DEGRADATION-CONSCIOUS ENERGY MANAGEMENT FOR RENEWABLE MICROGRIDS: A COMPARATIVE ASSESSMENT OF BATTERY AGING FUNCTIONS

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ABSTRACT

The integration of energy storage systems (ESS) into renewable-based microgrids is increasingly constrained by the lifetime limitations of batteries, making degradation-aware modeling a vital component of optimization frameworks. This study systematically evaluates the applicability of multiple cycle and calendar aging formulations derived from experimental findings by embedding them into a Python–Gurobi optimization framework for prosumer-based microgrid operation. Three representative models of each aging type are cross-combined to generate nine scenarios, of which five were retained for detailed analysis after excluding those that distorted the optimization results or conflicted with the operational logic of the developed energy management algorithm. The findings demonstrate that degradation model selection substantially influences both projected lifetime capacity fade and techno-economic outcomes, including cost of electricity (COE), renewable fraction (RF), and carbon emissions. Notably, sophisticated calendar aging models that account for state-of-charge effects amplify degradation under partial or high state of charge (SoC) conditions, yielding up to threefold higher capacity fade compared to simplified approaches. Meanwhile, the economic impact of degradation emerges indirectly through altered charging–discharging dynamics, as replacement costs are not explicitly monetized in the objective function. The results highlight that overlooking degradation pathways may lead to overly optimistic projections of system sustainability and renewable penetration. By confirming that degradation-aware optimization alters the operational feasibility and environmental footprint of microgrids, this work underscores the necessity of carefully selecting aging formulations in decision-making processes. The study contributes methodological insights into balancing cost minimization and battery health preservation, offering a foundation for future research on robust, degradation-conscious energy management in renewable-based microgrids.

Keywords: Battery degradation modeling, cycle and calendar aging, microgrid optimization, prosumer energy management, energy storage systems.

INTRODUCTION

The rapid deployment of renewable energy sources has transformed the structure of modern microgrids, where prosumers simultaneously generate and consume electricity while relying on energy storage systems to balance the inherent intermittency of renewable generation. Among various storage technologies, batteries play a critical role; however, their economic and technical performance is significantly influenced by degradation mechanisms that shorten their lifetime and increase overall system costs. Consequently, the integration of accurate degradation models into microgrid optimization frameworks has emerged as a crucial research direction in recent years (Muqeet et al., 2019).

A variety of approaches have been proposed in the literature to address battery aging in renewable-based systems. Multi-stage optimization strategies that jointly minimize lifecycle cost and account for degradation have demonstrated that aging-aware scheduling can substantially reduce curtailment and improve resource utilization (Faraji et al., 2020). Similarly, mixed-integer linear programming (MILP) formulations have been developed to incorporate linear degradation models, revealing that optimal battery sizing becomes markedly smaller once realistic lifetime effects are considered (Terkes et al., 2025). In parallel, detailed physicochemical lifetime models have been applied to residential PV-battery systems, highlighting the importance of depth of discharge (DoD), state of charge (SoC), and current-dependent factors in predicting battery replacement requirements (Sharma et al., 2024). Furthermore, comparative analyses of energy management strategies, such as rule-based control and linear programming, have shown that degradation-aware formulations not only improve economic returns but also extend service life by reducing unnecessary cycling (Khanahmadi et al., 2021). Beyond operational strategies, recent studies have explored advanced optimization frameworks for unit commitment and energy management that integrate battery aging constraints. Improved particle swarm optimization (PSO) algorithms have been employed to jointly optimize renewable resources, electric vehicles, and batteries, demonstrating enhanced robustness and reliability when degradation is considered (Terkes et al., 2024b). Degradation costs have also been explicitly modeled in community microgrids using modified PSO techniques with dynamic penalty functions, which significantly reduce operating costs while extending battery lifetime (Cardoso et al., 2018). In addition, lithium-ion storage planning studies incorporating both cycle and calendar aging have proposed dual formulations that enable more accurate sizing and reduce replacement frequency (Alramlawi and Li, 2020). From another perspective, multi-objective control approaches considering household loads and electric vehicles as virtual batteries have confirmed that cost reduction, emission mitigation, and battery life extension can be achieved simultaneously (Ouédraogo et al., 2021).

Metaheuristic-based energy management systems have further advanced the field by integrating fuzzy decision-making techniques with aging-aware objective functions, resulting in more balanced trade-offs between economy, emissions, and technical performance (Manoharan et al., 2024). Similarly, comparative analyses of different battery chemistries under deterministic, stochastic, and robust planning frameworks have highlighted the necessity of selecting appropriate storage technologies to mitigate uncertainty and degradation risks (Hossain et al., 2019). Taken together, these contributions demonstrate that degradation-aware optimization is indispensable for ensuring both the technical feasibility and economic viability of microgrids under renewable integration (Mostafa et al., 2020; Han, Li and Wang, 2022; Fallahifar and Kalantar, 2023; Alanazi et al., 2024).

Despite this progress, a critical gap remains regarding the applicability of different cycle and calendar aging models in optimization-based decision-making frameworks. Most existing studies adopt either simplified linear representations or single-chemistry assumptions, thereby limiting their generalizability across diverse scenarios. The present study addresses this gap by systematically evaluating multiple deterministic degradation functions derived from experimental findings. By combining three cycle-aging and three calendar-aging models into nine cross-scenarios and embedding them as operational constraints within a Python–Gurobi optimization framework, this research assesses their feasibility and influence on microgrid operation with heterogeneous prosumer profiles. The originality of this work lies in simultaneously questioning the practicality of incorporating such models into optimization problems and analyzing how different formulations affect the balance between economic

performance, environmental sustainability, and technical robustness. In doing so, the study contributes to advancing the methodological foundation for designing renewable-based microgrids that minimize electricity costs while explicitly accounting for the long-term implications of battery degradation.

MATHEMATICAL MODELING, OPTIMIZATION FRAMEWORK, AND PERFORMANCE METRICS

The simulations are carried out in the Python–Gurobi environment. Both electrical load and photovoltaic (PV) generation datasets are synthetically constructed, with Antalya selected as the case study region due to its high solar irradiation potential. PV generation profiles are obtained from PVGIS using the city's geographical coordinates, while load demand patterns are derived from HOMER. To capture variability, five distinct prosumer profiles are generated with stochastic elements incorporated. Following the approach in (Terkes et al., 2024a), the optimal PV and ESS capacities are determined using PSO, which minimizes electricity expenditures. As a result, the PV capacities for prosumers 1–5 are set to 5, 5, 4, 5, and 4.5 kW, respectively, while the corresponding ESS capacities are determined as 4, 5.5, 5.5, 5.5, 3, and 4 kWh. In the optimization framework, hourly demand and PV generation values from the Excel dataset are used as inputs. For each prosumer k and time step t, the total electrical load demand ($P_{k,t}^{L}$) is met by the combined contributions of PV-to-load ($P_{k,t}^{PV2L}$), ESS-to-load ($P_{k,t}^{B2L}$), and grid-to-load ($P_{k,t}^{G2L}$), as expressed in Equation (1). Similarly, the available PV generation ($P_{k,t}^{PV_{gen}}$) is allocated across PV-to-load, PV-to-ESS ($P_{k,t}^{PV2B}$), PV-to-grid ($P_{k,t}^{PV2G}$), and curtailed PV ($P_{k,t}^{PV_{cur}}$), as shown in Equation (2).

$$P_{k,t}^{L} = P_{k,t}^{PV2L} + P_{k,t}^{B2L} + P_{k,t}^{G2L} \quad , \quad \forall k,t \tag{1}$$

$$P_{k,t}^{PV_{gen}} = P_{k,t}^{PV2L} + P_{k,t}^{PV2B} + P_{k,t}^{PV2G} + P_{k,t}^{PV_{cur}} \quad , \quad \forall k,t \tag{2}$$

When the ESS reaches full charge and PV generation surpasses the local demand, the $P_{k,t}^{PV2G}$ export is capped at 40% of the installed PV capacity (C_k^{PV}), as expressed in Equation (3). This restriction is imposed to mitigate potential power quality issues in the distribution network, even though higher injections could provide additional revenue. The total grid injection, consisting of $P_{k,t}^{PV2G}$ and ESS-to-grid ($P_{k,t}^{B2G}$) flows, is further regulated by introducing binary variable u_{t1}, which prevents simultaneous grid import and export, as formulated in Equations (4)–(6). Likewise, a second binary variable u_{t2} ensures that ESS charging and discharging cannot occur within the same time step, as expressed in Equations (7)–(8). To enforce these operational constraints while maintaining feasibility, sufficiently large coefficients M and c are incorporated without violating the SoC boundaries.

$$P_{k,t}^{PV2G} \leq 40\% \,.\, C_k^{PV} \quad , \quad \forall k,t \tag{3}$$

$$P_{k,t}^{G_{injected}} = P_{k,t}^{PV2G} + P_{k,t}^{B2G} \quad , \quad \forall k,t \tag{4}$$

$$P_{k,t}^{G_{injected}} \leq M.u_{t1} \quad , \quad \forall k,t \tag{5}$$

$$P_{k,t}^{G_{used}} = P_{k,t}^{G2L} \leq M.(1-u_{t1}) \quad , \quad \forall k,t \tag{6}$$

$$P_{k,t}^{ESS_{chr}} \leq c.u_{t2} \quad , \quad \forall k,t \tag{7}$$

$$P_{k,t}^{ESS_{disch}} = c.(1-u_{t2}) \quad , \quad \forall k,t \tag{8}$$

The state of energy of the ESS ($SoE_{k,t}^{ESS}$) is updated according to Equation (9), which considers the state of the previous time step ($SoE_{k,t-1}^{ESS}$), the charging power ($P_{k,t}^{ESS_{chr}}$) adjusted by the charging efficiency (η_{chr}), and the

discharging power ($P_{k,t}^{ESS_{disch}}$) corrected by the discharging efficiency (η_{disch}). To preserve operational reliability, SoC boundaries are imposed between 20% and 90%.

$$SoE_{k,t}^{ESS} = SoE_{k,t-1}^{ESS} + P_{k,t}^{ESS_{chr}}\eta_{chr} - \frac{P_{k,t}^{ESS_{disch}}}{\eta_{disch}} \quad , \quad \forall k,t \tag{9}$$

Battery degradation is modeled by integrating both calendar aging and cycle aging mechanisms. Calendar aging reflects the gradual loss of capacity over time, even in the absence of active operation, and is influenced by factors such as temperature, SoC, and storage duration. In this study, three representative models are considered: **(i)** an Arrhenius-based model, where capacity loss (Q_{CalA}) increases exponentially with temperature and time (Equation (10)); **(ii)** a root-time model, which combines Arrhenius-type temperature dependence with a square-root time function (Equation (11)); and **(iii)** an extended multi-parameter model, explicitly incorporating SoC effects in addition to temperature and time dependencies (Equation (12)).

$$Q_{CalA1} = B.e^{-\frac{E_a}{R.T}}.t^z \tag{10}$$

$$Q_{CalA2} = A_0.e^{-\frac{E_a}{R.T}}.\sqrt{t} \tag{11}$$

$$Q_{CalA3}(t,T,SoC) = A.e^{B.SoC}.e^{-\frac{E_a+C.SoC}{R.T}}.t^z \tag{12}$$

Cycle aging, on the other hand, captures the degradation arising from repetitive charge–discharge cycling, and is governed by parameters such as cycle number, temperature, and C-rate. Three formulations are considered in this study. The first one is a C-rate and temperature-dependent model, where both effects are represented via exponential terms and the pre-exponential factor and activation energy are themselves functions of the C-rate, as shown in Equations (13)–(15). The second one is a dual-temperature model, which separately accounts for degradation contributions at low and high temperature regimes (Equation (16)). The third one is a throughput-based model, which directly relates capacity loss to cumulative Ah throughput and C-rate, thus providing a simple yet effective characterization of cycling-induced aging (Equation (17)).

$$Q_{CA1} = A(C).e^{-\frac{E_a(c)}{R.T}}.n^{0.74} \tag{13}$$

$$A(C) = e^{ac^2+bc+c} \tag{14}$$

$$E_a(c) = xe^{yc} + z \tag{15}$$

$$Q_{CA2} = A_L.e^{\frac{E_a^L}{R.T}} + A_h.e^{-\frac{E_a^h}{R.T}} \tag{16}$$

$$Q_{CA3} = A.C^B.throughput_{Ah} \tag{17}$$

In these formulations, the variable Q denotes the cumulative capacity loss estimated by each model. The degradation mechanisms are expressed as functions of several key parameters. The activation energy, denoted as E_a and represented in some cases with subscripts such as E_a^L, E_a^h, or $E_a(c)$, captures the sensitivity of electrochemical reactions to temperature in accordance with Arrhenius' law. The universal gas constant R and the absolute temperature T together determine the thermal contribution to degradation. Time t reflects the duration of storage in calendar aging models, while the SoC represents the average charge level of the battery, a factor that significantly accelerates calendar degradation at higher values. Also, the coefficients A, A_0, $A(C)$, A_L, and A_h serve as experimentally derived scaling factors calibrated under specific test conditions. Similarly, parameters B

and C, when used as empirical constants in the exponential or polynomial terms, adjust the influence of SoC and C-rate on the predicted degradation. In some calendar models, an additional time exponent z is included to generalize the temporal dependence. Collectively, these parameters establish a flexible framework in which temperature, cycling conditions, charge level, and operational history are simultaneously accounted for, allowing the models to reproduce a wide range of experimentally observed degradation behaviors. By incorporating both calendar and cycle aging pathways, the model ensures a more realistic estimation of long-term ESS performance under varying operational and environmental conditions.

Overall, the total degradation of the ESS is obtained by combining the selected calendar and cycle aging models, yielding the overall capacity loss ($Q_{k,t}^{tot}$). Consequently, the updated ESS capacity at time t is calculated as in Equation (18):

$$Q_{k,t}^{tot} = Q_{k,t}^{cyc} + Q_{k,t}^{cal} \quad , \quad \forall k, t \tag{18}$$

The developed model aims to minimize the total system cost based on the energy generation and consumption profiles of five distinct prosumers. The system is modeled on an hourly basis over a one-year horizon, considering the use of batteries, interactions with the grid, and the balance of PV generation for each prosumer. The objective function is therefore formulated to minimize the total cost, which comprises the expenses associated with electricity purchases from the grid, revenues from energy sales back to the grid, and incentives for prioritizing the charging of the ESS with PV generation, thereby encouraging self-consumption. Battery aging is not explicitly included as a cost component in the objective function; however, both calendar and cycle aging mechanisms are integrated into the model through operational constraints. In this way, the feasibility of operating strategies that prioritize self-consumption can be assessed while simultaneously observing the potential implications of neglecting battery degradation in the cost minimization process. Mathematically, the objective function can be expressed as:

$$TC_{k,t}^{MG} = P_{k,t}^{G_{used}} . Cost_{k,t}^{GP} - P_{k,t}^{G_{injected}} . Cost_{k,t}^{GS} \quad , \quad \forall k, t \tag{18}$$

$$objective = min\left(\sum_{k,t}\left(TC_{k,t}^{MG}\right) - \sum_{k,t}\left(P_{k,t}^{PV2B}\right)\right) \tag{18}$$

Here, $P_{k,t}^{G_{used}}$ represents the energy purchased from the grid by prosumer k at hour t in kilowatt-hours, $Cost_{k,t}^{GP}$ denotes the corresponding time-of-use (ToU) grid purchase price, $P_{k,t}^{G_{injected}}$ is the energy sold to the grid by prosumer k at hour t, and $Cost_{k,t}^{GS}$ indicates the grid feed-in tariff.

This study focuses on the suitability and selection of battery aging functions in a multi-stage microgrid framework that integrates renewable energy while accounting for both electricity cost minimization and battery health preservation. To represent degradation, deterministic and widely adopted formulations reported in the literature, derived from experimental findings, are employed for both cycle aging and calendar aging. Specifically, three representative models for cycle aging and three for calendar aging are considered, which are then cross-combined to construct nine distinct scenarios. These formulations are incorporated into the energy management algorithm, previously expressed through mathematical equations, and implemented in Python using Gurobi. The objective is not to minimize degradation directly but rather to examine how different aging models, when embedded in the optimization framework, influence operational outcomes in terms of economic efficiency, environmental sustainability, and technical feasibility. Furthermore, the applicability of each formulation within the optimization problem is critically assessed. In this way, the analysis addresses fundamental questions regarding the interplay between cost-effectiveness, sustainability, and technical feasibility, thereby revealing practical insights for prosumers in microgrids.

The optimization framework is implemented in Python using the Gurobi solver, ensuring efficient solution of the large-scale problem. The decision variables obtained from the solver are post-processed into hourly datasets for

each prosumer, which are subsequently exported to Excel for further evaluation. These outputs are assessed with respect to several techno-economic and environmental performance indicators, summarized in Table 1. The cost of electricity (COE, $/kWh) is defined as the ratio of the overall microgrid operational expenditure to the aggregate electricity demand. The renewable fraction (RF) quantifies the share of demand met by renewable resources and is expressed as one minus the proportion of grid-supplied power relative to the total load. To capture environmental impact, the carbon emissions are estimated by multiplying the grid-supplied electricity with the average emission factor of Türkiye's interconnected power system (0.4261 kg CO_2/kWh). For power balance, when PV output exceeds the load at a given interval, the feed-in power (P_F) represents the surplus energy injected into the grid after accounting for both load and energy storage system (ESS) operation. Conversely, if the load surpasses available PV generation, the grid import (P_G) is obtained as the residual demand not covered by PV and ESS. Self-consumption and self-sufficiency are captured through two complementary indices. The self-consumption ratio (SCR) measures the fraction of PV production utilized locally, computed as the difference between PV output and exported feed-in power normalized by total PV generation. In contrast, the self-sufficiency ratio (SSR) evaluates the share of demand satisfied through PV and ESS, obtained as one minus the ratio of grid-supplied energy to the total load. Thus, SCR indicates how efficiently on-site PV is consumed, whereas SSR reflects the dependency level on the external grid. Finally, in conditions where PV production exceeds demand and the ESS is fully charged, the excess generation is treated as curtailed. The curtailment rate (CE) is expressed as the ratio of curtailed energy to total PV generation, thereby representing the system's utilization efficiency.

Table 1. Decision Criteria

Metric	**Formulation**	**Metric**	**Formulation**
COE	$\frac{\sum(TotalCost)}{\sum(P_{load})}$	SCR	$\frac{\int P_{PV}dt - \int P_F dt}{\int P_{PV}dt}$
RF	$1 - \frac{\sum(P_{GP})}{\sum(P_{load})}$	SSR	$\frac{\int P_L dt - \int P_G dt}{\int P_L dt}$
CO_2	$0.4261 \sum P_{GP}$	CE	$\sum P_{curtailment}$

OPTIMIZATION RESULTS AND DISCUSSION

The performance evaluation of the proposed optimization framework is carried out under nine distinct degradation scenarios, each constructed by cross-combining three cycle aging (CA1–CA3) and three calendar aging (CalA1–CalA3) formulations. These scenarios are summarized in Table 1, which provides an overview of the modeling configurations. To highlight the techno-economic and environmental implications of different degradation pathways, representative results are reported for five prosumers across selected scenarios (S1, S2, S4, S5, S7), as shown in Table 2. Although nine scenarios were initially formulated, only five (S1, S2, S4, S5, and S7) were retained for detailed evaluation. The remaining cases were excluded because their results were found to distort the optimization outcomes and did not align with the operational logic of the developed energy management code. In particular, certain combinations of calendar and cycle aging models produced infeasible or inconsistent system behaviors, such as unrealistic self-sufficiency ratios or negative curtailment rates, which conflicted with the structural constraints of the optimization framework. Including such scenarios would have biased the comparative analysis, potentially masking the genuine impacts of degradation-aware formulations. Therefore, the discussion focuses on the subset of scenarios that ensured computational feasibility and meaningful interpretation within the proposed modeling environment.

Table 2. Cross-combination of Cycle Aging and Calendar Aging Models Forming Nine Scenarios

S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
CA1	CA2	CA3	CA1	CA2	CA3	CA1	CA2	CA3
CalA1			CalA2			CalA3		

Table 3. Optimization Outcomes of Selected Scenarios for Individual Prosumers

Prosumer	Parameter	S1	S2	S4	S5	S7
1	Aging (%)	0.2023	0.0631	0.6751	0.5353	0.3802
	• CA	0.1978	0.058	0.1978	0.058	0.2086
	• CalA	0.0045	0.0051	0.4773	0.4773	0.1716
	COE ($/kWh)	0.0299	0.0269	0.0299	0.0263	0.0317
	RF (%)	98.55	97.98	98.55	96.92	100
	SCR (%)	70.39	69.98	70.39	69.22	50
	SSR (%)	98.55	97.98	98.55	96.92	200
	CO_2 (kg/yr)	946.19	866.89	946.18	842.04	1611.3
2	Aging (%)	0.2501	0.0638	0.8411	0.6541	0.4632
	• CA	0.2445	0.0575	0.2445	0.0575	0.2610
	• CalA	0.0056	0.0063	0.5966	0.5966	0.2022
	COE ($/kWh)	0.0409	0.0387	0.0409	0.0380	0.0424
	RF (%)	77.64	76.95	77.64	76.22	21.64
	SCR (%)	70.64	70.02	70.65	69.35	71.10
	SSR (%)	77.64	76.95	77.64	76.22	58.98
	CO_2 (kg/yr)	1123.9	1067.6	1123.9	1037.5	995.16
3	Aging (%)	0.3369	0.0681	1.13	0.8556	0.6583
	• CA	0.3294	0.06	0.3294	0.06	0.3503
	• CalA	0.0075	0.0081	0.8006	0.7956	0.3080
	COE ($/kWh)	0.0472	0.0458	0.0472	0.0456	0.0488
	RF (%)	56.75	56.98	49.85	55.60	22.26
	SCR (%)	66.68	66.96	66.69	65.34	71.50
	SSR (%)	56.75	56.98	49.85	55.60	60.37
	CO_2 (kg/yr)	1318.3	1285.8	1140.1	1276.7	1172.3
4	Aging (%)	0.4975	0.0677	1.68	1.25	0.9024
	• CA	0.4863	0.055	0.4863	0.055	0.5212
	• CalA	0.0112	0.0127	1.19	1.20	0.3812
	COE ($/kWh)	0.0485	0.0481	0.0485	0.0467	0.0502
	RF (%)	49.85	49.85	49.85	50.76	14.57
	SCR (%)	86.02	86.01	86.02	87.60	68.16
	SSR (%)	49.85	49.85	49.85	50.76	51.57
	CO_2 (kg/yr)	1140.1	1123.4	1140.1	1081	1343.7
5	Aging (%)	0.9891	0.0784	3.35	2.45	2.18
	• CA	0.9666	0.06	0.9666	0.06	1.05
	• CalA	0.0225	0.0184	2.38	2.39	1.13
	COE ($/kWh)	0.0631	0.0621	0.0631	0.0622	0.0637
	RF (%)	24.47	24.55	24.47	24.46	50.41
	SCR (%)	85.15	85.43	85.15	85.13	86.14
	SSR (%)	24.47	24.55	24.47	24.46	103.81
	CO_2 (kg/yr)	1463.5	1439.8	1463.5	1443	1172.1

The results reveal that the choice of degradation model exerts a substantial influence on both the estimated lifetime losses and the operational outcomes of the microgrid. As seen in Table 2, the aging rate varies markedly across scenarios, with CalA3-based formulations (e.g., S4 and S5) yielding considerably higher capacity fade compared to simpler representations such as CalA1 (S1). This difference originates from the explicit consideration of SoC effects in CalA3, which amplifies degradation during extended periods of partial or high SoC storage. For instance, Prosumer 5 experiences an aging level of 3.35% under S4, while the corresponding value is below 1% under S1, underscoring how the selection of model significantly alters lifetime projections.

A closer inspection of the decomposition into cycle and calendar contributions highlights that cycle aging dominates the total degradation in scenarios with simplified calendar models, whereas the relative importance of calendar effects becomes pronounced under more sophisticated formulations. This finding is consistent across all prosumers, confirming that neglecting calendar influences may lead to underestimation of degradation in real-world applications.

From an economic perspective, the cost of electricity (COE) remains relatively stable across scenarios, typically in the range of 0.026–0.063 $/kWh, with slight increases in cases involving more aggressive aging models. These differences reflect the indirect impact of degradation constraints on operational flexibility rather than direct cost penalties, since battery replacement costs are not explicitly monetized in the objective function. Nonetheless, the observed trade-offs demonstrate that overly restrictive degradation-aware constraints may lead to higher reliance on grid imports, thereby raising COE values.

Regarding renewable penetration, the RF exhibits strong dependence on the scenario. Prosumers with larger PV-to-load ratios generally achieve higher RF values, yet the introduction of restrictive degradation models reduces renewable utilization in some cases. For example, Prosumer 1 maintains near-complete renewable coverage (98–100%) across scenarios, whereas Prosumer 5 exhibits RF values as low as 24% under S1 and S4, but this value improves to over 50% under S7 due to altered charging/discharging behavior driven by the degradation formulation.

Complementary performance indices further illustrate these dynamics. The SCR tends to remain high, particularly for prosumers with significant storage relative to load, exceeding 85% in several scenarios. However, the SSR displays wider variation, ranging from below 25% to above 100%, depending on the balance between local generation, storage operation, and grid exchanges. The CO_2 emissions follow a similar pattern, with higher grid dependency translating into increased carbon intensity. For example, Prosumer 3 emits around 1300 kg CO_2 annually under S1, while Prosumer 5 records lower emissions under S7 due to improved renewable utilization.

Overall, the comparative assessment reveals that the inclusion of detailed degradation models not only alters projected lifetime fade but also shapes the operational outcomes of the microgrid in terms of cost, renewable fraction, and carbon footprint. The results emphasize that model selection is not merely a methodological detail but a decisive factor influencing the practical feasibility and sustainability of microgrid operation. Hence, incorporating appropriate battery aging functions into optimization frameworks is essential for deriving realistic and actionable insights for both researchers and practitioners.

CONCLUSION AND FUTURE SUGGESTIONS

This study has revealed that the integration of experimentally derived degradation models into optimization frameworks significantly alters the projected performance of renewable-based microgrids. The results show that capacity fade varies widely depending on the selected formulation, with SoC–dependent calendar models yielding substantially higher degradation levels than simplified representations. These differences propagate to techno-economic and environmental outcomes, particularly in terms of renewable fraction, grid dependency, and carbon emissions. Importantly, the inclusion of sophisticated aging models revealed indirect economic effects, as constraints on charging and discharging dynamics led to higher reliance on grid imports and, consequently, to increases in the cost of electricity. At the same time, scenarios that produced inconsistent or infeasible outcomes were excluded from the analysis, since they distorted optimization results and conflicted with the operational logic of the energy management algorithm. This emphasizes the practical challenge of embedding complex degradation functions into computational models while preserving interpretability and feasibility.

Looking forward, several avenues of research emerge. First, future work should investigate hybrid formulations that balance model complexity with computational efficiency, potentially combining simplified empirical models with physics-informed corrections. Second, the economic dimension of battery degradation can be made more explicit by integrating replacement and recycling costs into the objective function, thereby linking technical aging constraints directly to financial outcomes. Third, further studies could extend the framework to different chemistries, environmental conditions, and uncertainty-aware formulations to capture the stochastic nature of renewable resources and load demand. Finally, coupling degradation-aware optimization with advanced control strategies such as reinforcement learning or digital twins may provide real-time adaptability, ensuring that microgrids remain both economically competitive and technically robust under long-term operational scenarios. By bridging methodological rigor with practical applicability, future studies can advance the role of degradation-aware frameworks in shaping the sustainable evolution of prosumer-driven microgrids.

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