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Optimizing the Energy Scheduling and Assessing Profitability of BESSs in Buildings Considering Battery Degradation

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***Abstract*—Battery energy storage systems (BESSs) are an emerging technology that can be integrated into buildings equipped with photovoltaic systems to reduce the electricity cost for prosumers in the face of volatile electricity prices. This work develops an optimization scheme for the energy scheduling of a BESS integrated in a residential building with photovoltaic systems considering a variable electricity pricing scheme and battery degradation. The proposed scheme is formulated as a linear program that can be solved fast and reliably over long-term time horizons, enabling its usage for both planning and operating strategies. Utilizing the developed optimization model, a financial analysis is performed to assess the long-term BESS profitability by calculating the *net present value* (NPV) and *internal rate of return* (IRR) using real data from a residential building. Simulation results demonstrate the increment of the NPV and IRR using the proposed optimization scheme compared to the corresponding scheme that ignores BESS degradation. The results also highlight that the proper selection of the penalty cost in cycle-based battery degradation cost models is critical for the enhancement of the battery profitability.**

***Index Terms*—Battery degradation, convex optimization, energy prosumers, energy storage systems, internal rate of return.**

I. INTRODUCTION

Battery energy storage systems (BESSs) are an emerging technology that supports the integration of renewable energy sources (RES) into the power system by providing several grid services, e.g., frequency regulation. Moreover, BESSs integrated into residential and industrial buildings equipped with Photovoltaic (PV) systems can reduce the electricity cost of prosumers by storing energy when selling prices are low and using or selling it when purchasing prices are high [1].

Optimization strategies that determine the power set-points of PV-BESS systems to minimize the buildings electricity cost are proposed in [2]–[4]. Specifically, the electricity cost of a single prosumer is minimized in [2], while the total electricity cost of all prosumers in a distribution grid is minimized in [3], [4]. However, the aforementioned works ignore the battery degradation which is crucial to be considered to ensure that the revenues derived from the operation of BESSs will cover their true operation and maintenance costs [5].

The cycle and calendar degradation are the main factors that affect the BESS lifetime [5], [6]. Specifically, calendar factors refer to the degradation of the BESS over time, regardless of operating conditions; thus, calendar degradation is usually ignored in optimization problems that aim to optimize the economic scheduling of BESSs [5], [7]. The cycle degradation refers to the number of operating cycles that a BESS can perform at a specific cycle depth, before reaching its end-of-life (EoL) [5].

Cycle-based degradation models that can be used in optimization formulations have been developed to model the degradation based on the operation of BESS. In [8], an optimal bidding strategy for BESSs in a day-ahead energy market is proposed that extends the battery lifetime by limiting the number of discharge cycles using a constraint. However, this approach leads to the same BESS operation regardless of the price variability, potentially resulting in reduced profits, especially during periods of high price fluctuations. A two-objective optimization scheme that maximizes arbitrage profits and minimizes the BESS degradation is proposed in [9]; however, the two objectives are conflicting and the selection of the most suitable Pareto optimal solution is challenging. To address this issue, one approach is to transform the two-objective function into a single aggregate objective function by multiplying the degradation function with a penalty cost. Specifically, the works in [5], [7], [10], [11] present cycle-based degradation cost models that are used in optimization problems to maximize daily arbitrage profits and minimize BESS degradation costs, where the penalty cost is replaced by the BESS capital cost. However, high BESS costs (high penalty costs) restrain BESS usage, reducing the arbitrage profits and hence the long-term battery profitability. Hence, there is a need to investigate the long-term BESS profitability under different BESS costs and penalty costs in the battery degradation cost models. However, the optimization schemes developed in [5], [7], [11] are mixed-integer programs which

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are challenging to solve for long-term time horizons.

This work develops an optimization scheme for the energy scheduling of a BESS integrated in a residential building with PV systems considering a variable electricity pricing scheme and battery degradation. The resulting problem is non-convex and hence challenging to solve due to the non-convex BESS constraints. To address this issue, a linear optimization scheme that can be fast and reliably solved over long-term time horizons is developed by incorporating a convex cycle-based battery degradation cost model and a relaxed BESS power loss model. In addition, the proposed scheme is also utilized to assess the long-term battery profitability under different BESS costs and penalty costs in the battery degradation cost model. Specifically, a financial analysis is performed to investigate the BESS profitability by calculating the *net present value* (NPV) and *internal rate of return* (IRR) using real data from a residential building. The main contributions of this work are the following:

1) Formulation of an energy management optimization problem for residential prosumers, utilizing a convex cycle-based degradation cost model and a relaxed BESS power loss model, that can be fast and reliably solved over long-term time horizons.
2) Investigation of the long-term BESS profitability based on real data from a residential building using the NPV and IRR financial metrics under different BESS costs and penalty costs in the battery degradation model.

The rest of this paper is organized as follows. Section II states the underlying problem and Section III formulates the energy management problem as a linear program. The methodology of calculating the NPV and IRR is provided in Section IV and simulation results are presented in Section V. Finally, conclusions are given in Section VI.

II. Problem Statement

This section states the underlying problem by (a) describing the PV-BESS system integrated in a building, (b) presenting the battery degradation cost model based on the rainflow cycle counting method, and (c) formulating the optimization problem of the energy management scheme.

A. PV-BESS System

This work considers a BESS integrated in a building with an installed PV system, which is connected to the power grid. The arrows in Fig. 1 indicate the possible power flow directions in the system. The power balance in the building is defined as

$$P_t^v + P_t^b + P_t^d = P_t^s + P_t^c + P_t^l, \quad \forall t \in \mathcal{T}, \tag{1}$$

where $\mathcal{T} = \{1, ..., T\}$ denotes the considered time horizon. Variables $P_t^c \geq 0$, $P_t^d \geq 0$, $P_t^s \geq 0$, and $P_t^b \geq 0$ denote the BESS charging power, BESS discharging power, selling power into the power grid, and buying power from the grid at time-step t in kW. Constants P_t^v and P_t^l denote the forecasted PV generation and load demand at t in kW.

The BESS state-of-charge (SoC) constraint is given by

$$C_{t+1} = C_t + \frac{\Delta T}{E}(-P_t^d/\eta^d + \eta^c P_t^c), \quad \forall t \in \mathcal{T}, \tag{2}$$

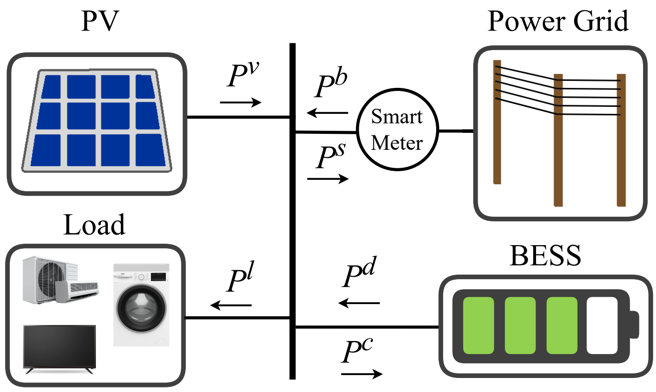

Fig. 1. Building configuration of an energy prosumer.

where variable C_t denotes the SoC of the BESS at time-step t and constants ΔT, E, η^d, and η^c denote the time-step duration in hours, the BESS rated capacity in kWh, and discharging and charging efficiencies. The SoC and power limits are set as

$$\underline{C} \leq C_t \leq \overline{C}, \; 0 \leq P_t^d \leq \overline{P}^d, \; 0 \leq P_t^c \leq \overline{P}^c, \; \forall t \in \mathcal{T}, \tag{3a}$$

$$C_0 = I, \quad C_{T+1} \geq C^f, \tag{3b}$$

where constants $\underline{C}$ and $\overline{C}$ denote the minimum and maximum SoC, $\overline{P}^d$, $\overline{P}^c$ the maximum discharging and charging power, and I and C^f the initial and final SoC over the considered time horizon, such that $\underline{C} \leq I \leq \overline{C}$ and $\underline{C} \leq C^f \leq \overline{C}$. Non-simultaneous charging and discharging is ensured by introducing complementarity constraints, defined as

$$P_t^d P_t^c = 0, \quad \forall t \in \mathcal{T}. \tag{4}$$

B. Battery Degradation

The cycle and calendar life are the main degradation factors that affect the BESS lifetime [5], [6]. Specifically, the calendar life refers to the battery aging over time, regardless of operating conditions; thus, the calendar life is usually ignored in optimization formulations [5], [7]. The cycle life represents the number of operating cycles that a BESS can perform under a specific depth-of-discharge (DoD), before reaching its EoL. A cycle is counted when a BESS charges [discharges] from a SoC level x_1 to x_2 and then discharges [charges] back to x_1. The DoD of a cycle is defined as the SoC distance between the x_1 and x_2, given by $|x_1 - x_2|$. The rainflow counting algorithm is widely used to identify the cycles and DoD for a given SoC profile [5]. Let $\mathcal{J} = \{1, ..., J\}$ denotes the set of cycles for a SoC profile, D_j the DoD of cycle $j \in \mathcal{J}$ in %, and $K_j = \{0.5, 1\}$ the length of cycle $j \in \mathcal{J}$, where $K_j = 0.5$ and $K_j = 1$ denote a half and full cycle, respectively. The rainflow algorithm is defined as

$$[\mathbf{K}, \mathbf{D}] = \texttt{Rainflow}(\mathbf{C}), \tag{5}$$

where $\mathbf{D}$, $\mathbf{K}$, and $\mathbf{C}$ denote the vector forms of D_j, $\forall j \in \mathcal{J}$, K_j, $\forall j \in \mathcal{J}$, and C_t, $\forall t \in \mathcal{T}$. The BESS degradation can be calculated for a given cycle under a specific DoD using the widely used empirical DoD stress function [5], [6], [11], $\Phi(D_j)$, which is derived from experimental data, given by

$$\Phi(D_j) = \beta_1 D_j^{(\beta_2)}, \tag{6}$$

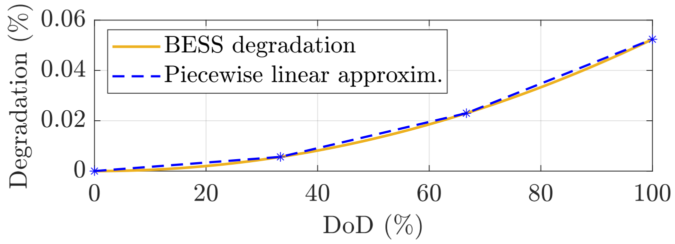

Fig. 2. BESS degradation in % as a function of the DoD. The convex degradation function is approximated using N piece-wise linear segments.

where $\beta_1 > 0$ and $\beta_2 > 1$ are constants. Fig. 2 depicts the degradation using the function $\Phi(D_j)$, indicating that cycles with higher DoD cause more severe BESS degradation. For example, a 20% full cycle DoD causes 0.002% degradation, while a 60% full cycle DoD causes 0.019% degradation. Therefore, the performance of cycles with high DoD should be avoided to reduce battery degradation. The total degradation cost is usually calculated as the product of the penalty cost R and the total degradation caused by all the half and full cycles [5], given by

$$F(\mathbf{C}) = R \sum_{j \in \mathcal{J}} K_j \Phi(D_j). \tag{7}$$

Function $F(\mathbf{C})$ depends on the BESS SoC over time, as represented by vector $\mathbf{C}$, through (5) and (6).

C. Energy Management Scheme

The energy management scheme minimizes the electricity bill of the prosumer and the BESS degradation cost by determining the BESS power set-points over the considered time horizon $\mathcal{T}$ under volatile electricity prices. Considering the PV-BESS building constraints and rainflow-based degradation model, the considered optimization problem is formulated as

$$\text{minimize} \quad \Delta T \sum_{t \in \mathcal{T}} (\lambda_t^b P_t^b - \lambda_t^s P_t^s) + F(\mathbf{C}), \tag{8a}$$

$$\text{subject to:} \quad (1) - (5), \tag{8b}$$

where constants λ_t^b and λ_t^s denote the cost of buying and selling energy at time-step t in €/kWh, where $\lambda_t^b > \lambda_t^s$, $\forall t \in \mathcal{T}$ in existing economic schemes available for energy prosumers (e.g., net-billing, variable-pricing). Note that non-convex constraints that ensure non-simultaneous buying and selling of power can be avoided [4], because objective (8a) is minimized when P_t^b is minimized, implying that $P_t^b P_t^s = 0$ when $\lambda_t^b > \lambda_t^s$, $\forall t \in \mathcal{T}$.

Although the penalty cost R in Problem 8 is usually replaced by the BESS cost [5], [11], [12], the proper selection of R is vital to enhance BESS profitability because this value provides a trade-off between arbitrage profits and expected BESS lifetime. Specifically, high values of R reduce the cycle degradation and hence increase the BESS lifetime but reduce the arbitrage profits due to the limited BESS operation. Moreover, Problem 8 is challenging to solve due to (a) the non-convex complementarity constraint (4) that involves a product of variables, and (b) the rainflow algorithm (5) that does not have an analytical mathematical expression and cannot be incorporated into an optimization formulation [5]. The aforementioned issues are addressed in the next sections.

III. Solution Methodology

This section reformulates the energy management problem of Section II as a linear program, which can be fast and reliably solved, by utilizing an approximate cycle-based BESS degradation model and eliminating the complementarity constraints.

A. Cycle-based Degradation Cost Model

To deal with the rainflow counting algorithm (5), which cannot be incorporated into a convex mathematical program, we utilize the approximate linear degradation model proposed in [5]. This model is derived by eliminating the rainflow algorithm and approximating the degradation function (6) using piecewise linear segments. The rainflow algorithm is eliminated by assuming that degradation only occurs during the discharging period of the BESS, such that one discharging half cycle is counted as one full cycle of the same DoD. Thus, the charging half cycles are ignored. This is a reasonable assumption when we consider the daily or annual BESS operation in electricity markets, i.e., considering a variable electricity scheme, because the charging and discharging half cycles are almost the same [5].

Degradation Cost Function. The convex DoD stress function, $\Phi(D_j)$, is approximated using a piecewise linear function with $\mathcal{N} = \{1, ..., N\}$ linear segments, as shown in Fig. 2 with $N = 3$. The degradation cost function of the approximate model is defined as

$$F^A(\mathbf{P}^{d,A}) = \Delta T \sum_{t \in \mathcal{T}} \sum_{n \in \mathcal{N}} c_n^A P_{t,n}^{d,A}, \tag{9}$$

where variable $P_{t,n}^{d,A} \geq 0$ denotes the BESS discharging power for time-step $t \in \mathcal{T}$ and linear segment $n \in \mathcal{N}$, $\mathbf{P}^{d,A}$ the vector form of $P_{t,n}^{d,A}$, $\forall t \in \mathcal{T}$, $n \in \mathcal{N}$, and constant c_n^A the degradation cost associated with DoD segment $n \in \mathcal{N}$. Constant c_n^A is calculated for each segment $n \in \mathcal{N}$ using the degradation function $\Phi(D_j)$, penalty cost R, discharging efficiency η^d, and BESS capacity $\hat{C}$ [5], as

$$c_n^A = \frac{R}{\eta^d \hat{C}} N \left(\Phi\left(\frac{n}{N}\right) - \Phi\left(\frac{n-1}{N}\right) \right). \tag{10}$$

Constraints. Considering the set of linear segments $\mathcal{N}$, the approximate model reformulates constraint (2), $\forall t \in \mathcal{T}$, $n \in \mathcal{N}$, as

$$C_{t+1,n}^A = C_{t,n}^A + \frac{\Delta T}{E}(-P_{t,n}^{d,A}/\eta^d + \eta^c P_{t,n}^{c,A}), \tag{11}$$

where variables $P_{t,n}^{c,A} \geq 0$, and $C_{t,n}^A \geq 0$ denote the charging power and SoC of the BESS for each time $t \in \mathcal{T}$ and DoD segment $n \in \mathcal{N}$. The SoC of each DoD segment is set as

$$C_{t,n}^A \leq \overline{C}_n^A, \quad \forall t \in \mathcal{T}, n \in \mathcal{N}, \tag{12a}$$

$$C_{1,n}^A = I_n^A, \quad \forall n \in \mathcal{N}, \tag{12b}$$

where constants $\overline{C}_n^A$ and I_n^A denote the maximum and initial SoC of the BESS in segment n, respectively. Considering that all DoD segments have the same SoC limits, then it is true that $\overline{C}_n^A = 100/N$ %, $\forall n \in \mathcal{N}$. The total discharging/charging power and SoC in the BESS at time t are equal to

$$P_t^d = \sum_{n\in\mathcal{N}} P_{t,n}^{d,A}, \quad P_t^c = \sum_{n\in\mathcal{N}} P_{t,n}^{c,A}, \qquad \forall t \in \mathcal{T}, \quad (13a)$$

$$C_t = \sum_{n\in\mathcal{N}} C_{t,n}^A, \qquad \forall t \in \mathcal{T}. \quad (13b)$$

The constraints presented in (3a)-(3b) are also included in the model. Since the degradation cost function is convex monotonically increasing, it is true that $c_n^A \le c_{n+1}^A$. This implies that the BESS always discharges from the DoD segments with the lower degradation cost to the segments with higher cost.

B. Energy Management Optimization Problem

Utilizing the cycle-based degradation cost model, the energy management optimization problem, defined as Problem $\mathcal{P}^y$, is reformulated as

$$\mathcal{P}^y : \begin{cases} \text{minimize} & \Delta T \sum_{t\in\mathcal{T}} (\lambda_t^b P_t^b - \lambda_t^s P_t^s) + F^A(\mathbf{P}^{d,A}), \\ \text{subject to} & (1), (3a), (3b), (11) - (13b). \end{cases}$$

The non-convex complementarity constraints (4) are eliminated in Problem $\mathcal{P}^y$; thus, the optimal solution is generated when charging and discharging do not simultaneously occur. The minimization of the electricity bill of the prosumer in $\mathcal{P}^y$ is an incentive to ensure non-simultaneous charging and discharging, as simultaneous charging and discharging increase the BESS power losses [13] and hence reduce the profitability of the producer. Problem $\mathcal{P}^y$ is a linear program.

IV. Calculating the Financial Metrics

This section presents the NPV and IRR metrics that are used to assess the battery profitability. The NPV and IRR are the most widely-used techniques for evaluating investment projects (see [14], Chapter 5). Towards this direction, the annual electricity cost savings, Γ, are calculated as

$$\Gamma = \gamma_2 - \gamma_1, \quad (14)$$

where γ_1 and γ_2 denote the annual electricity cost, i.e., $\Delta T \sum_{t\in\mathcal{T}} (\lambda_t^b P_t^b - \lambda_t^s P_t^s)$, of the prosumer when the BESS is considered and ignored, respectively, such that $\gamma_2 \ge \gamma_1$ and $\Gamma \ge 0$. Specifically, the annual electricity cost savings Γ can be calculated by solving Problem $\mathcal{P}^y$ for an 1-year time horizon $\mathcal{T}$. Using the decisions of the BESS SoC obtained from the solution of $\mathcal{P}^y$ into the Rainflow algorithm in (5), the total cycle degradation $Q(\mathbf{C}^S)$ in % can be calculated as

$$Q(\mathbf{C}^S) = \sum_{j\in\mathcal{J}} k_j \Phi(D_j). \quad (15)$$

Considering that the total degradation is the summation of the cycle and calendar degradation [5], the total annual cycle-calendar degradation, $\hat{Q}(\mathbf{C}^S)$, is expressed as

$$\hat{Q}(\mathbf{C}^S) = Q(\mathbf{C}^S) + \Psi, \quad (16)$$

where constant Ψ denotes the annual self life loss of the battery. For example, the annual self life loss is 10% when the calendar life of the BESS is 10 years [5]. Assuming the same annual BESS operation throughout its lifetime, the expected BESS lifetime, L, in years is set as

$$L = 100/\hat{Q}(\mathbf{C}^S). \quad (17)$$

To calculate the NPV, we estimate the *present value* of the annual electricity cost savings considering a discount rate or an opportunity cost of capital. The discount rate considers factors such as the risk associated with the investment and inflation. Assuming constant annual electricity cost savings over the BESS lifetime L, the value of the electricity cost savings for each year $l \in \mathcal{L} = \{1, ..., L\}$ is calculated as

$$\hat{\Gamma}_l = \Gamma/(1+\zeta)^l, \quad l \in \mathcal{L}, \quad (18)$$

where ζ denotes the discount rate in %. For example, for $\Gamma = 1000$, $\zeta = 5\%$, and $L = 4$ the present value of the electricity cost savings reduces over the years to $\hat{\mathbf{\Gamma}} = \{952.4, 907.0, 863.8, 822.7\}$. The NPV is calculated as the sum of all present values of each year's electricity cost savings minus the BESS capital cost, Ω, given by

$$\text{NPV} = \sum_{l\in\mathcal{L}} \hat{\Gamma}_l - \Omega. \quad (19)$$

In this work, the BESS cost Ω can be different from the penalty cost R. A positive NPV indicates a profitable investment (the higher the better). Using (18) and (19), the IRR is determined as the value of discount rate that makes the NPV equal to zero

$$\sum_{l\in\mathcal{L}} \Gamma/(1+\text{IRR})^l - \Omega = 0, \quad (20)$$

The IRR indicates the annual expected rate of return from investing in the BESS.

V. Simulation Results

This section evaluates the performance of the proposed optimization scheme compared to the corresponding scheme that ignores battery degradation. In addition, the long-term BESS profitability is investigated by calculating the NPV and IRR under different BESS capital costs, Ω, and values of the penalty cost R. Similarly with [2], we formulate a linear energy management optimization problem that ignores BESS degradation, defined as Problem $\mathcal{P}^n$, as

$$\mathcal{P}^n : \begin{cases} \text{minimize} & \Delta T \sum_{t\in\mathcal{T}} (\lambda_t^b P_t^b - \lambda_t^s P_t^s), \\ \text{subject to} & (1) - (3b). \end{cases}$$

The performance of Problems $\mathcal{P}^y$ and $\mathcal{P}^n$ is investigated by presenting (a) daily results that illustrate the BESS operation and (b) annual results that show the estimated IRR and NPV. All problems are coded in Matlab and solved using optimization solver Gurobi [15] on a personal computer with 16 GB RAM and an Intel Core-i7 2.11 GHz processor. The horizon is set to one day and one year for the daily and annual results, respectively, with hourly time intervals.

The performance of all problems is evaluated using real PV generation and load demand data from a residential building located in Nicosia, Cyprus with an installed PV system of 5 kW. We consider an integrated BESS with capacity of 5 kWh

TABLE I

DAILY RESULTS USING PROBLEMS $\mathcal{P}^n$ AND $\mathcal{P}^y$: DAILY ELECTRICITY COST, DAILY CYCLE DEGRADATION $Q(\mathbf{C}^S)$ IN %, DAILY CYCLE-CALENDAR DEGRADATION $\hat{Q}(\mathbf{C}^S)$ IN %, AND EXPECTED BESS LIFETIME (L) IN YEARS.

	Electric. cost (€)	$Q(\mathbf{C}^S)$	$\hat{Q}(\mathbf{C}^S)$	L
No BESS	-4.19	-	-	-
No degrad. ($\mathcal{P}^n$)	-4.86	0.0654	0.0882	3.1
Battery degrad. ($\mathcal{P}^y$)	-4.47	0.0067	0.0295	9.3

($E = 5$), maximum charging and discharging power of 5 kW ($\overline{P}^c = \overline{P}^d = 5$), minimum and maximum SoC of 0.15 and 0.95 ($\underline{C} = 0.15$ and $\overline{C} = 0.95$), and one-way efficiency of 96% ($\eta^d = \eta^c = 0.96$). The initial and final energy stored in the BESS is set to $0.25E$ kWh ($I = C^f = 0.25$). This work considers the polynomial DoD stress function in (6), where $\beta_1 = 5.24 \times 10^{-4}$, $\beta_2 = 2.03$ [5] and $N = 10$ piecewise linear segments. The BESS calendar life is set to 12 years, i.e., the annual self life loss, Ψ, is 8.333%. The cost of buying and selling energy, λ_t^b and λ_t^s, is obtained from the ESIOS variable electricity pricing scheme based on 2.0TD tariff for active energy invoicing (buying price) and on self-consumption surplus energy compensation mechanism (selling price) [16]. Note that this work does not consider bad data in the electricity prices, load demand, and PV generation.

A. Daily Results

The performance of Problem $\mathcal{P}^y$ is investigated and compared with the solution of Problem $\mathcal{P}^n$ by presenting the daily BESS operation for the day 04/04/2022. For the daily results, we set the penalty cost to 500 €/kWh ($R = 500 \times E$). Fig. 3 depicts the real curves of the PV generation, load demand, and electricity prices for buying and selling energy which are used as input in $\mathcal{P}^y$ and $\mathcal{P}^n$.

Figs. 4(a)-(c) illustrate the daily results obtained by solving Problems $\mathcal{P}^y$ and $\mathcal{P}^n$. Specifically, Fig. 4(a) presents the buying and selling power into the grid based on the PV generation, load demand, and BESS discharging/charging power shown in Fig. 4(b). Moreover, Fig. 4(c) depicts the BESS SoC based on the BESS discharging/charging power. As shown in Fig. 4(c), Problem $\mathcal{P}^n$ that ignores BESS degradation performs two cycles with 75% DoD (the SoC varies from 20% to 95%), overusing the BESS compared to $\mathcal{P}^y$ that performs one cycle with 30-35% DoD. As shown in Table I, Problem $\mathcal{P}^n$ yields the lowest electricity cost of -4.86 € (the negative value indicates revenues), increasing the daily revenues by 0.67 € compared to the case where the BESS is ignored. However, Problem $\mathcal{P}^n$ presents a high daily cycle-calendar degradation of 0.0882% which results to an expected BESS lifetime of only 3.1 years. Problem $\mathcal{P}^y$ generates an electricity cost of -4.47 €, increasing the daily revenues by 0.28 € compared to the case where the BESS is ignored. Although Problem $\mathcal{P}^y$ reduces the revenues compared to $\mathcal{P}^n$ due to the conservative BESS operation, Problem $\mathcal{P}^y$ reduces the daily cycle-calendar BESS degradation from 0.0882% to 0.0295% which increase the expected BESS lifetime from 3.1 to 9.3 years.

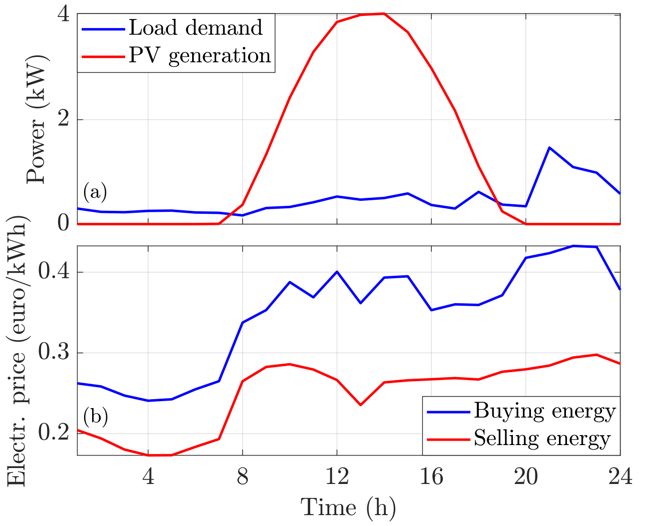

Fig. 3. Input data in Problems $\mathcal{P}^y$ and $\mathcal{P}^n$: (a) Load and PV generation and (b) electricity prices for buying and selling energy for 04/04/2022.

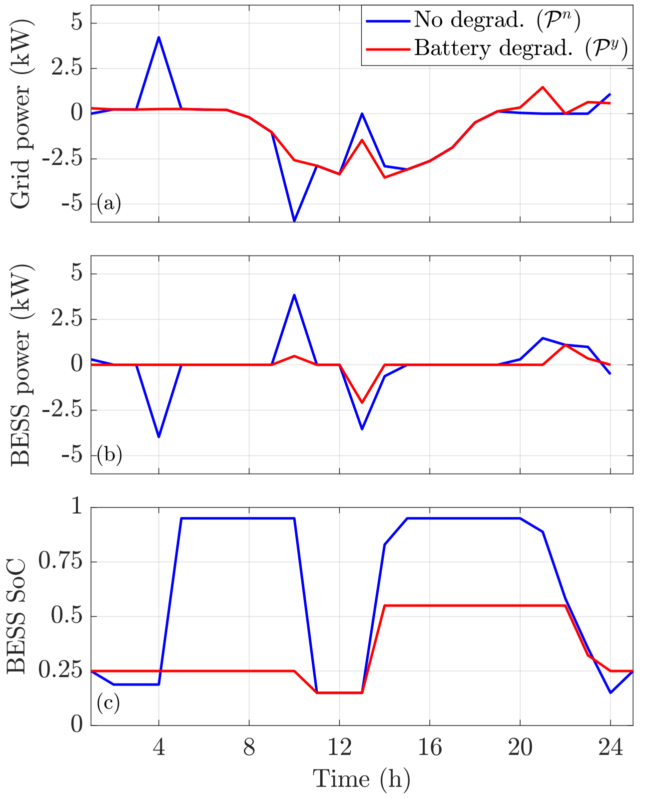

Fig. 4. Daily results for 04/04/2022 using Problems $\mathcal{P}^y$ and $\mathcal{P}^n$: (a) Buying (+) and selling (-) power into the grid, (b) BESS discharging (+) and charging (-) power, and (c) BESS SoC.

B. Annual Results

The performance of Problems $\mathcal{P}^y$, and $\mathcal{P}^n$ is investigated for the period 01/04/2022-31/03/2023 by calculating the NPV and IRR under different penalty costs, R, and BESS costs, Ω. We consider a discount rate ζ of 4% (see [14], Chapter 7).

Table II demonstrates the annual electricity cost savings, according to (14), and expected BESS lifetime, according to (17), using Problems $\mathcal{P}^n$ and $\mathcal{P}^y$, respectively, considering different penalty costs, R, in $\mathcal{P}^y$. As expected, Problem $\mathcal{P}^n$

TABLE II
THE ANNUAL ELECTRICITY COST SAVINGS, Γ, AND EXPECTED BESS LIFETIME, L, UNDER DIFFERENT PENALTY COSTS, R, USING PROBLEMS $\mathcal{P}^n$ AND $\mathcal{P}^y$

Problem	$\mathcal{P}^n$	$\mathcal{P}^y$	$\mathcal{P}^y$	$\mathcal{P}^y$
Penalty cost (R)	-	$100 \times E$	$300 \times E$	$500 \times E$
Electricity cost savings (€)	243.4	231.8	187.6	142.2
BESS lifetime (years)	4.3	5.6	7.6	9.2

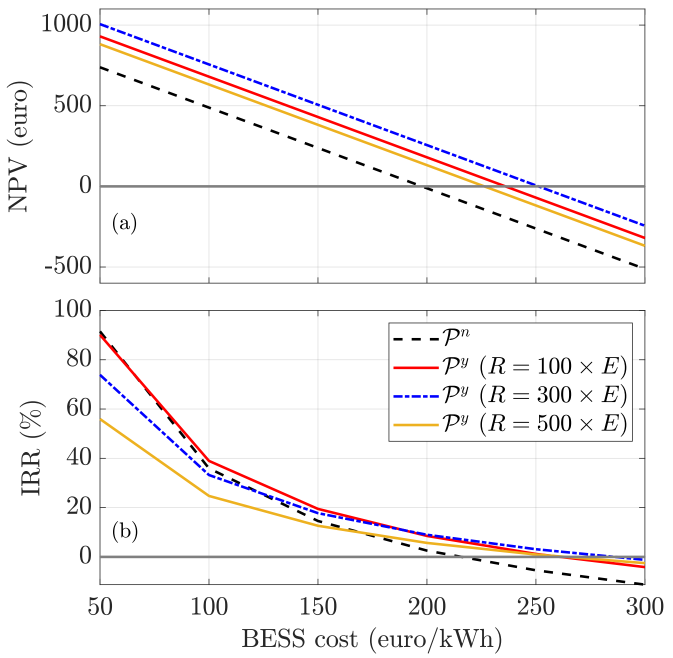

Fig. 5. The NPV (a) and IRR (b) under different BESS costs, Ω, using Problems $\mathcal{P}^n$ and $\mathcal{P}^y$, considering different penalty costs, R, in $\mathcal{P}^y$.

presents the highest electricity cost savings (243.4 €) but yields the lowest expected BESS lifetime (4.3 years) because it ignores BESS degradation. As shown in Table II, Problem $\mathcal{P}^y$ reduces the electricity cost savings from 231.8 to 142.2 € when the penalty cost R increases from 500 to 2500; however, the expected BESS lifetime increases from 5.6 to 9.2 years.

Figs. 5(a) and (b) depict the NPV and IRR, calculated according to Section IV, under different BESS costs for Problems $\mathcal{P}^n$ and $\mathcal{P}^y$, considering different penalty costs in $\mathcal{P}^y$. As shown in Fig. 5(a), Problem $\mathcal{P}^y$ yields higher NPV values compared to $\mathcal{P}^n$ for all BESS costs and penalty costs, R, indicating the superiority of Problem $\mathcal{P}^y$ compared to $\mathcal{P}^n$. Interestingly, Problem $\mathcal{P}^y$ for $R = 300 \times E$ yields the highest NPV for all BESS costs and therefore achieves the highest battery profitability. Fig. 5(a) highlights that the proper selection of penalty cost R in battery degradation cost models is critical for the enhancement of the battery profitability. Fig. 5(b) shows the increment of the annual expected rate of return as the BESS cost reduces. Figs. 5(a) and (b) indicate that the usage of the BESS in this application is profitable when its cost is under 250 €/kWh. Note that non-simultaneous charging and discharging of the BESS is always satisfied in the simulation results, obtaining the optimal solution.

VI. CONCLUSIONS

This work develops a linear optimization problem for the energy scheduling of a BESS integrated in buildings with PV systems, considering a cycle-based battery degradation cost model. The developed linear optimization problem can be solved fast and reliably over a long time horizon, enabling its usage for both planning and operating strategies. Using the developed optimization model, the BESS profitability is investigated by calculating the NPV and IRR utilizing real data from a residential building. Simulation results show that the usage of the BESS in this application is profitable when its cost is under 250 €/kWh. The results also highlight that the proper selection of the penalty cost R in battery degradation cost models is critical for the enhancement of the battery profitability; however, the optimal selection of R in the proposed scheme is challenging. To address this issue, future work will develop an iterative algorithm to maximize BESS profitability by optimizing the penalty cost R.

REFERENCES

[1] L. Park et al., "Prosumer Energy Management Considering Contract With Consumers Under Progressive Pricing Policy," in *IEEE Access*, vol. 8, pp. 115789-115799, 2020.

[2] L. Tziovani et al., "Energy scheduling in non-residential buildings integrating battery storage and renewable solutions," in *Proc. IEEE ENERGYCON*, Limassol, Cyprus, 2018, pp. 1-6.

[3] J. Hu, Y. Li and H. Zhou, "Energy Management Strategy for a Society of Prosumers Under the IOT Environment Considering the Network Constraints," in *IEEE Access*, vol. 7, pp. 57760-57768, 2019.

[4] L. Tziovani et al., "Energy Management and Control of Photovoltaic and Storage Systems in Active Distribution Grids," in *IEEE Trans. on Power Systems*, vol. 37, no. 3, pp. 1956-1968, May 2022.

[5] B. Xu et al., "Factoring the Cycle Aging Cost of Batteries Participating in Electricity Markets," in *IEEE Trans. on Power Systems*, vol. 33, no. 2, pp. 2248-2259, March 2018.

[6] B. Xu et al., ""Modeling of Lithium-Ion Battery Degradation for Cell Life Assessment," in *IEEE Trans. on Smart Grid*, vol. 9, no. 2, pp. 1131-1140, March 2018.

[7] J. Lee and Y. Kim, "Novel battery degradation cost formulation for optimal scheduling of battery energy storage systems," in *International Journal of Electrical Power & Energy Systems*, vol. 137, May 2022.

[8] H. Mohsenian-Rad, "Optimal Bidding, Scheduling, and Deployment of Battery Systems in California Day-Ahead Energy Market," *IEEE Trans. on Power Systems*, vol. 31, no. 1, pp. 442-453, Jan. 2016.

[9] Arpit Maheshwari et al., "Optimizing the operation of energy storage using a non-linear lithium-ion battery degradation model," in *Applied Energy*, vol. 261, March 2020.

[10] Y. Shi et al., "A Convex Cycle-based Degradation Model for Battery Energy Storage Planning and Operation," in *Proc. IEEE ACC*, Milwaukee, WI, USA, 2018, pp. 4590-4596.

[11] K. Antoniadou-Plytaria et al., "Market-Based Energy Management Model of a Building Microgrid Considering Battery Degradation," in *IEEE Trans. on Smart Grid*, vol. 12, no. 2, pp. 1794-1804, March 2021.

[12] C. Liu et al., "A MILP-Based Battery Degradation Model for Economic Scheduling of Power System," in *IEEE Trans. on Sustainable Energy*, vol. 14, no. 2, pp. 1000-1009, April 2023.

[13] L. Tziovani et al., "Successive convexification algorithms for optimizing power systems with energy storage models," in *IEEE Trans. on Smart Grid*, vol. 15, no. 2, pp. 1807-1820, March 2024.

[14] R. Brealey, S. Myers, and F. Allen, "Principles of Corporate Finance," 10th edition, McGraw-Hill/Irwin, 2010.

[15] Gurobi Optimization, LLC, "Gurobi Optimizer Reference Manual," 2023. [Online]. Available: "http://www.gurobi.com".

[16] Spanish electricity market. [Online]. Available: "https://www.esios.ree.es/en".