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Techno-economic profitability of grid-scale battery storage allocation in European wholesale markets under a novel operation optimization strategy

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ABSTRACT

This study evaluates the techno-economic benefits of grid-scale battery storage allocation across 25 European countries, each with distinct wholesale price variation patterns. The evaluation is based on a novel optimization-based operation strategy, which adapts to the volatile nature of electricity markets. By making smart decisions on key operational factors, the strategy optimizes battery scheduling in the day-ahead market, maximizing profits while minimizing degradation and extending battery lifespan. Additionally, a behavior-aware battery management strategy is developed to accurately simulate real-world performance and degradation. The study identifies the most attractive European markets for grid-scale battery storage by evaluating multiple key economic metrics, including annual profit per unit of energy installed, battery lifetime, total revenue, net present value, return on investment, and payback period.

The findings show that, under the proposed strategy, battery storage integration generates significant positive profits in 23 European countries. Romania, Latvia, Lithuania, and Estonia emerge as top performers, offering high profitability, short payback periods, and long-term financial sustainability. In contrast, Spain, Portugal, and Norway are currently unprofitable, though sensitivity analysis suggests that a 75 % reduction in battery costs could make these markets viable for investment.

Introduction

Energy storage systems have emerged as a crucial solution for meeting the flexibility needs in the transition towards decarbonized electricity generation [1–3]. According to the International Energy Agency, the deployment of energy storage to support the electricity grid is projected to increase by about 40-fold by 2040 [4]. This dramatic surge is driven by the escalating penetration of renewable energy sources and the rapid adoption of electric vehicles, which vastly increases the complexity and demand on power systems. These factors make energy storage solutions essential for maintaining grid balance and meeting future energy needs [5–7]. Among the various energy storage technologies, battery storage has emerged as a superior option for grid-scale applications due to its scalability, ease of installation, high flexibility, and low maintenance cost [8–10]. In particular, lithium-ion (Li-ion) batteries are the most widely used technology for grid-scale storage because of their high efficiency, long life cycle, and cost reduction potential [11–13].

By the end of 2022, the total installed grid-scale battery storage capacity reached nearly 28 GW. Installations surged by more than 75 % in 2022 alone compared to 2021, with approximately 11 GW of new storage capacity added. China, the United States, and Europe led the market in grid-scale battery storage additions, with nearly 5 GW, 4 GW, and 1 GW of new installations, respectively [14]. This significant increase in storage capacity underscores the growing importance of batteries in power systems across various regions [15,16]. On the other hand, in developed economies with deregulated energy markets, such as those in Europe, energy storage systems need to demonstrate profitability to attract investors and encourage their deployment [17]. In recent years, European day-ahead electricity prices have experienced significant fluctuations due to various economic and geopolitical factors [18]. This volatility offers a unique opportunity for battery storage to participate in the arbitrage market [16]. By purchasing electricity during low-price periods and selling it during high-price periods, battery storage not only generates revenue but also reduces the load on the grid during peak hours, thereby enhancing grid stability and reliability [19–21]. The economic viability of Li-ion battery storage has been

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Nomenclature

Abbreviations

$ICC_{battery}$	Initial investment cost of a battery
LF	Battery lifetime
OCV	Open circuit voltage
RTP	Real-time price
SOC	Battery state of charge
SOH	Battery state of health

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
m	Number of days over project life;
NOC	Number of cycles per day
opt	optimal
$P^{ch}_{min,t}$	Maximal charge power at time t
$P^{dch}_{max,i}$	Maximal discharge power at time t
$P_{ch,t}$	Charge power at time t
$P_{dch,t}$	Discharge power at time t
PI	Profitability Index (%)
PPEI	Annual average profitability per energy installed (€/MWh/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

Greek Symbols

$\delta_{Replace}$	Battery replacement indicator

evaluated in several markets. Bradbury et al. [22] conducted a comparative analysis of seven U.S. electricity markets to evaluate the internal rate of return (IRR) for various energy storage technologies utilized for price arbitrage. Their findings revealed that Li-ion batteries consistently achieved an IRR below zero in all seven markets. Metz and Saraiva [19] analyzed German electricity prices from 2011 to 2016. Their sensitivity analysis revealed that price volatility must increase sevenfold for battery storage to be financially viable through price arbitrage. Using electricity price data from 2017 to 2018, Campana et al. [23] examined the feasibility of Li-ion batteries in Johannesburg, Stockholm, and Rome. Their analysis showed that the net present values (NPVs) for Li-ion batteries were negative at current costs, identifying specific costs and battery capacity as the main cost drivers. Komorowska et al. [24] analyzed Polish day-ahead electricity prices from 2016 to 2020 to evaluate the economic feasibility of energy storage for price arbitrage. Their findings revealed that, although Li-ion batteries had substantially higher NPVs compared to hydrogen storage, the NPVs were still negative. The sensitivity analysis indicated that positive NPVs could only be achieved if capital investment costs were reduced by 75 %.

Despite the growing interest in battery storage allocation for price arbitrage, most evaluations have been limited to a single market or country. This has left a significant gap in research that optimally compares the techno-economic viability of Li-ion batteries across European day-ahead electricity markets. To date, only two studies [16,25] have evaluated the competitiveness of battery storage in the context of the European day-ahead electricity market. Núñez et al. [16] based their analysis on data from 2019, while Komorowska and Olczak [25] included data from 2021 to 2022, reflecting the increased price volatility due to the war in Ukraine. Both studies concluded that, under current investment costs for Li-ion batteries, the NPV remained negative across all studied European countries. However, these studies are constrained by specific assumptions and methodologies that limit their applicability in maximizing profit across multi-market scenarios. A key limitation is that their price arbitrage strategy relied on historical data. This static approach, commonly used in the field [24,26,27], assumes fixed times for daily charging and discharging of battery storage. However, this approach may not fully capture price arbitrage potential under the volatile day-ahead electricity market, where the optimal price differentials may occur at times different from those initially planned. Moreover, the assumption of fixed charge and discharge durations (i.e., C-rate) can significantly limit the arbitrage strategy's flexibility in capturing higher price differential [28]. In contrast, using adjustable C-rate offers a solution by allowing battery to respond to price spikes more efficiently, maximizing potential profits. These studies are further limited by restricting the system to one cycle per day, whereas allowing for multiple cycles could enhance flexibility and capture more significant price differentials within a day [29].

Another critical and often overlooked factor in existing research is battery degradation. Designing a price arbitrage strategy that focuses exclusively on revenue without accounting for degradation may pose challenges, as degradation can drastically diminish battery performance, leading to inaccurate revenue estimates, and increased replacement costs. Many studies in the field either completely ignored degradation [16,22,24,25,27,30–38] or calculate battery ageing post-optimization [39–44], thereby failing to integrate its effects into strategy's operational decisions. In real-world applications, battery systems operate under dynamic operational conditions, and battery degradation follows a non-linear behavior. Consequently, a comprehensive understanding of battery degradation mechanisms and their key influencing factors is crucial for the development of optimal operational strategies [45].

Reviewing the existing literature reveals that the effectiveness of price arbitrage with battery storage in dynamic electricity markets depends on the flexibility of decision-making regarding several key individual factors. These factors include (a) how frequently the battery is charged and discharged each day, (b) when to charge and discharge within each cycle, and (c) at what rate to charge and discharge each cycle. These factors significantly impact both revenue generation and battery degradation. For instance, increasing the rate or number of cycles per day can enhance revenue but also accelerate degradation. Conversely, slower or fewer cycles can prolong battery lifespan at the cost of lower revenue. Striking the right balance between these factors is challenging, but essential for optimizing profitability. However, existing price arbitrage strategies often overlook to consider these factors and their interconnected effects simultaneously, leading to suboptimal battery utilization. The methods used for charging and discharging to capitalize on price differentials within dynamic electricity markets can significantly impact battery degradation rate, lifespan, operational costs, revenue generation, replacement costs, and environmental effects, all of which collectively determine the overall profitability of battery storage applications. Therefore, there is a significant need to develop a price arbitrage strategy that adapts to the volatile nature of different day-ahead electricity markets and make intelligent decisions on key profit-influencing factors to not only maximize revenue but minimize battery degradation costs and extend battery lifetime. Although this increases problem complexity, it has the potential to significantly enhance profitability. Moreover, a significant research gap exists in the comprehensive evaluation of the techno-economic profitability of grid-scale Li-ion battery allocation across European day-ahead electricity markets, particularly under a sophisticated, flexible, and smart arbitrage strategy. This study addresses this gap by proposing a smart, optimization-based price arbitrage strategy that adapts with different day-ahead market conditions, while conducting a comprehensive economic assessment. Our approach uniquely evaluates the profitability of battery storage allocation across different European markets. By providing a more accurate and realistic assessment of battery storage potential under volatile market conditions, this study aims to identify which European wholesale markets offer the most promise for battery storage allocation.

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

- The primary goal of this study is to evaluate the techno-economic profitability of grid-scale battery storage across 25 European countries, each characterized by distinct wholesale price variation patterns. The evaluation is conducted using a novel optimization-based price arbitrage strategy, applied for the first time in this context. This approach identifies the most suitable European wholesale markets for battery storage allocation by thoroughly assessing key indicators, including annual profit per unit of MWh installed, battery lifetime, total revenue, net present value, return on investment and payback period.
- A novel optimization-based scheduling strategy is proposed to optimize battery utilization for price arbitrage in the dynamic day-ahead electricity market. This strategy simultaneously makes smart decisions on critical factors to find the optimal balance between maximizing daily revenue and minimizing battery degradation costs. The ultimate goal is to sustain long-term profitability and extend the battery's operational lifespan.
- A battery operational management strategy is developed, which is behavior-aware, to effectively simulate battery performance under real-world operational conditions. This strategy accounts for factors such as estimating current–voltage behavior, cyclic and calendar capacity degradation, remaining useful battery life, and internal states like state of charge (SOC) and state of health (SOH).
- This study integrates technical performance with economic outcomes, creating a unified framework that connects battery operations with financial viability. This integration is essential to ensure that the proposed strategy is both technically robust and economically feasible across diverse market conditions.

Method

Section 2.1 details the battery behavior modelling scenario employed in this study. Section 2.2 outlines the proposed optimization-based price arbitrage strategy framework, optimization objectives, decision variables, and procedures. Section 2.3 presents the system operational management strategy. Finally, Section 2.4 presents the financial metrics used for profitability assessment in this study.

Scenario for battery modelling

This study selected a LFP battery, which is preferred option for grid-scale applications due to its cost-effectiveness, intrinsic safety, energy density, extended lifetime, rapid charging/discharging capabilities, and use of non-toxic materials [12,46,47]. Table A1 provides technical specifications of the LFP battery used in this study (Appendix A). As illustrated in Fig. 1, this study implements a comprehensive battery modeling scenario to efficiently estimate key battery parameters, such as voltage-current characteristics, capacity degradation, remaining useful life, and internal states. The methods employed to precisely estimate these battery parameters are briefly explained in the following section.

In this study, the battery current–voltage characteristics are estimated using the Rint electrical model, chosen as a trade-off between accuracy and computational time [9]. The studied model is based on an equivalent electrical circuit composed of internal resistance and an open-circuit voltage (OCV) source, as shown in Fig. B1 (Appendix B). Eqs. (1) and (2) represent the terminal voltage during charging and discharging, respectively, as a function of varying operational conditions, such as the state of charge, charge/discharge modes, load current, and temperature.

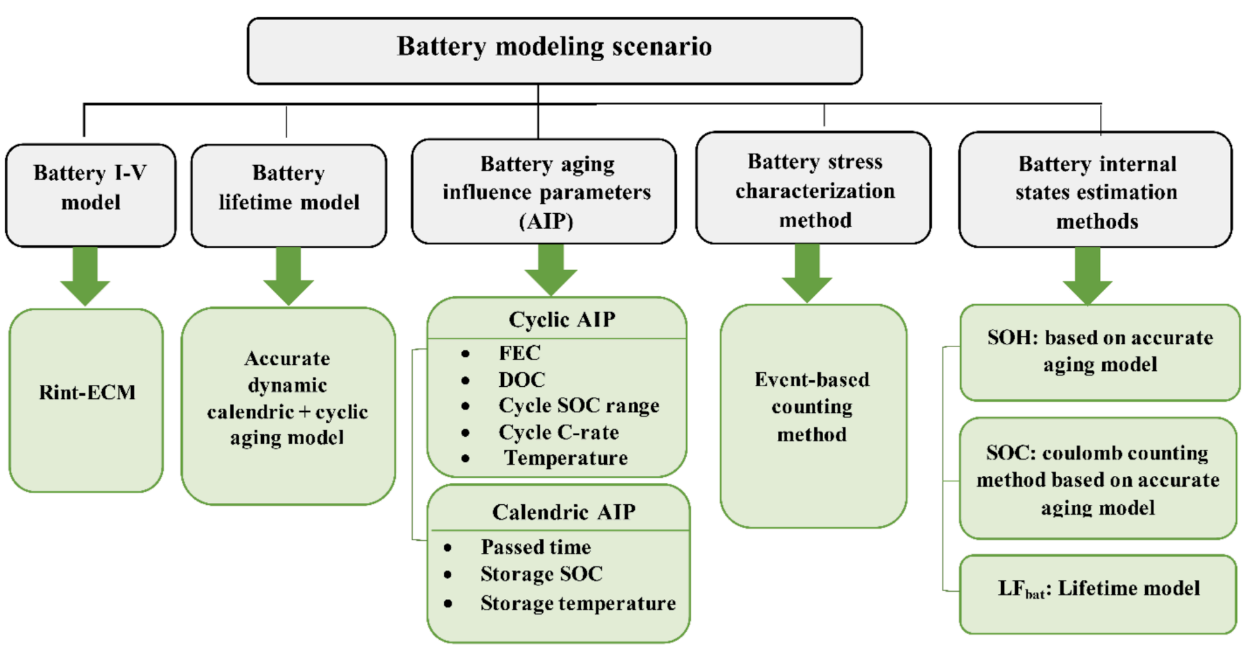


Fig. 1. Overview of the battery modeling scenario.

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

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

To enhance model accuracy, the OCV and internal impedance are modeled as functions of operating conditions. The OCV characteristics of the LFP/C battery cell in this study were derived from [48], which were determined via a laboratory OCV-SOC test conducted in steps of 5 % SOC for both charging and discharging modes, as shown in Fig. B1b (Appendix B). Moreover, the internal resistance of the LFP/C battery cell was derived from [48], which was measured at various states using a modified version of the hybrid pulse power characterization (HPPC) test, as shown in Fig. B1c (Appendix B). These curves are implemented in the model as a look-up table, enabling dynamic adjustment of these parameters based on operational conditions.

It is worth mentioning that, for this grid-scale analysis, the battery system is assumed to operate at a regulated ambient temperature of 25 °C, typical for stationary applications [46,48].

The validity of the presented battery performance model has been demonstrated by comparing the model-based simulation voltage curve with the measured voltage profile [48]. The model estimates the voltage behavior with high accuracy, achieving a maximum error of less than 0.7 %, a mean error below 0.19 %, and a coefficient of determination (R^2) between 0.98 and 0.992 across various C-rates. These results indicate a strong agreement between the measured and simulated voltage profiles. For further details on the battery performance model, refer to Ref. [9].

Understanding and accurately modeling battery aging is essential for optimizing energy storage systems and minimizing long-term costs. Li-ion batteries undergo two forms of aging: cyclic aging during use and calendric aging during storage. The key factors influencing cyclic aging include depth of cycle (DOC), current rate (C-rate), SOC level, cycle frequency, and temperature, while calendric aging is driven by storage SOC, the time elapsed since the beginning of life (BOL), and temperature [46–49]. Battery degradation exhibits non-linear behavior under dynamic operational conditions; thus, a model that can accurately estimate both calendric and cyclic aging under such conditions is required. In this study, a sophisticated battery capacity degradation model [46,47] is implemented to account for all possible factors influencing aging. The model estimates the battery's end of life (EOL) and capacity loss due to calendric aging and cyclic aging under dynamic conditions. The calendric capacity fade, as shown in Eq. (3), is a function of storage SOC and the time elapsed since BOL. The cyclic capacity fade, as shown in Eq. (4), depends on DOC, C-rate, and the full equivalent cycle (FEC). The total capacity fade is calculated by superimposing the calendric and pure cyclic capacity fade models, as shown in Eq. (5).

The reference values of α_1, α_2, β_1, β_2, γ_1, and γ_2 are provided in Table C1 (Appendix C), and the FEC formulation is given in Eq.(C1) in Appendix C. The implementation under dynamic conditions requires differential forms of the aging equations to account for changes in storage or cycling conditions. Detailed derivations of how to apply the calendric and cycling ageing model under dynamic operational conditions are available in the authors' previous work [45].

The model's accuracy has been validated by [46,47] through comprehensive studies under dynamic stress profiles, demonstrating its ability to estimate capacity fade with high precision, even over long-time scales and varying profiles.

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

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

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

An event-based counting method also known as the half-cycle counting method, employed in contexts involving dynamic conditions for aging estimation, is implemented to characterize battery stress after each load alternation (i.e., transitioning from charging to discharging or vice versa) by detecting sign changes in battery power or the SOC gradient [46]. After each half cycle (one charging or discharging phase), the cycle depth, cycle C-rate, and SOC level are detected and provided as inputs to the cyclic aging model. The calendric and cyclic aging contributions are then calculated and summed up to estimate the total capacity degradation. By accurately capturing partial cycles and stress fluctuations, this approach ensures a precise estimation of battery aging under dynamic operational conditions.

The battery's internal states, specifically the SOC and SOH, are critical parameters that need to be tracked to ensure efficient and safe battery operation. Precise monitoring of these states necessitates efficient estimation methods to prevent potential failures. SOC represents the current energy level of the battery and is estimated at each time step using the Coulomb counting method, as shown in Eq. (6). The Coulomb counting method, which is widely used for SOC estimation, calculates the SOC by integrating the current flowing into or out of the battery over time [48,50]. During charging, the SOC increases as current flows into the battery, while during discharging, it decreases as current flows out.

SOH indicates the current degree of battery degradation and is quantified at each time step using Eq. (7). It should be noted that the battery is constrained from charging and discharging simultaneously, as constraint in $(S_{\mathrm{ch}} + S_{\mathrm{dch}}) \leq 1$ in Eq. (6).

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

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

Optimization-based price arbitrage strategy

To maximize sustained profitability in a dynamic day-ahead electricity market through battery price arbitrage, it is vital to develop a strategy that effectively manages battery usage by simultaneously considering all key factors that influence revenue, capacity degradation, battery lifespan, and their interrelated impacts. This study proposes an innovative smart price arbitrage strategy designed to make intelligent decisions across a broad range of key factors. These factors include determining the optimal number of charge–discharge cycle for each day, identifying the best timing for charging and discharging during each cycle, and optimizing the durations and rates for charge and discharge per cycle. As discussed in the introduction, these factors are crucial because they directly influence the profitability of price arbitrage by impacting both revenue generation and the costs associated with battery degradation. By striking the right balance among these factors, strategy aims not only to maximize daily revenue but also minimize daily aging costs, ultimately seeking to maximize sustained profitability, while prolonging the battery's lifespan. Throughout the scheduling process, the scenario involves closely monitoring battery behavior, including performance, calendric and cyclic aging. So, by considering their interconnected effects on decision variables, the flexibility in achieving optimal outcomes increases. Fig. 2 outlines the optimization framework overview, illustrating the interaction between the "scheduling" and "operation" phases to achieve the targeted goals. Leveraging day-ahead real-time pricing (RTP) electricity price profiles from each market, the "scheduling phase" focuses on generating optimized daily plans for the

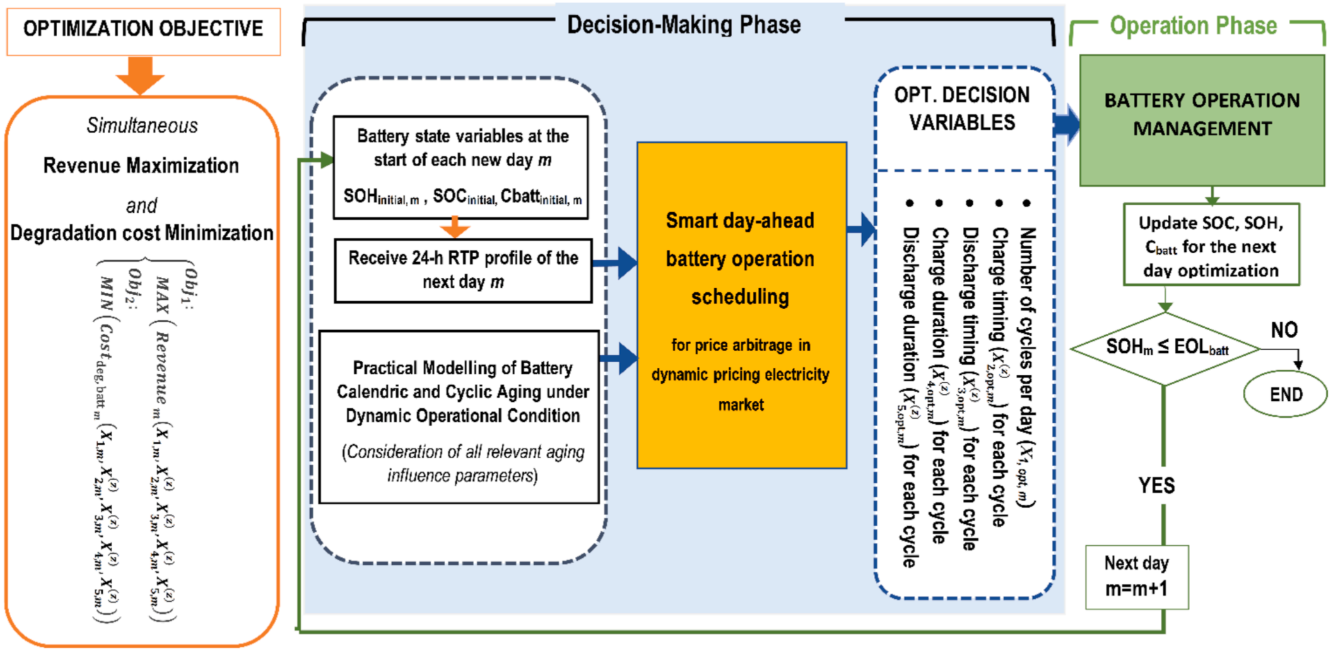


Fig. 2. Overall framework for optimizing battery operation scheduling.

following day to ensure efficient battery usage. These plans are subsequently provided to the "battery operation management module" (refer to Section 2.4 for more details) to oversee the battery charging and discharging actions based on the planned provided.

The optimization and simulation in this study were carried out using our own coding in MATLAB 2022b. This software was chosen for its robust computational and optimization capabilities, which are well-suited for the modeling tasks involved in this research.

Subsections 2.2.1–2.2.2 elaborate on the formulations of the optimization objective functions and decision variables. Subsections 2.2.3–2.2.4 present the optimization state variables and operating constraints. The optimization procedure will be detailed in Subsection 2.2.5.

Optimization objective function

As shown in Eq. (8), the proposed strategy focuses on the simultaneous optimization of two key objectives: maximizing daily revenue ($Revenue_m$) and minimizing daily degradation costs ($Cost_{\text{deg,batt}_m}$), with the goal of determining the optimal profit, as depicted in Eq. (9). These objectives are influenced by a range of decision variables (Section 2.3.2). The formulation of daily revenue and degradation costs are illustrated in Eqs. (D1), and (D2) in Appendix D.

$$\left\{\begin{array}{l}\text{Maximize}: Revenue_m\left(X_{1,m}, X_{2,m}^{(z)}, X_{3,m}^{(z)}, X_{4,m}^{(z)}, X_{5,m}^{(z)}\right)\\ \text{Minimize}: Cost_{\text{deg,batt}_m}\left(X_{1,m}, X_{2,m}^{(z)}, X_{3,m}^{(z)}, X_{4,m}^{(z)}, X_{5,m}^{(z)}\right)\end{array}\right. \rightarrow \text{maximize} Profit_m; m$$
$$= 1, \cdots, \text{daystillEOL} \tag{8}$$

Optimization decision variables. The optimization decision variables (X_i) are detailed in Eqs. (10)-(14). These variables encompass the cycle frequency for each day ($X_{1,m}$), the charging ($X_{2,m}^{(z)}$) and discharging ($X_{3,m}^{(z)}$) durations for each cycle, as well as the charging ($X_{4,m}^{(z)}$) and discharging ($X_{5,m}^{(z)}$) timings for each cycle.

$$\left\{\begin{array}{l} X_{1,m} = NOC_m; z = \begin{cases} 0, & X_{1,m} = 1\ (\text{daily-periodicity}) \\ 1,2 & X_{1,m} = 2\ (\text{semi-daily periodicity}) \end{cases} \\ X_{2,m}^{(z)} = d_{\text{ch},m}^{(z)} = \begin{cases} d_{\text{ch},m}^{(0)}; & X_{1,m} = 1 \\ (d_{\text{ch},m}^{(1)}, d_{\text{ch},m}^{(2)}); & X_{1,m} = 2 \end{cases} \\ X_{3,m}^{(z)} = d_{\text{dch},m}^{(z)} = \begin{cases} d_{\text{dch},m}^{(0)}; & X_{1,m} = 1 \\ (d_{\text{dch},m}^{(1)}, d_{\text{dch},m}^{(2)}); & X_{1,m} = 2 \end{cases} \\ X_{4,m}^{(z)} = t_{\text{ch, start},m}\left(X_{2,m}^{(z)}, RTP_m\right) = \begin{cases} t_{\text{ch,start},m}^{(0)}; & X_{1,m} = 1 \\ (t_{\text{ch,start},m}^{(1)}, t_{\text{ch,start},m}^{(2)}); & X_{1,m} = 2 \end{cases} \\ X_{5,m}^{(z)} = t_{\text{dch, start},m}(X_{3,m}^{(z)}, RTP_m) = \begin{cases} t_{\text{dch,start},m}^{(0)}; & X_{1,m} = 1 \\ (t_{\text{dch,start},m}^{(1)}, t_{\text{dch,start},m}^{(2)}); & X_{1,m} = 2 \end{cases} \end{array}\right. \tag{14}$$

As presented in Eq. (10), when z = 0, it represents daily periodicity, where the battery can complete one full charge and discharge cycle during a single day. In this case, five decision variables must be

$$Profit_{\text{opt},m}(X_{1,\text{opt},m}, X_{2,\text{ opt},m}, X_{3,\text{ opt},m}, X_{4,\text{ opt},m}, X_{5,\text{ opt},m}) = MAX\left(Revenue_m\left(X_{1,m}, X_{2,m}^{(z)}, X_{3,m}^{(z)}, X_{4,m}^{(z)}, X_{5,m}^{(z)}\right) - Cost_{\text{deg,batt}_m}\left(X_{1,m}, X_{2,m}^{(z)}, X_{3,m}^{(z)}, X_{4,m}^{(z)}, X_{5,m}^{(z)}\right)\right) \tag{9}$$

determined for each day (m), as outlined in Eqs. (11)-(12). In contrast, when z = 1 or z = 2, it signifies semi-daily periodicity, where the battery can undergo two full charge and discharge cycles within a 24-hour period. The day is divided into two periods. The first cycle (z = 1) cover period from 00:00 to 12:00, and the second cycle (z = 2) covers the period from 12:00 to 24:00. In this case, nine decision variables need to be determined for day m: four variables for the first semi-daily periodicity, which include start times for charging ($t^{(1)}_{\text{ch,start},m}$) and discharging ($t^{(1)}_{\text{dch,start},m}$), as well as the durations of charging ($d^{(1)}_{\text{ch},m}$) and discharging cycle ($d^{(1)}_{\text{dch},m}$); Similarly, four variables for the second semi-daily periodicity including charge and discharge timing ($t^{(2)}_{\text{ch,start},m}, t^{(2)}_{\text{dch,start},m}$) and their respective charge and discharge durations ($d^{(2)}_{\text{ch},m}, d^{(2)}_{\text{dch},m}$).

Optimization state variables. As described in Eq. (15), battery state variables are updated every hour and communicated to the decision maker daily. On the project's first day (m = 1), the initial SOC is set to the maximum level, and the battery is in an unused condition. For all subsequent days (m ≠ 1), the initial SOC, SOH, and battery capacity are initialized based on to the updated state variables from the final hour of the previous day.

$$\begin{cases} U^1_m = SOC_{\text{initial},m} = \begin{cases} SOC_{\text{final},m-1}\left(X_{1,\text{opt},m}, X^{(z)}_{2,\text{ opt},m}, X^{(z)}_{3,\text{ opt},m}, X^{(z)}_{4,\text{ opt},m}, X^{(z)}_{5,\text{ opt},m}\right); m \neq 1 \\ SOC_{\text{Min}}\ ; m = 1 \end{cases} \\ U^2_m = SOH_{\text{initial},m} = \begin{cases} SOH_{\text{final},m-1}\left(X_{1,\text{opt},m}, X^{(z)}_{2,\text{ opt},m}, X^{(z)}_{3,\text{ opt},m}, X^{(z)}_{4,\text{ opt},m}, X^{(z)}_{5,\text{ opt},m}\right); m \neq 1 \\ SOH_{\text{BOL}}\ ; m = 1 \end{cases} \\ U^2_m = C_{\text{batt initial},m} = \begin{cases} C_{\text{batt final},m-1}\left(X_{1,\text{opt},m}, X^{(z)}_{2,\text{ opt},m}, X^{(z)}_{3,\text{ opt},m}, X^{(z)}_{4,\text{ opt},m}, X^{(z)}_{5,\text{ opt},m}\right); m \neq 1 \\ C_{\text{batt BOL}}\ ; m = 1 \end{cases} \end{cases} \tag{15}$$

Optimization operating constraints. To ensure the battery functions efficiently and safely, it is essential to follow the specific operating constraints, as outlined in Eq. (16). In this study, $\delta_{\text{Replace}} = 75\ \%$ is used as the threshold battery replacement. Consequently, the battery is considered to reach its end-of-life when its SOH drops to 75 %, which aligns with the warranty condition of the LFP/c battery. The constraints $NOC_m \leq 2$ limits the number of charge and discharge cycles per day to a maximum of two. As specified Eq. (16), the battery is permitted to function within defined maximum charge and discharge power ($P^{\text{ch}}_{\text{min,t}} and P^{\text{dch}}_{\text{max,t}}$) which are determined by based on the battery's available capacity and the maximum allowable charge and discharge C-rates. The optimization of C-rates is achieved through the optimization of charge/discharge durations. As the C-rate is mathematically defined as the inverse of the duration (C-rate $\frac{1}{\text{Duration}}$), optimizing the charge/discharge durations effectively optimizes the corresponding C-rates. Therefore, the charge and discharge C-rates are determined daily, corresponding to $\frac{1}{X_{2,\text{ opt,m}}}$ for charging and $\frac{1}{X_{3,\text{ opt,m}}}$ for discharging throughout the project period.

$$\begin{cases} SOH_m \leq \alpha_{\text{Replace}} \rightarrow EOL_{\text{batt}} \rightarrow \alpha_{\text{Replace}} = 75\% \\ SOC_{\min} \leq SOC_i \leq SOC_{\max} \\ NOC_m \leq 2 \\ P^{\text{ch}}_{\min,t}.S_{\text{ch}} \leq P_{\text{batt},t} \leq P^{\text{dch}}_{\max,t}.S_{\text{dch}} \rightarrow \begin{cases} P^{\text{ch}}_{\min,t} = \dfrac{-C_{\text{batt}_t}}{d^{(z)}_{ch,m}} \times (SOC_{\max} - SOC_{\min}) \\ P^{\text{dch}}_{\max,t} = \dfrac{C_{\text{batt}_t}}{d^{(z)}_{dch,m}} \times (SOC_{\max} - SOC_{\min}) \\ S_{\text{ch}} + S_{\text{dch}} \leq 1 \end{cases} \end{cases} \tag{16}$$

Optimization procedure. The optimization process is detailed in the following steps:

1. The optimization process begins by initializing the battery state variables (SOC, and battery capacity) in accordance with Eq. (15).
2. Each day (m), the decision-maker receives a 24-hour ahead RTP profile.
3. For that day, the number of daily cycles $X_{1,m}$ is initialized, with the cycle index z set based on the number of cycles: z = 0 for one cycle, and z = 1, 2 for two cycles. The optimization process systematically tests both options (one or two cycles) to identify the optimal solution based on the daily price profile, ensuring that the number of cycles is not predetermined but rather dynamically selected to maximize daily profit. Notably, if cycling the battery is not profitable, the battery remains in idle mode ($NOC_m = 0$).
4. Given the number of cycles for day m, the charge and discharge durations ($X^{(z)}_{2,\ m}$, and$X^{(z)}_{3,\ m}$) are initialized as illustrated in Eqs. (14) and (15). Notably, the charge and discharge durations for each cycle may differ, ranging from 1 to 10 h for a daily cycle (z = 0), and from 1 to 6 h for semi-daily cycle (z = 1, 2). The upper and lower limits were selected based on practical operational constraints and battery degradation considerations. For daily periodicity (z = 0), the upper limit of 10 h corresponds to a low C-rate (0.1C), which minimizes degradation while ensuring that a full-charge–discharge cycle fits within a 24-hour period. Similarly, the lower limit of 1 h allows the battery to respond rapidly to price spikes with a high C-rate (1C). For semi-daily periodicity (z = 1,2), the upper limit of 6 h ensures that a full charge–discharge cycle fits within the available 12-hour windows,

preventing overlapping cycles while minimizing degradation by operating at a moderate C-rate (approximately 0.2C).

5. For each set of charge and discharge durations, the charge and discharge start times that achieve the maximum daily price differential are then identified. A detailed explanation of the methodology used to determine the optimal start times for charging and discharging $X^{(z)}_{4,m}$, and$X^{(z)}_{5,m}$) is provided in Appendix E.
6. With the identified charge and discharge timing, the objective function is calculated via the operational management strategy as outlined in section 2.4.
7. The results are stored in a data center.
8. The steps are repeated for all possible combinations of decisions variables.
9. The optimal daily objective function value and the corresponding set of decision variables are identified from stored data.
10. The optimal operation schedule for day m ($X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}$) is then sent to the battery operation module to run the battery according to the optimal schedule and update its state variables as shown in Eq. (15).
11. The updated states are then communicated back to the decision maker to inform operation scheduling for the next day (m + 1).
12. This process is repeated daily until the battery SOH reaches the EOL criteria.
13. Finally, the financial metrics, as illustrated in Eqs. (17)-(22), are reported

Operational management strategy

In this study, an operational management strategy is implemented to simulate the operation of a grid-connected battery system over the project's lifespan. This involves charging and discharging the battery according to optimal schedules generated by the proposed operation scheduling strategy. To ensure efficient battery management, the strategy is capable of accurately monitoring battery behavior under realistic operational conditions. Simulations are conducted on an hourly basis until it reaches battery end of life. Fig. 3 illustrates the flowchart of the proposed operational management strategy. A brief explanation of how the operational management strategy works is as follows: the strategy begins by receiving daily input data such as 24-hour electricity price profile, battery SOC, SOH, capacity, and operating constraints, as well as the optimal daily operation schedule, which includes the allowable cycle frequency per day, optimal timing, as well as durations for each charge and discharge cycle. The battery is charged during the identified charging timeframe ($t_{ch,start,m} \leq t_m \leq t_{ch,start,m} + d_{ch}$), at the maximum permissible rate ($P^{ch}_{min,t}$) using low-price grid power. Conversely, the battery is discharged with the maximum allowable rate ($P^{ch}_{max,t}$) when the current time of day m is within the detected optimal discharge

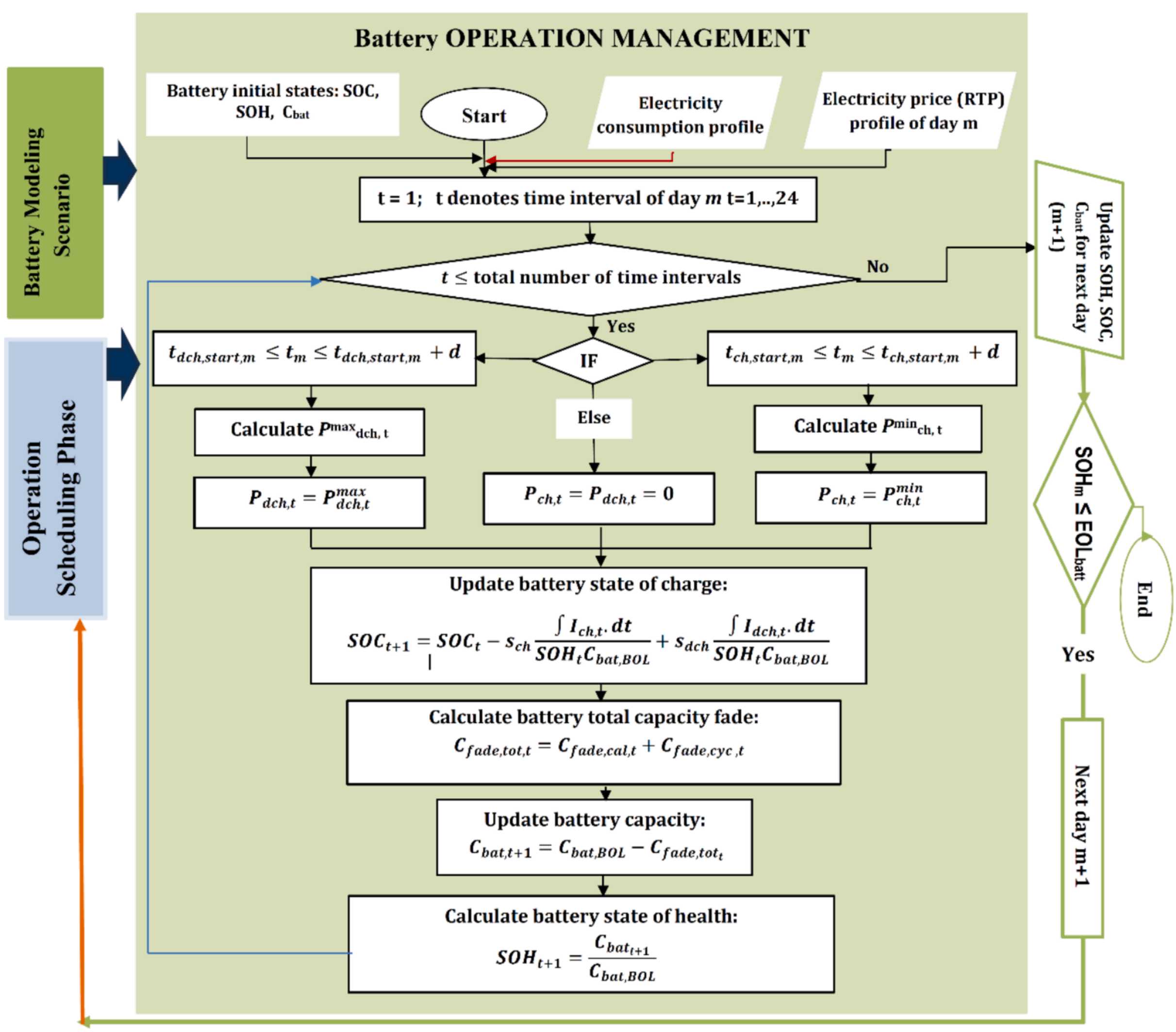


Fig. 3. Flowchart of battery operation management strategy.

timeframe ($t_{dch,start,m} \leq t_m \leq t_{dch,start,m} + d_{dch}$). During all other time intervals, the battery remains idle, with no charging or discharging activities. At each time intervals, the following steps are performed:

- Update battery SOC, according to Eq. (6).
- Detect battery ageing influence parameters though stress detection method as described in Section 2.2.
- Calculate the calendric and cyclic capacity degradation using the ageing models described in Section 2.2.
- Update the battery SOH based on the current capacity of battery, (Eq. (7))

This process is consecutively repeated until the end of day. At the end of day, the updated battery states (SOC, SOH, and capacity) are communicated to the decision maker to inform the scheduling of the next day battery operations.

Metrics for profitability assessment

- *Total revenue, and profit:* The total revenue and profit over the project's lifetime are determined using the present value (PV) method, as detailed in Eqs. (17) and (18). This approach involves converting all projected future cash flows into their present-day equivalents by applying a selected discount rate. This calculation ensures that the time value for money is accounted for, allowing for an accurate assessment of the project's financial performance over time.

$$\mathrm{Revenue}^{\mathrm{PV}}_{\mathrm{opt,\ tot}} = \sum_{n=1}^{LF_{\mathrm{bat}}(\mathrm{yr})} \frac{\left(\sum_{m=1}^{365} Revenue_{\mathrm{opt},m}\right)_n}{(1+\mathrm{interest}_{\mathrm{rate}})^n} \tag{17}$$

$$\mathrm{NPV} = \sum_{n=1}^{LF_{\mathrm{bat}}(\mathrm{yr})} \frac{\left(\sum_{m=1}^{365} Revenue_{\mathrm{opt},m}\right)_n}{(1+\mathrm{interest}_{\mathrm{rate}})^n} - ICC_{\mathrm{battery}} \tag{18}$$

- *PI (profitability index):* is an important financial metric used to compare the potential profitability of various capital projects and to determine how much return you get on the investment. The PI, as shown in Eq. (19), is calculated as the ratio of the total discounted profit to the initial investment cost in the battery.

$$\mathrm{PI}\ (\%) = \frac{\mathrm{NPV}}{ICC_{\mathrm{battery}}} \times 100 \tag{19}$$

- *Annual average PPEI (profit per unit of energy installed):* is a key economic metric that evaluates the financial returns of energy storage per unit of energy capacity, offering valuable insights for informed decision-making in assessing the profitability of energy storage projects. As presented in Eq. (20), the annual average PPEI is calculated by dividing the present value of the total profit by the battery's nominal capacity and the battery lifetime.

$$\mathrm{PPEI}\ (€/\mathrm{kWh/yr}) = \frac{\mathrm{Profit}^{PV}_{\mathrm{opt,\ tot}}}{C_{\mathrm{batt,\ BOL}} \times LF} \tag{20}$$

- *PBP (Payback period):* as indicated in Eq. (21), is a financial indicator that estimates how long it will take for an investment to generate positive cash flows and recover the initial investment cost.

$$\mathrm{PBP}\ (\mathrm{yr}) = \frac{m\left(\left(\sum_m Revenue_{\mathrm{opt},m} - ICC_{\mathrm{battery}}\right) \geq 0\right)}{365} \tag{21}$$

- *Battery Lifetime (LF_{bat}):* in this study, the battery lifetime is not predefined, instead, it is estimated using a realistic capacity degradation model, as detailed in Section 2.2. It is important to note that in this study, the battery lifetime is considered as the project lifespan. As indicated in Eq. (22), the battery lifetime is defined as the period from the beginning of life until the SOH reaches the threshold indicating the battery EOL state.

$$LF_{\mathrm{bat}}(\mathrm{yr}) = \frac{m_{SOH_m \leq \alpha_{\mathrm{Replace}}}}{365} \tag{22}$$

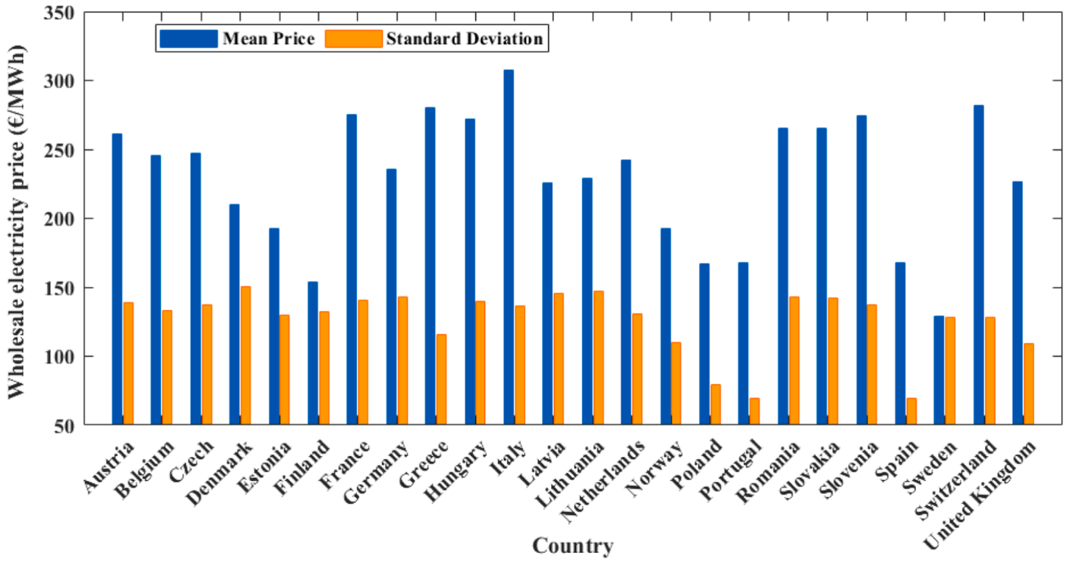
Case study

This study evaluates the economic viability of allocating grid-scale Li-ion battery storage systems across European countries, each marked by unique wholesale electricity price patterns. The analysis covers 25 countries, including Sweden, Switzerland, Spain, Slovakia, Slovenia, Romania, Portugal, Poland, the Netherlands, Norway, Lithuania, Latvia, Italy, Hungary, Greece, Germany, Luxemburg, France, Finland, Estonia, Denmark, the Czech Republic, Belgium, and Austria, and the United Kingdom. In this study, the 24-hour day-ahead real-time pricing (RTP) profile is provided as input to the decision-maker and is based on real-world day-ahead electricity price data. Hourly electricity price data for 25 European countries were collected from ENTSO-E [51] for the entire year. ENTSO-E publishes day-ahead market prices that reflect actual wholesale electricity pricing across Europe. Therefore, this approach represents a realistic real-world scenario in which decision-makers typically receive day-ahead pricing information to plan operations. Since visualizing hourly price data for all 25 countries over an entire year is impractical, key statistical insights are presented instead to provide a comprehensive yet concise overview. These insights include the average electricity spot prices, standard deviations (SD), and the average daily price differentials, which effectively capture key pricing trends and market volatility while maintaining readability. Table 1 provides statistical information on wholesale electricity prices across Europe. For a clearer representation, Fig. 4a presents the average electricity spot prices along with the standard deviations (SD) for 25 European countries for the sample year 2022. The calculated standard deviations indicate the degree of price volatility within each market. Additionally, Fig. 4b shows the average daily electricity price differential, which represents the difference between the daily maximum and minimum electricity prices.

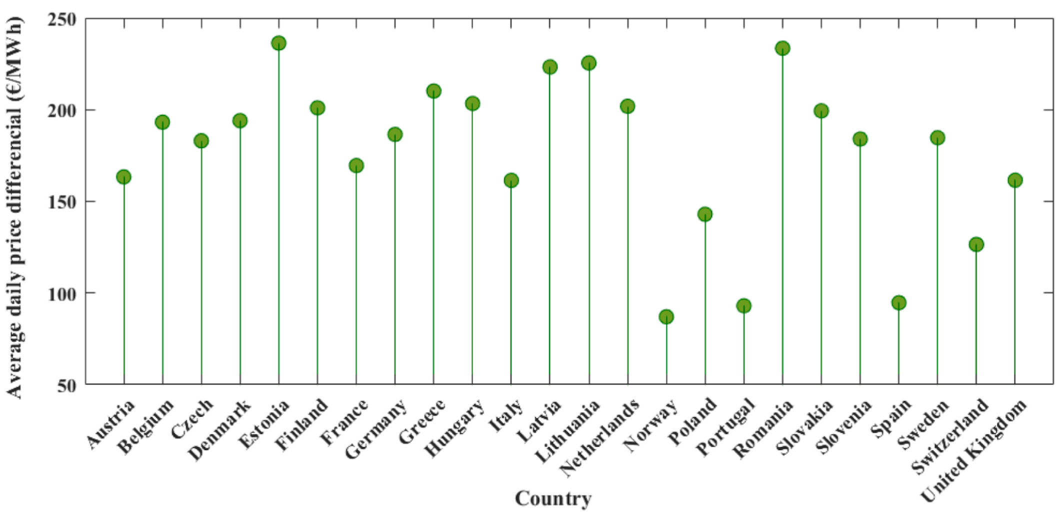
As shown in Fig. 4a, and Table 1, countries in Northern Europe generally have lower electricity prices, with Sweden standing out with

Table 1
Statistics on wholesale electricity prices in Europe.

Country	Mean price (€/MWh)	SD (€/MWh)	Mean gap (€/MWh)
Austria	261.3	138.5	163.3
Belgium	245.2	133.4	193.2
The Czech Republic	247.5	137.5	183.04
Denmark	210.1	150.2	194.03
Estonia	192.3	129.5	236.3
Finland	154	132.4	201.02
France	275.1	140.5	169.5
Germany-Luxemburg	235.4	142.8	186.5
Greece	279.9	116.1	210.2
Hungary	271.7	139.8	203.4
Italy	307.8	136.6	161.4
Latvia	225.9	145.4	223.3
Lithuania	229.2	147.03	225.5
The Netherlands	242.5	130.4	201.9
Norway	192.5	109.8	87
Poland	166.7	79.5	143
Portugal	167.9	69.1	93
Romania	265.3	142.9	233.5
Slovakia	264.9	142.4	199.4
Slovenia	274.5	136.9	184
Spain	167.5	69.4	94.7
Sweden	129.2	127.9	184.7
Switzerland	281.7	128.2	126.5
The United Kingdom	226.8	109.1	161.5



(a)



(b)

Fig. 4. Wholesale electricity prices in Europe: (a) mean price (blue bars) and SD (orange bars); (b) mean daily electricity price differential (2022). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the lowest mean price on the list, at 129 €/MWh. Conversely, countries in Southern Europe, such as Italy and Greece, tend to have higher electricity prices.

In terms of price volatility, Denmark, Lithuania, and Latvia experienced the highest levels, with standard deviations of 150.3 €/MWh, 147.1 €/MWh, and 145.1 €/MWh, respectively. In contrast, Portugal and Spain recorded the lowest price volatilities, with SDs of 69.1 €/MWh and 69.4 €/MWh, respectively. Notably, both Portugal and Spain exhibit mid-level prices combined with relatively small standard deviations, indicating that their daily price fluctuations are minor.

The analysis of average daily electricity price differentials, as shown in Fig. 4b, further highlights regional disparities. Countries like Estonia, Romania, Lithuania, Latvia, Greece, Hungary, and the Netherlands reported high differentials, exceeding 200 €/MWh. In contrast, Norway, Portugal, and Spain showed lower daily price differentials, falling below 100 €/MWh. This underscores the importance of understanding regional differences in electricity market dynamics.

Results and discussion

The results of this study are presented in two subsections. Subsection 4.1 discusses the financial viability of grid-scale battery storage allocation, using comprehensive economic performance metrics, obtained based on the smart optimization-based price arbitrage strategy for 25 European electricity markets. Subsection 4.2 evaluates the sensitivity of the economic assessment to changes in battery price and discount rates.

Techno-economic assessments of battery storage in European countries

Table 2 illustrates the techno-economic results derived from system simulations using the proposed novel optimization-based arbitrage strategy. Figs. 5-7 compare the profitability of the studied grid-scale battery storage systems across 25 European wholesale markets, highlighting the economic performance differences in each region. Fig. 5 illustrates the annual average profit per unit of battery energy installed

Table 2
Detailed techno-economic analysis obtained given the smart price arbitrage strategy for 25 European countries.

Country	PPEI (k€/MWh/yr)	LF_{batt} (yr)	NPV (k€)	PI (%)	PBP (yr)
Austria	14.9	10.5	157.6	39.4	6.9
Belgium	27.7	10	276.2	69.04	5.4
The Czech Republic	23.1	10.4	238.6	59.7	5.8
Denmark	25.1	10.6	264.9	66.2	5.7
Estonia	37.5	10.2	383	95.7	4.6
Finland	22.5	11.1	248.6	62.2	6.2
France	17.9	10.4	187.3	46.8	6.5
Germany-Luxemburg	24.5	10.5	257.5	64.4	5.6
Greece	31.6	9.9	313.6	78.4	4.9
Hungary	28.7	10	285.6	71.4	5.2
Italy	14.5	10.5	151.7	37.9	6.9
Latvia	37.9	10.1	383	95.8	4.6
Lithuania	37.7	10.1	379.5	94.8	4.7
The Netherlands	31.1	10	309.6	77.4	5
Norway	−6.3	13.4	−83.9	−20.9	None
Poland	8.1	11.6	93.2	23.6	8.7
Portugal	−5.9	11.9	−71.4	−17.9	None
Romania	38.4	9.8	374.3	93.6	4.5
Slovakia	27.2	10.1	273.1	68.3	5.4
Slovenia	21.8	10.1	220.4	55.1	5.9
Spain	−5.5	11.9	−645.7	−16.1	None
Sweden	20.2	11.6	233.6	58.4	6.6
Switzerland	5.1	11.1	57	14.1	9.4
The United Kingdom	10.1	10.6	106.5	26.6	7.8

(left Y-axis), along with the estimated battery lifetime until 25 % capacity degradation (right Y-axis).

Fig. 6 presents the net present value (NPV) on the left Y-axis, and the corresponding return on investment (PI) on the right Y-axis. Fig. 7 shows the total revenue gained (left Y-axis), along with the payback period (right Y-axis). While each financial metric is individually informative, they are interconnected and collectively provide a comprehensive assessment of the economic viability of battery storage projects across different markets.

By comparing the financial results shown in Figs. 5-7, it is observed that *Romania, Latvia, Lithuania, and Estonia* stand out as the most attractive markets for grid-scale battery storage investments due to their great combination of high profitability, long battery life, fast return on investment, and long-term sustainability. For further illustration of top-performing countries, Romania leads with an average PPEI of 38.4 k€/MWh/yr, the highest among all countries, demonstrating the highest annual profit generated per unit of installed energy capacity. Latvia (37.9 k€/MWh/yr), Lithuania (37.7 k€/MWh/yr), and Estonia (37.5 k€/MWh/yr) also demonstrate excellent efficiency, ranking them among the most profitable markets in Europe. Another critical factor is battery lifetime as it influences the sustainability of profit over time. In all four countries battery lifetimes, as shown in Fig. 5 (right axis), last around 10 years, which ensures that long-term profit. This highlights the strategy's ability to optimally utilize battery storage in leveraging price differentials to maximize revenue, while extending battery life. Given battery lifetime, the NPV is particularly high in these markets. Latvia and Estonia both lead with 383 k€, followed closely by Lithuania (379.5 k€) and Romania (374.3 k€). These high NPVs indicate that battery storage projects in these countries are expected to generate substantial total profits over battery lifetime. Moreover, another important factor to evaluate is how long it will take to recover the initial investment cost, which serves as a complementary indicator of financial viability. As shown in Fig. 7 (right axis), in all four countries, battery investments have short payback periods ranging from 4.5 to 4.7 years, with Romania offer the fastest payback at 4.5 years. This means investors will quickly recover their initial investments and begin generating profit within a few years. Considering all these factors together, results show that, the PI, which measures how much return you get for the investment, exceeds 90 % in all four countries: Latvia at 95.8 %, Estonia at 95.7 %, Lithuania at 94.8 %, and Romania at 93.6 %. This shows that these investments almost double the initial cost, ensuring strong financial returns. Accordingly, Romania, Latvia, Lithuania, and Estonia offer a highly attractive combination of profitability, quick investment recovery, and long-term financial stability. Investors seeking efficient, profitable, and fast-return markets will find these countries to be the best choices for grid-scale battery storage investment.

Following the top-performing countries, Greece, the Netherlands, Hungary, Belgium, and Slovakia still offer strong profitability over the project's lifetime, though at slightly lower levels compared to the leading markets. Their annual average PPEI ranges from 32 k€/MWh

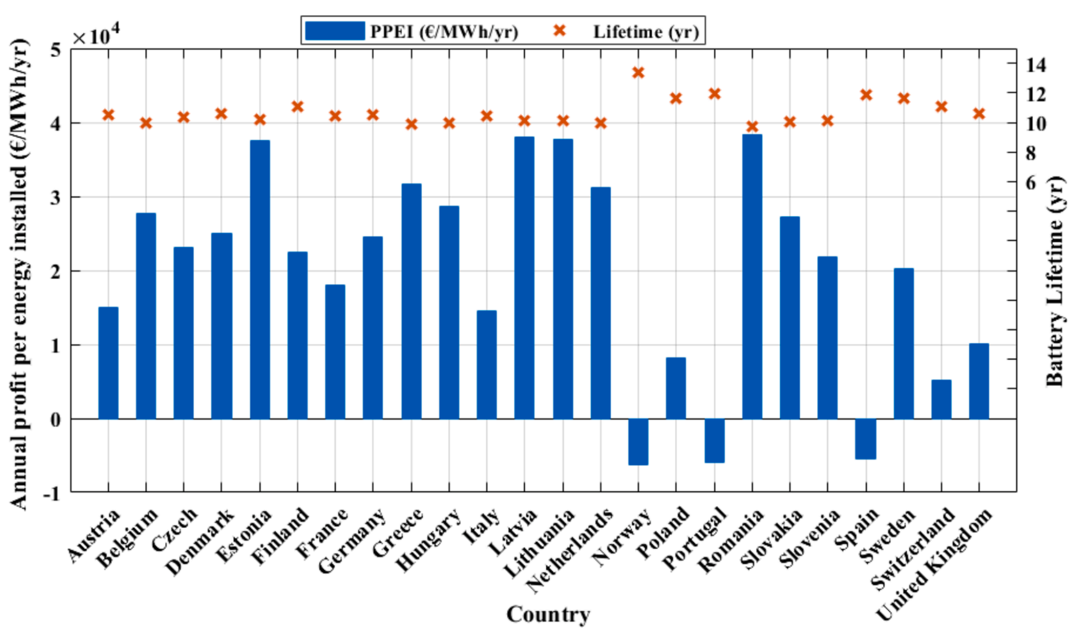


Fig. 5. Comparative analysis of annual average PPEIs (left Y-axis) and estimated battery lifetimes (right Y-axis) for European countries, obtained under the smart price arbitrage strategy (C_{batt} = 1MWh).

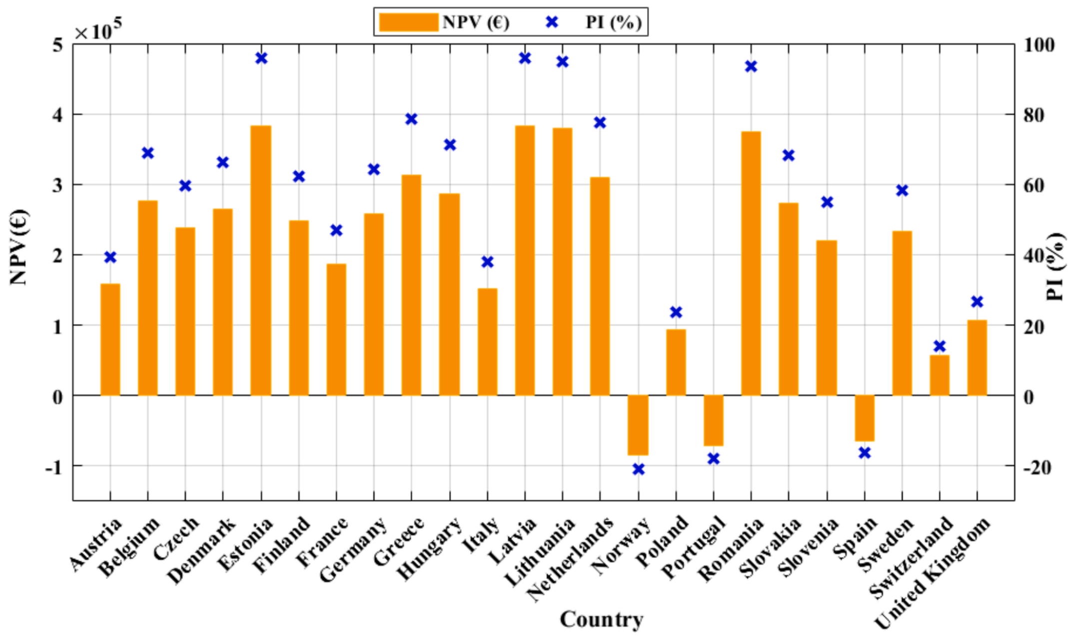


Fig. 6. Comparative analysis of NPV (left Y-axis) and profitability index (right Y-axis) for European countries, obtained under the smart optimization-based price arbitrage strategy (C_{batt} = 1MWh).

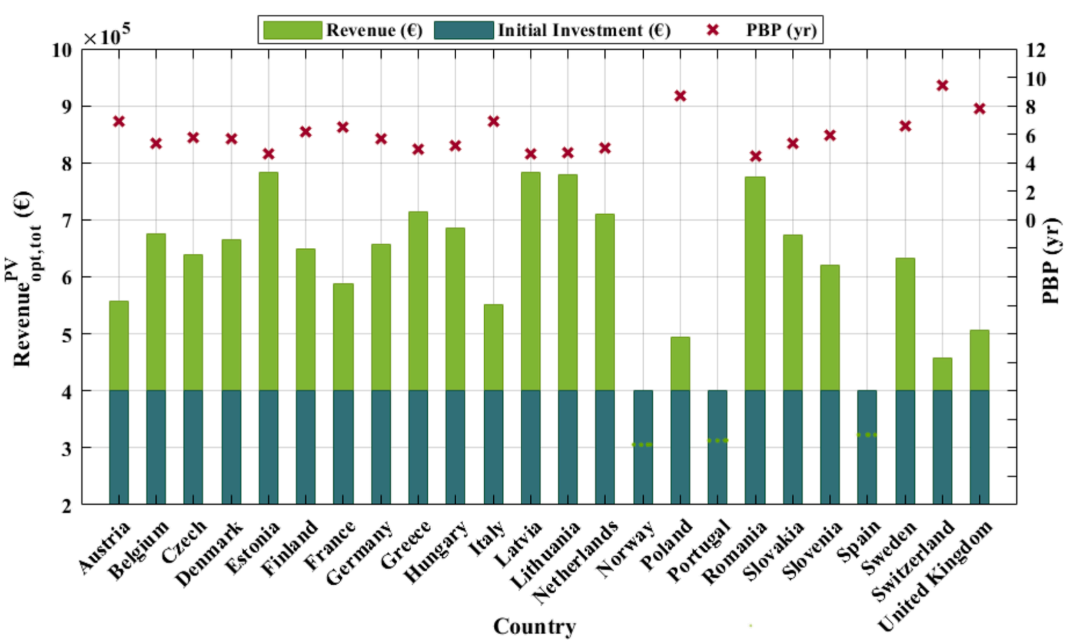


Fig. 7. Comparative analysis of total revenue (left Y-axis) and payback period (right Y-axis) for European countries, obtained under the smart optimization-based price arbitrage strategy (C_{batt} = 1MWh).

(for Greece) to 27 k€/MWh (for Slovakia), with battery lifetimes around 10 years. The Profitability Index (PI) for these countries falls between 80 % (for Greece) and 70 % (for Slovakia), and their payback periods are slightly longer, ranging from 5 to 5.4 years.

Allocating battery storage in the markets of Denmark, Germany, Finland, the Czech Republic, Sweden, and Slovenia leads to moderate profitability, reduced by approximately 30–42 % compared to top-performing countries. The NPV values ranging from 220 k€ in Slovenia to 265 k€ in Denmark. The return on investment, as indicated by PI values, falls between 55 % and 66 %, reflecting moderate financial returns. The Payback Period in these markets is relatively favorable, ranging from 5.6 to 6.6 years. The battery lifetime across these countries spans from 10 to 11.6 years, ensuring sustained profitability after the initial capital recovery, though returns will accumulate more slowly compared to higher-performing markets. These markets are best suited for investors seeking steady, long-term growth rather than rapid returns. Among this group of countries, it is noteworthy that Sweden's annual profit per unit of energy installed (20.2 €/MWh/yr) is lower than Slovenia's (21.8 €/MWh/yr), contributing to Sweden's longer payback period. However, Sweden's higher NPV compared to Slovenia can be attributed to its longer battery lifetime—about 1.5 years more—resulting in greater sustained profitability over time. This makes Sweden more attractive in terms of long-term profit generation, but less appealing for investors prioritizing a faster return on investment.

Among the 25 studied European countries, the United Kingdom, Poland, and Switzerland showed minimal positive profitability and longer payback periods, with Switzerland showed the least positive profit. Annual average profitability in these markets is relatively low, ranging from 5 to 10 k€/MWh/yr, though battery lifetimes remain favorable at 10.5 to 11 years. The return on investment ranges from 14 % to 27 %, reflecting limited financial returns, compared to top-performing- and moderate-markets. Additionally, these markets feature payback periods between 7 and 10 years, indicating that investors will face a substantial delay in recovering their initial capital. These extended payback periods are attributed to less favorable market conditions, including reduced opportunities for arbitrage.

On the other hand, as shown in Fig. 6, grid-scale battery storage allocation in Spain, Portugal, and Norway leads to negative NPVs, making them currently unprofitable for investment. This is primarily due to low mean price gaps and minimal price volatility, which severely limit the potential for profitable price arbitrage. Norway is the most financially risky, with an NPV of −83.9 k€, followed by Portugal (−71.4 k€), and Spain −64.6 k€. Despite the relatively long battery lifetimes in these markets, the generated revenue is insufficient to cover the initial investment, resulting in no possible payback during project life. Battery storage Investments in these countries lead to losses with −20.9 % (Norway), −17.9 % (Portugal), −16.1 % (Spain), making them highly unattractive, and high-risk for investors. In is worth mentioning that battery lifetimes in these countries range from 12 to 14 years, the longest observed. However, this advantage is overshadowed by the poor financial performance. The longer battery lifetimes are attributed to the strategy's ability to adapt operations efficiently in unfavorable market conditions, minimizing degradation by avoiding unnecessary cycling and optimizing power rates and cycle numbers. However, longer battery lifetimes do not necessarily translate into higher profitability. From an investor's perspective, battery lifetime is most beneficial when combined with a short payback period, as it ensures several years of profit after the initial investment is recovered. This underscores the importance of evaluating profitability through multiple metrics collectively.

The results of the analysis show significant variation in the financial and operational performance of grid-scale battery storage systems across Europe.

Overall, the results demonstrate that, under the proposed smart price arbitrage strategy, the integration of battery storage into various European electricity markets can generate significant positive profits in most countries. This outcome contrasts with other studies conducted under the same market conditions and time frame, where negative profits were reported due to different strategic approaches. The findings of this study emphasize the crucial role of an effective price arbitrage strategy that adapts to the volatile nature of electricity markets and makes optimal decisions on a wide range of factors impacting project profitability by accounting revenue maximization, degradation costs minimization, battery lifetime extension, and considering their interconnected effects.

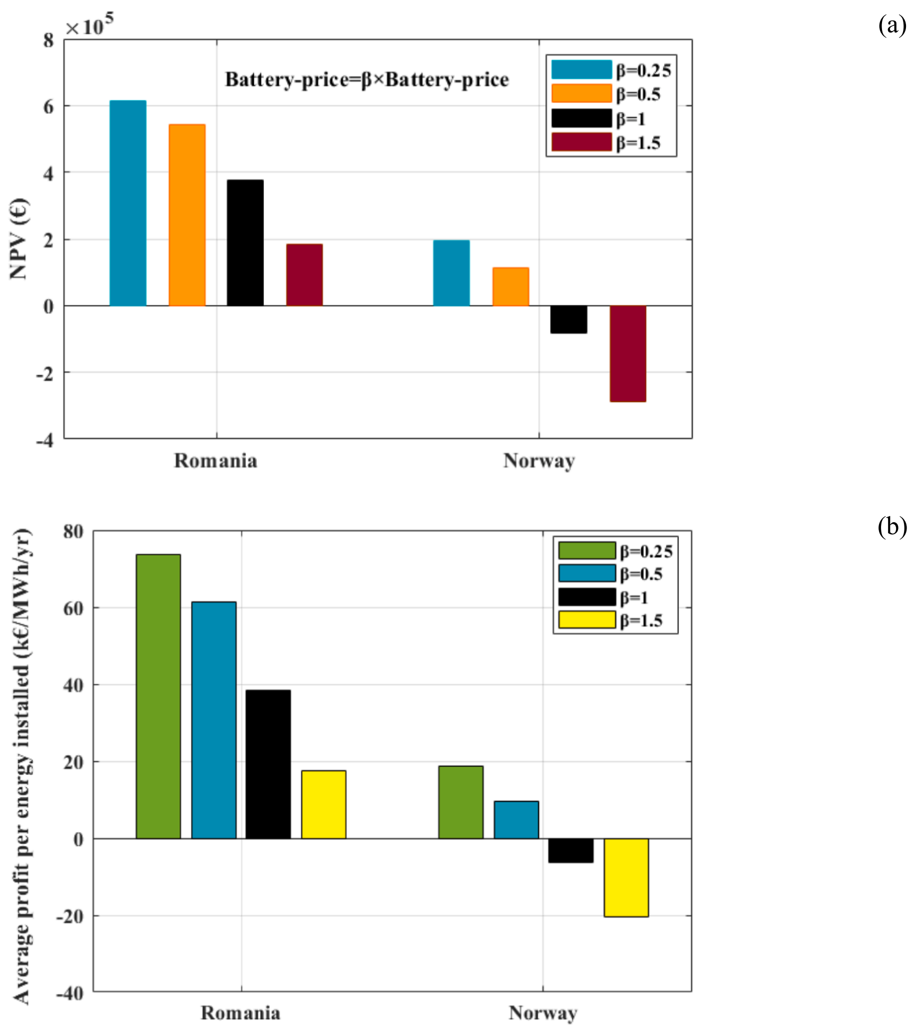


Fig. 8. The sensitivity of NPV, and average PPEI to battery price changes in the most profitable (Romania) and least profitable (Norway) markets.

Sensitivity analysis

The economic assumptions, particularly the discount rate and battery price, have a significant impact on the outcomes of the economic assessments. A sensitivity analysis is conducted to examine how the results vary under different assumptions. For sake of consciousness, the analysis focuses on two countries: Romania, the most profitable market, and Norway, the least profitable.

Sensitivity to battery price

Fig. 8 compares the sensitivity of NPV, and annual average profit per unit of energy installed in Romania and Norway across different battery price scenarios, highlighting the financial impact of changing costs. The results show that Romania consistently shows positive NPVs across all price scenarios, demonstrating financial robustness. Even with a 50 % increase in battery prices, the project remains profitable, though the NPV decreases by 50.7 % compared to the reference price. A 75 % reduction in battery price leads to a 63.5 % increase in NPV for Romania compared to the reference case, highlighting the substantial financial benefits of lower battery costs.

In contrast, Norway demonstrates much higher sensitivity to battery price changes. A 75 % reduction in battery prices results in a 331.8 % increase in NPV, turning it positive. The PPEI shifts from a −6.3 k€ loss per MWh installed to a + 18.7 k€ return per MWh installed. However, with a 50 % increase in battery prices, the NPV declines by 243.9 %, emphasizing how rising costs drastically affect Norway's project viability.

Overall, the analysis clearly demonstrates that battery price is a critical determinant of project success. While Romania's project remains viable under all price scenarios, Norway's financial viability is highly dependent on substantial cost reductions.

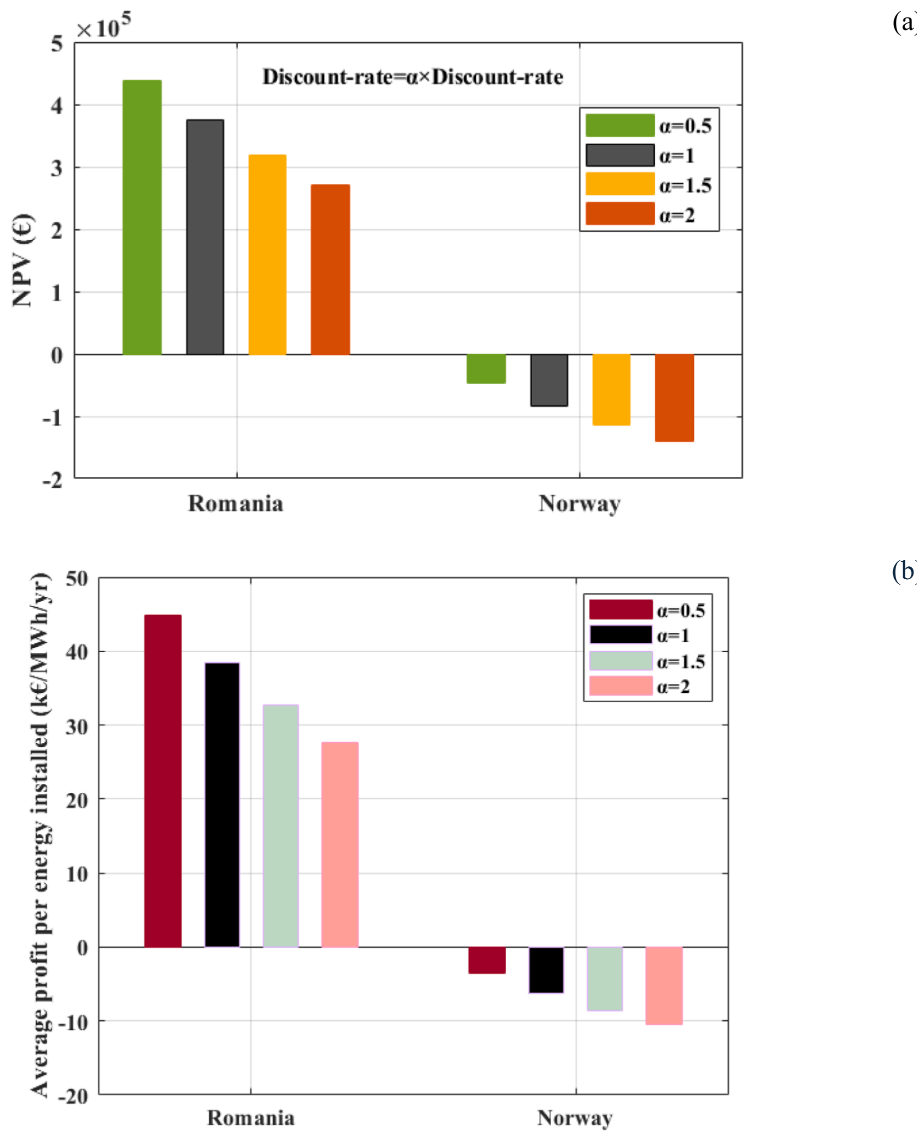


Fig. 9. The sensitivity of NPV, and average PPEI to discount rate changes in the most profitable (Romania) and least profitable (Norway) markets.

Sensitivity to discount rate

Fig. 9 illustrates the impact of discount rate changes on the NPV results for Romania and Norway. The results showed that Romania demonstrates positive NPV across all discount rate scenarios. Even as the discount rate rises to 8 %, Romania's NPV decreases by approximately 30 %, but remains positive. This indicates that despite higher discount rates, battery storage investments in Romania continue to be profitable.

In contrast, Norway shows negative NPV, across all discount rate scenarios, making it an unprofitable market for battery storage investments under the given conditions. Even with a 50 % reduction in the discount rate, Norway's NPV improves by about 45 %, yet remains negative. As the discount rate increases, the financial outlook worsens further. A 200 % increase in the discount rate results in Norway's NPV dropping to −140,340 €, highlighting the increasing losses.

The results highlight that Norway's project remains unprofitable across all discount rate scenarios. While lower discount rates marginally improve NPV, the project fails to achieve financially viable even at the most favorable discount rate (2 %).

Conclusion

The following conclusions can be drawn:

- Romania, Latvia, Lithuania, and Estonia showed the most attractive markets in Europe across all metrics, offering an ideal combination of high profitability, short payback periods, and long-term financial sustainability. Romania leads with an impressive annual average profit per MWh installed of 38,400 €/MWh/yr, the estimated battery lifetime of around 10 years, and the shortest payback period of approximately 4.5 years, ensuring rapid returns on investment. The profitability index of around 93 % nearly doubles the initial investment, underscoring strong financial returns. These markets offer a strategic advantage for investors seeking both quick returns and long-term stability, even under fluctuating battery prices.
- Following the most profitable countries, markets such as Greece, the Netherlands, Hungary, Belgium, and Slovakia, while still profitable from both short- and long-term perspectives, showed slightly longer payback periods. These markets led to an annual average PPEI ranging from 27,000 to 32,000 €/MWh/yr, with battery lifetimes of around 10 years, payback periods of 5 to 5.4 years, and profitability indexes between 70 % and 80 %, indicating solid but slower financial returns.
- On the lower end, the United Kingdom, Poland, and Switzerland show minimal profitability, with annual average PPEI as low as 5–10 k€/MWh/yr. Despite favorable battery lifetimes of 10.5 to 11 years, these markets experience long payback periods of 7 to 10 years and limited financial returns between 14 to 27 %, reflecting higher investment risks.
- Notably, Spain, Portugal, and Norway demonstrate the least profitable markets in Europe due to negative NPVs, making them currently unprofitable for investment, with Norway leading as the least profitable. However, sensitivity analysis reveals that a 75 % reduction in battery costs could transform these negative NPVs into positive outcomes, shifting the average PPEI from a −6,300 €/MWh/yr loss to a + 18,700 €/MWh/yr gain. This underscores the critical role of battery cost management in improving market viability and highlights the need for policy interventions to enhance financial incentives in underperforming markets.
- These findings emphasize the importance of evaluating battery viability through multiple economic metrics, enabling decision-makers and investors to thoroughly assess a project's financial feasibility from various perspectives. A broader perspective on viability is essential, as outcomes that appear favorable under one economic metric might be less attractive when assessed using alternative metrics.

CRediT authorship contribution statement

Masoume Shabani: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Formal analysis, Conceptualization. **Mohadeseh Shabani:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software. **Jinyue Yan:** 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.

Appendix A

Table A1
Specification of the LFP battery, and system assumptions.

Parameter	Value
Battery chemistry	$LiFePO_4/C$
Battery nominal voltage	3.2 V
Discharge cut-off voltage	2.5 V
Charge cut-off voltage (V)	3.6 V
Battery maintenance cost (% of investment/year)	0.5 %
Battery energy specific price (€/kWh)	400
Discount rate	4 %

Appendix B

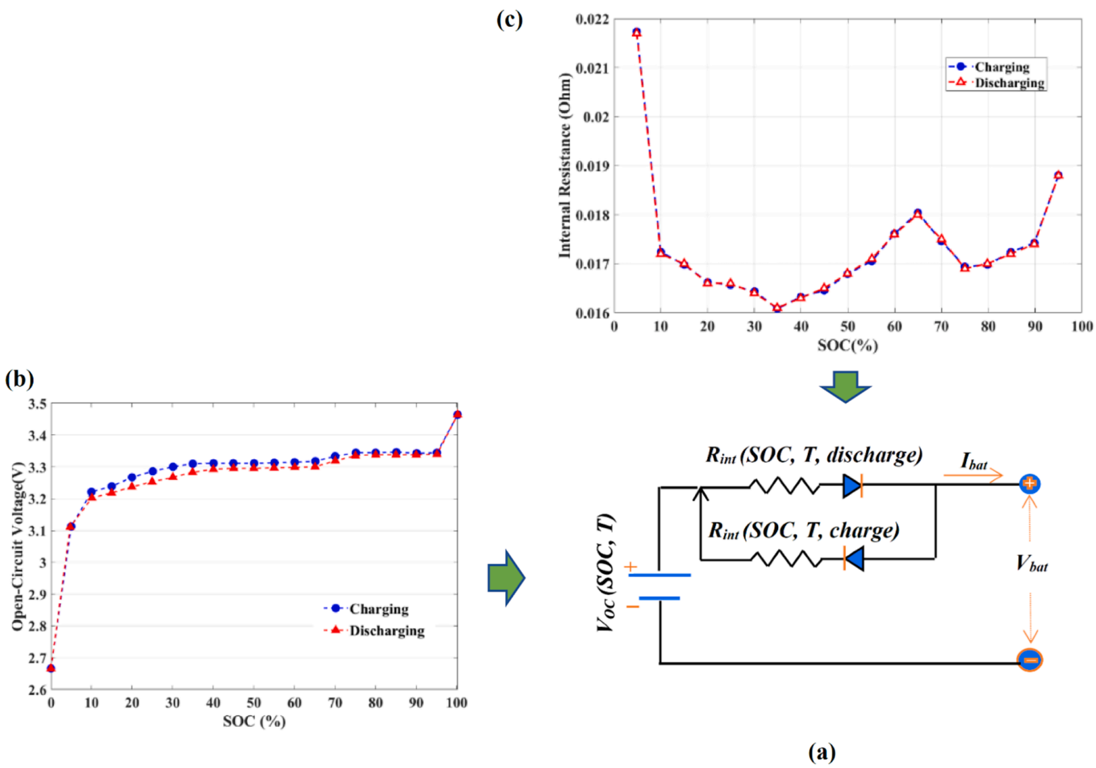


Fig. B1. (a) Equivalent circuit of Rint Electrical model (b) open circuit voltage vs the state of charge at T = 25 °C; (c) internal resistance vs the state of charge at T = 25 °C.

Appendix C

Table C1
Battery aging parameters [46,47].

Parameter	Value
α_1	2.8575
α_2	0.60225
β_1	0.0630
β_2	0.0971
γ_1	4.0253
γ_1	1.0923

The full equivalent cycle (FEC) represents the total number of full charge–discharge cycles the battery has undergone. It is calculated as the ratio of the cumulative capacity throughput to twice the nominal battery capacity at the BOL. The formulation is expressed as:

$$FEC = \frac{C_{\text{batt, cum}}}{2 \times C_{\text{batt, BOL}}} = \frac{C_{\text{batt, cum, ch}} + C_{\text{batt, cum, dch}}}{2 \times C_{\text{batt, BOL}}} \tag{C1}$$

Where $C_{\text{batt, cum}}$ is the total cumulative capacity throughput over the elapsed time period, including both charge and discharge capacities. The $C_{\text{batt, BOL}}$ is the nominal battery capacity at the beginning of life.

The cumulative capacity throughput is calculated by integrating the absolute value of the battery current over the simulation time period. This approach ensures that the FEC accounts for all charge–discharge activity during the simulation, providing an accurate representation of the battery's utilization.

Appendix D

$$Revenue_m\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right) = \begin{cases} \left(\sum_{t=1}^{24}\left(\left(P_{\mathrm{dch},t} \times El_{\mathrm{w},t}\right) - \left(P_{\mathrm{ch},t} \times El_{\mathrm{w},t}\right)\right)\right)_{m,\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right)}, z = 0 \\ \sum_{z=1}^{2}\left(\sum_{t=1}\left(\left(P_{\mathrm{dch},t} \times El_{\mathrm{w},t}\right) - \left(P_{\mathrm{ch},t} \times El_{\mathrm{w},t}\right)\right)\right)_{m,\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right)}, z = 1,\ 2 \end{cases} \tag{D1}$$

$$Cost_{\mathrm{deg,batt}_m}\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right) = \begin{cases} \dfrac{C_{\mathrm{fade,\ tot}_m}\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right)}{1-\alpha_{\mathrm{replace}}} \times ICC_{\mathrm{battery}}, & z = 0 \\ \sum_{z=1}^{2} \dfrac{C^{z}_{\mathrm{fade,\ tot}_m}\left(X_{1,m}, X^{(z)}_{2,m}, X^{(z)}_{3,m}, X^{(z)}_{4,m}, X^{(z)}_{5,m}\right)}{1-\alpha_{\mathrm{replace}}} \times ICC_{\mathrm{battery}}, & z = 1, 2 \end{cases} \tag{D2}$$

Appendix E

Given each 24-hour ahead RTP profile, the moving average (MA) of RTP prices at time t (where t represents the hour of the day) for each examined charge/discharge duration on day m is calculated using Eq. (E1) in Appendix E. To determine the optimal charge and discharge start times for each charge/discharge duration on day m, the minimum and maximum values of the MA RTP profile are calculated using Eq. (E2) in Appendix E. The time indices corresponding to the maximum and minimum MA RTP values are then identified, as shown in Eq. (E3) in Appendix E. These indices define the charge and discharge start times ($X^{(z)}_{4,m}$, and $X^{(z)}_{5,m}$) at which the maximum daily price differential is achieved

$$\begin{cases} MA^{(z)}_{RTP,m,d^{(z)}_{ch,m}}(t_z) = \sum_{k=t_z}^{t_z+d^{(z)}_{ch,m}-1} \dfrac{RTP_m(k)}{d^{(z)}_{ch,m}}; \\ MA^{(z)}_{RTP,m,d^{(z)}_{dch,m}}(t_z) = \sum_{k=t_z}^{t_z+d^{(z)}_{dch,m}-1} \dfrac{RTP_m(k)}{d^{(z)}_{dch,m}}; \end{cases} t_z = \begin{cases} 1, 2, \cdots, 24 - d^{(z)}_{ch,m} + 1 \\ 1, 2, \cdots, 24 - d^{(z)}_{dch,m} + 1 \\ 1, \cdots, 12 - d^{(z)}_{ch,m} + 1 & \text{if} z = 0 \\ 1, \cdots, 12 - d^{(z)}_{dch,m} + 1 & \text{if} z = 1 \\ 13, \cdots, 24 - d^{(z)}_{ch,m} + 1 & \text{if} z = 2 \\ 13, \cdots, 24 - d^{(z)}_{dch,m} + 1 \end{cases} \tag{E1}$$

$$MA^{(z)}_{RTP,m,d^{(z)}_{ch,m},MIN} = Min\left(MA^{(z)}_{RTP,m,d^{(z)}_{ch,m}}(t_z)\right); MA^{(z)}_{RTP,m,d^{(z)}_{ch,m},MAX} = Max\left(MA^{(z)}_{RTP,m,d^{(z)}_{ch,m}}(t_z)\right); \tag{E2}$$

$$t^{(z)}_{\mathrm{ch,\ start},d^{(z)}_{ch,m},m} = t_z@MA^{(z)}_{RTP,m,d^{(z)}_{ch,m},MIN}; t^{(z)}_{\mathrm{dch,\ start},d^{(z)}_{dch,m},m} = t_z@MA^{(z)}_{RTP,m,d^{(z)}_{dch,m},MAX} \tag{E3}$$

Data availability

The authors do not have permission to share data.

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