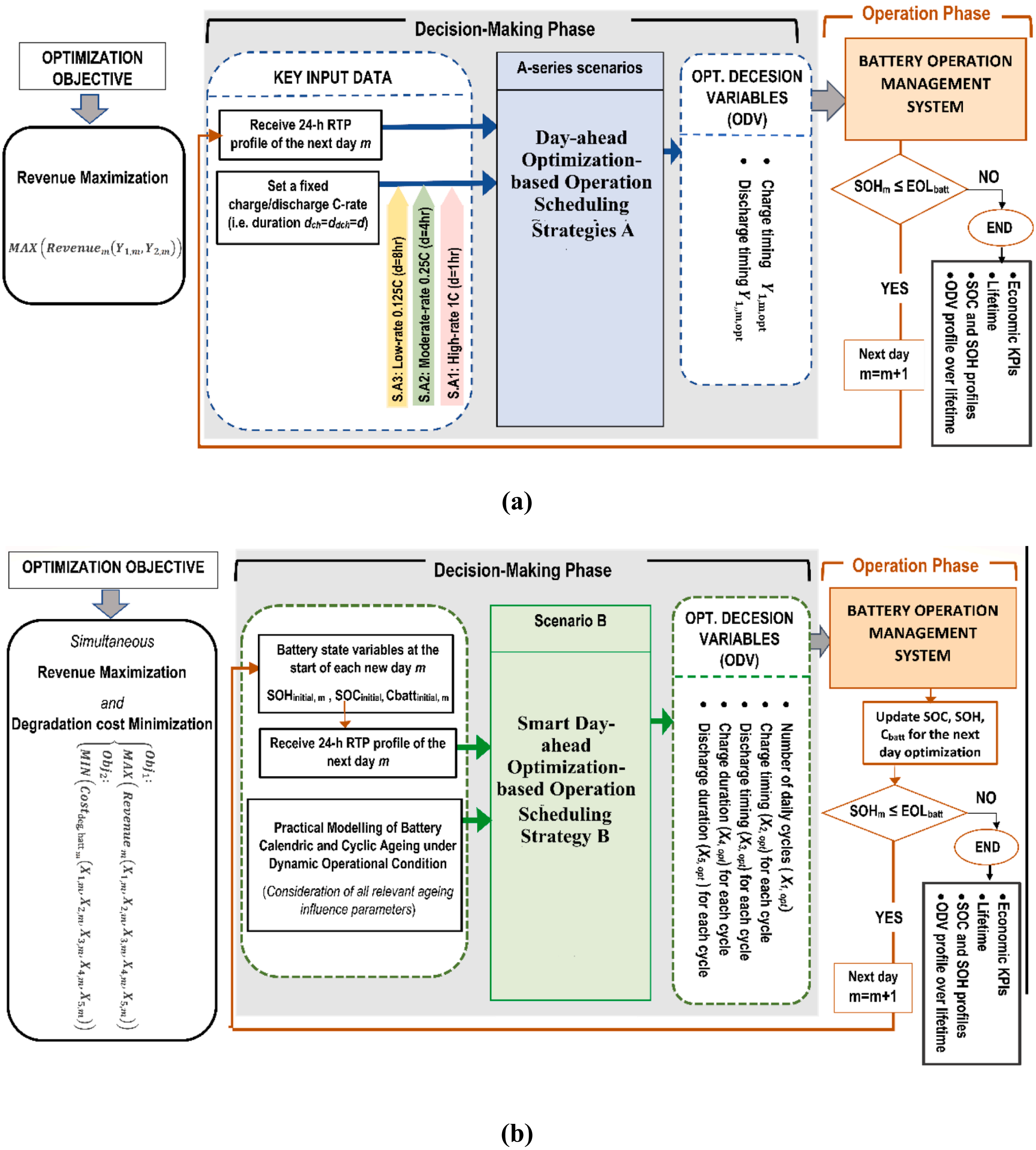


Fig. 1. Illustration of the proposed scenarios for optimal battery operation scheduling, (a) A-series scenario: short-term profitability optimization; (b) Scenario B: short- and long-term profitability optimization.

of cycles to two per day can help to capture multiple significant price differentials within a day, potentially boosting revenue. However, it is vital to consider the costs associated with faster degradation. If the daily profit ** from two cycles per day surpasses that of fewer cycles even under higher degradation cost, then it is more beneficial to stick with more cycles per day. Otherwise, it is better to extend the battery's lifespan by reducing the daily cycle count. Moreover, charging or discharging the usable battery capacity at higher rates (faster charge) can potentially increase revenue but also hasten degradation. Conversely charging or discharging at lower rates (slower charge) can result in reduced revenue generation but also less degradation. The challenge lies in striking the right balance.

Another challenge lies in the effectiveness of this strategy in capturing the impact of battery performance and degradation on the aforementioned factors under dynamic operational conditions. In light of this, the gap pertains to the absence of an efficient "battery behavior-aware" price arbitrage strategy that simultaneously consider multiple crucial aspects of battery behavior under realistic operational conditions, including: (a) efficient estimation of battery performance, (b) precise prediction of calendric and cyclic capacity degradation, (c) proper prediction of battery state-of-charge (SOC), state-of-health (SOH), and state-of-power (SOP), (d) accurate estimation of remaining useful life (RUL).

Another research gap lies in evaluating the long-term impact of battery utilization over its lifetime. Th profitability assessment in existing studies in field usually rely on short-term simulation which typically lasts only a few days, weeks or one year_may inadequately capture the full complexity of how batteries age and perform over their entire operational lifespan. Accordingly, it is imperative to conduct long-term analysis of battery operation until it reaches its end-of-life (EOL) criterion. Such a comprehensive and long-term analysis is a necessity to provide decision-makers and battery owners with a thorough understanding of battery profitability in practical applications.

However, the daily scheduling of battery operations up to the point where the battery reaches its EOL, presents another challenge: the need for effective coordination between the scheduling phase and the operation module.

In summary, by addressing all these challenges, the main contribution is to develop smart operation scheduling strategies that effectively and efficiently utilize batteries under the RTP electricity scheme, ensuring both maximum profitability and longevity. This comprehensive approach aims to bridge existing gaps in literature and provide valuable insights for decision-makers and battery owners in practical applications.

The main contributions of the present study are summarized as follows:

- As illustrated in Fig. 1, this study proposes two scenarios aimed at optimizing battery operation scheduling within the day-ahead RTP electricity market. The primary objective is efficient utilization of battery to maximize profitability through simultaneous consideration of key influencing factors on revenue generation, capacity fade, lifetime, and their interconnected impacts. The scenarios differ in their conceptual approaches to achieving profitability, as outlined below:

(i) Short-term profitability optimization: the proposed scenario (as depicted in Fig. 1a) prioritizes immediate revenue gains. Although strategy takes into account the impact of operation on degradation, it does not optimize the long-term consequences beyond that objective, since its primary focus is on immediate revenue maximization. The scenario achieves this objective through identifying the maximum daily electricity price differential considering a fixed charge and discharge durations. To further explore the impact of different durations on optimization

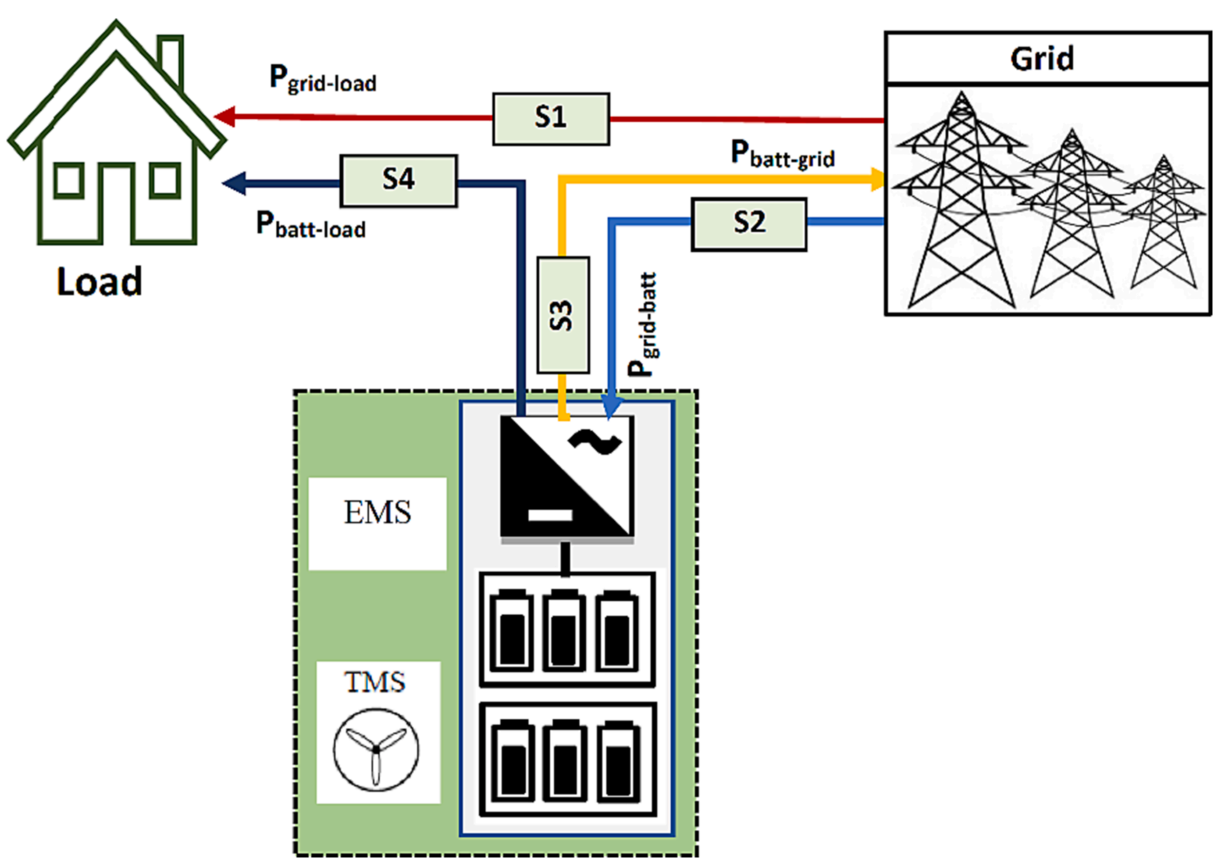


Fig. 2. Configuration of the investigated grid-connected battery system.

objective, battery degradation and longevity, we propose three variations of charge and discharge rates: high, moderate, and low. These variations divide the scenario into three subsequent scenarios, allowing for a detailed exploration of their respective effects.

(ii) Short-term and long-term profitability optimization: the proposed scenario (as illustrated in Fig. 1b) introduces a novel and intelligent operation scheduling strategy which expands its focus beyond immediate gains and encompasses sustained profitability over an extended period. This strategy simultaneously makes optimal decisions on a wide range of crucial factors that influence both daily revenue and daily degradation. These factors include determining the optimal cycles for each specific day, identifying optimal hours for charging and discharging during each cycle, and finding the optimal durations for charge and discharge per cycle. The objective is to simultaneously maximize daily revenue generation while minimizing daily battery degradation cost. Finding the right balance is crucial for maximizing long-term profit and extending the battery's lifespan.

- A battery behavior-aware management strategy is conducted to accurately simulate battery operation in both scenarios. The strategy can effectively estimate voltage-current behavior, calendric and cyclic capacity fades, remaining useful life, and internal-states such as state of charge (SOC) and state of health (SOH) under real-life operational conditions, thereby ensuring efficient battery management adaptable to practical application.
- Project economic viability under both scenarios is assessed by an extensive set of economic key performance indicators (KPIs), including the present values of total revenue, as well as profit over project life, profitability index, profitability per energy installed, and payback period.
- The study evaluates the impact of battery price, battery size on optimal decision making within the proposed scheduling strategy, as well as their effects on the lifetime, and economic KPIs to assess the importance of changing these parameters.
- Unlike conventional simulations that typically last for only a few days or a year, daily operation scheduling is performed under both scenarios until the battery reaches the EOL. This approach ensures an effective long-term assessment of profitability, which is of high importance due to the battery's changing performance over time, driven by its nonlinear degradation behavior.
- An algorithm is conducted to effectively coordinate the "scheduling phase" with the "operation module" to ensure updating and sending the current battery state information to scheduling phase to facilitate the next day operation planning.

Methods

Section 2.1 presents the schematic layout of the studied system. Section 2.2 and 2.3 illustrate the battery system modelling method applied in this study. Section 2.5 describes the problem description. Finally, Section 2.6 presents the operative hypotheses and system operational strategy.

System layout description

The figure displayed in Fig. 2 illustrates the configuration of the residential grid-connected battery system under investigation. The system comprises an AC battery equipped with an integrated inverter, enabling the direct conversion of its stored DC power into AC power. Additionally, a temperature controller is employed to regulate the temperature of the battery system. The electric grid and a load are also integral components of the system. In essence, the system leverages the price arbitrage strategy, wherein the battery is charged during off-peak hours and the stored electricity is discharged during periods of high prices.

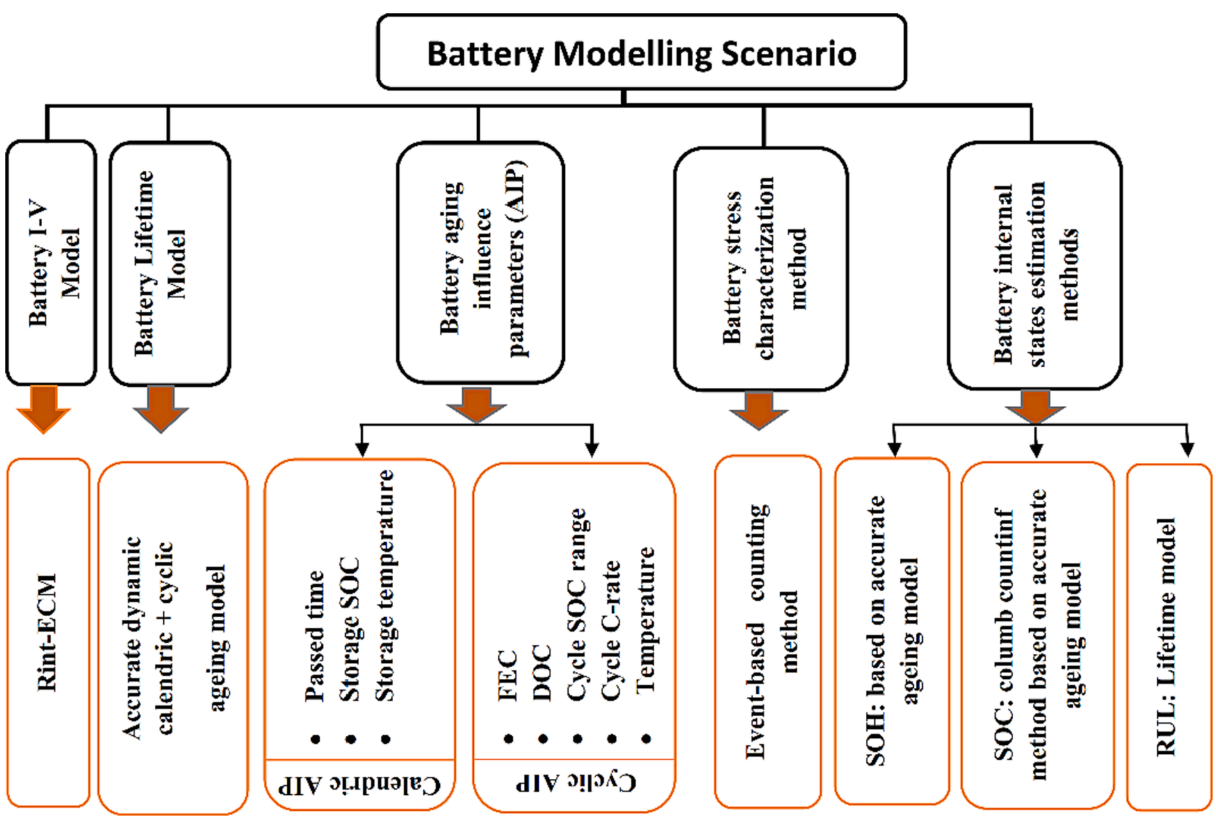


Fig. 3. Illustration of the conducted battery modelling scenario.

Battery modelling scenario

The Lithium-iron phosphate (LFP/C) type of Li-ion batteries has gained significant attention for its suitability in stationary applications due to its safety, long lifespan, fast charging/discharging rate, durability, and use of non-toxic materials [13,56,57]. In this study, an LFP battery with detailed technical specifications [58] outlined in Appendix A (Table A1) is utilized.

In this study, we conduct a detailed battery modelling scenario, as depicted in Fig. 3. The scenario incorporates specific methods for reliable estimation of various battery parameters, including voltage-current characteristics, capacity degradation, remaining useful lifetime, and internal states. A detailed exposition of each method is provided in the subsequent sections, outlining the techniques employed to accurately estimate these key battery parameters.

The battery's current–voltage relationship is described by the Rint electrical model [39], chosen as trade-off between the accuracy and computational time. The internal parameters of the Rint electrical model conducted in this study are a function of operating conditions, which improve the model accuracy. Eqs. (1) and (2) illustrate the model's ability to capture the charging and discharging terminal voltages as function of operational conditions. Additional details regarding the studied battery performance model can be found in the author's previous work [12].

$$V_{ch,t}(SOC_t,T,I_t) = OCV_{ch}(SOC_t,T,I_t) + I_{ch,t} \times R_{ch}(SOC_t,T,I_t) \tag{1}$$

$$V_{dch,t}(SOC_t,T,I_t) = OCV_{dch}(SOC_t,T,I_t) + I_{dch,t} \times R_{dch}(SOC_t,T,I_t) \tag{2}$$

In this study, a practical aging model, developed and validated by Naumann et al. [52,53] under dynamic stress profiles, is employed to simulate battery lifetime and capacity degradation under real-life operational conditions. The total capacity degradation of the battery at each time interval is represented by Eq. (5), derived by combining the calendric capacity degradation model (Eq. (3)) and the cyclic capacity degradation model (Eq. (4)). This model effectively estimates capacity degradation during both storage and operation, taking into account various factors such as storage SOC, cycle depth, elapsed time since the beginning of life (BOL), full equivalent cycle (FEC), and cycle charge/discharge rate. For a more detailed understanding, a complete description of the implemented aging model and guidelines on its application under diverse operational conditions can be found in [54].

$$C_{\mathrm{fade,\,cal}_t}(SOC, time) = \left(\alpha_1 (SOC - 0.5)^3 + \alpha_2\right).time^{0.5} \tag{3}$$

$$C_{\mathrm{fade,\,cyc}_t}(C_{rate}, DOC, FEC) = (\beta_1.C_{rate} + \beta_2) \times \left(\gamma_1 (DOC - 0.6)^3 + \gamma_2\right) \times (FEC)^{0.5} \tag{4}$$

$$C_{\mathrm{fade,\,tot}_t}(SOC,\ time, C_{rate},\ DOC,\ FEC) = (C_{\mathrm{fade,\,cal}_t}(SOC,\ time) + C_{\mathrm{fade,\,cyc}_t}(C_{rate},\ DOC,\ FEC)) \times C_{\mathrm{batt,\,BOL}} \tag{5}$$

The battery's SOC and SOH are crucial internal parameters that indicate the remaining charge level and the level of battery degradation, respectively. Accurate tracking of these parameters requires reliable state prediction methods. As shown in Eq. (6), the SOC at each time interval is estimated using the Coulomb counting method. The constraint (S2 + S3,4) ≤ 1 in Eq. (7) ensures that the battery is not allowed to simultaneously charge and discharge. Since the self-discharge rate of Li-ion batteries is low per month [59], the calculations in this study do not take into account the impact of Li-ion self-discharging. The battery's SOH at each time interval is quantified by Eq. (7).

$$SOC_{t+1} = SOC_t - s_2 \frac{\int I_{ch,t} dt}{SOH_t C_{batt,BOL}} + s_{3,4} \frac{\int I_{dch,t} dt}{SOH_t C_{batt,BOL}} \begin{cases} I_{ch,t} < 0 \\ I_{dch,t} > 0 \\ S_2 + S_{3,4} \leq 1 \end{cases} \tag{6}$$

$$SOH_t = \frac{C_{\mathrm{batt}_t}}{C_{\mathrm{batt,\,BOL}}} \times 100 = \frac{C_{\mathrm{batt,BOL}} - C_{fade,tot_t}}{C_{batt,BOL}} \times 100 \tag{7}$$

Optimizing battery operation scheduling

To achieve efficient and optimal day-ahead battery operation scheduling in the context of price arbitrage within the real-time electricity market, two scenarios are proposed. The main goal of both scenarios is to maximize profitability through efficient battery utilization; however, they differ in terms of strategic approaches to achieve profitability. Scenario A focuses on short-term profitability, and scenario B aims to ensure sustained profitability. Subsections 2.3.1 and 2.3.2 elaborate on Scenario A and Scenario B, respectively. Subsections 2.3.3 and 2.3.4 present the optimization formulations for Scenario A and Scenario B, respectively. The optimization algorithms for Scenario A and B are elaborately illustrated in Subsection 2.3.5.

Scenario A: Description

Scenario A, as shown in Fig. 1(a), introduces a day-ahead operation scheduling strategy that aims to optimize short-term profitability by prioritizing revenue gains. To achieve this objective, the scenario identifies the most favorable times for charging and discharging based on 24-h ahead RTP electricity profile to find the maximum possible daily price differential considering a fixed charge and discharge rate It is important to note that the scenario takes the battery degradation into account and assesses the long-term impact of the approach on battery lifetime and profitability. However, since its primary focus is on revenue maximization, it does not "optimize" the long-term consequences of degradation beyond that objective. To explore the impact of different charge and discharge rates on optimization objective, and battery longevity, Scenario A is evaluated under three variations of charge and discharge rates: high, moderate, and low, which are elaborately explained as follows:

- *Scenario A1* (also referred to as S. A1)*:* it employs a high charge /discharge rate of 1C to allow the battery to quickly reach full capacity within an hour.
- *Scenario A2* (also referred to as S.A2): it provides a "more balance" between revenue generation and battery life longevity by maintaining a moderate charge/discharge rate of 0.25C, enabling the battery to achieve full capacity within a 4-hour duration.
- *Scenario A3* (also known as *S. A3)*: maximizes the daily revenue while maintaining a low battery degradation rate by utilizing a low charge and discharge rate of 0.125C to allow the battery to reach full capacity over 8-hour daily period. The strategy tracks the most profitable times over 8-hour within a day to ensure maximum possible daily revenue, while also minimizing the impact on the battery's long-term life.

Scenario B: Description

To optimize the flexibility of the price arbitrage strategy in capturing maximum profit potential under dynamic RTP electricity schemes, thereby ensuring sustained profitability, it is crucial to develop a strategy that can optimally manage both battery degradation and revenue gain potentials. As mentioned in the introduction section, the potential for price arbitrage with battery storage is influenced by several factors.

These factors include (i) how frequently the battery is charged and discharged each day, (ii) when to charge and discharge within each cycle, and (iii) for how long to charge and discharge with each cycle. These factors have a significant impact not only on revenue generation but also on battery degradation. Therefore, finding the right balance between revenue generation and degradation costs is critical to ensure a profitable management strategy. Scenario B, as shown in Fig. 1 (b), introduces a smart strategy capable of making intelligent decisions on a wide range of decision-variables to simultaneously maximize daily revenue and minimize daily degradation costs, ensuring long-term profitability, and extending the battery's lifetime. Leveraging day-ahead RTP profile, the decision maker determines the most efficient way to schedule battery's operation for the following day. This includes the optimal number of cycles per day, the best times, as well as rates, and durations for each charging and discharging cycles. The scenario incorporates a thorough monitoring of calendric and cyclic battery degradation throughout the scheduling process, considering all relevant key parameters. This enables flexible optimization of decision variables and objective functions.

Scenario A: Optimization objective function, decision variables and constraints

Scenario A objective function: the objective function solely aims to maximize daily revenue ($Revenue_m$) as defined in Eq. (8). The optimal daily profit as indicated in Eq. (9) is obtained by subtracting the battery daily degradation cost ($Cost_{\mathrm{deg,batt}_m}$) from the optimized daily revenue ($Revenue_{\mathrm{opt},m}$), resulting in the highest daily profit that the system can achieve.

Scenario A decision variables: The decision variables Y_i include the daily charge and discharge timing ($t_{\mathrm{ch,\ start},m}$, $t_{\mathrm{dch,\ start},m}$), as shown in Eq. (10), which are influenced by the RTP within a day, and the charge/discharge duration (d). In scenario A, the allowable charge and discharge durations are assumed to be constant and identical for each cycle. Specifically, the battery is designed to charge during (d)-low price hours and discharge during (d)-high price hours, using its full usable capacity during both periods.

Scenario A operating constraints: In order to ensure proper battery operations, it is crucial that battery states be monitored and be within permissible operating constraints as described in Appendix B (Eq. (B1)). The $\mathrm{NOC_m} \leq 1$ constraint in Eq. (B1) ensures that the battery is charged and discharged no more than once per day. The battery is allowed to operate within the maximum charge and discharge power ($P^{\mathrm{ch}}_{\mathrm{min,t}} and P^{\mathrm{dch}}_{\mathrm{max,t}}$) which are determined by considering the battery's available capacity and maximum allowable charge/discharge C-rate. In scenario A, the maximum allowable C-rates for both the charge and discharge process are constant and identical, equivalent to (1/d) over the project's lifespan.

shown in Eq. (11), is to strike a balance between maximizing daily revenue and minimizing battery daily degradation costs ($Cost_{\mathrm{deg,batt}_m}$) to find optimal profit as shown in Eq. (12), which are influenced by a wide range of decision variables. Appendix B elaborates how the system's daily revenue and degradation costs are calculated.

Scenario B decision variables: The scenario's decision variables are shown in Eqs. (13)-(17), which includes the number of cycles per day ($X_{1,m}$), the charging and discharging durations per cycle ($X^{(z)}_{2,m}$, $X^{(z)}_{3,m}$) as well as charge and discharge timings ($X^{(z)}_{4,m}$, $X^{(z)}_{5,m}$) for each cycle. As shown in Eq. (13), a z-value of 0 (z = 0) indicates daily periodicity, where the battery can be fully charged and discharged once within a 24-hour period. In this case, five unknown variables need to be identified for each day (m), as indicated in Eqs. (14)-(17). On the other hand, a z-value of 1 or 2 (z = 1 or z = 2) indicates a semi-daily periodicity, where the battery can be fully charged and discharged twice within a day. The first semi-daily periodicity (z = 1) spans from midnight (00:00) to noon (12:00), and the second semi-daily periodicity (z = 2) spans noon (12:00) to midnight (24:00). In this case a total of nine unknown variables must be identified for day m: four for the first semi-daily periodicity, i.e. charge and discharge timing ($t^{(1)}_{\mathrm{ch,start},m}$, $t^{(1)}_{\mathrm{dch,start},m}$), charge and discharge durations ($d^{(1)}_{\mathrm{ch},m}$, $d^{(1)}_{\mathrm{dch},m}$); and four for the second semi-daily periodicity including charge and discharge timing ($t^{(2)}_{\mathrm{ch,start},m}$, $t^{(2)}_{\mathrm{dch,start},m}$) along with their corresponding durations ($d^{(2)}_{\mathrm{ch},m}$, $d^{(2)}_{\mathrm{dch},m}$). Therefore, to achieve the optimal solution, the optimization algorithm must carefully consider and select the appropriate decision variables. By doing so, they can ensure that the management strategy is provided with accurate and reliable data to help optimize the performance of the battery system. Further details on the optimization algorithm are provided in the next section.

Scenario B state variables: the battery state variables, as indicated in Eq. (18), are updated hourly and reported to the decision maker on a daily basis. On the first day of the project, denoted as m = 1, the initial SOC is set to the maximum SOC ($\mathrm{SOC_{max}}$) and the battery is unused. For subsequent days where m ≠ 1, the initial SOC, SOH, and capacity of the battery are equal to the updated state variables at the end of previous day, where "the end of the previous day" refers to "the last hour of the previous day".

Scenario B operating constraints: To ensure safe and reliable operation of the battery, operating constraints must be followed, as outlined in Appendix B (Eq. (B5)). The $\mathrm{NOC_m} \leq 2$ constraint in Eq. (B5) restricts the number of charge and discharge cycles per day to no more than two. As shown in Eq. (B5), the battery is allowed to operate within the maximum charge and discharge power ($P^{\mathrm{ch}}_{\mathrm{min,t}} and P^{\mathrm{dch}}_{\mathrm{max,t}}$) which are determined by considering the battery's available capacity and maximum allowable charge and discharge C-rates. In scenario B, the

Scenario A

Objective function:

$$\text{Maximize:} Revenue_m\left(Y_{1,m}, Y_{2,m}\right) \rightarrow Revenue_{\mathrm{opt},m}\left(Y_{1,\mathrm{opt},m}, Y_{2,\mathrm{opt},m}\right) \tag{8}$$

$$Profit_{\mathrm{opt},m}\left(Y_{1,\mathrm{opt},m}, Y_{2,\mathrm{opt},m}\right) = Revenue_{\mathrm{opt},m}\left(Y_{1,\mathrm{opt},m}, Y_{2,\mathrm{opt},m}\right) - Cost_{\mathrm{deg,battery}_m} \tag{9}$$

Decision variabels:

$$Y_{1,m} = t_{\mathrm{ch,\ start},m} = f(RTP_m, d); Y_{2,m} = t_{\mathrm{dch,\ start},m} = f(RTP_m, d); \quad m = 1, \ldots, \textit{days over project life} \tag{10}$$

Scenario B: Optimization objective function, decision variables and constraints

Scenario B objective functions: the objective of Scenario B, as

maximum allowable C-rates for both the charge and discharge processes are optimized on a daily basis and may be unequal, equivalent to ($\frac{1}{d_{\mathrm{ch},m}}$, and $\frac{1}{d_{\mathrm{dch},m}}$) over the project's lifespan.

Scenario B

Objective function:

$$\begin{cases} \text{Maximize} : Revenue_m\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right) \\ \text{Minimize} : Cost_{\text{deg,batt}_m}\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right) \end{cases} \rightarrow \text{maximize} Profit_m; m = 1, \cdots, \text{days till EOL} \tag{11}$$

$$Profit_{\text{opt},m}\left(X_{1,\text{opt},m}, X^{(z)}_{2,\text{opt},m}, X^{(z)}_{3,\text{opt},m}, X^{(z)}_{4,\text{opt},m}, X^{(z)}_{5,\text{opt},m}\right) = MAX\left(Revenue_m\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right) - Cost_{\text{deg,batt}_m}\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right)\right) \tag{12}$$

Decision variables

$$X_{1,m} = NOC_m; \quad X_{1,m} | X_{1,m} \in \mathbb{N}, 1 \leqslant X_{1,m} \leqslant 2; \quad z = \begin{cases} 0, X_{1,m} = 1(\text{daily-periodicity}) \\ 1, 2 X_{1,m} = 2(\text{semi-daily periodicity}) \end{cases} \tag{13}$$

$$X^{(z)}_{2,m} = d^{(z)}_{ch,m} = \begin{cases} d^{(0)}_{ch,m}; & X_{1,m} = 1 \\ (d^{(1)}_{ch,m}, d^{(2)}_{ch,m}); & X_{1,m} = 2 \end{cases} \quad \begin{cases} X^{(z)}_{2,m} | X^{(z)}_{2,m} \in N, 1 \le X^{(z)}_{2,m} \le 10 z = 0 \\ X^{(z)}_{2,m} | X^{(z)}_{2,m} \in N, 1 \le X^{(z)}_{2,m} \le 6 z = 1, 2 \end{cases} \tag{14}$$

$$\left\{ X^{(z)}_{3,m} = d^{(z)}_{dch,m} = \begin{cases} d^{(0)}_{dch,m}; & X_{1,m} = 1 \\ (d^{(1)}_{dch,m}, d^{(2)}_{dch,m}); & X_{1,m} = 2 \end{cases} \right\} \quad \begin{cases} X^{(z)}_{3,m} | X^{(z)}_{3,m} \in N, 1 \le X^{(z)}_{3,m} \le 10 z = 0 \\ X^{(z)}_{3,m} | X^{(z)}_{3,m} \in N, 1 \le X^{(z)}_{3,m} \le 6 z = 1, 2 \end{cases} \tag{15}$$

$$X_{4,m} = t_{ch,start,m}(X_{2,m}, RTP_m) = \begin{cases} t^{(0)}_{ch,start,m}; & X_{1,m} = 1 \\ (t^{(1)}_{ch,start,m}, t^{(2)}_{ch,start,m}); & X_{1,m} = 2 \end{cases} \tag{16}$$

$$X_{5,m} = t_{dch,start,m}(X_{3,m}, RTP_m) = \begin{cases} t^{(0)}_{dch,start,m}; & X_{1,m} = 1 \\ (t^{(1)}_{dch,start,m}, t^{(2)}_{dch,start,m}); & X_{1,m} = 2 \end{cases} \tag{17}$$

State variables

$$\begin{cases} U^1_m = SOC_{\text{initial},m} = \begin{cases} SOC_{\text{final},m-1}\left(X_{1,\text{opt},m}, X^{(z)}_{2,\text{opt},m}, X^{(z)}_{3,\text{opt},m}, X^{(z)}_{4,\text{opt},m}, X^{(z)}_{5,\text{opt},m}\right); m \neq 1 \\ SOC_{\text{Min}}\ ; m = 1 \end{cases} \\ U^2_m = SOH_{\text{initial},m} = \begin{cases} SOH_{\text{final},m-1}\left(X_{1,\text{opt},m}, X^{(z)}_{2,\text{opt},m}, X^{(z)}_{3,\text{opt},m}, X^{(z)}_{4,\text{opt},m}, X^{(z)}_{5,\text{opt},m}\right); m \neq 1 \\ SOH_{\text{BOL}}\ ; m = 1 \end{cases} \\ U^2_m = C_{\text{bat initial},m} = \begin{cases} C_{\text{bat final},m-1}\left(X_{1,\text{opt},m}, X^{(z)}_{2,\text{opt},m}, X^{(z)}_{3,\text{opt},m}, X^{(z)}_{4,\text{opt},m}, X^{(z)}_{5,\text{opt},m}\right); m \neq 1 \\ C_{\text{bat BOL}}\ ; m = 1 \end{cases} \end{cases} \tag{18}$$

Optimization algorithms for scenario A and scenario B

Fig. 1(a) and (b) provide an overview of the overall optimization framework for both Scenario A and Scenario B, showcasing how the scheduling strategy and battery operation management interact for achieving desired objectives of each scenario. The "scheduling phase" focuses on creating optimized daily schedules for optimal battery utilization. These schedules are then fed into the "operation module" to manage the battery's charging and discharging actions accordingly. This process continues until the battery SOH reaches the EOL criterion.

The optimization problem involves dynamic scheduling, with decision variables and objective functions changing daily. The scheduling phase of both scenarios depends on receiving a 24-h ahead RTP electricity profile. However, Scenario B requires additional updated information, including battery SOC, SOH, and capacity, for planning the next day's operations. A step-by-step explanation of the optimization algorithms in the scheduling phase of both scenarios can be found in next sections.

Optimization procedure in scenario A. The optimization procedure in **Scenario A** is illustrated in Fig. 1a and the process is elaborately explained as follows:

1. Receive the initial states of battery, i.e. SOC, SOH, and battery capacity
2. For each day *m*, scheduling phase receives 24-hour ahead RTP profile.
3. Receive the fixed predefined charge /discharge durations (d), which is 1-hour for S. A1, 4-hour for S.A2, and 8-hour for S.A3 as illustrated in Eq. (B.1).
4. To determine the best times for charge and discharge actions, first calculate the moving average (MA) of RTP in time *t*, corresponding to the charge/ discharge duration *d* in the day *m* according to Eq. (C1) in Appendix C.
5. Determine the minimum and maximum MA RPT corresponding to the charge/discharge durations (*d*) within day (*m*) (as shown in Eq. (C2) in Appendix C), to identify the charge and discharge start times of day m (as shown in Eq. (C3) in Appendix C). The identified charge and discharge schedule are the optimal solution which leads to maximum possible price differential at day m.
6. Send the identified optimal charge and discharge timing to the "operation module" to manage system accordingly and update battery states and back to step 2.
7. Stop optimization process, when battery reaches end of life criteria (SOH = 75 %).
8. Report battery lifetime, present value of profit, revenue, PI, PPEI, and payback period, as described in Eqs. (19)-(24).

Optimization procedure in scenario B. The optimization procedure in **Scenario B** is illustrated in Fig. 1b and described in detail using a step-by-step approach presented as follows:

1. Initialize the battery state variables according to Eq.(18), i.e. SOH, SOC, and battery capacity
2. For each day *m*, receive the 24-hour ahead RTP profile.
3. For each day *m*, initialize the number of daily cycle ($X_{1,m}$) and set z accordingly. if the number of cycle is one, then z = 0, and if the number of cycle is two, then z = 1, 2
4. For the given number of cycles for day m, initialize the charge and discharge durations ($X^{(z)}_{2,m}$, and$X^{(z)}_{3,m}$) as illustrated in Eqs. (14) and (15). It is worth noting that in Scenario B, the battery's charge and discharge durations for each cycle can be unequal, and as shown in Eqs. (14) and (15) can vary between 1-hour and 10-hour for daily periodicity (z = 0) and vary between 1-hour to 6-hour for semi-daily periodicity (z = 1, 2).

5. Given each set of charge and discharge durations, calculate the MA RTP of time t at day m, as described in Eq. (C4) in Appendix C.
6. To identify the best charge and discharge timing ($X^{(z)}_{4,m}$, and$X^{(z)}_{5,m}$) given each charge and discharge durations, firstly the minimum and maximum MA RTP, corresponding to the charge and discharge durations are calculated through Eq. (C5) in Appendix C, then the charge and discharge start times under which the maximum daily price differential is attained are determined via Eq. (C6) in Appendix C.
7. Given the identified charge and discharge timing corresponding to a set of charge and discharge durations, the objective function is calculated through the operational strategy as illustrated in section 2.4.
8. Store the objective function value in a data center.
9. Update the charge and discharge durations and repeat steps 3–7 for all combination of charge and discharge durations.
10. Update the number of cycles, and repeat steps 4–9 for all possible cycle per day
11. Identify the best daily objective function value and the corresponding set of daily decision variables from the data center.
12. Send the optimal operation scheduling for day m ($X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}$) to the battery "operation module". The system will then operate the battery based on this optimal scheduling and update its states according to Eq. (18).
13. The updated battery states are then sent back to the decision maker (Step2) to use for planning the next day's (m + 1) operations.
14. The process 2–13 is repeated daily until the battery SOH reaches the EOL criteria.
15. Report battery lifetime, present value of profit, revenue, PI, PPEI, and payback period, as described in Eqs. (19)-(24).

Description of key economic performance indicators (KPIs) for scenario A and scenario B

The battery lifetimes in both scenarios are not predetermined and are predicted using a realistic ageing model (as described in Section 2.2) that is influenced by the battery's dynamic operation within the system. The battery operation is dependent on optimized daily scheduling specific to each scenario. In this study, we use $\delta_{\text{Replace}} = 75\ \%$ as the battery replacement indicator, and as shown in Eqs. (B1) and (B5) the battery's end-of-life occurs in the application when the battery SOH reaches 75 %, matching the warranty condition of the LFP/c battery. It is worth noting that battery lifetime is regarded as project lifetime. The battery lifetime is defined as the time elapsed since BOL until the battery's SOH reaches the capacity indicating the EOL state, as depicted in Eq. (19).

To provide a more complete evaluation of the economic feasibility of project under both scenarios, an extensive set of indicators are considered, including the present values of total revenue, as well as profit over project life, profitability index, profitability per installed energy, and payback period.

The total revenue and profit over the project's lifespan, as shown in Eqs. (20) and (21), are calculated using the present value (PV) method, which involves converting all projected future cash flows into present equivalent values by using a chosen discount rate. In this study, the real discount rate is chosen as 4 % by considering the current loan rate in Sweden [60].

PI, or profitability index, is a useful financial tool for comparing the potential profitability of different investment projects and determining if a project is worth pursuing. As shown in Eq. (22), PI is a ratio of total discounted profit to initial battery investment.

PPEI, or profit per energy installed, is an important economic indicator that measures the profitability of energy storage per unit of energy capacity. This information is valuable for project developers, investors and policymakers in determining the viability of energy storage projects. As shown in Eq. (23), the yearly average PPEI is obtained by diving the present value of total profit by the nominal capacity of battery and the total project life (i.e. battery life).

As shown in Eq. (24), the payback period is another useful financial metric which provides an estimate of how long it will take for an investment to start generating positive cash flows, and how long it will take to recoup the initial investment cost.

$$LF_{\text{bat}}(\text{yr}) = \frac{m_{SOH_m \le \alpha_{\text{Replace}}}}{365} \tag{19}$$

$$\text{Revenue}^{\text{PV}}_{\text{opt, tot}} = \sum_{n=1}^{LF_{\text{bat}}(\text{yr})} \frac{\left(\sum_{m=1}^{365} Revenue_{\text{opt},m}\right)_n}{(1+\text{interest}_{\text{rate}})^n} \tag{20}$$

$$\text{Profit}^{PV}_{\text{opt, tot}} = \sum_{n=1}^{LF_{\text{bat}}(\text{yr})} \frac{\left(\sum_{m=1}^{365} Revenue_{\text{opt},m}\right)_n}{(1+\text{interest}_{\text{rate}})^n} - ICC_{\text{battery}} \tag{21}$$

$$\text{PI }(\backslash\%)) = \frac{\text{Profit}^{PV}_{\text{opt, tot}}}{ICC_{\text{battery}}} \times 100 \tag{22}$$

$$\text{PPEI}(€/\text{kWh/yr}) = \frac{\text{Profit}^{PV}_{\text{opt, tot}}}{C_{\text{batt, BOL}} \times LF} \tag{23}$$

$$\text{Payback (yr)} = \frac{m\left(\left(\sum_m Revenue_{\text{opt},m} - ICC_{\text{battery}}\right) \ge 0\right)}{365} \tag{24}$$

Operational strategy and battery management system

In this study, a straightforward operational strategy, leveraging dynamic electricity prices is conducted for a residential grid-connected battery system. This strategy is employed to simulate the system's operation over the project's lifetime. The operational strategy takes input data such as hourly electricity consumption, hourly electricity price profiles, battery SOC and SOH values, initial capacity at BOL, battery operating control parameters (e.g., allowable charge/discharge rates), and the allowable SOC operation window. It is important to note that the system simulation is conducted on an hourly basis, with the estimated battery lifetime considered as the project's overall duration. Throughout the project lifespan, the annual hourly electricity price and consumption profiles are kept unchanged. The output data of the operational strategy are hourly system operations data, such as the battery power flow, SOC, SOH, the battery calendric and cyclic capacity fades, and daily revenue, and profit over project life. A step-by-step description of system operational strategy are as follows:

- Strategy receives daily operations schedule including, the permissible number of cycles per day, the timing for charging and discharging, and the corresponding durations for each cycle.
- If the current time of day *m* falls within the permissible charging period of day m, ($t_{ch,start,m} \le t_m \le t_{ch,start,m} + d_{ch}$), the battery is charged using low-cost grid power at the maximum allowable charging rate ($P^{\text{ch}}_{\text{min,t}}$).
- If the current time of day (m) falls within the permissible discharge period of day m ($t_{dch,start,m} \le t_m \le t_{dch,start,m} + d_{dch}$), the battery is discharged to meet the demand as much as possible during high-price periods. If the maximum allowable discharge power ($P^{\text{ch}}_{\text{max,t}}$) exceeds the load, the surplus power is exported to the grid. However, if the load exceeds the maximum allowable discharge power, the deficit power is sourced from the grid.
- During other periods, the battery remains idle and neither charges nor discharges. In such instances, the demand is fulfilled solely by the grid.
- At each time interval, the following steps are carried out:

- The battery SOC is updated, as explained in Section 2.2.
- Battery ageing influence parameters are detected through stress detection method.
- Both the calendric and cyclic capacity fades of the battery are calculated using the ageing models outlined in Section 2.2.
- The battery capacity is adjusted according to the estimated capacity fade, and subsequently, the SOH of the battery is updated based on the available battery capacity.

• The previously described procedure is consecutively repeated until the end of day.
• At the end of day, the battery states are sent back to the decision maker to use for planning the next day battery performance.

Case study

The proposed strategies in this study are implemented for two common types of Swedish family houses, equipped with and without district heating (DH). The house equipped with DH has an annual electricity consumption of 4,300 kWh, while the house without DH consumes around 10,700 kWh per year. Fig. 4 shows the hourly electricity usage for households located in Västerås, Sweden. The data regarding the hourly electricity consumption throughout the year is collected through electric meters and provided by the homeowners.

The retail price of electricity in Sweden is determined by a range of factors, including the type of clients, geographical locations, local electricity markets, taxes, and other elements [61]. When studying the residential case, the retail price of electricity can be analyzed as comprising two main components: the Electricity Spot Price and the Fixed Fee. The Electricity Spot Price (ElSpot price) represents the day-ahead hourly price which in this study obtained from the Nord Pool bidding electricity market [62]. The Nord Pool spot market, known as the world's first international spot power exchange market. Operating as a day-ahead market, the Nord Pool spot market enables the trading of power contracts with a minimum duration of one hour for delivery on the subsequent day. Fig. 5 depicts the hourly ElSpot price in 2022 specifically for the SE3 bidding area in Sweden. The Fixed Fee incorporates various elements, such as energy tax, electricity transfer fee, value-added tax (VAT), and similar factors. A detailed explanation of how the electricity price is formulated and calculated can be found in Appendix D.

Results and discussion

The results of this study are presented in three subsections. Subsection 3.1 discusses and compares the economic profitability of the battery system under the proposed operation scheduling optimization scenarios. Subsection 3.2 presents the optimized operating performance obtained from the proposed scenarios. Additionally, subsection 3.3 examines the impact of battery price and size on the optimal operation scheduling specifically under Scenario B.

Assessing economic profitability of studied battery storage under scenario A and scenario B

Fig. 6 and Table 1 illustrates the results obtained from scenarios A1-A3, and scenario B, providing comprehensive insights into the financial performance of each scenario. The results are presented for two types of residential houses: those with and without DH. The house with DH is equipped with a 5kWh battery system, while the house without DH is equipped with a larger 10 kWh battery system. Each figure displays two variables on the Y-axes. Fig. 6a shows the average yearly PPEI on the left Y-axis, and the lifetime on the right Y-axis. Fig. 6b shows the present value of total profit obtained over project life on the left-Y-axis and the profitability index on the right Y-axis. Fig. 6c demonstrates the present value of total revenue generated over project life (left Y-axis) and the payback period (right Y-axis).

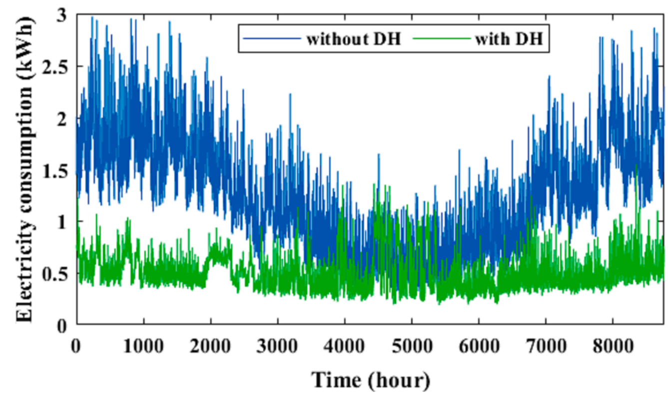


Fig. 4. The electricity consumption patterns: houses with and without DH.

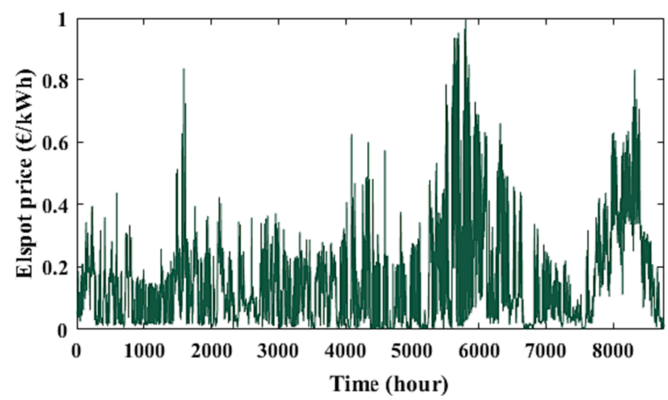


Fig. 5. The hourly profile of the Elspot price including VAT, 2022 [43].

The comparison of the estimated battery lifetimes under each scenario highlights the importance of battery daily operation scheduling on the long-term project performance. As depicts in Fig. 6a, it can be observed that scenario S.A3 resulted in the longest battery lifetime of 14.8 years, while scenario S.A1 leads the shortest lifetime of 10.1 years. The predicted lifetimes under scenarios S.A2 and S.B are 13.6 and 12.5 years, respectively, falling within two previously mentioned extremes. Although the daily operation scheduling of battery under scenario S.A3 is the most effective in terms of extending the battery's lifespan, with increases of 8.8 %, 18.4 % and 46.5 % compared to scenarios S. A2, S.B, and S.A1, respectively, a longer battery lifetime does not necessarily translate to higher profitability. Evaluation of other economic performance metrics reveals that S.A3 is the worst scenario in terms of profitability as the revenue generated under this scenario is insufficient to offset the initial investment. This is evidenced by a negative net present value, and an average yearly PPEI of −3€/kWh/yr. This is because S.A3 followed a predefined and "low" charge/discharge rate, which forces the battery to operate under conditions with the lowest degradation rate, but also limits the revenue-generation potential. In other words, although the battery's lifespan was extended, the revenue generated was insufficient to justify the battery investment cost over its lifetime. In contrast to S.A3, both S.A1 and S.A2 of the A-series scenarios resulted in positive net present values despite having shorter battery lifetimes. The reason for this is that the higher charge/discharge rates imposed in these scenarios (ie. S.A1, and S.A2), allowing for higher revenue generation potential despite the higher degradation rates. This comparison shows that while extending the battery lifespan is desirable, it is not always the most profitable strategy, and factors such as revenue generation and net present value must be considered when designing battery operation schedules for a project. For instance, it can be observed that although scenario S.A1 allows for capturing the highest daily price differential by

Table 1
Detailed economic assessment results obtained under operation scheduling of S. A1-S.A3 and S.B for house with and without DH.

	House with DH; $C_{bat,BOL} = 5$ kWh				House without DH; $C_{bat,BOL} = 10$ kWh			
	S.A1	S.A2	S.A3	S.B	S.A1	S.A2	S.A3	S. B
LF_{bat}(yr)	10.1 yr	13.6 yr	14.8 yr	12.5 yr	10.1 yr	13.6 yr	14.8 yr	12.2 yr
$Revenue^{PV}_{opt,\ tot}$(€)	2,418 €	2,624 €	1,781€	3,117 €	4,836 €	5,249 €	3,560	6,335 €
$Profit^{PV}_{opt,\ tot}$(€)	+418 €	+624 €	−219	1,117 €	836 €	1,249 €	−440 €	2,335 €
PI (\%))	+21 %	+31 %	−11 %	+56 %	+21 %	+31 %	−11 %	+58 %
PPEI(€/kWh/yr)	+8.3	+9.2	−3	+18	+8.3	+9.2	−3	+19.2
Payback (yr)	7.8 yr	9.3 yr	none	7.1 yr	7.8 yr	9.3 yr	none	6.7 yr

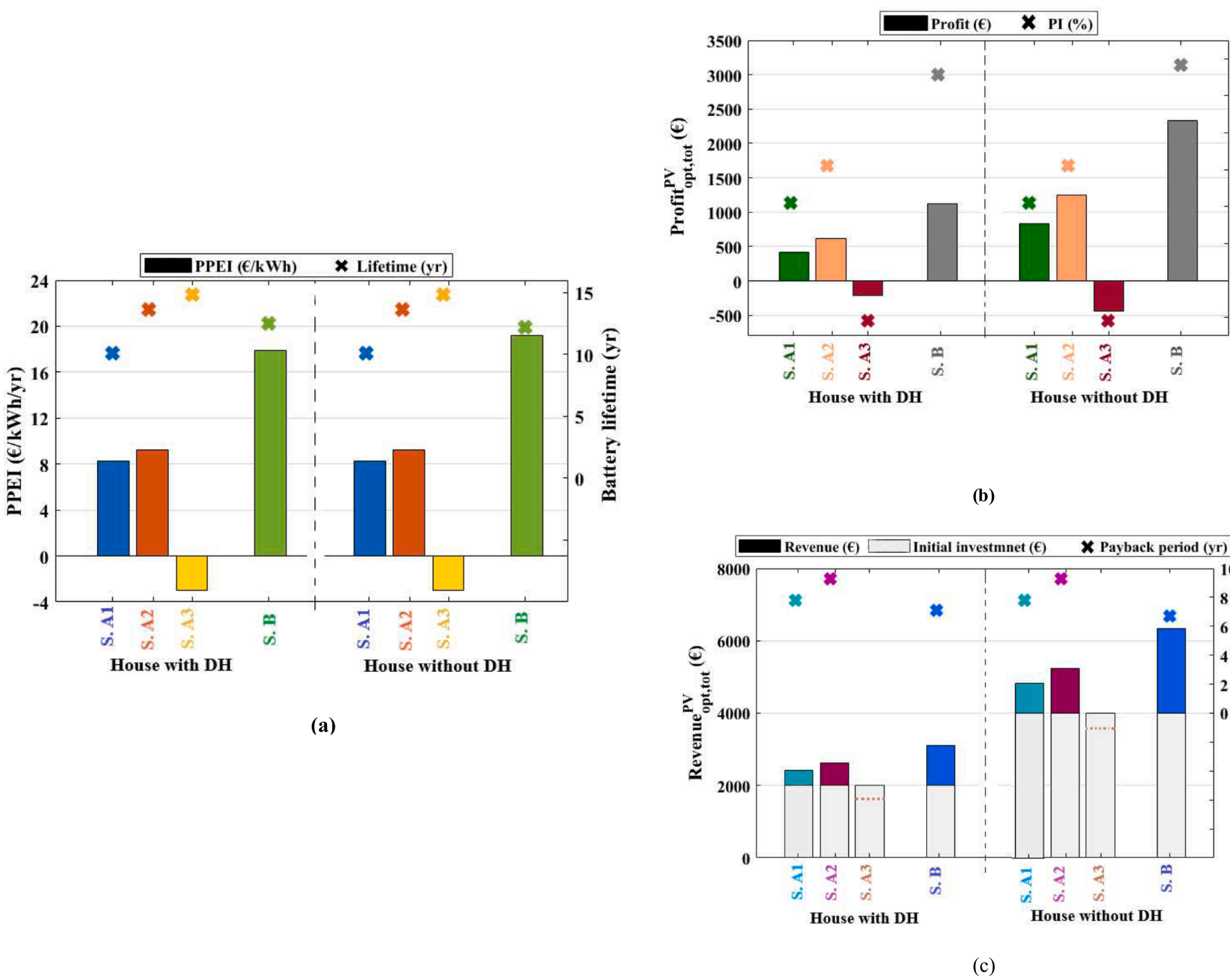


Fig. 6. Comparative analysis of obtianed KPIs: (a) PPEI and battery lifetime; (b) Present value of total profit and profitability index; (c) prsent value of total revenue and payback period, for opertaion schduling under scenario A (S.A1-S.A3) and Scnerio B (S.B) for house with DH ($Cap_{batt} = 5$kWh) and house without DH ($Cap_{batt} = 10$kWh).

imposing a "high" fixed charge/discharge rate due to the taking advantage of the lowest and highest RTP of each day, it is less profitable than S.A2. The profitability index (PI) of S.A2 is 31.2 % with an average yearly PPEI of 9.2 €/kWh/yr, while S. A1 lead to a PI of 20.9 % and average yearly PPEI of 8.2 €/kWh/yr. The higher profitability and lifetime are due to maintaining a ''moderate'' charge/discharge rate which provides a more balance between revenue generation and battery life longevity. Conversely, S. A1 incurs a high degradation cost, leading to the shortest lifetime and the lowest positive profitability in the long run. It's important to consider other factors beyond just profitability and lifetime when evaluating the viability of each scenario. For example, despite having a higher lifetime and PPEI, the payback period of S.A2 is about 1.5 years longer than S.A1, which may make S.A2 less attractive to investors who prioritize quicker returns on their investment. Compared to the A-series scenario, scenario S.B stands out as the most attractive and effective option in terms of long-term profitability and sustainability. It offers numerous advantages, including the highest potential for revenue generation and profit, and the shortest payback period, making it financially viable and feasible option, and a reasonable lifespan that promotes sustainability over a longer period. As observed that its PPEI value (18 €/kWh/yr) is twice as high as the highest PPEI value in S.A2 (9.2 €/kWh/), indicating that scenario S.B has a more promising financial outlook to generate significantly more profit, despite having a slightly shorter lifetime than S.A2 (12.5 year). This is because S.B finds an optimal trade-off between short-term and long-term profitability and sustainability when selecting the optimal daily operation scheduling, whereas S.A solely prioritizes immediate revenue generation without optimizing its long-term impact on sustainability and profitability. Therefore, it is crucial to strike an optimal balance between battery degradation and revenue generation when designing a battery operation scheduling strategy, in order to simultaneously achieve both long battery life and economic profitability.

Operating performance of battery under scenario A and scenario B

To understand the degradation behavior of the studied battery under operational scheduling under proposed scenarios, Fig. 7 illustrates the estimated rate of capacity fade of battery until the end of its life (SOH $\leq$ 75 %) corresponding to all four scenarios. This rate accounts for both calendric (time-based) and cyclic (usage-based) capacity fades of the battery. It can be observed that the degradation rate is notably high in the S.A1 scenario. This can be attributed to the influential role of battery C-rate, which is one of the factors that significantly affects battery degradation. In S.A1, a fixed high C-rate was considered, resulting in accelerated degradation. On the other hand, the S.A2 and S.A3 scenarios follow a sequential order in terms of degradation rate since degradation cost optimization was not prioritized in these scenarios. Similarly, a fixed rate was employed. However, in the S.B scenario, degradation cost optimization was achieved while maintaining a balance with revenue generation. Consequently, the battery was able to dynamically adjust its power rating to meet the defined objectives. It is worth noting that this graph provides valuable insights into the impact of different scenarios on battery degradation rates and emphasizes the importance of considering optimization strategies to mitigate degradation costs while achieving revenue objectives.

To provide a more comprehensive understanding of the daily operation scheduling obtained under scenario B, the optimized daily charge and discharge durations $\left(d^{(z)}_{ch,opt}, d^{(z)}_{dch,opt}\right)$, as well as the optimal daily cycles are presented in this section. For sake of consciousness, we specifically show the results for a selected month, from1st to 30th June. Fig. 8a and Fig. 8b illustrate these results for the 1st and 10th-yaer optimization, respectively. In Fig. 8a and 8b, the upper graph displays the optimized durations for daily charge and discharge. On the other hand, the lower graph in Fig. 8a and 8b shows the number of daily cycles observed during the simulation and optimization process. B. It is important to note that the number of daily cycles affects the z-value: when there is only one daily cycle, the z-value is zero, indicating a single optimal charge and discharge duration. In cases where there are two daily cycles, the z-value includes 1 and 2, representing separate optimal charge and discharge durations for the first and second semi-daily periods (z = 1 and z = 2, respectively). It is worth mentioning that we did not present this information for the other scenarios, S.A1-S.A3, as the number of daily cycles and charge and discharge duration were assumed to be fixed and not subject to optimization. However, in scenario B, the dynamic charge and discharge rate, as well as the cycle count, play a significant role in battery degradation cost. Observing the results, it can be observed that although the annual electricity price and consumption profile remained unchanged over the project's lifespan, the operation scheduling differs between the 1st- year and the 10th- year due to the dynamic charge and discharge rates and cycles, which impact battery degradation costs. Notably, in the later years, the battery tends to undergo two cycles per day instead of one, as the degradation rate slows

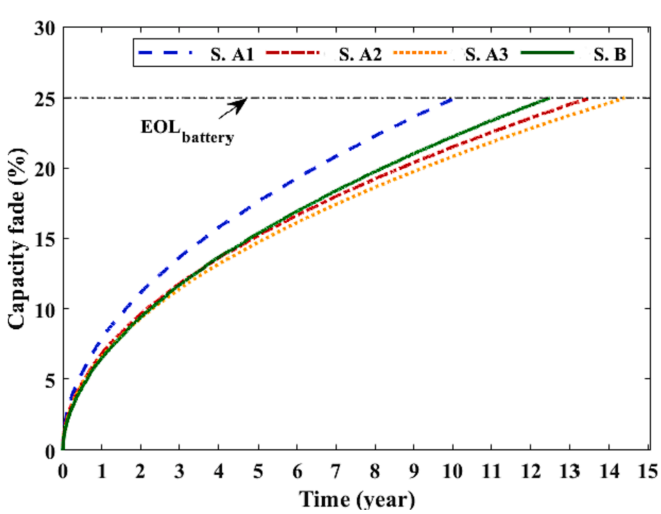
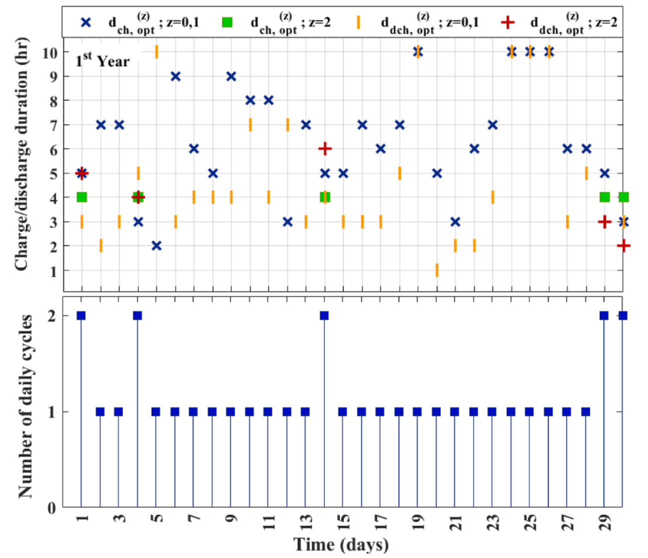
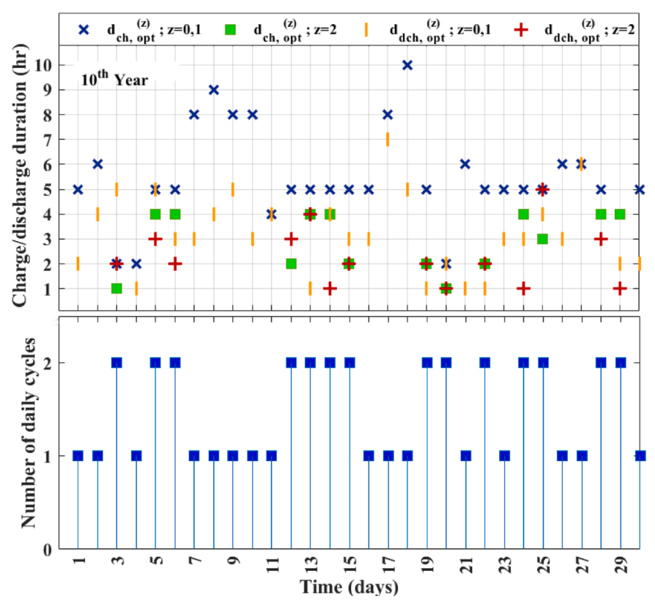


Fig. 7. The capacity fade of battery over its lifetime for battery operation scheduling of scenarios S.A1-A3 and S.B (house with DH).



(a)



(b)

Fig. 8. Optimized daily charge and discharge durations $\left(d^{(z)}_{ch,opt}, d^{(z)}_{dch,opt}\right)$ (upper graph) and number of cycles (lower graph) under battery operation scheduling for Scenario S.B throughout the selected month of June (1st-30th), relative to selected years (a) 1st-Year, and (b) and 10th-Year optimization for a house with DH.

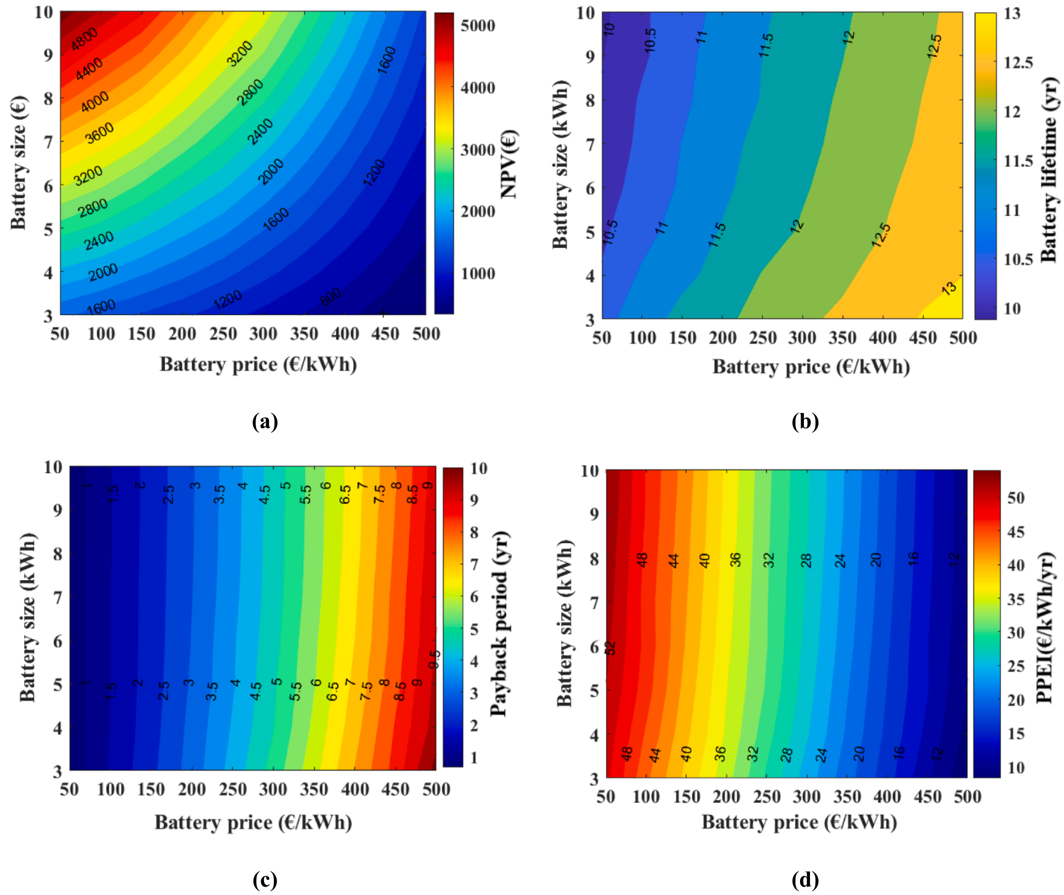


Fig. 9. Impact of different battery sizes and battery price variations on economic assessment, including (a) present value of total profit, (b) estimated lifetime, (c) payback period, and (d) PPEI, obtained under scenario S. B for a house with DH.

down compared to the earlier years. For instance, in the first year, there were five instances in June where the battery underwent two cycles per day (1st, 4th, 14th, 29th, and 30th days), whereas in the tenth year, this occurred fourteen times.

Table A1
Characteristics of the studied Li-ion battery cells.

Parameter	Value
Battery chemistry	$LiFePO_4/C$
Battery nominal voltage	3.2 V
Nominal capacity	2.5 Ah
Discharge cut-off voltage	2.5 V
Charge cut-off voltage (V)	3.6 V
Battery calendric lifetime until 80 % capacity ($LF^{80\%}_{Calendar}$)	15 years
Battery cycle life until 80 % capacity ($LF^{80\%}_{Cycle}$)	10,000 FEC
Battery maintenance cost (% of investment/year)	0.5 %
Battery energy specific price (€/kWh)	400

Table D1
Electricity price components[1].

Symbol	Parameter	Value
C_i	ElSpot price	Illustrated in Fig. 5
C_2	Energy Tax, incl. VAT	0.45 SEK/kWh
C_3	Electricity transfer fee, incl. VAT	0.2875 SEK/kWh
C_4	Grid benefit compensation	0.035 SEK/kWh
C_5	Tax reduction	0.6 SEK/kWh

[1] The cost information in this study is presented in Euro. 1EUR = 10.526 SEK; The exchange rate among Euro, and SEK (currency in Sweden) are based on the average monthly rate in 2023. The rate currency is retrieved from https://www.x-rates.com/average/.

Sensitivity analysis

The dynamic nature of the Li-ion battery market, driven by ongoing innovations and developments, makes it challenging to plan for long-term energy system optimization. Therefore, to evaluate the effectiveness of our proposed optimal operation scheduling strategy in the face of changing Li-ion battery prices, we conducted a sensitivity analysis. Specifically, we evaluated the impact of battery size and price on the economic KIPs obtained under the best strategy, i.e., S.B's optimal operation scheduling. This analysis provides valuable insights into the impact of these variables on profitability and sustainability.

Fig. 9a-d display the profit, lifetime, payback period, and PPEI obtained from the system simulation under S.B with varying battery prices and sizes.

The results show that for a given battery size, the lower battery prices correspond to increased profitability over project life as shown in Fig. 9a. Additionally, there is a slight decrease in battery life, as illustrated in Fig. 9b. This reduction in battery prices also leads to a significant decrease in the payback period as shown in Fig. 9c. This is because by decreasing the battery price, the cost of degradation is also reduced, enabling for a strategy that schedules battery operation to generate higher revenue but faster degradation. Although degradation occurs faster, the low cost of degradation resulting from the low battery price still leads to higher profits than slower degradation conditions. As shown in Fig. 9d, a decrease in battery price from 400 €/kWh (the current market price) to 50 €/kWh leads to a significant increase in the average yearly PPEI, from 16 to 18 €/kWh/yr to 48–52 €/kWh/yr, even though it slightly shortens battery life from 12 to 13 yr to 10–11 yr.

The results show that larger battery sizes lead to higher profits as shown in Fig. 9a, as the battery can store more energy during off-peak hours and sell more during peak price periods. However, as indicated in Fig. 9d the average yearly PPEI remains relatively stable. This stability is due to the higher investment cost associated with larger batteries, which counterbalances the increased profits. Moreover, the larger battery size does not significantly impact battery life.

Conclusion

- This study introduced innovative optimization-based battery operation scheduling strategies, aiming to achieve both maximized profitability and longevity. Through the evaluation of battery performance and economic outcomes under proposed scenarios in this study, the research endeavors to offer insights into the design of an efficient day-ahead battery operation scheduling strategy for optimal battery utilization in price arbitrage under real-time pricing electricity schemes, ensuring sustained profitability. The novelty of this work is manifested in its simultaneous exploration of a wide range of key influencing factors affecting key aspects of profitability, including revenue gains, capacity degradation, operation-dependent lifetime, and their interconnected effects. This approach stands in contrast to existing price arbitrage strategies that often simplified or overlooked critical objectives and factors during the design phase, relying on assumptions and objective functions that neglect the comprehensive consideration of these influencing factors.
- The battery operation scheduling under A-series scenarios led to outcomes that were perceived positively from certain economic perspectives, but they were considered unfavorable when evaluated using other economic metrics. For instance, results showed that scenario S.A3 demonstrated the most efficient operation scheduling in terms of extending the battery's lifespan estimated at 14.8 years, while it was the worst scenario in terms of profitability resulting in negative profit with average yearly PPEI of −3€/kWh/yr. On other hand, both S.A1 and S.A2 of the A-series scenarios resulted in positive profit with average yearly PPEI of 8.3 €/kWh/yr and 9.2 €/kWh/yr, despite having shorter battery lifetimes, estimated at 10.1 yr and 13.6 yr, respectively. The higher profitability and lifetime obtained under operation scheduling of S.A2 are due to maintaining a ''moderate'' charge/discharge rate which provides a more balance between revenue generation and battery life longevity. Furthermore, despite having a higher lifetime and PPEI, the payback period of S.A2 is about 1.5 years longer than S.A1, which may make S.A2 less attractive to investors who prioritize quicker returns on their investment. This limitation stems from the fixed charge/discharge rate set by the A-series scenarios. The A-series scenarios solely focused on revenue generation without optimizing its long-term impact on longevity and profitability. Consequently, this restricts the algorithm's ability to fully explore favorable arbitrage opportunities presented by dynamic RTP electricity profiles.
- In contrast, battery operation scheduling under scenario S.B outperforms the A-series scenario in terms of long-term profitability and sustainability, providing valuable insights into efficient and viable battery operation scheduling in the RTP market. It offers several advantages, including the highest potential for revenue generation, as well as profit, and the average yearly PPEI value of 18 €/kWh/yr twice as high as the highest PPEI value in A-series scenario. Furthermore, it has the shortest payback period (7.5 years), making it a financially viable and feasible option. Despite this, it maintains a reasonable lifespan (12.5 years), promoting sustainability over a longer period. These findings highlight the critical importance of striking an optimal balance between battery degradation cost and revenue generation through careful optimization of all key factors such as number of daily cycles, rates, durations, and schedules for charging and discharging. These factors play a crucial role in influencing both revenue generation and battery degradation.
- Evaluation of the impact of battery size, and price on optimal operation scheduling and financial outcomes under scenario B showed that a decrease in battery price from 400 €/kWh (the current market price) to 50 €/kWh leads to a significant increase in the average yearly PPEI, from 16 to 18 €/kWh/yr to 48–52 €/kWh/yr, and significant rapid return on investment, from 7.5 years to 1 years, even though it slightly shortens battery life from 12 to 13 yr to 10–11 yr.
- The results showed that larger battery sizes lead to higher profits as the battery can store more energy during off-peak hours and sell more during peak price periods. However, as in the average yearly PPEI remains relatively stable. This stability is due to the higher investment cost associated with larger batteries, which counterbalances the increased profits.
- Results highlights that considering multiple economic metrics in battery operation scheduling evaluation plays a crucial role in enabling decision-makers and investors to comprehensively assess the economic feasibility of a project and gaining a broader perspective on its viability.
- The insights derived from our study empower researchers, decision-makers, and battery owners to grasp the optimal utilization of batteries under dynamic RTP electricity schemes. This understanding allows for the maximization of revenue while extending battery lifetime, ensuring long-term profitability and sustainability. These findings hold substantial importance for individuals involved in strategic decision-making and the implementation of practical solutions within the energy sector. Notably, the results of this study, which were evaluated for LFP/C batteries, and the methodology implemented, are applicable to other types of batteries and across various Real-Time Pricing markets

While some prior research may have addressed some aspects of price arbitrage, the novelty of our research is underscored by the development and evaluation of scenario A and Scenario Bcenarios, each shedding light on distinct aspects of optimal battery operation scheduling. A-series scenarios, though revealing positive economic outcomes from specific perspectives, highlight the limitations stemming from a singular focus on revenue generation, and the analysis of the impact of different charge/discharge rates (low, moderate, high) showed that charging or discharging at higher rates (faster charge) can potentially increase revenue but also hasten degradation. And Conversely charging or discharging at lower rates (slower charge) can result in reduced revenue generation but also less degradation, highlighting the importance of the strategy that enables the battery to dynamically adjust its power rating to meet defined objectives effectively.

In contrast, B-series scenarios outperform A-series in terms of long-term profitability and sustainability, emphasizing the pivotal importance capable of making intelligent decisions for charge and discharge actions play significant role in maximizing profitability and battery longevity.

CRediT authorship contribution statement

Masoume Shabani: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Mohadeseh Shabani:** Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Fredrik Wallin:** Writing – review & editing. **Erik Dahlquist:** Writing – review & editing. **Jinyue Yan:** Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Data availability

The authors do not have permission to share data.

Acknowledgement

Authors would like to thank the support from the Swedish Energy Agency, and from the Kowledge Foundation (kKKS) project “flexibility through synergies of big data, novel technologies and innovative markets (FELEXERGY)”.

Appendix A

.

Appendix B

Eq. (B1) illustrates battery permissible operating constraints in Scenario A, ensuring proper battery operations.

Eqs. (B2)-(B4) illustrates how the objective function for scenario A is derived. Eq. (B3) summarizes how the system’s daily revenue is obtained, which can be categorized into two parts. The first part is the electricity reduction revenue, which comes from the difference between the peak electricity prices (in which the load met by the battery ($P_{\text{batt-load},t} \times El_{r,t}$)), and the off-peak electricity prices (in which the electricity is bought from the grid for charging the battery ($P_{\text{grid-batt},t} \times El_{r,t}$)). The second part is the electricity export revenue, which means that the surplus electricity will be exported to the grid ($P_{\text{batt-grid},\,t} \times El_{w,t}$). The exported electricity is sold at wholesale price. The battery daily degradation cost, as outlined in Eq. (B4), takes into account the daily capacity loss due to calendric and cyclic degradation under realistic operational conditions, as well as the battery’s initial cost.

Scenario A

Battery operating constraints

$$\begin{cases} SOH_m \leqslant \alpha_{Replace} \rightarrow EOL_{batt} \rightarrow \quad \alpha_{Replace} = 75\% \\ d = d_{ch,m} = d_{dch,m} = \begin{cases} 1 - hr\,S.\ A1 \\ 4 - hr\,S.\ A2 \\ 8 - hr\,S.\ A3 \end{cases} \\ SOC_{\min} \leqslant SOC_t \leqslant SOC_{\max} \\ NOC_m \leqslant 1 \\ P^{ch}_{\min,t} \cdot S_{ch} \leqslant P_{batt,t} \leqslant P^{dch}_{\max,t} \cdot S_{dch} \rightarrow \end{cases} \tag{B1}$$

Derivation of objective function:

$$Profit_{\text{opt},m} = Revenue_{\text{opt},m} - Cost_{\text{deg,battery}_m} \tag{B2}$$

$$Revenue_m = \sum_{t=1}^{24} \left(\left(P_{\text{batt-load},t} \times El_{r,t} \right) - \left(P_{\text{grid-batt},t} \times El_{r,t} \right) + \left(P_{\text{batt-grid},t} \times El_{w,t} \right) \right)_m \tag{B3}$$

$$Cost_{\text{deg,batt}_m} = \frac{C_{\text{fade, tot}_m}}{1 - \alpha_{\text{Replace}}} \times ICC_{\text{batt}} \tag{B4}$$

Eqs. (B6)-(B8) demonstrate the derivation of the objective function for scenario B. Eq. (B7) and (B8) summarizes how the system’s daily revenue and degradation costs are calculated In the case of semi-daily periodicity, both the daily revenue and degradation cost (as shown in Eq. (B7) and (B8)) are calculated by summing up the generated revenue and degradation cost over the first and second cycles per day.

Scenario B

Battery operating constraints

$$\begin{cases} SOH_m \leqslant \alpha_{Replace} \rightarrow EOL_{batt} \quad \rightarrow \quad \alpha_{Replace} = 75\% \\ SOC_{\min} \leqslant SOC_i \leqslant SOC_{\max} \\ NOC_m \leqslant 2 \\ P^{ch}_{\min,t} \cdot S_{ch} \leqslant P_{batt,t} \leqslant P^{dch}_{\max,t} \cdot S_{dch} \rightarrow \begin{cases} P^{ch}_{\min,t} = \dfrac{-C_{batt_t}}{d^{(z)}_{ch,m}} \times (SOC_{\max} - SOC_{\min}) \\ P^{dch}_{\max,t} = \dfrac{C_{batt_t}}{d^{(z)}_{dch,m}} \times (SOC_{\max} - SOC_{\min}) \\ S_{ch} + S_{dch} \leqslant 1 \end{cases} \end{cases} \quad \text{(B5)}$$

Derivation of objective function

$$Profit_{\mathrm{opt},m} = MAX\left(Revenue_{\ m}(X_{1,m}, X_{2,m}, X_{3,m}, X_{4,m}, X_{5,m}) - Cost_{\mathrm{deg,batt}_m}(X_{1,m}, X_{2,m}, X_{3,m}, X_{4,m}, X_{5,m})\right) \text{(B6)}$$

$$Revenue_m\ (X_{1,m},\ X_{2,m}, X_{3,m}, X_{4,m}, X_{5,m}) = \begin{cases} \left(\sum_{t=1}^{24} \left((P_{batt-load,t} \times El_{r,t}) - (P_{grid-batt,t} \times El_{r,t}) + (P_{batt-grid,t} \times El_{w,t}) \right) \right)_{m,X_{1,m},\ X_{2,m},X_{3,m},X_{4,m},X_{5,m}} &, X_{1,m} = 1 \\ \sum_{z=1}^{2} \left(\sum_{t_z} \left((P_{batt-load,t} \times El_{r,t}) - (P_{grid-batt,t} \times El_{r,t}) + (P_{batt-grid,t} \times El_{w,t}) \right) \right)^{z}_{m,X_{1,m},\ X_{2,m},X_{3,m},X_{4,m},X_{5,m}} &, X_{1,m} = 2 \end{cases} \quad \text{(B7)}$$

$$\mathrm{Cost}_{deg,batt\ m}(X_{1,m},\ X_{2,m}, X_{3,m}, X_{4,m}, X_{5,m}) = \begin{cases} \dfrac{C_{fade,\ tot_m}(X_{1,m},\ X_{2,m}, X_{3,m}, X_{4,m}, X_{5,m})}{1 - \alpha_{replace}} \times ICC_{battery}, X_{1,m} = 1 \\ \sum_{z=1}^{2} \dfrac{C^{z}_{fade,\ tot_m}(X_{1,m},\ X_{2,m}, X_{3,m}, X_{4,m}, X_{5,m})}{1 - \alpha_{replace}} \times ICC_{battery}, X_{1,m} = 2 \end{cases} \quad \text{(B8)}$$

Appendix C

In Scenario A, the moving average (MA) of RTP in time *t*, corresponding to the charge/ discharge duration *d* in the day *m* is calculated through to Eq. (C1). The minimum and maximum MA RPT corresponding to the charge/discharge durations (*d*) within day (*m*) is calculated via Eq. (C2)), to identify the charge and discharge start times of day m as shown in Eq. (C3).

Scenario A

$$MA_{\mathrm{RTP}_m}(t) = \textstyle\sum_{k=t}^{t+d-1} RTP(k)/d;\ t = 1, \cdots, 24 - d + 1 \quad \text{(C1)}$$

$$MA_{\mathrm{RTP}_{m,\mathrm{Min}}} = Min(MA_{\mathrm{RTP}_m}(t)); MA_{\mathrm{RTP}_{m,\ \mathrm{Max}}} = Max(MA_{\mathrm{RTP}_m}(t)) \quad \text{(C2)}$$

$$t_{\mathrm{ch,\ start,\ opt},m} = t_m @ MA_{\mathrm{RTP}_{m,\mathrm{Min}}}; t_{\mathrm{dch,\ start,opt},m} = t_m @ MA_{\mathrm{RTP}_{m,\mathrm{Max}}} \quad \text{(C3)}$$

In scenario B, the MA RTP of time t at day m is calculated via Eq. (C4), given each set of charge and discharge durations ($d^{(z)}_{\mathrm{ch},m}$, and $d^{(z)}_{\mathrm{dch},m}$). The minimum and maximum MA RTP, corresponding to the charge and discharge durations, as illustrated through Eq. (C5), to identify the charge and discharge schedule as shown via Eq. (C6), corresponding to the charge and discharge durations, under which the maximum daily price differential is attained.

Scenario B

$$\begin{cases} MA^{(z)}_{RTP,m,d^{(z)}_{ch,m}}(t_m) = \sum_{k=t_z}^{t_z+d^{(z)}_{ch,m}-1} \dfrac{RTP_m(k)}{d^{(z)}_{ch,m}}; \\ MA^{(z)}_{RTP,m,d^{(z)}_{dch,m}}(t_m) = \sum_{k=t_z}^{t_z+d^{(z)}_{dch,m}-1} \dfrac{RTP_m(k)}{d^{(z)}_{dch,m}}; \end{cases} t_z = \begin{cases} 1, 2, \ldots, 24 - d^{(z)}_{ch,m} + 1 \\ 1, 2, \ldots, 24 - d^{(z)}_{dch,m} + 1 \\ 1,\ \ldots,\ 12 - d^{(z)}_{ch,m} + 1 \\ 1,\ \ldots,\ 12 - d^{(z)}_{dch,m} + 1 \\ 13, \ldots, 24 - d^{(z)}_{ch,m} + 1 \\ 13, \ldots, 24 - d^{(z)}_{dch,m} + 1 \end{cases} \quad \text{(C4)}$$

$$MA^{(z)}_{RTP,m,d^{(z)}_{ch,m},MIN} = Min\left(MA^{(z)}_{RTP,m,d^{(z)}_{ch,m}}(t_z)\right); MA^{(z)}_{RTP,m,d^{(z)}_{ch,m},MAX} = Max\left(MA^{(z)}_{RTP,m,d^{(z)}_{ch,m}}(t_z)\right); \quad \text{(C5)}$$

$$t^{(z)}_{\mathrm{ch,\ start},d^{(z)}_{ch,m},m} = t_m @ MA^{(z)}_{RTP,m,d^{(z)}_{ch,m},MIN}; t^{(z)}_{\mathrm{dch,\ start},d^{(z)}_{dch,m},m} = t_m @ MA^{(z)}_{RTP,m,d^{(z)}_{dch,m},MAX} \quad \text{(C6)}$$

Appendix D

The purchase of imported electricity is based on the retail electricity price ($EL_{r,i}$), as described in Eq. (D1). This price incorporates factors such as the Elspot price (c_i), electricity transfer fees, energy tax, and other relevant charges. On the other hand, the sale of exported electricity is determined by the wholesale electricity price ($EL_{w,i}$) as shown in Eq. (D2). This price considers the ElSpot price, along with subsidies such as grid benefit compensation (c_2) and tax reduction (c_3) into account. The specific values for c2, c3, c4, and c5, are mentioned in Eqs. (D1) and (D2), can be found in Table D1.

$$EL_{r,i}\left(\frac{€}{kWh}\right) = c_i + c_2 + c_3 \tag{D1}$$

$$EL_{w,i}\left(\frac{€}{kWh}\right) = c_i + c_4 + c_5 \tag{D2}$$

References

[1] Huang WC, Zhang Q, You F. Impacts of battery energy storage technologies and renewable integration on the energy transition in the New York State. Adv Appl Energy 2023 Feb;1(9):100126.
[2] Victoria M, Zhu K, Brown T, Andresen GB, Greiner M. The role of storage technologies throughout the decarbonisation of the sector-coupled European energy system. Energy Convers Manage 2019;201:111977.
[3] Guerra K, Gutiérrez-Alvarez R, Guerra OJ, Haro P. Opportunities for low-carbon generation and storage technologies to decarbonise the future power system. Appl Energy 2023 Apr;15(336):120828.
[4] Chapaloglou S, Nesiadis A, Atsonios K, Nikolopoulos N, Grammelis P, Carrera A, et al. Microgrid energy management strategies assessment through coupled thermal-electric considerations. Energy Convers Manage 2021 Jan;15(228):113711.
[5] Xu X, Zhang Z, Yuan J, Shao J. Design and multi-objective comprehensive evaluation analysis of PV-WT-BG-Battery hybrid renewable energy systems in urban communities. Energy Convers Manage: X 2023 Apr;1(18):100357.
[6] Luo Z, Peng J, Tan Y, Yin R, Zou B, Hu M, et al. A novel forecast-based operation strategy for residential PV-battery-flexible loads systems considering the flexibility of battery and loads. Energy Convers Manage 2023 Feb;15(278):116705.
[7] Palizban O, Kauhaniemi K. Energy storage systems in modern grids—Matrix of technologies and applications. J Energy Storage 2016 May;1(6):248–59.
[8] Yousri D, Farag HE, Zeineldin H, El-Saadany EF. Integrated model for optimal energy management and demand response of microgrids considering hybrid hydrogen-battery storage systems. Energy Convers Manage 2023 Mar;15(280):116809.
[9] Dhundhara S, Verma YP, Williams A. Techno-economic analysis of the lithium-ion and lead-acid battery in microgrid systems. Energy Convers Manage 2018 Dec;1(177):122–42.
[10] Ji M, Zhang W, Xu Y, Liao Q, Klemeš JJ, Wang B. Optimisation of multi-period renewable energy systems with hydrogen and battery energy storage: A P-graph approach. Energy Convers Manage 2023 Apr;1(281):116826.
[11] Olabi AG, Wilberforce T, Sayed ET, Abo-Khalil AG, Maghrabie HM, Elsaid K, et al. Battery energy storage systems and SWOT (strengths, weakness, opportunities, and threats) analysis of batteries in power transmission. Energy 2022 Sep;1(254):123987.
[12] Shabani M, Dahlquist E, Wallin F, Yan J. Techno-economic impacts of battery performance models and control strategies on optimal design of a grid-connected PV system. Energy Convers Manage 2021 Oct;1(245):114617.
[13] Hesse HC, Schimpe M, Kucevic D, Jossen A. Lithium-ion battery storage for the grid—A review of stationary battery storage system design tailored for applications in modern power grids. Energies 2017 Dec;10(12):2107.
[14] Shahid S, Agelin-Chaab M. A review of thermal runaway prevention and mitigation strategies for lithium-ion batteries. Energy Convers Manage: x 2022 Oct;13:100310.
[15] Staffell I, Rustomji M. Maximising the value of electricity storage. J Energy Storage 2016 Nov;1(8):212–25.
[16] Núñez F, Canca D, Arcos-Vargas Á. An assessment of European electricity arbitrage using storage systems. Energy 2022 Mar;1(242):122916.
[17] Metz D, Saraiva JT. Use of battery storage systems for price arbitrage operations in the 15-and 60-min German intraday markets. Electr Pow Syst Res 2018 Jul;1(160):27–36.
[18] Dufo-López R. Optimisation of size and control of grid-connected storage under real time electricity pricing conditions. Appl Energy 2015 Feb;15(140):395–408.
[19] Harrold DJ, Cao J, Fan Z. Data-driven battery operation for energy arbitrage using rainbow deep reinforcement learning. Energy 2022 Jan;1(238):121958.
[20] Mayyas A, Chadly A, Amer ST, Azar E. Economics of the Li-ion batteries and reversible fuel cells as energy storage systems when coupled with dynamic electricity pricing schemes. Energy 2022 Jan;15(239):121941.
[21] Berg K, Resch M, Weniger T, Simonsen S. Economic evaluation of operation strategies for battery systems in football stadiums: a Norwegian case study. J Energy Storage Feb. 2021;34:102190.
[22] Komorowska A, Olczak P, Hanc E, Kaminski J. An analysis of the competitiveness of hydrogen storage and li-ion batteries based on price arbitrage in the day-ahead market. Int J Hydrog Energy Aug. 2022;47(66):28556–72.
[23] Mustafa MB, Keatley P, Huang Y, Agbonaye O, Ademulegun OO, Hewitt N. Evaluation of a battery energy storage system in hospitals for arbitrage and ancillary services. J Energy Storage 2021 Nov;1(43):103183.
[24] Peñaranda AF, Romero-Quete D, Cortés CA. Grid-scale battery energy storage for arbitrage purposes: A colombian case. Batteries 2021 Sep 3;7(3):59.
[25] Shabani M, Wallin F, Dahlquist E, Yan J. The impact of battery operating management strategies on life cycle cost assessment in real power market for a grid-connected residential battery application. Energy 2023 May;1(270):126829.
[26] Telaretti E, Sanseverino ER, Ippolito M, Favuzza S, Zizzo G. A novel operating strategy for customer-side energy storages in presence of dynamic electricity prices. Intelligent Industrial Systems 2015 Oct;1:233–44.
[27] Díaz G, Gómez-Aleixandre J, Coto J, Conejero O. Maximum income resulting from energy arbitrage by battery systems subject to cycle aging and price uncertainty from a dynamic programming perspective. Energy 2018 Aug;1(156):647–60.
[28] Fridgen G, Kahlen M, Ketter W, Rieger A, Thimmel M. One rate does not fit all: An empirical analysis of electricity tariffs for residential microgrids. Appl Energy 2018 Jan;15(210):800–14.
[29] Paterakis NG, Erdinç O, Catalão JP. An overview of demand response: Key-elements and international experience. Renew Sustain Energy Rev 2017 Mar;1(69):871–91.
[30] Hu Z, Kim JH, Wang J, Byrne J. Review of dynamic pricing programs in the US and Europe: Status quo and policy recommendations. Renew Sustain Energy Rev 2015 Feb;1(42):743–51.
[31] Shcherbakova A, Kleit A, Cho J. The value of energy storage in South Korea's electricity market: A Hotelling approach. Appl Energy 2014 Jul;15(125):93–102.
[32] Telaretti E, Ippolito M, Dusonchet L. A simple operating strategy of small-scale battery energy storages for energy arbitrage under dynamic pricing tariffs. Energies 2015 Dec 25;9(1):12.
[33] Mohsenian-Rad H. Optimal bidding, scheduling, and deployment of battery systems in California day-ahead energy market. IEEE Trans Power Syst 2016;31(1):442–53.
[34] Han X, Lu L, Zheng Y, Feng X, Li Z, Li J, et al. A review on the key issues of the lithium ion battery degradation among the whole life cycle. Etransportation 2019 Aug;1(1):100005.
[35] Hu X, Xu L, Lin X, Pecht M. Battery lifetime prognostics. Joule 2020 Feb 19;4(2):310–46.
[36] Stroe DI. Lifetime models for Lithium-ion batteries used in virtual power plant applications. Ph.D. dissertation. Aalborg, Denmark: Dept. of Energy Tech., Aalborg University; 2014.
[37] Terlouw T, AlSkaif T, Bauer C, van Sark W. Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies. Appl Energy Apr. 2019;239:356–72.
[38] Lujano-Rojas JM, Dufo-López R, Bernal-Agustín JL, Catalão JP. Optimizing daily operation of battery energy storage systems under real-time pricing schemes. IEEE Trans Smart Grid 2016 Aug 24;8(1):316–30.
[39] Shafiee S, Zamani-Dehkordi P, Zareipour H, Knight AM. Economic assessment of a price-maker energy storage facility in the Alberta electricity market. Energy 2016;111:537–47.
[40] Bradbury K, Pratson L, Patiño-Echeverri D. Economic viability of energy storage systems based on price arbitrage potential in real-time US electricity markets. Appl Energy 2014 Feb;1(114):512–9.
[41] Ahlert KH, Van Dinther C. Sensitivity analysis of the economic benefits from electricity storage at the end consumer level. In2009 IEEE Bucharest PowerTech 2009 Jun 28 (pp. 1-8). IEEE.
[42] Sioshansi R, Denholm P, Jenkin T, Weiss J. Estimating the value of electricity storage in PJM: arbitrage and some welfare effects. Energy Econ 2009;31(2):269–77.
[43] Walawalkar R, Apt J, Macini R. Economics of electric energy storage for energy arbitrage and regulation in New York. Energy Policy 2007;35:2258–568.
[44] Degradation-conscious physics-based lithium-ion battery model for use in power system planning studies. Appl Energy 2019;248:512–25.
[45] Xu B, Zhao J, Zheng T, Litvinov E, Kirschen DS. Factoring the cycle aging cost of batteries participating in electricity markets. IEEE Trans Power Syst 2018;33(2):2248–59.
[46] Kazemi M, Zareipour H. Long-term scheduling of battery storage systems in energy and regulation markets considering battery's lifespan. IEEE Trans Smart Grid 2018;9(6):6840–9.
[47] Tan X, Wu Y, Tsang DHK. A stochastic shortest path framework for quantifying the value and lifetime of battery energy storage under dynamic pricing. IEEE Trans Smart Grid 2017;8(2):769–78.
[48] Namor E, Torregrossa D, Sossan F, Cherkaoui R, Paolone M. Assessment of battery ageing and implementation of an ageing aware control strategy for a load leveling application of a lithium titanate battery energy storage system. In: 2016 IEEE 17th Workshop on Control and Modeling for Power Electronics (COMPEL); 2016. p. 1–6.
[49] Lai CS, McCulloch MD. Levelized cost of electricity for solar photovoltaic and electrical energy storage. Appl Energy 2017 Mar;15(190):191–203.
[50] Maheshwari A, Paterakis NG, Santarelli M, Gibescu M. Optimizing the operation of energy storage using a non-linear lithium-ion battery degradation model. Appl Energy 2020 Mar;1(261):114360.
[51] Wankmüller F, Thimmapuram PR, Gallagher KG, Botterud A. Impact of battery degradation on energy arbitrage revenue of grid-level energy storage. J Energy Storage 2017;10:56–66.