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Optimizing battery discharge and charge strategies for enhanced Microgrid performance

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Abstract: This study aims to enhance the technical, economic, and environmental performance of hybrid microgrids (MGs) through optimal battery charging and discharging decisions. A simulation-based design integrating photovoltaic generation, battery energy storage, and diesel backup was used to evaluate multiple control strategies under identical operating conditions. A multi-objective optimization model based on the NSGA-II algorithm minimized total lifecycle cost and carbon emissions while ensuring operational resilience. The findings revealed that optimized scheduling is highly effective in enhancing renewable use, stabilizing battery state-of-charge, and virtually eliminating the need for diesel generators, resulting in over 90% cost reduction and minimal emission penalties. The optimized system showed improved net load profiles, longer battery life, and greater robustness compared to non-optimized operation. The study concludes that a battery-centric, intelligent control, and component-sizing approach is superior to renewable oversizing for the sustainability of MGs. Practically, the results show that innovative energy management can enable resilient, low-carbon, and cost-effective MG operations without increasing renewable capacity.

Keywords: *Battery energy storage, Charge–discharge optimization, Energy management systems, Microgrids, Renewable energy integration, System resilience.*

1. Introduction

The rapid transition from high-carbon to low-carbon energy systems worldwide has accelerated the adoption of renewable energy sources (RES), electric vehicles (EVs), and distributed energy resources in microgrids (MGs) [1, 2]. The ability to work disconnected or with the main grid, improve resiliency, and enable high integration of intermittent renewable power generation, including solar photovoltaics (PVs) and wind energy, is one of the reasons MGs have become an essential part of contemporary power systems [3, 4]. Renewable generation variability and growing demand variability, however, present significant operational challenges, particularly in providing system stability, efficiency, and economic viability [5].

BESS can be important in overcoming these challenges by providing energy buffering, peak shaving, load shifting, and frequency and voltage regulation in MGs [6, 7]. Despite their technical benefits, batteries are still constrained by degradation, limited cycle life, and efficiency loss when subjected to uncoordinated, frequent charging and discharging [8]. The inefficient operation of the battery also contributes to aging, increases lifecycle costs, and worsens the overall performance of the MG due to increased power losses, oscillations, and dependence on backup generation [9, 10].

The recently proposed MG energy management methods are either based on mixed-integer linear programming (MILP) and heuristic tools, or artificial intelligence and reinforcement learning, to optimize battery charging and discharging [11, 12]. These measures are very beneficial for saving money, reducing emissions, and increasing the use of renewable energy. However, most strategies are

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overly dependent on prediction accuracy, computationally expensive, or do not consider battery health parameters such as state-of-charge (SoC), depth of discharge, and cycling frequency [6, 13].

The engineering aspect is not only about optimizing energy flows but also about creating solid, practical charging-discharging policies that balance short-term operational efficiency with long-term asset upkeep [14]. Recent work on hybrid alternating current (AC)/direct current (DC) and DC MGs provides evidence that effective battery management, accompanied by load allocation, converter limitations, and realistic system profiles, can result in substantial grid imports and conversion losses with high charging and discharging efficiencies [9, 15]. However, the benefits are highly sensitive to the timing and method of charging and discharging batteries.

In addition, the increasing functionality of EVs as portable storage units offers increased complexity and opportunity. It has been demonstrated that cooperative battery control, accounting for EV charging demand, renewable availability, and market feedback, plays a major role in enhancing the economic and environmental performance of the MG [16, 17]. However, the literature presents a breakdown of strategies in which convergent approaches are limited, which, simultaneously, supports the performance of MGs, their battery life, and their operation in a disordered environment [18].

It is against this background that the optimization of battery discharge and charge, therefore, is a key, unsolvable issue in MG engineering. It is necessary to have systematic methods that unify physical constraints in batteries, incorporate uncertainty-driven decision-making, provide real-time flexibility, and be calculably feasible and practical within actual MG settings [19]. It was found that smart, battery-centric control is among the determinants for enhancing the utilization of renewable energy, stabilizing system operation, and reducing the use of conventional generation [20]. A balanced energy-efficiency and renewable absorption approach that automatically preserved battery health by controlling SoC was implemented, resulting in reduced SoC change and avoiding deep discharge, as indicated by reduced SoC oscillation, and the introduction of the battery charge/discharge optimization idea into one MG energy management system [21-23]. The analysis considered the changing load profile, generation profile time variability, and operational restraints, enabling net load parity and practically eliminating the need for diesel-generating facilities.

The key performance indicators comparison, including general system cost, use of renewable resources, access to energy, and operational consistency, revealed substantial economic benefits and resilience enhancements associated with optimized battery operation compared to non-optimized system operation [24, 25]. Prior studies showed that performance improved mainly because of better operational coordination and component size, rather than increased renewable capacity. Therefore, this paper elevates the role of battery management to a central design and control role, beyond its auxiliary role, to one that significantly redefines MG behavior, with strategies that are technically and practically sound in the actual MG world [26, 27].

1.1. Motivation

The rationale for this research is the growing disconnect between the technical capacity of battery energy storage systems and their actual performance in MG operation. It is common knowledge that batteries are one of the enabling factors of renewable-dominated MGs, but their benefits are often compromised by inept or violent charging and discharging policies that prioritize short-term gains over the long-term well-being of the systems [28].

At the engineering level, battery degradation occurs due to frequent cycling, deep discharging, and poor coordination with renewable energy production, hastening degradation, increasing replacement costs, and diminishing the MG's reliability, particularly in isolated or resource-constrained systems [9]. Most existing optimization techniques, academically, are overly forecast-based, prone to uncertainty, or inadequately tested across different work environments [11].

Moreover, the increasing proportion of EVs, hybrid storage units, and DC MGs underscores the need to develop intelligent and adaptable battery systems that can respond to variability without incurring increased computational effort or communication costs [13, 16]. The problem of optimizing battery charging and discharging is not only about minimizing costs but also about enabling resilient, sustainable MG operations that must be scaled. The motivation behind this work is the need to re-evaluate the concept of battery operation as a control problem with performance requirements, and this discussion is grounded in the physical constraints and engineering realities of a system. The overall objective of the study was to develop optimized battery charging and discharging schedules that are properly optimized and evaluated to deliver meaningful improvements in the technical, economic, and environmental aspects of MG.

2. Related Review

2.1. MGs and the Central Role of Battery Energy Storage Systems

Microgrids (MGs) have gained popularity as a viable, scalable method for integrating renewable energy sources (RES) into modern power systems, thereby enhancing reliability, resiliency, and sustainability [29]. MGs reduce the need for central grids and transmission losses, especially in regions with weak grid infrastructure or high renewable connections [9, 30]. Nevertheless, the variability and unpredictability of renewable energy production are curbing the functionality of MGs. Figure 1 shows that an MG consists of PV generation, battery energy storage, controllable loads, and a centralized controller. The system enables localized energy generation and storage, coordinated dispatch for replenishment, and reduces renewable intermittency through smart battery control and adaptive control. Most importantly, it improves the sustainability, reliability, and overall operational performance of the MG [31, 32].

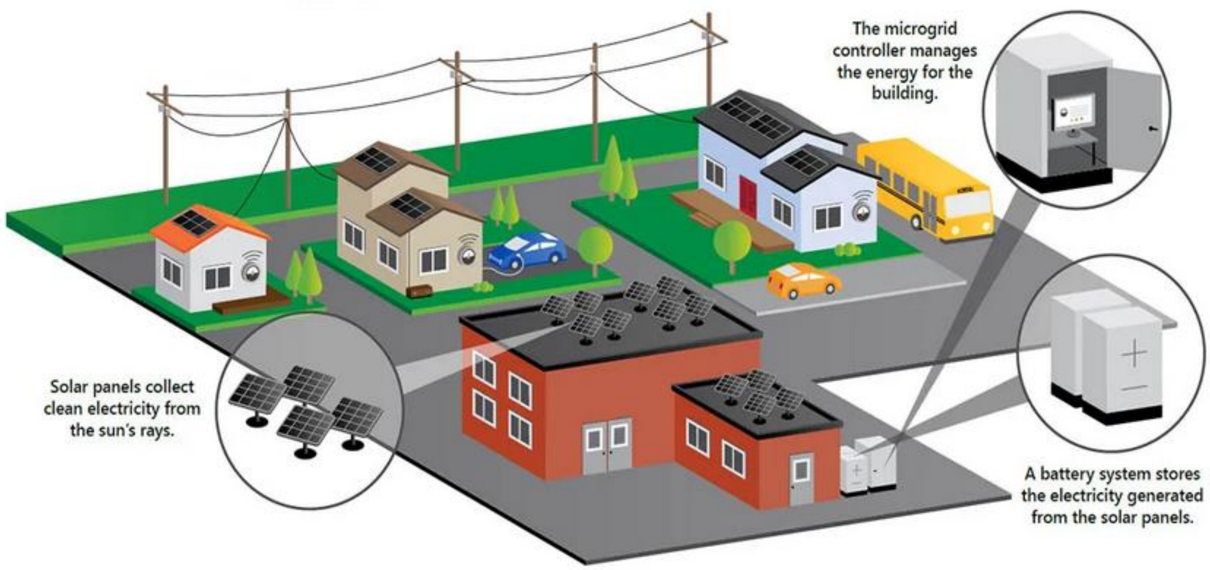

Figure 1.
Architectural Overview of a Renewable-Integrated MG with Centralized Energy Management.

BESS is often seen as the underlying technology that enables MGs to overcome these shortcomings. It has a low battery capacity, creating a time gap between generation and consumption, allowing it to store excess renewable energy and release it later when demand is high, or generation is low [6, 33]. In addition to energy balancing, BESSs can be used for voltage regulation, frequency stabilization, peak shaving, and reserve provision, making them a necessity for both AC and DC MG architectures [15]. Even though they have benefits, batteries are costly and tend to wear out. They are quite critical of operational choices, including charge rate, depth of discharge, recurrence, and coordination with renewable output and load demand. The effectiveness of an MG has therefore not been influenced solely

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by the battery's capacity but also by the smartness and robustness of charging and discharging techniques [26, 32].

2.2. Conventional Battery Charging and Discharging Strategies

Preliminary methods for battery operation in MGs were mostly rule-based, with pre-established SoC or time-based schedules [23, 26]. Such approaches were straightforward and easy to apply, yet they were unable to account for dynamic system conditions, including renewable variability, load uncertainty, and electricity price variations [10]. Figure 2 demonstrates how traditional rule-based battery operation in MGs operates, with charging and discharging governed by a fixed SoC level or preset schedules. The battery and loads are fed by both renewable generation and conventional generators. They do not account for load uncertainty, variability in renewable generation, or battery degradation, which may lead to excessive cycling, accelerate aging, and deteriorate economic performance in the long term.

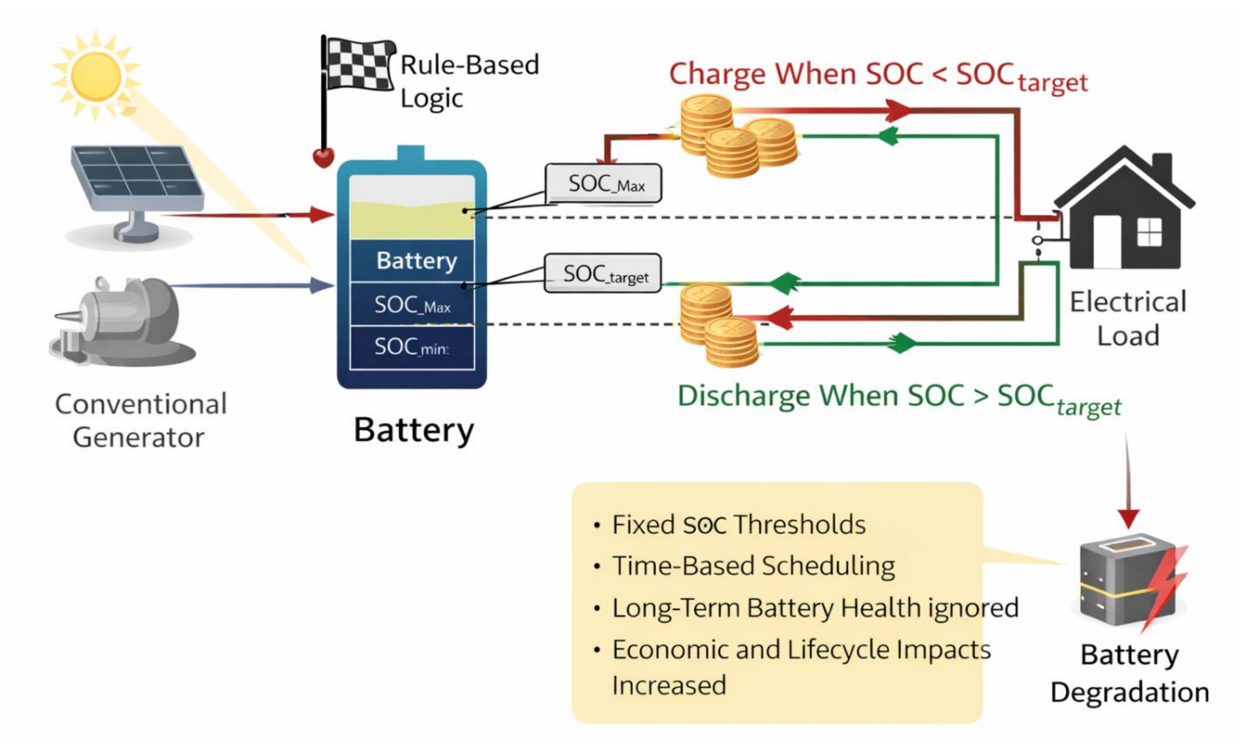

Figure 2.
Schematic Representation of Rule-Based Battery Charging and Discharging Logic in Conventional MGs.

The regulations are typically geared toward short-term system stability or cost reduction, without necessarily considering the long-term health of the battery. Under such schemes, frequent charging and deep discharges can cause rapid battery degradation, as Colucci et al. [6] also note; this may result in high lifecycle costs and low economic feasibility. In technical terms, rule-based control is attractive for simple systems, but it is not viable for current MGs that are highly penetrated by renewable energy and bi-directional power flows [34].

2.3. Optimization-Based Battery Management Approaches

Optimization-based battery management strategies have been the focus of the literature to overcome the weaknesses of rule-based control. These methods model battery charging and discharging as decision variables in an energy management optimization problem, with the objective typically to minimize operational costs, emissions, or power loss [24, 34]. Figure 3 presents a battery management model involving optimization, in which a centralized MG energy management system (EMS) determines a battery charging and discharging solution by solving an optimization problem subject to system constraints. Renewable generation, load demand, and generator availability are jointly considered to reduce costs, emissions, and power losses whilst accounting for SoC limits and operational feasibility [23, 31].

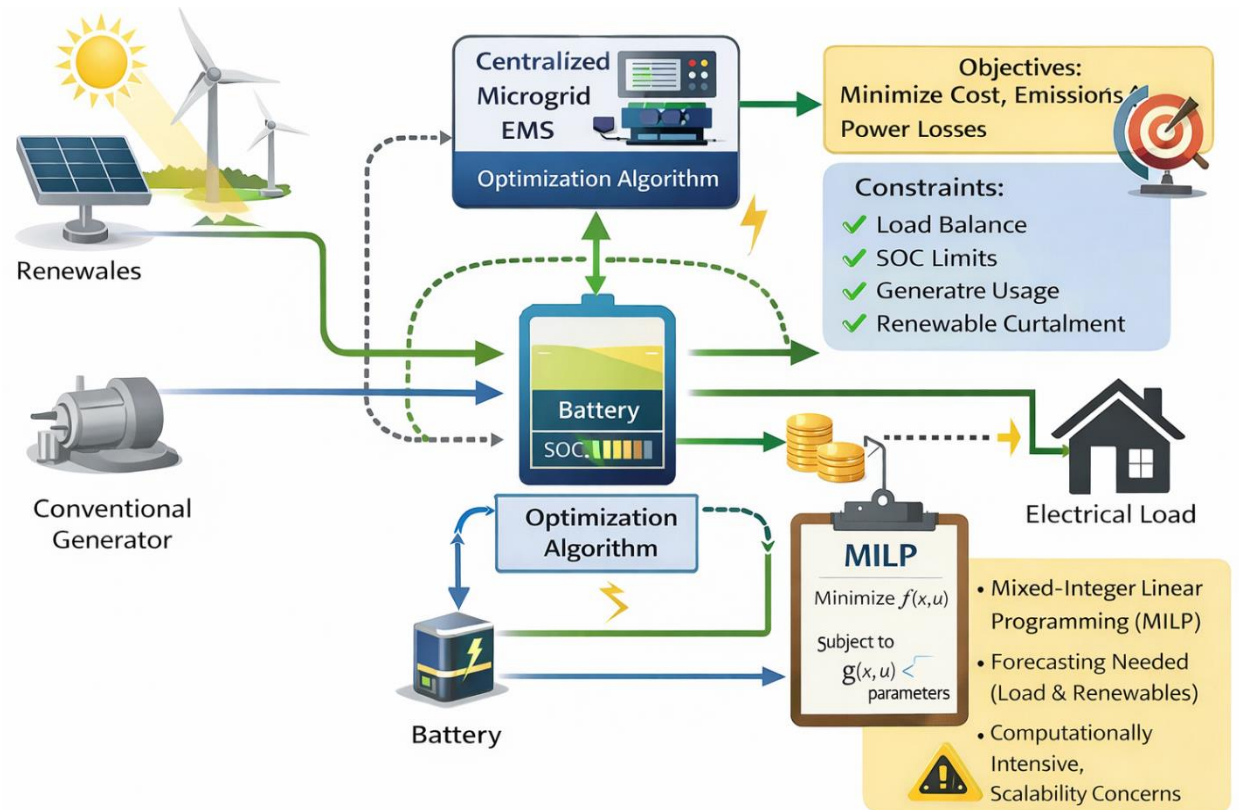

Figure 3.
Schematic Diagram of Optimization-Driven Battery Dispatch within an MG EMS.

MILP has proven to be among the most popular techniques because it can handle discrete decisions and system constraints with high precision. The results of the research by Moosavi et al. [30] show that MILP-based optimization of battery schedules can significantly reduce pollution levels and costs of executing MG processes, and enhance the use of renewable energy. Similarly, Li et al. [10] report that optimized organized battery and EV charging will lead to significant cost reductions compared with rule-based baselines. However, there are practical problems facing optimization-based approaches. Academically, many of their formulations assume ideal foresight of both load and renewable generation, which is unrealistic in reality. Regarding engineering, the issues of computational complexity and scalability remain, especially in real-time applications and large-scale multi-MG systems [16].

2.4. Heuristic and Metaheuristic Optimization Techniques

To overcome computational challenges, scholars have researched heuristic and metaheuristic algorithms, such as particle swarm optimization (PSO), differential evolution (DE), genetic algorithms, and hybrid methods [35, 36]. These methods offer flexibility when dealing with nonlinearities and intricate constraints, without necessarily making rigid assumptions of strict convexity or a linear object of study [10]. The Krill Herd algorithm is a battery dispatch optimization algorithm that enables reductions in operating costs and emissions in MGs with renewable generation and EV charging [17]. Lower computational costs have also been achieved through the competitive performance of hybrid heuristic methods like PSO-DE [10]. Although such heuristic approaches may be appealing in theory, they do not necessarily achieve global optimality and typically require extensive parameter tuning. Additionally, they can vary widely in outcomes across different conditions, making them less resilient in highly uncertain operating environments [37].

2.5. Artificial Intelligence and Data-Driven Battery Optimization

Over recent years, artificial intelligence (AI) has advanced, enabling the optimization of battery charging and discharging using data. Machine learning models are increasingly used to predict battery states, load demand, and renewable generation, enabling more adaptive and anticipatory control strategies [38, 39]. A two-self-attention neural network with time-series prediction proposed by Tu et al. [13] will assist in the optimal charging and discharging of batteries in DC systems. Their model had higher prediction and charging efficiency than traditional methods. Reinforcement learning, on the same note, enables the battery to optimize dispatch policies by adapting to a changing environment without requiring explicit system modeling [12, 34]. Academically, AI-based strategies will mark an innovation in the paradigm of adaptive, self-developing energy management. However, in engineering, there are still challenges in making data available, interpretable, trainable, and deployable in safety-critical power systems. Moreover, most AI models focus on short-term performance metrics, with little consideration of battery degradation and lifecycle [39, 40].

2.6. Battery Degradation and Lifecycle-Aware Optimization

The explicit incorporation of the battery degradation model into charging/discharging optimization is a rapidly expanding research area. Colucci et al. [6] acknowledge that reducing electricity costs alone is insufficient, and aggressive cycling may shorten battery life, rendering these devices a cost-neutral option. Figure 4 shows a battery management scheme based on a lifecycle-aware approach, with clear use of degradation variables in the MG energy optimization. The schematic illustrates that state-of-health, depth-of-discharge, cycle count, and temperature limits have been used to determine charging and discharging in the EMS. The framework was cost-efficient, and battery life was considered balanced by having operational objectives and degradation-sensitive constraints. It also indicated the positive effect of integrated control in reducing excessive stress from cycling and storage, leading to a more reliable system in the long run and optimizing the process in accordance with realistic engineering requirements [25].

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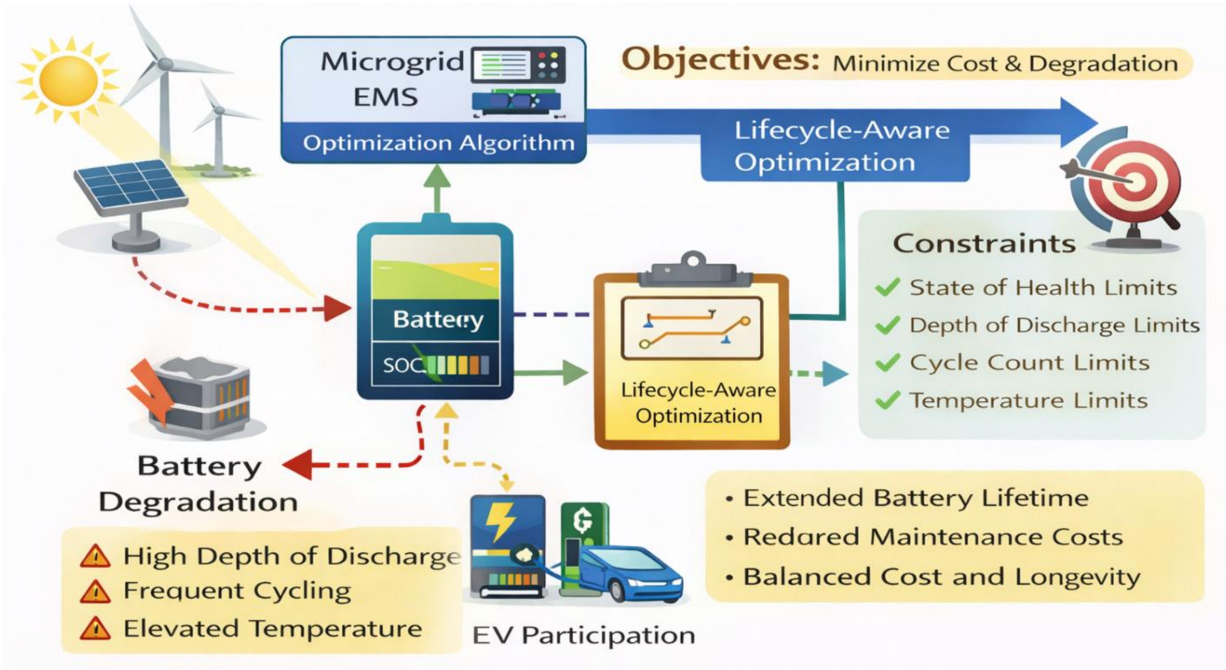

Figure 4.
Schematic Framework for Degradation-Aware and Lifecycle-Conscious Battery Energy Optimization.

The state-of-health (SoH) constraints, combined with lifecycle-sensitive optimization and depth-of-discharge and cycle-aging constraints enabled by SoH guidelines, can facilitate a study to reveal significant changes in battery lifetime at a satisfactory operational level He et al. [41] and Tang et al. [42]. Taye [9] shows that DC MGs can introduce concerted efforts to manage energy to reduce stress and volatility in storage, thereby improving system stability and battery life. The operational designs of MG, although these advances have been made, are not well represented by lifecycle-conscious optimization, which is a problem between engineering practice and research models.

2.7. Hybrid AC/DC and DC MGs: Implications for Battery Strategies

With the advent of hybrid AC/DC and all-DC MGs, entirely new aspects have emerged in battery optimization. Charalambous et al. [15] acknowledge the importance of DC loads and direct reliance on renewable sources in the context of hybrid AC/DC MGs, which allows eliminating losses during AC-to-DC (or vice versa) conversion and grid imports in the hybrid AC/DC MGs with the help of effective battery control practices. The differences in the structures of both hybrid AC/DC and all-DC MGs, and their consequences for battery control, are shown in Figure 5. The AC/DC design features alternating-current and direct-current buses connected by bidirectional converters, enabling support for a wide range of loads and generation sources with minimal conversion loss [43, 44]. A DC MG uses only one DC bus to connect renewable sources, battery storage, and DC loads, eliminating power conversion stages and making the system more efficient [45]. The figure illustrates the key features of battery-control system integration for voltage stabilization, power flow matching, and overcycling in both architectures. It makes clear that there is a need for more efficient battery strategies to address the MG topology and control imperatives.

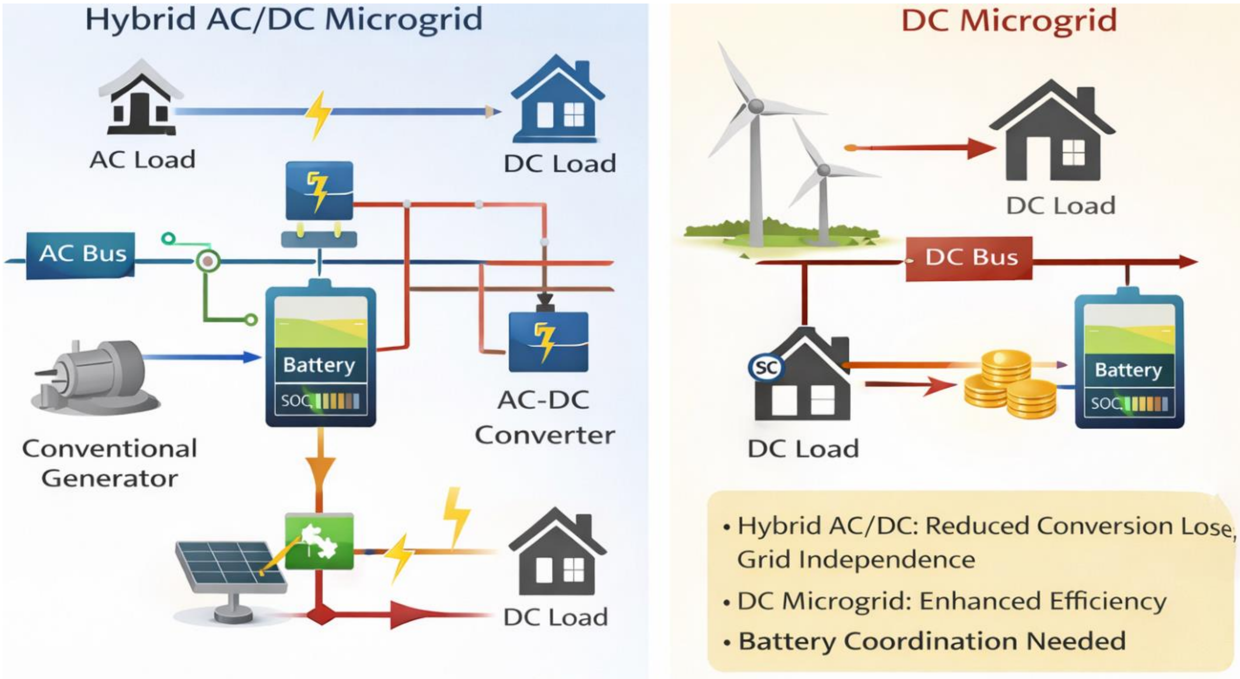

Figure 5.
Architectural Configuration of Hybrid AC/DC and Fully DC MG Topologies.

Specifically, DC MGs have fewer converters, higher efficiency, and a simpler control structure. However, they must be synchronized with the battery systems to maintain voltage levels and prevent over-cycling [9, 46]. These results show that the best battery policies are closely tied to the architecture and must be informed by the peculiarities of AC, DC, or hybrid systems.

2.8. Multi-MG and EV-Integrated Systems

As MGs increasingly interconnect to form multi-MGs, battery optimization should consider factors of coordination, fairness, and privacy. There is a comparison among individual, community-based, and cooperative optimization strategies [16, 45] where a coordinated battery usage approach can greatly reduce total system costs but increase the complexity of data sharing and control. Figure 6 depicts a networked energy system in which various MGs coordinate their energy management systems, leveraging EVs as mobile storage. The MGs have their own EMS and batteries, and inter-MG energy transfers enable the optimization and minimization of community-level expenses. The figure demonstrates bidirectional vehicle-to-grid and vehicle-to-load interactions, as well as the contribution of EVs to flexibility and ancillary support. Central coordination enables common optimization benefits but also highlights issues of control complexity, information exchange, and privacy, underscoring the need for scalable, fair strategies for battery coordination in interconnected MG environments [39, 40].

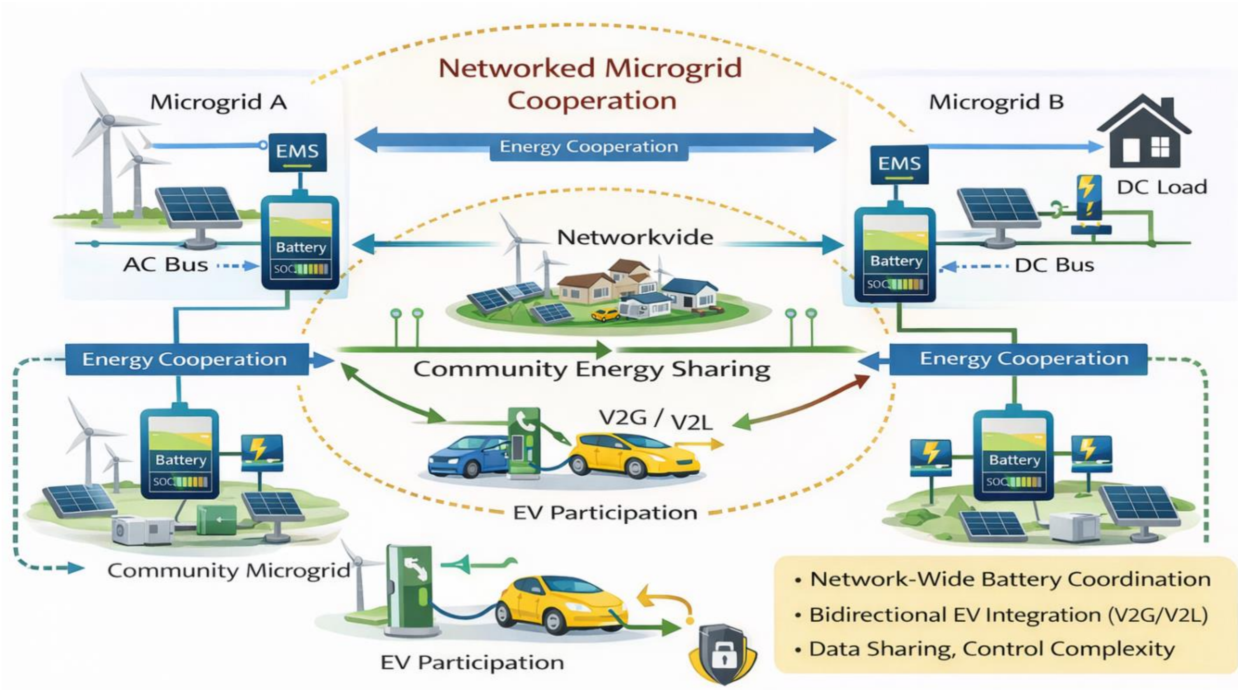

Figure 6.
Schematic Architecture of Coordinated Multi-MG Operation with EV-Integrated Energy Storage.

Batteries become even more complicated with the introduction of EVs as mobile storage units. The EV charging requirement creates additional uncertainty while offering flexibility in terms of vehicle-to-grid and vehicle-to-load options [17, 41]. This means effective battery charge-discharge plans should align stationary and mobile storage systems to achieve the best gains at the system level.

2.9. Research Gaps Identified

Despite progress in MG energy management has been significant, several gaps in the current literature remain that this research aims to address. Previous studies have focused on optimizing the charge-discharge characteristics of batteries, primarily to reduce operating costs or emissions, without paying much attention to battery degradation and lifecycle aspects [30, 33]. These strategies improve short-term performance but reduce long-term system sustainability by increasing the aging rate of storage and decreasing storage capacity. To counter this drawback, the current research will implement battery operation under a controlled SoC regime, thereby eliminating unreasonable cycling and deep discharge, and reconciling asset maintenance with operational optimization [23, 34].

In addition, many current studies are highly dependent on accurate forecasts of loads and renewable generation to achieve optimal scheduling results [13, 17]. This dependence reduces resilience to uncertainty and imposes practical restrictions on real-world MGs, where stochastic behavior is more common. Conversely, this paper employs a system-level energy management approach, offering greater operational flexibility, net-load smoothing, less sensitivity to forecast errors, and increased robustness to variable operation. Another issue concerns the computational complexity of advanced optimization models, such as mixed-integer and AI-based models, which makes their real-time implementation prohibitively expensive, despite their potential effectiveness [16, 30]. This paper attempts to address this difficulty by showing that much more can be accomplished with coordinated component sizing and without excessive operational-scheduling complexity in the algorithms, thereby increasing engineering feasibility.

Also, component sizing, operational control, and battery management have typically been perceived as disjointed problems, leading to poorer outcomes across the system [9, 45]. This paper will address this gap by taking a more holistic approach, optimizing battery operation, dispatchable generation reliance, and renewable energy use in a single study. Lastly, most studies justify their techniques through simulation but are often not applied to real-world cases or over long periods, especially for DC and hybrid MGs [43, 46]. The study, by applying its framework to a realistic hybrid MG configuration over a long working lifetime, contributes to the existing body of literature on more practically relevant, deployable, and viable battery charge/discharge strategies.

Table 1.
Comparison of Representative Studies on Battery Charge–Discharge Optimization in MGs.

Study	MG Type	Optimization / Control Method	Battery Focus	Key Contributions	Limitations
Colucci et al. [6]	AC MG	Survey / Taxonomy	Cost & Degradation	Comprehensive classification of battery operation strategies	No validation or implementation
Aldosari et al. [17]	AC MG	Heuristic (Krill Herd Algorithm)	Cost & Emissions	Multi-objective optimization with BESS and EV integration	Strong reliance on forecasts
Charalambous et al. [15]	Hybrid AC/DC	Optimization Framework	Efficiency	Reduced conversion losses and grid imports	Limited battery aging consideration
Tu et al. [13]	DC System	AI (DSAN–N-BEATS)	Efficiency & Prediction	Accurate SoC forecasting and charging optimization	Data-intensive and black-box
Moosavi et al. [30]	AC MG	MILP	Cost, Losses, Emissions	Multi-objective scheduling under operational constraints	High computational burden
Taye [9]	DC MG	Coordinated Control (Fuzzy + Droop)	Stability & Lifespan	Improved voltage stability and reduced storage stress	Case-specific architecture
Ahsan and Musilek [16]	Multi-MG	Game Theory / ADMM	Cost & Fairness	Cooperative battery utilization across MGs	Communication and coordination overhead
Li et al. [10]	AC MG	Hybrid PSO–DE	Cost & Battery Cycling	Improved economic dispatch with reduced cycling	No explicit degradation model
Sun et al. [12]	AC MG	Reinforcement Learning	Cost & Adaptability	Adaptive battery dispatch under uncertainty	Training instability
Mohamadi et al. [11]	AC MG	Multi-objective Optimization	Cost & Reliability	Trade-off analysis between cost and reliability	Limited real-time feasibility

3. Methodology

3.1. Research Design

This research used a simulation-based design to evaluate advanced control strategies for MG EMSs. The methodological design incorporated RES, BESS, and traditional backup generation within a single MG. To provide consistency and reproducibility of findings, several control algorithms were implemented, tested, and compared under the same operating conditions systematically. The analysis was based on the most important performance dimensions, such as system resilience, the use of renewable energy, and energy availability, which are commonly considered critical indicators of MG performance in the literature [6, 28]. Figure 7 demonstrates the methodology used in this research, which proposes using simulation-based MG modeling, battery charge-discharge optimization, and performance analysis in that order to evaluate economic, technical, and environmental impacts under optimized and non-optimized operating strategies.

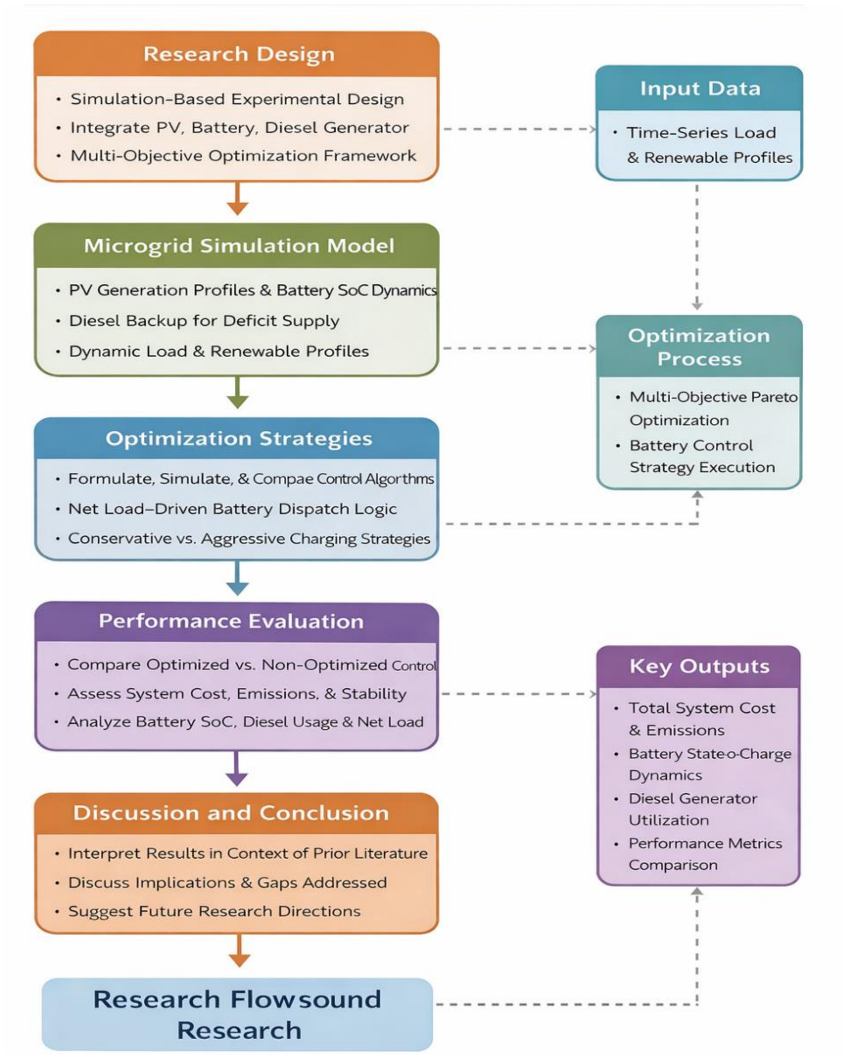

Figure 7.
Schematic Diagram of the Research Flow.

The multi-objective optimization model was used to determine optimal control parameters and component sizes. Such practice enabled a systematic trade-off among conflicting goals, including cost-efficiency, emission reduction, and operational robustness, in line with modern MG optimization research [17]. The combination of simulation-based assessment and optimization-based design in the research methodology ensured that dynamic operational performance and long-term system performance were thoroughly evaluated.

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3.2. MG System Model

The MG system discussed in the present paper was based on three major subsystems: renewable energy production, energy storage, and traditional backup generation. The PV power profiles represented renewable generation and were modeled as time-series data reflecting solar availability variability. The BESS was modeled as an energy storage system with specified energy capacity, charging and discharging power constraints, SoC constraints, round-trip efficiency losses, and self-discharge effects. A traditional backup power source, a diesel generator, was also added to provide power when renewable energy and battery discharge were insufficient to meet load demand, which aligns with MG configurations widely reported in the literature [9, 33].

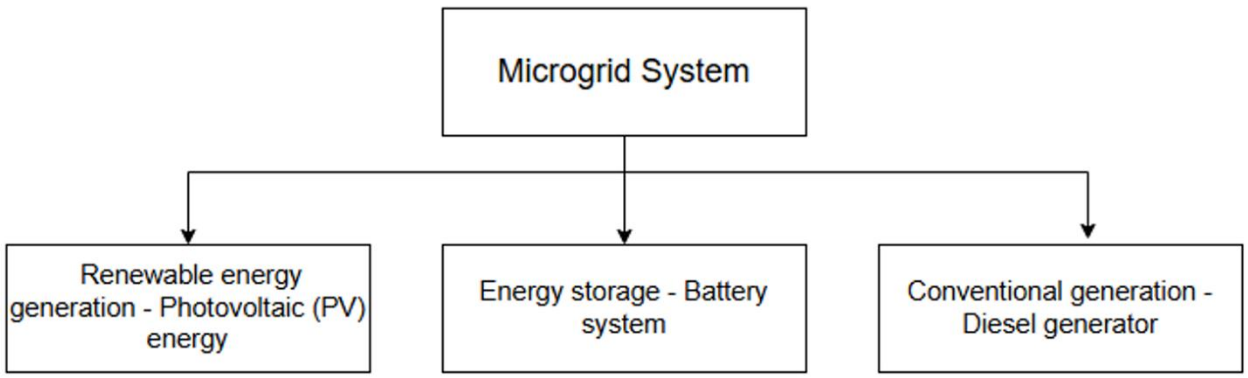

Figure 8.
MG system design.

Load demand and renewable generation were modeled as discrete time-series profiles, and system performance was analyzed at constant time steps over a specified simulation period (Figure 8). The interactions among load demand, renewable availability, storage operation, and generator dispatch were explicitly modeled at each time step, enabling the dynamic behavior of the microgrid to be represented under various operating conditions.

3.3. Control Strategies

Five MG control strategies were introduced and tested to evaluate alternative operational philosophies. These strategies included both reactive strategies that reacted immediately to load conditions and sophisticated adaptive and predictive strategies that incorporate past performance history and expectations of future situations. Either control strategies, prescribed dispatch strategies, battery charging or discharging, or the use of renewable energy at each time step. Specific attention was paid to the strategies that would provide cost efficiency, maximize the use of renewable sources, and create system resilience during periods of peak demand or when renewable sources would be insufficient, as previous investigations of MG control and energy management had focused on [7, 12].

3.4. Energy Storage Management

The use of energy through battery operation was controlled by well-organized energy management policies that determined the direction of charging and discharging responses in response to current system conditions. The approach clearly accounts for operational constraints, including minimum and maximum SoCs, charging and discharging efficiencies, and self-discharge losses [23, 43]. The different philosophies of storage operations were considered, including conservative reserve-conservation policies, aggressive renewable-absorption policies, and forecast-based policies that predict future net load conditions. Utilization and efficiency measures were used to assess battery behavior, providing quantitative data on the efficacy of specific control measures for exploiting storage flexibility without affecting operational stability, as found by Colucci et al. [6].

3.5. Renewable Energy Utilization Assessment

Quantitative measures of renewable energy performance were performed based on the quantifiable utilization, penetration, and curtailment. Renewable utilization was the ratio of available renewable energy effectively utilized by the load or captured in the battery. Renewable penetration was used to define the role of renewable sources in total energy production and in supplying the load during the simulation period [21, 41]. Curtailment analysis identified cases where renewable energy was not taken up due to storage or load capacity constraints, indicating inefficiencies in renewable integration. All these measures provided detailed evidence that the MG used renewable resources through various control strategies, in line with common evaluation practices in MG research [17, 33].

3.6. Resilience Evaluation Framework

The composite resilience index used to measure system resilience assesses the MG's capability, in the event of disturbances and other unfavorable operating conditions, to continue supplying energy to its customers. It incorporates energy availability, battery reserve adequacy, and generator reliability into a single normalized metric within its resilience framework [35, 43]. The analysis of load shedding was conducted to measure unmet demand in terms of frequency, magnitude, and time period. Measurements of recovery time were obtained to determine the rate at which the system returned to normal functioning after a disturbance. The framework enabled the holistic evaluation of MG strength, not through traditional economic or efficiency indicators, but rather according to recent resilience-based MG studies [9].

3.7. Validation and Comparative Analysis

A systematic validation system was used to evaluate each control strategy, ensuring consistency and reproducibility. Each algorithm was run under the same load and renewable-generation conditions, and the systems' states were monitored throughout the simulation. All scenarios were analyzed in terms of resilience, renewable integration, energy availability, and storage utilization measures, and compared to determine the strengths, weaknesses, and functional applicability of each strategy [44, 46]. This practice meant that control logic could be used to explain performance differences rather than external variability.

3.8. System Formulations

At each discrete time step t, the MG was required to satisfy the power balance between load demand and renewable generation. The net load was defined as

$$Pnet(t) = Pload(t) - Pren(t)$$

Where:

$Pload(t)$ is the load demand at time (t), and

$Pren(t)$ is the renewable power generation.

A positive value of $Pnet(t)$ indicates a power deficit that must be supplied by the battery or conventional generator, while a negative value indicates excess renewable generation that can be stored or curtailed. Battery dynamics were modeled using a SoC balance equation that accounted for charging, discharging, efficiency losses, and self-discharge.

$$SOC(t+1) = SOC(t) + \eta ch \cdot P\_ch(t) \cdot \Delta t - (Pdis(t) \cdot \Delta t) / \eta dis - \lambda \cdot \Delta t$$

Where:

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$SOC(t+1)$ is the battery state of charge at time (t),
$P\_ch(t)$ and $Pdis(t)$ are the charging and discharging powers,
ηch and ηdis are charging and discharging efficiencies,
λ is the self-discharge rate, and
Δ is the simulation time step.
The SoC is constrained within operational limits:

$$SOC\_min \leq SOC(t) \leq SOC\_max$$

Renewable curtailment is defined as the unused portion of available renewable energy:

Where:
$Eren, used$ is the renewable energy consumed or stored, and
$Eren, avail$ is the total available renewable energy.
Energy availability measures the system's ability to meet total energy demand over the simulation horizon:

$$Aenergy = 1 - (Eshed / Edemand)$$

Where:
$Eshed$ is the total energy not supplied due to load shedding, and
$Edemand$ is the total energy demand.
The overall resilience of the MG is quantified using a weighted resilience index:

$$R = 0.4 \cdot Aenergy + 0.3 \cdot Abattery + 0.3 \cdot Agen$$

Where:
$Abattery$ represents battery reserve adequacy, and
$Agen$ represents generator reliability.
The resilience index satisfies:
$0 \leq R \leq 1$

3.9. Multi-Objective Optimization

Component sizes, including battery capacity, diesel generator rating, and PV installed capacity, were optimized using the Platypus implementation of the NSGA-II algorithm over 100 generations. The two goals were the reduction of the overall life-cycle price in United States dollars and the reduction of carbon dioxide equivalent expressed in kilograms of CO_2e. The battery capacity was limited to 0–1000 kWh, the diesel generator to 0–2000 kW, and PV was limited due to constraints. The ultimate system configuration has been chosen as the viable Pareto solution with the least weighted total cost, in line with the practice of selecting the optimal solution in multi-objective MG optimization [30, 33].

4. Results and Performance Evaluation

This chapter presented the experimental results obtained from the simulation of a hybrid MG system operating under non-optimized and optimized strategies over a one-week horizon of 168 hours. The MG consisted of PV generation, battery-based energy storage, and a diesel generator with a variable load. The optimized configuration used an energy management approach where they focused on the use of renewable energy, the SoC of the batteries was kept within the safety operating ranges, and reliance on the use of diesel generation was minimized. The performance of the system was measured with respect to its behavior, component size, economic cost, and environmental impact.

The Pareto-optimal solutions identified during this research demonstrated that significant cost reductions could be achieved without proportional increases in carbon emissions. The selected compromise solution represented the best balance between economic and environmental performance,

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ensuring coordination in battery-energetic storage systems that prioritize the economic viability of MGs without compromising their lower emissions. The Pareto front obtained after the multi-objective optimization process was plotted in Figure 9 and depicted a trade-off between total life-cycle cost and carbon dioxide equivalent emissions. Each blue point on the scatter plot corresponded to a Pareto-optimal solution identified by the NSGA-II algorithm, while the purple square represented the non-optimized baseline configuration. The chosen optimized solution, marked with a red star, was on the Pareto front and showed a significant decrease in total cost, with practically no penalty in emissions compared to the baseline.

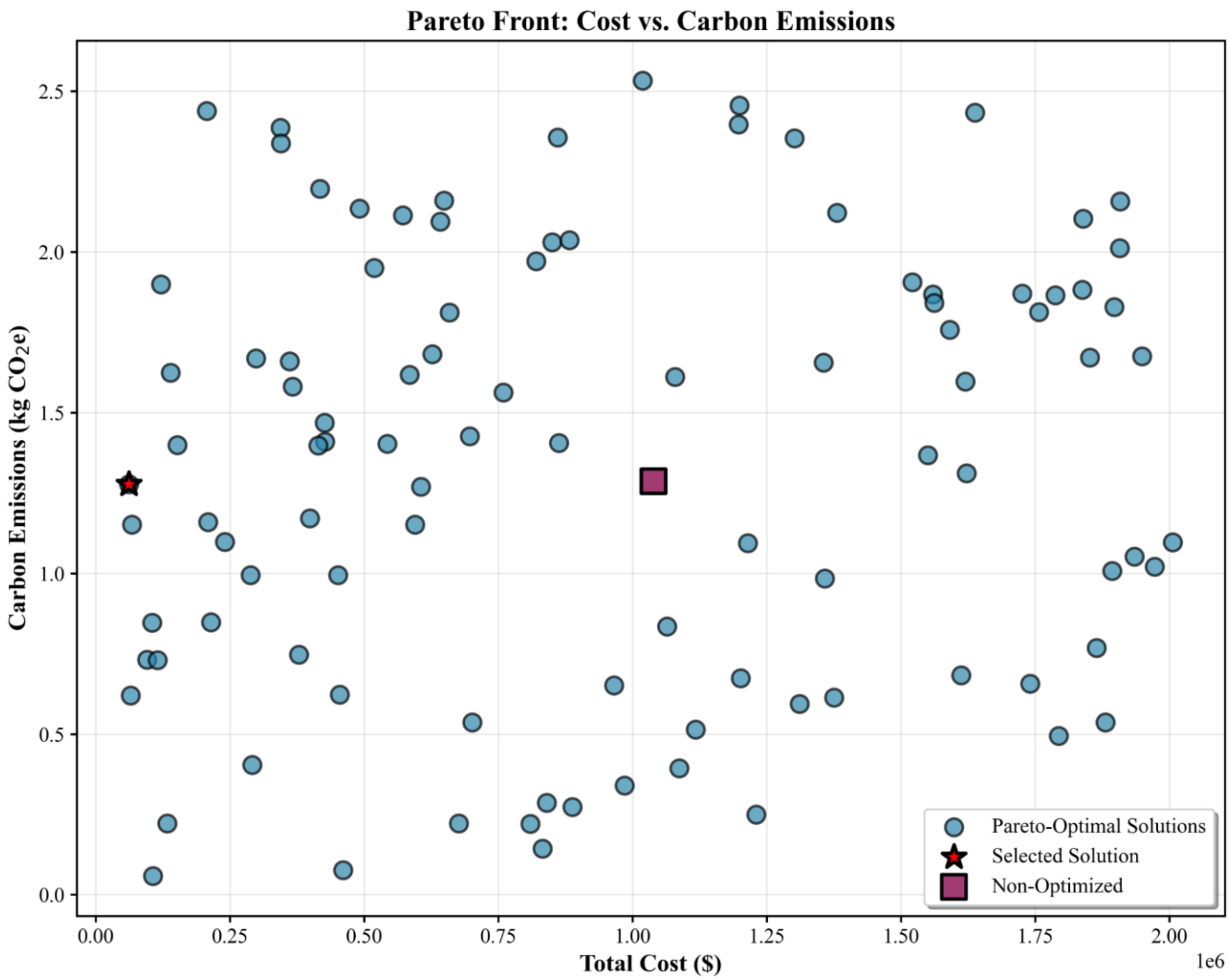

Figure 9.
Pareto-Optimal Trade-Off between Total Lifecycle Cost and Carbon Emissions for MG Design.

This finding showed that major economic gains are achievable without having an adverse impact on environmental performance, and aligns with the results provided by Moosavi et al. [30], who revealed that there was a significant dominance of coordinated storage and renewable dispatch in driving cost savings rather than marginal improvements in emissions. In contrast to heuristic-only methods reported in previous studies, the Pareto-based selection enabled a clear analysis of trade-offs and avoided arbitrary objective weighting, aligning with best practices in multi-objective optimization of MGs [24, 37].

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This study found that optimized scheduling improved coordination between load demand and PV generation, thereby minimizing net load variability. The faster net load profiles permitted much more regulated behavior of battery SoCs without going into deep discharge or over-cycling. As a result, the need to use the diesel generator was reduced to almost none, meaning that fossil-fuel-based generation was successfully replaced by battery and renewable energy management [4, 23]. Combined, these results indicate that optimization increased energy equilibrium, the permanence of fame, and the dependability of supply, while simultaneously reducing operational strains on traditional generation assets in the MG.

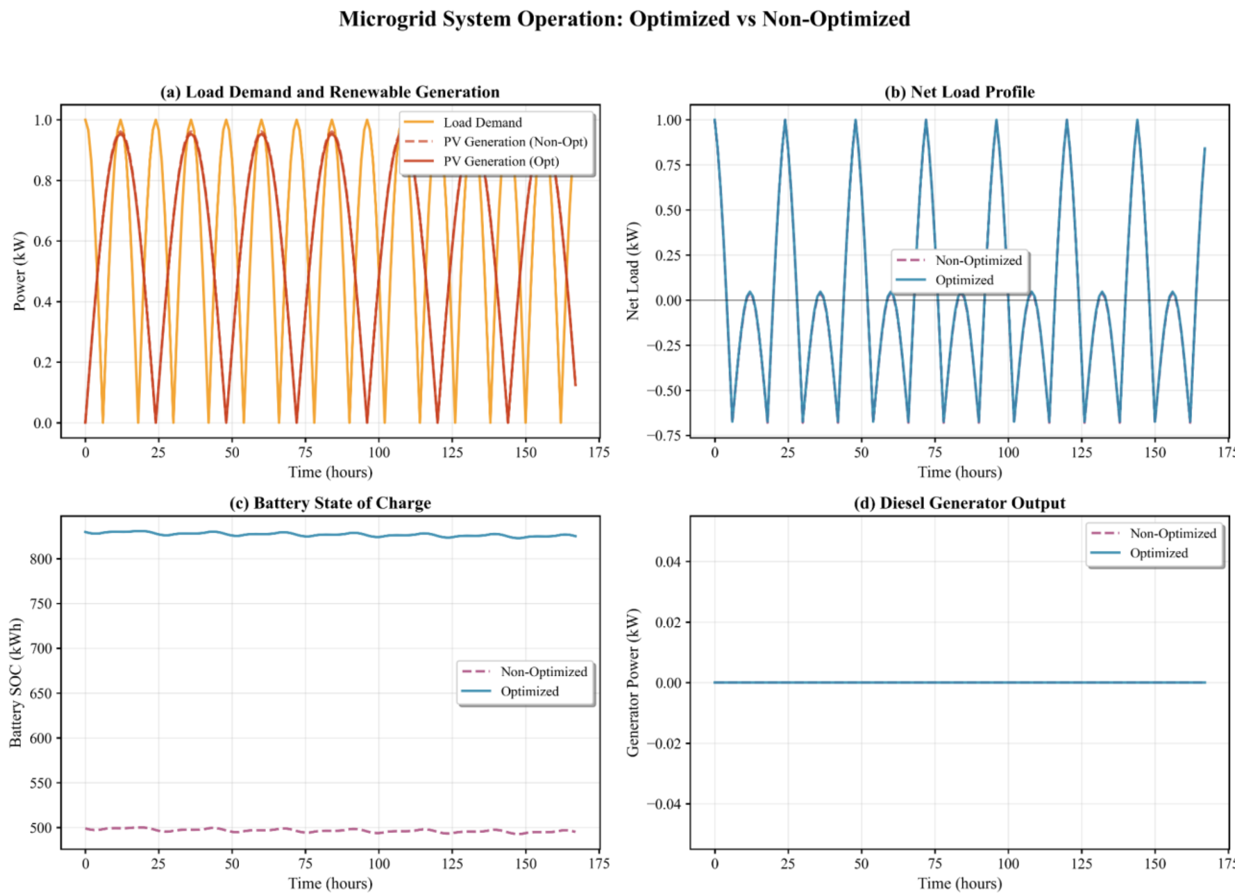

Figure 10.
Comparative Operational Dynamics of Optimized and Non-Optimized MG Energy Management.

Figure 10(a) compares the PV generation and load demand profiles for non-optimized and optimized operation plans. The load showed a daily periodicity, whereas PV generation exhibited a strong diurnal cycle due to sunlight availability. In the non-optimized case, the PV output was not in phase with the load, leading to overproduction and underutilization of renewable assets and greater reliance on dispatchable assets. The optimized system, in contrast, was much more attuned to load demand and PV output, enabling it to charge excess storage and limit discharge during peak demand, thereby increasing the system's share of renewable energy. Similar enhancements were also found in hybrid AC/DC MGs by Charalambous et al. [15] and in DC MGs using coordinated energy management by Taye [9]. The current findings build on those results by demonstrating that such alignment may be achieved through, first, operational optimization and, second, renewable over-sizing.

Figure 10(b) shows the net load curves for the non-optimized and optimized situations, with the net load curve being the difference between load demand and renewable generation. Positive net loads indicate an energy deficit, and negative net loads indicate a renewable energy surplus. The non-optimal system had large variations in net load, with frequent and large positive peaks, indicative of reliance on battery discharge and diesel generation. Compared with the optimized system, the optimized system was able to smooth the net load profile by far and minimize the variability and intensity of load oscillations [47]. This flattening effect helped achieve a better supply-demand balance by optimally scheduling storage and renewable resources, consistent with the results of Colucci et al. [6], who identified net-load smoothing as a successful indicator for dispatching batteries. The optimized strategy demonstrated excellent stability compared to the rule-based strategy, which was typically reported in the literature under minimal extreme operating conditions.

Figure 10(c) depicts the battery SoC tracks over the length of the simulation. An approximately 34% lower average SoC in the non-optimized case, with strong fluctuations, increased the likelihood of the battery entering deep discharge and degrading faster. This has already been recognized as one of the major drawbacks of uncoordinated or reactive strategies for managing batteries [6, 28]. The battery SoC under the optimized strategy operated over a narrower, more consistent range. The controller used the battery to its full capacity during renewable surplus periods and discharged it during peak periods, thereby significantly increasing system resilience and reducing battery loading. This goal is conducive to lifecycle-conscious control goals as argued by Taye [9]. The results show that better SoC control can be achieved without complex degradation models when energy timing is maximized.

The comparison of the diesel generator output under both operating strategies is shown in Figure 10(d). Generators were continuously used in a non-optimized system to bridge energy gaps, consuming more fuel and emitting more pollution. On the other hand, the optimized system eliminated diesel generators over the simulation horizon, highlighting the importance of increased renewable penetration and battery storage as potential replacements for fossil-generated power. Similar decreases in generator use were reported by Charalambous et al. [15] and Aldosari et al. [17], but in those papers, increased penetration of renewables or more complex control structures were required. The current findings indicated that the mere use of strategic storage sizing and scheduling can provide almost zero dependence on generators in hybrid MGs.

The size component report in this research suggests that optimization processes prioritized the system design towards traditional generation oversizing rather than improved energy storage capacity. The growth in battery size provided greater buffering for renewable energy, thus increasing operational flexibility; the decrease in the size of the diesel-generating power was significant, indicating little dependence on fossil-based call-up power [24, 48]. The almost-stable PV capacity implies that the main way to boost performance is through the strategic use of storage and the sizing and control of dispatchable resources, rather than installing more renewable resources.

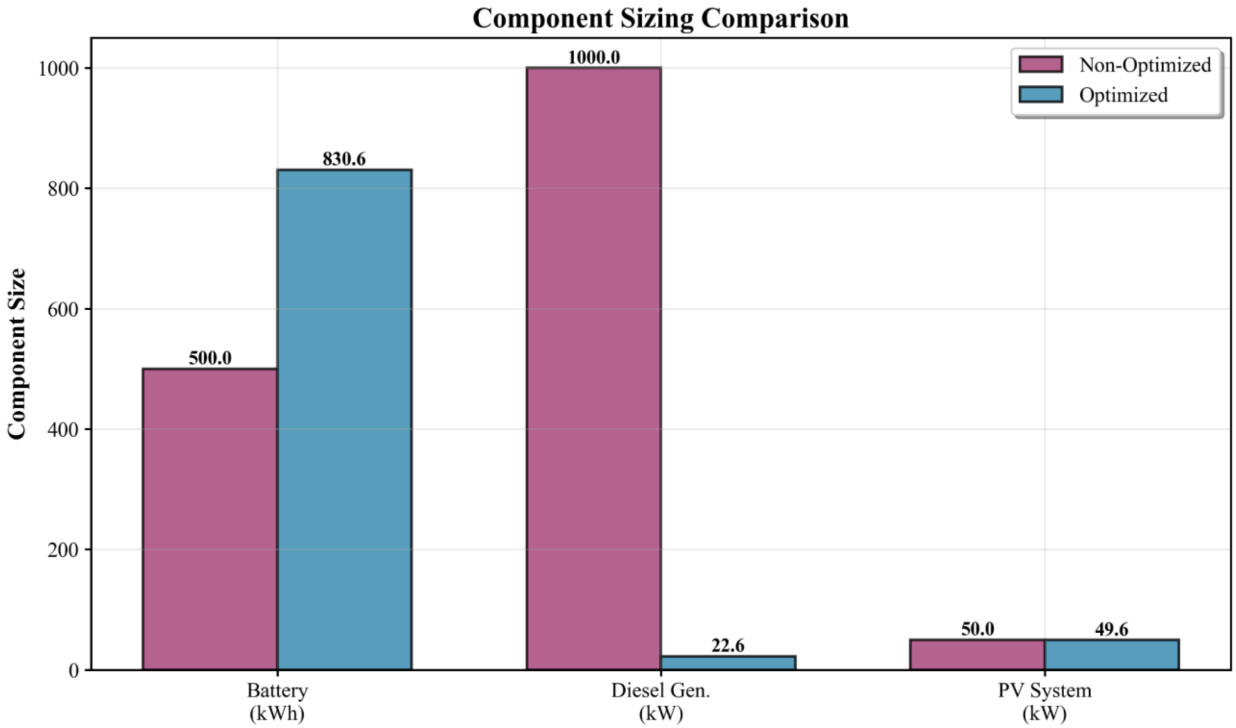

Figure 11.
Optimized versus Non-Optimized Component Sizing for Hybrid MG Configuration.

Figure 11 compares the installed capacities of selected major components of the system in the non-optimized and optimized settings. The non-optimized and optimized setups had battery capacities of 500 kWh and 830.6 kWh, respectively, offering better buffer capacity to absorb renewable energy. Conversely, generator capacity decreased by almost 1,000 kW to about 22.6 kW, reducing reliance on traditional generation. These observations show that intelligent system architecture and operational optimization, rather than overly renewable oversizing, were the main drivers of performance improvement. This conclusion is supported by Moosavi et al. [30], who highlight that optimized storage sizing, in most instances, results in higher system benefits than renewable capacity.

The economic analysis presented in this paper shows that optimization reduces the system's total cost by using smaller-capacity diesel generators, decreasing fuel consumption, and eliminating operational inefficiencies, thereby improving overall economic feasibility. At the same time, the environmental analysis indicates a decrease in carbon emissions, which can be explained by the insignificant production of fossil fuels and the high share of renewable energy sources and battery storage [49, 50]. Even though the reduction in emissions is small over the studied time frame, the overall economic and environmental performance of such a strategy suggests that battery-based energy management optimization may enable cost-effective operation and help achieve the carbon reduction goals in the aforementioned MGs in the long term [20, 43].

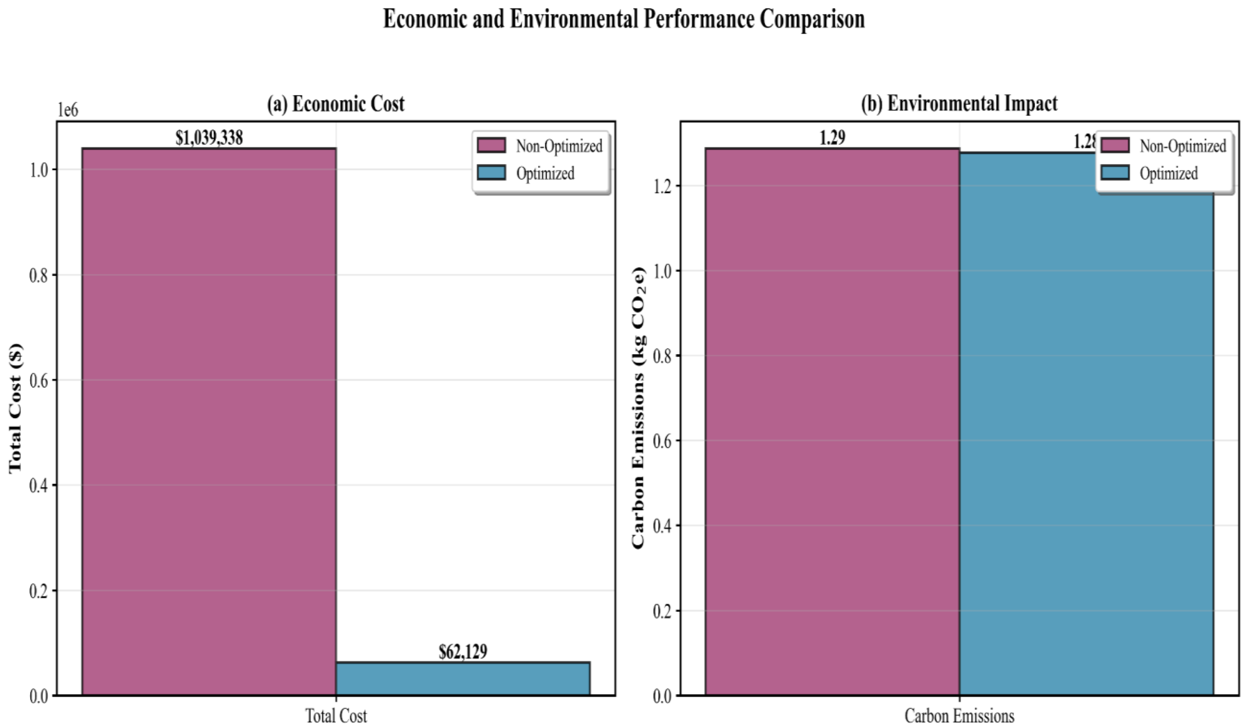

Figure 12.
Comparative Economic and Environmental Performance of Optimized and Non-Optimized MG Operation.

In Figure 12(a), the overall system costs in both cases are compared. The non-optimal setup has a cumulative cost of about $1,039,338, mostly due to fuel consumption, and has an excessively large diesel generator capacity. However, the optimized system attains a total cost of about $62,129, which is more than a 90 percent reduction in cost. This significant improvement can be attributed to decreased fuel consumption, reduced fuel generation capacity, and better utilization of RESs. This level of cost minimization exceeds that of previous studies, which in most cases targeted small-scale enhanceability through dispatch optimization alone [17]. Figure 12(b) presents a comparison of carbon dioxide emissions, with the non-optimized case emitting about 1.29 kg CO_2e and the optimized case emitting 1.28 kg CO_2e. Although the absolute decrease is small within one week, it nearly eliminates diesel generator operation. Over longer time horizons or larger systems, this change would lead to significant long-term reductions in cumulative emissions, aligning with decarbonization goals [15].

However, the findings show that the optimized MG operation is highly effective in enhancing the use of renewable energy, stabilizing battery SoC, minimizing diesel generator use, generating significant economic savings, and minimizing environmental impact. The findings can be compared with those of previous studies, showing that coordinating energy management and component sizing optimization can achieve excellent performance without the complexity of systems. The effectiveness of this optimization framework in improving the technical, economic, and environmental performance of hybrid MG systems is justified by these results.

5. Discussion and Conclusion

The findings clearly indicate that optimized battery charging and discharging schemes are a determining factor in the better technical, economic, and environmental performance of hybrid MG systems. The simulation results indicate that organized energy management, when coupled with multi-objective optimization, achieves significantly higher performance than non-optimized operation across all dimensions considered. The results are consistent with and relevant to the literature on MG optimization and battery-based energy management.

Operationally, the operational argument of the optimized case, the enhanced matching between PV generation and load demand, proves the main point delivered by Charalambous et al. [15] i.e., that smart scheduling of storage resources has a greater impact on MG efficiency than capacity expansion of renewable sources. Unlike the non-optimized system, where considerable temporal disparity between supply and demand was observed, the optimized system shifted energy across time with the help of the battery, thereby causing less volatility in net load [51]. It has been previously noted that this net load smoothing effect aligns with the observations of Colucci et al. [6], who list the decrease in net load fluctuations as a crucial indicator of battery dispatch efficiency and a robust system as a whole.

The control via optimization is again supported by the battery SoC behavior. The battery is also operated within a smaller, better SoC range in the optimized setup, and therefore, there is less risk of deep discharge and over-cycling. The behavior itself would address issues of battery degradation and shortened lifespan caused by aggressive or poorly coordinated control plans in the previous literature [6, 7]. Even though the control algorithm does not include explicit degradation models, the findings indicate that implicitly guided battery health is possible by solely designing an effective energy scheduling, which can serve as valuable information that complements other lifecycle-aware optimization efforts suggested in Moosavi et al. [30].

The almost impeccable elimination of diesel generators in the optimized design is one of the most conspicuous discoveries of this paper. This finding highlights the advantages of optimizing battery capacity and deploying intelligent dispatch logic. Similar decreases in the dependency of generators are documented in the literature, specifically in studies of coordinated control and hybrid MG designs [28, 33]. However, the majority of these studies have demanded greater renewable infiltration or multi-layer decision-making domination. The current study shows that significant generator displacement can be achieved primarily by optimizing sizing and scheduling, without requiring changes to renewable capacity. This fact supports the thesis that storage optimization is a cost-efficient channel to a decarbonized MG operation [52, 53].

The component-sizing results also support this conclusion. The optimized system has a much larger battery, a much smaller diesel generator, and virtually no change in PV capacity. This finding aligns with the conclusions of Moosavi et al. [30], who state that over-sizing of traditional generation is commonly an offsetting factor to poor control rather than a real system requirement. In comparison, the optimized structure showed that reallocation of investment to storage capacity yielded better performance. This supports the change in MG design philosophy from generation-dominated sizing to storage-dominated optimization, as increasingly championed in the literature [22, 49].

The economic aspect of the study was that the extent of cost reduction was much greater than reported in similar studies. The net present value of lower fuel usage, lower generator capacity, and greater use of renewable energy results in extended economic value, with a net value of around 90 percent lower total system cost compared to the non-optimized base. Despite Moosavi et al. [30] and Aldosari et al. [17] also reporting significant cost savings at optimized dispatch scales, the current results demonstrate that the combination of operational optimization and component sizing delivers much higher economic benefits. This finding highlights the shortcomings of research studies that evaluate operational control in isolation and disregard prior system-design deliberations.

Environmentally speaking, the one-week horizon during which the reduction in carbon emissions was observed was not large. The fact that the diesel generator was almost off in the optimized MG already indicates that emissions were near the lowest possible level, assuming the renewable capacity [26, 31]. Small-scale emission cuts can seem minimal in an optimization model, but, as Charalambous et al. [15] argue, their effects over time or across different MGs can be huge. The findings, therefore, confirm the potential for decarbonizing MGs over time through optimized operation, rather than indicating minimal environmental impact.

Collectively, these results demonstrate that the gains from optimization go beyond incremental efficiency improvements. Rather, it is highly optimized battery charge and discharge strategies that fundamentally transform the behavior of MGs, not only by stabilizing operation but also by minimizing the need to deploy conventional generation and enabling component sizing to make the operation more rational. Compared with previous research that focused separately on specific elements of MG performance, the current study is more comprehensive, as it presents the dynamics of operations alongside economic and environmental effects [54, 55].

This research has important implications for research and practice. These results highlight the importance of an integrated approach to energy management that includes operational control, system sizing, and multi-objective optimization. The current research indicates that the next generation of work must focus on resilience, battery health, and long-term economic performance, as suggested by Colucci et al. [6]. For practitioners and system designers, the study shows that significant performance improvements can be achieved without increasing renewable capacity, provided that battery systems are properly sized and used sensitively [54, 55]. This applies specifically to remote and islanded MGs, which frequently restrict renewable growth, but where storage optimization can still be done. In terms of policy and planning, the results show that developing advanced EMSs and storage-centric design solutions is crucial, and the specific focus on renewable capacity targets should be limited [21, 38]. Optimized MG operation offers an avenue to simultaneously realize energy security, cost reduction, and emissions reduction, thereby contributing to overall sustainability and electrification strategies.

In conclusion, the current study has shown that optimizing the battery charging and discharging schedule is a significant way to enhance the technical, economic, and environmental performance of hybrid MGs. The MG has improved its utilization of renewable energy and balanced its batteries through coordinated energy management and the optimization of multiple objectives, avoiding as much diesel generation as possible and significantly reducing costs. Such findings are complementary and also complement the available literature, in that intelligently storage-concentrated optimization can emerge as superior to the conventional, optimization-heavy design methods. The general analysis findings indicate that battery-based optimization of resilient, cost-effective, and low-carbon MG operation remains a critical enabler of sustained resilience, providing a strong basis for investigation and practical application. Future research should integrate real-time uncertainty-aware control with explicit battery degradation models across networked MGs.

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Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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