electronics

MDPI

Review

A Review of Energy Storage Economics, Load Forecasting, and Hybrid Control Strategies for AC Microgrids in Modern Power Systems

Yaser Ibrahim Rashed Alshdaifat, Krishnamachar Prasad * and Jeff Kilby

School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, Auckland 1010, New Zealand; yaser.alshdaifat@autuni.ac.nz (Y.I.R.A.); jeffrey.kilby@aut.ac.nz (J.K.)
* Correspondence: krishnamachar.prasad@aut.ac.nz

Abstract

As power grids transition towards highly renewable generation on a global scale, maintaining dynamic stability is becoming a major challenge. Replacing traditional synchronous generators with inverter-based renewables strips the grid of rotational inertia, leaving active distribution networks highly vulnerable to frequency deviations and voltage spikes. To avoid expensive poles and wires upgrades, Battery Energy Storage Systems (BESS) are increasingly being deployed as Non-Network Solutions (NNS). However, the current literature reveals a distinct gap between the macro-scale economic planning of these storage assets and the micro-scale dynamic control actually required to keep the grid resilient. To address this gap, this review proposes a multi-layer deterministic synthesis framework that links physical renewable modelling, degradation-aware techno-economic planning, deterministic forecasting, and EMS dispatch through offline time-domain control validation for AC-microgrid energy storage integration. The research examines how advanced central control units within battery management systems can rigorously and jointly estimate State of Charge (SoC) and State of Energy (SoE) to ensure accurate grid-aware dispatch. Furthermore, the study explores the integration of degradation-aware economic modelling in HOMER Pro with dynamic transient control in MATLAB/Simulink R2025b, driven by hybrid metaheuristic optimization algorithms like Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO). This analysis demonstrates that integrating energy storage must be treated as a tightly coupled multidimensional optimization problem to successfully deliver the secure and sustainable infrastructure needed to solve the modern energy trilemma.

Keywords: energy storage systems; non-network solutions (NNS); techno-economic optimization; active distribution networks; hybrid metaheuristics; battery management systems (BMS); grid resilience

Academic Editors: Teodora Lazar and Dragos Pasculescu

Received: 6 May 2026
Revised: 3 June 2026
Accepted: 5 June 2026
Published: 9 June 2026

1. Introduction

The global energy landscape is presently undergoing a significant paradigmatic transformation, shifting from a centralized, fossil-fuel-based generation model toward a decentralized, decarbonized framework supported by Renewable Energy Sources (RES). This transition is intricately linked to the broader integration of distributed energy resources (DER), including electric vehicles (EV), battery storage, and flexible demand, within both transport and power systems [1,2]. At the same time, power planners are increasingly required to accommodate high proportions of renewables while maintaining system adequacy, flexibility, and reliability [3]. This transition is fundamentally driven by the need to address the Energy Trilemma, which demands a balance between energy security, social equity, and environmental sustainability.

However, the rapid deployment of stochastic resources, particularly solar photovoltaic (PV) and wind, introduces structural challenges for modern power systems. As Inverter-Based Resources (IBR) progressively replace traditional synchronous generators, the grid loses the rotational inertia that historically buffered frequency deviations and enhanced dynamic stability [3]. Without this inherent inertia, power systems become more vulnerable to rapid frequency excursions, voltage instability, and power-quality issues, especially in distribution networks with significant PV penetration [4,5]. To mitigate these risks, Energy Storage Systems (ESS) have emerged as critical assets rather than optional add-ons. Distributed and grid-scale storage can provide peak shaving, voltage regulation, frequency support, grid support in weak networks, and improved utilization of excess renewable generation [3–6]. Nonetheless, energy storage system integration is no longer a simple hardware installation task. It has evolved into a complex multi-objective optimization problem that must simultaneously consider economic viability, degradation-aware sizing and placement, forecasting uncertainty, power system constraints, and advanced control strategies [7–11].

NNSs represent strategic and flexible alternatives to capital-intensive grid expansions; this approach has gained prominence as a method to defer or eliminate the need for traditional pole-and-wire upgrades by strategically deploying BESS to manage peak loads and thermal constraints. While a growing body of literature extensively covers individual aspects of grid modernization, most existing reviews treat economic planning, automation, and dynamic control as isolated domains. Conventional reviews frequently overlook the tightly coupled interdependencies between macro-scale investment decisions, such as degradation-aware BESS sizing, and the micro-scale time-domain control required to maintain stability in low-inertia grids. Consequently, there is a critical need for a holistic review that bridges long-term techno-economic planning with short-term operational stability assessment through offline simulation. Hirsch et al. [12] reviewed microgrid technologies, key drivers, applications, ownership models, regulatory issues, and outstanding challenges. Their review provides a broad overview of microgrid development and highlights the role of distributed energy resources in improving resilience and renewable-energy integration. As reported in [13,14], recent studies also highlight the importance of degradation-aware BESS allocation, cycle and calendar ageing, renewable-energy network planning, energy storage integration, load electrification, power quality, grid congestion, system stability, and technical and economic performance indicators. However, these studies mainly address broad microgrid development, degradation-aware BESS planning, and network-level energy-transition challenges. They do not specifically provide an integrated synthesis linking energy storage economics, degradation-aware planning, deterministic forecasting, optimization-based EMS operation, and offline dynamic control validation for AC-microgrid energy storage integration. Therefore, the gap addressed in this review is the lack of a unified framework connecting long-term techno-economic storage planning with short-term operational forecasting and dynamic stability assessment in AC microgrids.

To address this critical gap, this review paper examines these dimensions under the unifying theme of optimal energy storage integration in modern power systems. It focuses on three key perspectives: Non-Network Solutions (NNS) for grid deferral, deterministic load forecasting for operational certainty, and hybrid control strategies for dynamic stability. The primary contributions of this review are fourfold. First, it offers a critical synthesis of current NNS deployment strategies, demonstrating how strategic energy storage can defer physical infrastructure upgrades while balancing short-term economic gains with long-term battery degradation. Second, it provides a comprehensive evaluation of structured forecasting and optimization techniques required to manage the multidimensional uncertainties of stochastic renewable generation. Third, it delivers an in-depth analysis of hybrid metaheuristic control strategies, such as GWO-PSO, and their effectiveness in enhancing transient stability and dynamic performance within low-inertia, inverter-dominated grids. Finally, it proposes a multi-scale validation framework that connects economic planning in HOMER Pro, meso-scale generation and degradation analysis in PVsyst, and micro-scale dynamic stability modelling in MATLAB/Simulink.

1.1. Grid Stability and Low-Inertia Stability Challenges

A fundamental technical issue associated with grids dominated by RES stems from the inherent characteristics of photovoltaic and wind generation. Traditional synchronous generators naturally offer rotational inertia, which helps stabilize frequency during disturbances; in contrast, generation interfaced with inverters does not possess any intrinsic inertial response. As the integration of renewables continues to rise, this transition towards low-inertia operation leads to increased rates of change in frequency, reduced damping, and greater susceptibility to even slight imbalances between supply and demand [8]. These stability issues are further intensified by the unpredictable nature of weather conditions. PV output can experience rapid and substantial fluctuations over short time scales due to cloud transients, while variations in wind speed introduce short-term changes in mechanical input power. Under such circumstances, system operators are forced to utilize costly spinning reserves, engage fast-ramping units, or limit renewable generation to preserve grid stability. In distribution networks, a high penetration of PV systems also causes voltage increases, reverse power flow, and additional strain on traditional voltage regulation devices, such as on-load tap changers and capacitor banks, which are too slow to respond to rapid fluctuations in renewable output. Furthermore, integrating energy storage into traditional AC networks demands highly complex synchronization circuitry. While some research suggests transitioning to DC microgrids to bypass these specific AC synchronization hurdles, the fundamental reality of modern infrastructure is that AC microgrids remain dominant; therefore, resolving these AC-specific stability challenges through advanced hybrid control strategies is essential [11].

The absence of rotational inertia in inverter-dominated networks significantly exacerbates frequency excursions and voltage instability. Research indicates that without coordinated BESS response, traditional voltage regulation devices are frequently bypassed by fast transients. Integrating advanced hybrid control algorithms directly mitigates these physical issues; for example, predictive controllers successfully reduce Total Harmonic Distortion to 1.22 percent (down from 6.00 percent) and improve the Voltage Deviation Index to 4.85 percent under dynamic loads. Furthermore, advanced energy storage systems can provide real power compensation instantaneously within 0.2 s upon detecting a critical rate of change in frequency event. This mathematical precision proves that sub-second offline time-domain simulation control is essential to maintain transient stability in modern AC microgrids.

1.2. Framework for Energy Storage System Integration

The integration of energy storage systems into renewable-rich power systems represents a multidimensional challenge that spans long-term planning, short-term operational scheduling, and dynamic control assessment through offline simulation. Although recent advances in battery technologies have improved efficiency, scalability, and cost-effectiveness, effective energy storage system deployment cannot be achieved through hardware-oriented design alone; instead, system performance and overall value are governed by the interaction between economic feasibility, renewable generation uncertainty, and the dynamic control requirements imposed by power electronic interfaces and grid stability constraints. A growing body of literature highlights that energy storage integration decisions made at the planning stage directly influence operational flexibility, degradation behaviour, and dynamic performance assessed through offline simulation. For example, power system planning studies demonstrate that energy storage must be coordinated with other flexible resources to accommodate high renewable penetration while maintaining reliability and economic efficiency. At the same time, degradation-aware allocation and sizing studies show that operational strategies such as arbitrage, peak shaving, and grid support services can significantly affect battery lifetime and long-term investment returns; these findings underscore the need to jointly consider economic modelling and lifecycle degradation in energy storage system integration [12–14]. Furthermore, the stochastic nature of renewable generation and load demand introduces substantial uncertainty into energy storage system operation. Reviews on hybrid renewable energy systems and industrial energy management consistently report that inaccurate forecasting of photovoltaic output, wind availability, and demand profiles leads to suboptimal energy storage scheduling and reduced system performance [15]. Consequently, deterministic forecasting techniques and uncertainty-aware energy management frameworks have become essential components of modern integration; they enable initiative-taking rather than reactive operational decision-making. Dynamic control assessment through offline simulation plays a critical role in translating planning and scheduling decisions into stable system operation. Studies on distributed battery energy storage implementation, DC microgrids, and hybrid microgrids demonstrate that conventional rule-based controllers are often insufficient under fast-varying renewable conditions. This inadequacy strongly motivates the adoption of optimization-based and hybrid control methods. Advanced mathematical approaches, such as metaheuristic-based optimization, have shown improved capability in balancing stability objectives, economic targets, and computational efficiency in complex energy storage system applications [16,17]. To capture these tightly coupled dimensions, this review structures the energy storage system integration problem around three interdependent pillars: economic modelling and lifecycle degradation, deterministic forecasting under renewable uncertainty, and optimization-based hybrid control methods. Unlike the broader review perspectives in [12–14], which mainly examine microgrid technologies, degradation-aware BESS allocation, renewable-energy network planning, distribution and transmission system challenges, energy storage integration, power quality, grid congestion, system stability, and technical and economic performance indicators, this review focuses specifically on linking storage economics, forecasting, optimization, and offline dynamic control validation for AC-microgrid energy storage integration. This framework provides a coherent basis for synthesizing recent advances in energy storage system planning, operation, and control; it explicitly highlights the interdependencies that must be addressed to achieve reliable, cost-effective, and scalable energy storage integration in renewable-dominated power systems [18].

Integration frameworks that decouple planning from operation often overlook the cumulative impact of forecast errors. Current studies demonstrate that prioritizing the State of Energy reduces capacity estimation errors by 5 percent. This highlights that the nexus between planning and dynamic control is not merely conceptual but a direct driver of capital efficiency and reliability.

1.2.1. Economic Modelling and Lifecycle Degradation

The economic viability of Energy Storage System deployment is primarily determined by the Levelized Cost of Storage (LCOS), which encompasses capital expenditures, efficiency losses, operational expenses, and long-term degradation. Battery degradation, influenced by cycle ageing, depth-of-discharge patterns, and calendar ageing, can diminish usable capacity and lead to considerable replacement costs. Consequently, modern optimization frameworks are progressively incorporating degradation-aware modelling, which guarantees that operational strategies prolong battery lifespan while preserving economic feasibility.

Modern optimization frameworks show that incorporating degradation-aware modelling is critical. Static planning models often trap planners in local optima, whereas models that dynamically adjust for depth of discharge and calendar ageing yield superior results. For example, integrating calendar ageing into operational planning effectively lowers battery degradation and extends the physical life of the battery. Quantitative assessments demonstrate that degradation-aware dispatch strategies can reduce total battery ageing by approximately 6.3 percent daily. Furthermore, advanced algorithms achieve a 7 to 21 percent reduction in costs for hybrid microgrid sizing compared to traditional baseline models. This confirms that precise economic modelling is the primary lever for financial viability.

1.2.2. Deterministic Forecasting Under Renewable Uncertainty

Dependable Energy Storage System scheduling is significantly reliant on precise, deterministic modelling of photovoltaic output, wind availability, and fluctuations in load. Traditional statistical models, such as ARIMA and SARIMA, are commonly utilized; however, they demonstrate constraints when faced with non-stationary or highly volatile scenarios. In contrast, advanced deterministic and parametric modelling frameworks offer enhanced accuracy in the presence of intricate nonlinear patterns without relying on black-box algorithms. These structured methodologies empower the Energy Management System (EMS) to operate proactively, thereby enhancing stability, reducing operational expenses, and minimizing uncertainties associated with renewable variability. At larger scales, planning and operation frameworks increasingly couple these deterministic models with optimization routines to handle high proportions of renewables and flexible resources. Such structured approaches empower the EMS to operate proactively rather than reactively, thereby enhancing both stability and cost efficiency. The transition from statistical to structured deterministic modelling is substantiated by measurable gains. State-of-the-art frameworks drastically compress forecasting errors, which directly informs optimal battery dispatch. For instance, implementing advanced time series models reduces the Mean Absolute Percentage Error to between 0.8 percent and 2.6 percent for energy consumption forecasting. Furthermore, high-fidelity demand prediction achieves Root Mean Square Error values of 3.85 percent for short-term horizons. This precision is not just academic; it enables proactive scheduling that can decrease load shedding by 25 percent compared to traditional deterministic scheduling. By providing exceptionally reliable predictions, the energy management system proactively balances demand and prevents the costly overcommitment of storage resources.

1.2.3. Optimization-Based and Hybrid Control Methods

Control strategies determine how BESS interacts with PV systems, loads, and the electrical grid during offline simulation of microgrid operation. Conventional rule-based and linear controllers provide ease of use but struggle in dynamic environments characterized by high levels of renewable energy. Optimization-based methods, such as Model

Predictive Control (MPC), enhance tracking precision but introduce significant computational challenges at larger scales. Metaheuristic algorithms, including PSO, GWO, and their hybrid forms such as GWO-PSO, strike an effective balance between robustness and computational efficiency. This facilitates multi-objective optimization under uncertain conditions. Their capacity to harmonize stability objectives, economic targets, and offline simulation constraints renders them essential in contemporary control frameworks. The efficiency gap between conventional and hybrid control is pronounced. While rule-based controllers often struggle during rapid frequency events, hybrid metaheuristic frameworks (such as the Grey Wolf Optimizer and Particle Swarm Optimization) significantly accelerate transient response. For example, implementing advanced predictive controls achieves tracking response time improvements of 35 percent and reduces Total Harmonic Distortion to exactly 1.22 percent. Furthermore, these methods consistently improve steady state-of-charge tracking performance by 3.1 percent, providing the precise dynamic support required to maintain stability in low-inertia grids.

1.3. Review Scope and Methodological Approach

The literature screening process was structured using a PRISMA-informed approach to improve transparency, traceability, and reproducibility. A PRISMA-informed approach was adopted because the aim of this paper is to provide a structured technical review of energy storage economics, forecasting, optimization, and control strategies in modern AC microgrids, rather than to conduct a full systematic review limited to one narrow research question. Nevertheless, the main PRISMA stages, including identification, screening, retrieval, eligibility assessment, and inclusion, were followed to ensure that the selected studies were relevant, traceable, and systematically justified. The search was conducted across IEEE Xplore, ScienceDirect, Scopus, and Web of Science, which were selected because they index major peer-reviewed publications in electrical engineering, renewable energy systems, microgrids, power electronics, and energy management. The research covered literature published between 2012 and 2026 and used keyword combinations related to microgrid, energy storage system, distributed energy resources, non-network solutions, battery management systems, grid resilience, supercapacitors, pumped hydro storage, forecasting, optimization, techno-economic assessment, and control. Additional search terms included grid inertia, energy storage system optimization, battery degradation, forecasting uncertainty, hybrid metaheuristics, ESS economics, HOMER Pro, MATLAB/Simulink, and PVsyst.

To ensure that the review captured the main relevant and representative literature, studies were included when they addressed at least one of the main technical themes of the paper: system-level energy storage integration, renewable intermittency, forecasting, techno-economic assessment, optimization, battery degradation, or microgrid control. Priority was given to peer-reviewed studies that presented methodological rigour, quantitative assessment, modelling or simulation results, practical validation, or the use of contemporary engineering tools for system-level analysis. Studies were excluded when they were duplicates, outside the scope of electrical distributed energy resources or renewable-energy-based microgrids, focused primarily on battery chemistry or materials rather than system-level integration, addressed unrelated automation topics, or lacked sufficient methodological or quantitative relevance to the review objectives.

As illustrated in Figure 1, the initial database search identified 186 records. After removing 26 duplicate records, 160 records were screened by title and abstract. At this stage, 35 records were excluded because they were not aligned with the review scope. The remaining 125 reports were sought for retrieval, of which two reports could not be retrieved. Therefore, 123 full-text reports were assessed for eligibility. During the full-text assessment, 20 reports were excluded because they lacked sufficient technical depth, quantitative assessment, practical validation, or direct relevance to ESS-based microgrid modelling, forecasting, optimization, techno-economic assessment, or control. Following this process, 103 studies were included in the final literature synthesis. These studies were grouped into key thematic categories covering ESS integration, forecasting, techno-economic assessment, optimization, and control. This structured screening process ensured that the final literature set captured the main research directions required to analyze the interaction between storage economics, renewable intermittency, grid resilience, and control performance in modern AC microgrids.

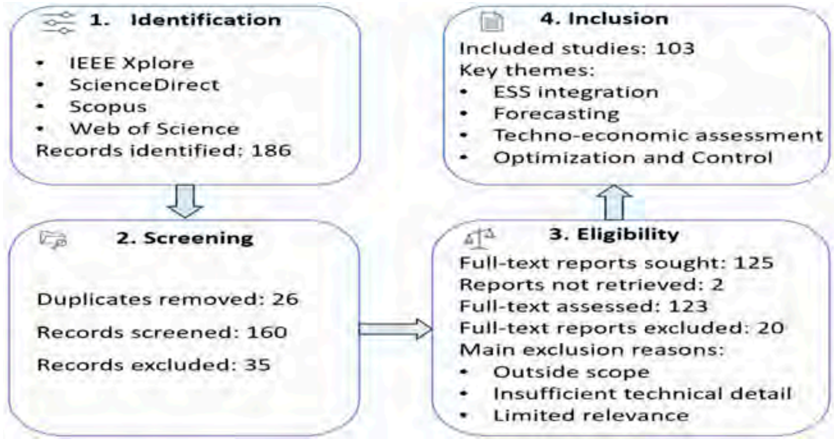

Figure 1. PRISMA-informed literature screening and inclusion flowchart.

The framework integrates renewable generation modelling, physical system simulation, long-term techno-economic planning, deterministic forecasting, and short-term dynamic control validation into a unified workflow for AC-microgrid energy storage planning. As illustrated in Figure 2, renewable generation profiles, load demand, battery parameters, tariff structures, and grid constraints are processed through interconnected modelling and validation layers using tools such as PVsyst/ETAP, HOMER Pro, and MATLAB/Simulink to support optimal BESS sizing, dispatch coordination, and system stability assessment. The framework explicitly links long-term planning objectives, including NPC, LCOE, and storage sizing, with short-term operational stability metrics such as frequency response, voltage regulation, and transient performance. Operational results from MATLAB/Simulink dynamically update system constraints and input parameters, enabling iterative refinement of BESS sizing, dispatch strategies, and transient stability performance.

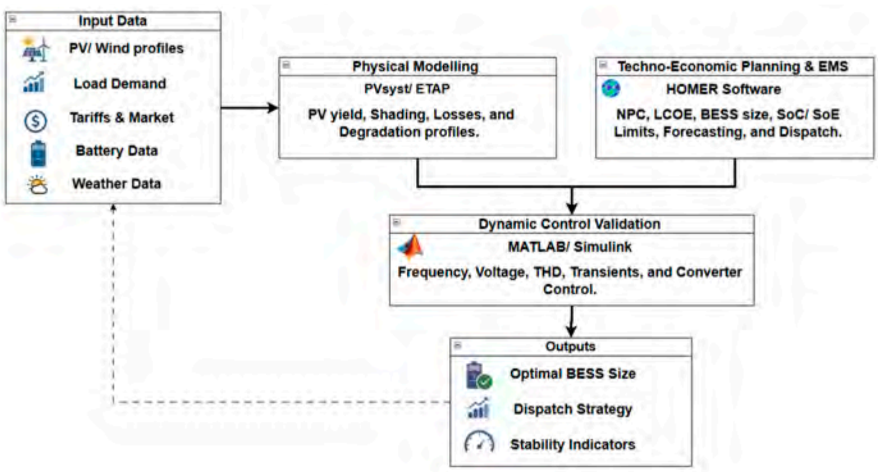

Figure 2. Proposed multi-layer framework for AC-microgrid energy storage integration.

2. Energy Storage Technologies and Architecture

Advanced control algorithms and optimization frameworks play a key role in the effective integration of energy storage systems into renewable-based power systems; however, their performance is limited by the underlying storage technology and the architectural configuration in which it is deployed. The successful deployment of energy storage systems is heavily contingent on the selection of appropriate storage technologies and the design of system architectures that are compatible with the physical characteristics of the power system, the operational goals of the application, and the economic constraints. The physical properties of energy storage technologies vary significantly with respect to energy and power density, dynamic response capability, efficiency, cycle life, and degradation behaviour. These factors not only determine the short-term performance of a storage device under a given set of operating conditions, but also its long-term reliability, economic viability, and grid service appropriateness. For example, high energy density and moderate response times are beneficial for energy shifting and peak shaving, while high power density and ultra-fast dynamics are more suitable for frequency regulation, voltage support, and mitigation of renewable intermittency. Therefore, the suitability of specific ESS technology for applications such as renewable smoothing, peak demand reduction, synthetic inertia provision, or long-duration energy balancing is significantly different for AC microgrids compared to utility-scale power systems. In parallel with technology selection, the architectural configuration through which storage is integrated into the power system plays a decisive role in determining overall system performance. The choice between AC-coupled, DC-coupled, and hybrid integration topologies directly affects conversion efficiency, power flow controllability, fault management, and the degree of coordination achievable between renewable generation and storage resources.

Moreover, integration topology has important practical implications, including the ease of retrofitting storage into existing installations, protection and grounding requirements, scalability of future system expansion, and compatibility with advanced energy management systems. AC-coupled architectures are often favoured for their modularity and deployment flexibility, particularly in retrofit scenarios, whereas DC-coupled configurations enable tighter electrical and control-level integration between renewable sources and storage at the cost of increased control and protection complexity. Hybrid architecture attempts to reconcile these trade-offs and is increasingly explored in systems characterized by high renewable penetration, heterogeneous loads, and stringent performance requirements. In this context, a comprehensive understanding of both energy storage technologies and system integration architectures is essential for the informed design and evaluation of modern renewable energy systems. Decisions made at the technology and topology levels impose fundamental constraints on achievable control performance, economic optimization, and system resilience.

Accordingly, this section provides a structured review of the dominant ESS technologies and integration architectures reported in recent literature. Emphasis is placed on clarifying their operational roles, elucidating key performance trade-offs, and highlighting the implications of technology–architecture co-design for advanced energy management and optimization frameworks. This foundational discussion establishes the context for the subsequent analysis of economic modelling, deterministic load and generation modelling, and hybrid control strategies presented in later sections of this review.

As shown in Figure 3, power flows from renewable sources, such as PV modules and wind turbines, through dedicated converters directly into a common AC-microgrid bus. A bidirectional DC/AC grid-tied inverter (VSI) enables the BESS to absorb excess generation or discharge power to meet demand; meanwhile, the central EMS coordinates forecasting and offline time-domain control using telemetry data from the grid and generation sources.

By treating every generation and storage asset as an independent parallel node, this AC-coupled configuration allows bidirectional power flow to be seamlessly managed across the bus to reliably supply the Local AC Loads and interact with the broader Utility Grid. This parallel architecture empowers the EMS to execute precise, grid-aware dispatch based on rigorous SoE estimations, successfully bridging the critical gap between macro-scale economic planning and micro-scale dynamic stability.

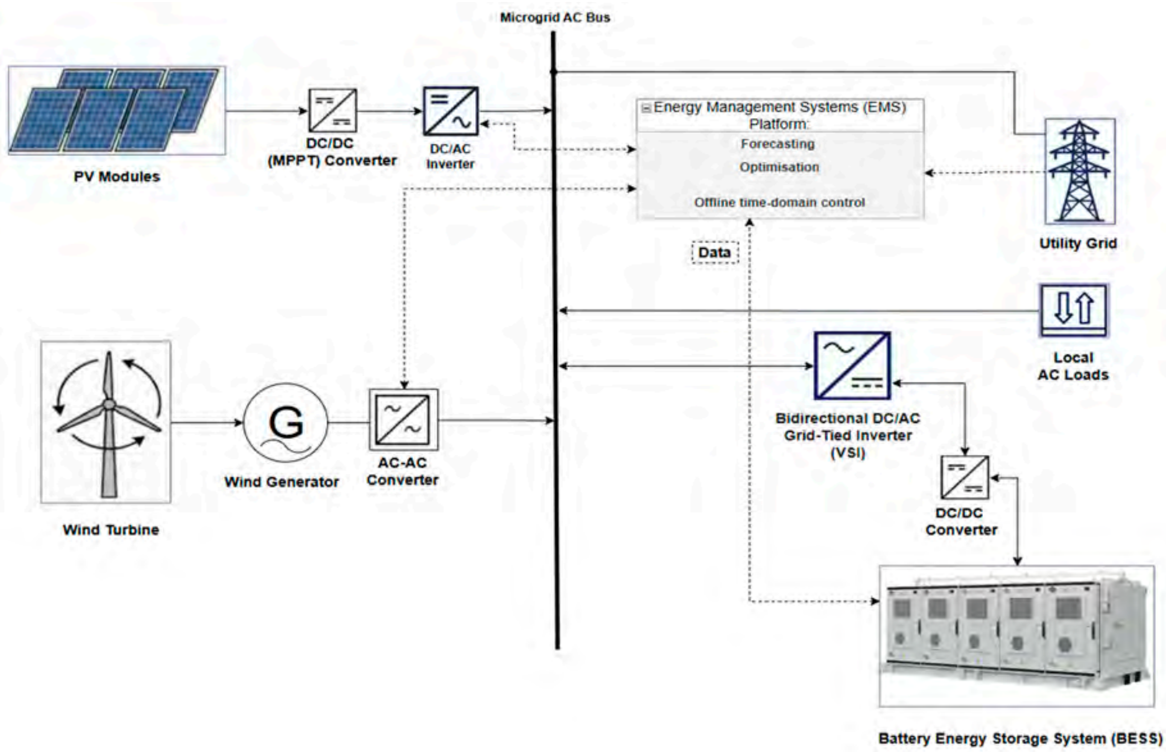

Figure 3. Proposed AC-coupled hybrid renewable energy microgrid architecture.

2.1. Energy Storage Technology Overview

Energy storage technologies deployed in modern power systems include lithium-ion batteries, flow batteries, lead–acid batteries, and supercapacitors; each technology exhibits distinct electrochemical or electrostatic characteristics that determine its energy and power capability, response speed, lifetime, and degradation behaviour, dictating its suitability for specific grid services. Lithium-ion batteries dominate residential, commercial, and utility-scale energy storage applications due to their high energy density, high round-trip efficiency, and favourable cycling performance. These characteristics make them well suited for energy arbitrage, peak shaving, renewable generation smoothing, and ancillary grid services. However, lithium-ion batteries are sensitive to operating conditions such as high C-rates, deep depth-of-discharge cycling, and elevated temperatures, which accelerate capacity fade and internal resistance growth. As a result, their effective utilization increasingly depends on degradation-aware operational and optimization strategies that explicitly account for lifetime impacts. Flow batteries, particularly vanadium redox systems, offer long cycle life and the ability to independently size power and energy capacity [19].

This decoupling makes them attractive for long-duration storage and high-cycling applications, including renewable firming and capacity adequacy support. Despite these advantages, their lower energy density and higher capital costs limit widespread deployment, confining most applications to large-scale stationary installations. Lead–acid batteries remain relevant in low-cost backup and off-grid applications where simplicity and low initial investment are prioritized. However, limited cycle life, reduced depth-of-discharge (DoD) tolerance, and lower efficiency restrict their suitability for systems with high renewable penetration and frequent cycling requirements.

Supercapacitors are characterized by extremely high power density and ultra-fast response times, but extremely low energy density. These properties make them effective for transient power support, voltage stabilization, mitigation of rapid PV output fluctuations, and the provision of synthetic inertia. While unsuitable for standalone energy balancing, supercapacitors provide significant value when integrated with batteries in hybrid configurations.

Beyond electrochemical batteries and pumped hydro storage, a comprehensive microgrid framework must consider other mechanical, thermal, and chemical storage mediums to support grid stability. Compressed air energy storage provides scalable long-duration storage by compressing air in underground caverns or tanks, although it operates at a lower round-trip efficiency of 40 to 70 percent. For high-power and short-duration needs, such as fast frequency stabilization, flywheels are effective mechanical storage systems. Furthermore, hydrogen and fuel-cell-based storage serves as an emerging alternative for long-term storage by converting stored hydrogen gas back into electricity, with system lifespans reaching around 10,000 operating hours. Finally, thermal energy storage systems, using media such as hot water tanks or phase-change materials, provide a flexible asset for shifting heating and cooling loads to integrate intermittent generation, typically offering operational lifespans of around 15 years.

Table 1 compares major energy storage technologies in terms of energy density, response time, lifespan, and key applications. The comparison supports the review by showing how different technologies serve distinct roles in modern power systems, from fast frequency support to long-duration and bulk energy storage. These differences are important for lifecycle-aware techno-economic assessment, particularly when considering degradation, replacement needs, and long-term planning in renewable-integrated power systems.

Table 1. Comparison of energy storage technologies.

Technology	Energy Density	Response Time	Lifespan	Key Applications
Lithium-ion	High	Less than 1 s	10 to 15 years	Peak shaving, energy shifting
Flow Batteries	Low	Seconds	10,000–20,000 cycles	Long-duration storage
Lead–Acid	Low	Seconds	5 to 15 years	Backup power
Supercapacitors	Very Low	Milliseconds	Up to 1,000,000 cycles	Fast frequency support
Pumped Hydro Storage	Low	15 to 30 s	50 to 100 years	Bulk energy storage
Flywheels	Low	Seconds	Up to hundreds of thousands of cycles	Fast frequency support
Compressed Air	Low	Minutes	20 to 40 years	Long duration and bulk energy storage
Hydrogen and Fuel Cells	High	Seconds to minutes	Around 10,000 operating hours	Long-term chemical storage
Thermal Storage	Variable	Minutes	Around 15 years	Heating and cooling load shifting

2.2. Energy Storage Integration Topologies

Beyond storage technology selection, the electrical arrangement of renewable generators, energy storage devices, and power electronic interfaces, referred to as the integration topology, plays a critical role in determining overall system efficiency, flexibility, and controllability. Current research and practical implementations primarily focus on three configurations: AC-coupled systems, DC-coupled systems, and hybrid storage architectures. The Hybrid Energy Storage System (HESS), most commonly combining batteries and supercapacitors, has gained increasing attention in AC microgrids. In such systems, batteries manage medium- to long-term energy balancing, while supercapacitors handle fast transients and high-power events. This functional separation reduces high C-rate stress on batteries, mitigates degradation, and improves overall system resilience and lifetime performance.

2.2.1. AC-Coupled Systems

In AC-coupled architectures, the PV generation and battery energy storage systems are connected to a common AC bus through separate inverters; AC-coupled systems are suitable for retrofitting existing PV installations, as storage can be added without major modification to the PV-side hardware; AC-coupled systems also have modular expansion and clear functional separation between generation and storage subsystems, but typically need multiple power conversion stages, thus losing a significant amount of energy through conversions from DC to AC and then back to DC for charging before being reconverted to AC for grid injection, which lowers the overall efficiency compared to DC-coupled architectures. As shown in Figure 4, RES and the battery system each connect to a shared AC bus through their own inverters, making this design flexible and easy to add to existing systems; however, this requires multiple conversions of electricity, resulting in higher losses and lower efficiency than with a DC-coupled system.

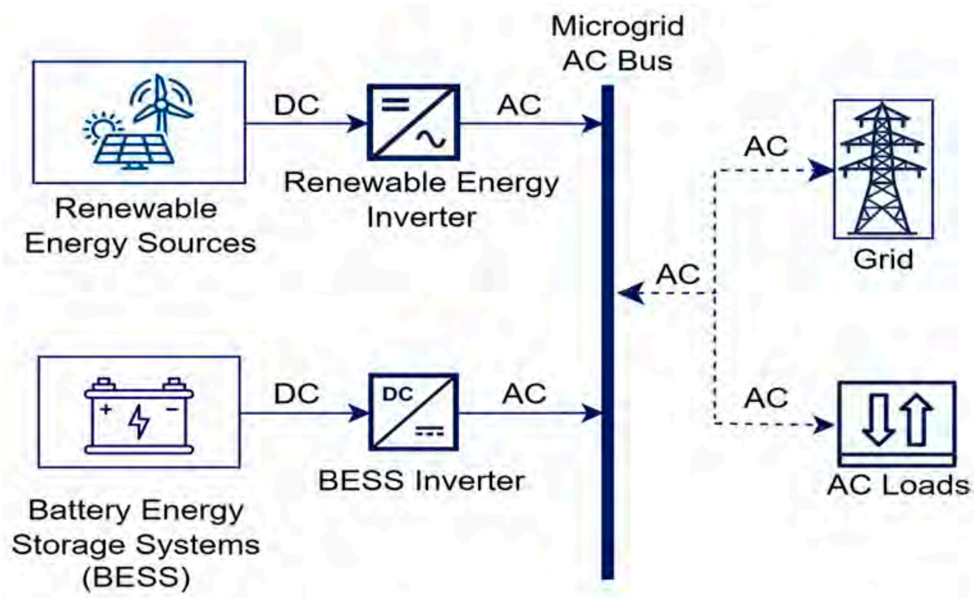

Figure 4. AC-coupled architecture.

2.2.2. DC-Coupled Systems

DC-coupled architectures connect PV arrays and energy storage systems to a shared DC bus via DC–DC converters, with a single inverter interfacing the DC bus to the grid or AC loads. This configuration reduces the number of conversion stages and enables direct PV-to-battery charging, leading to improved system efficiency. DC-coupled systems are particularly suitable for new installations and advanced AC microgrids, where DC-bus voltage regulation and coordinated power flow control can be implemented within the energy management system [20–22]. However, these benefits come at the cost of increased control and protection complexity. Recent studies indicate that implementing DC distribution for commercial fleets can result in significant reductions in CAPEX and OPEX while increasing system efficiency by approximately 3% compared to AC distribution. Figure 5 shows the DC-coupled configuration with dedicated converters to integrate RES and BESS through a common DC bus, while a single grid-forming inverter connects the stabilized DC bus to the grid and AC loads. Compared with the AC-coupled alternatives, this configuration reduces power conversion stages, enables direct PV-to-battery charging, and improves system efficiency.

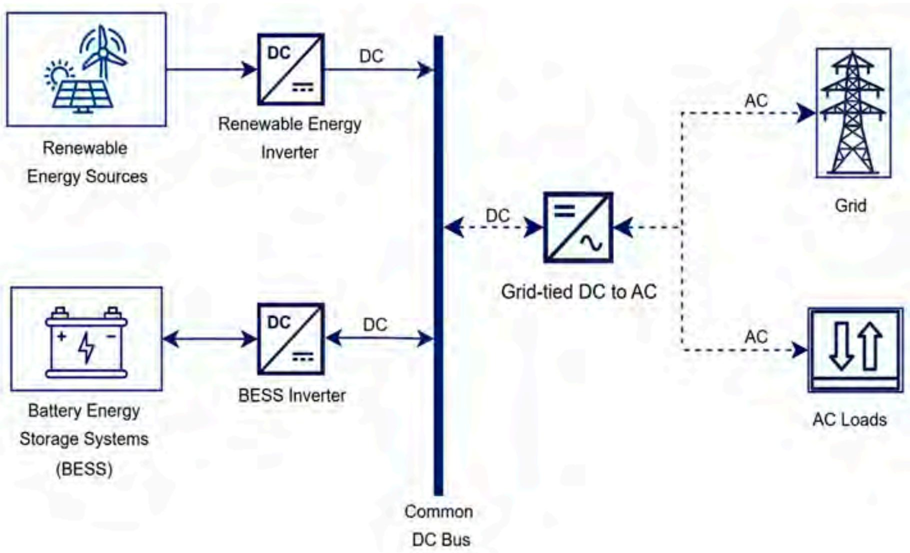

Figure 5. DC-coupled architecture.

2.2.3. Hybrid Energy Storage Architectures

Hybrid energy storage architectures integrate multiple storage technologies, most commonly batteries, to exploit complementary energy and power characteristics. These configurations are increasingly adopted in AC microgrids and high-renewable-penetration systems where both long-duration energy balancing and fast transient response are required. In DC-based hybrid architectures, the supercapacitor branch buffers high-frequency PV and load fluctuations, while the battery branch manages medium- to long-term energy exchange. This coordinated operation reduces battery cycling severity, mitigates degradation, and aligns naturally with degradation-aware planning and control frameworks. This infrastructure simplifies the process of integrating photovoltaics (PVs) and storage systems, reducing the number of required converters and enhancing scalability. As shown in Figure 6, a DC-coupled HESS architecture can integrate RES, lithium-ion batteries, and supercapacitors on a common DC bus with dedicated bidirectional DC-DC converters for each storage asset. The batteries provide the sustained balancing, and the supercapacitors provide the transient buffering, thus reducing the high-frequency stress on the batteries and decreasing degradation, while a single centralized grid-tied inverter manages the efficient delivery of stabilized power to the grid and AC loads.

As shown in Table 2, a HESS integrates the high energy density and ultra-fast response capabilities of standalone units to overcome the limitations of each architecture, enabling supercapacitors to buffer transient stress and extend battery lifetime in unstable renewable energy systems.

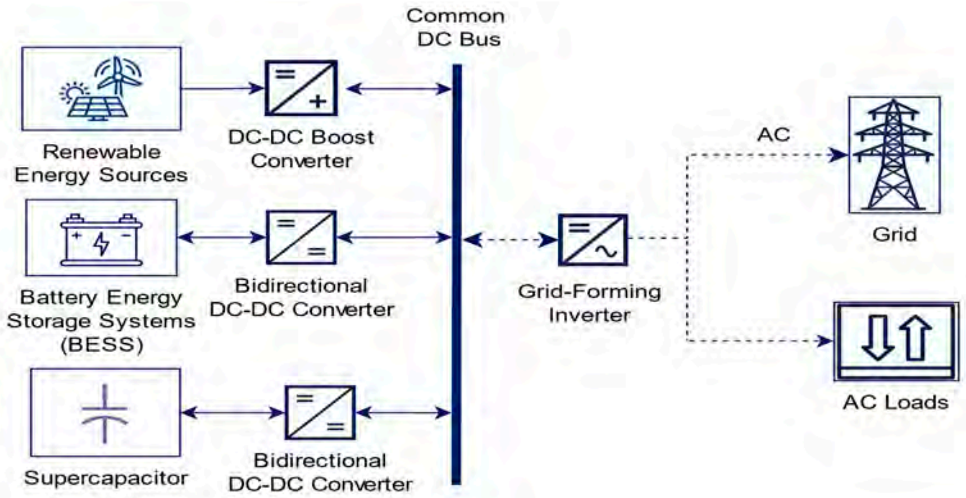

Figure 6. DC-coupled HESS.

Table 2. Comparison of storage configurations.

Feature	Battery-Only	Supercapacitor-Only	HESS (Battery + SC)
Response Time	Moderate	Ultra-fast	Multi-scale (Fast and Slow)
Energy Capability	High	Very Low	High
Degradation Stress	High	Low	Reduced (SC buffers stress)
Lifetime	Shorter	Very Long	Extended (Battery protected)
Primary Use	Energy shifting	Transient mitigation	Microgrids with high variability

2.2.4. Solid-State Transformers in Hybrid AC and DC Microgrids

Solid-state transformers (SSTs) are emerging power electronic interfaces that enable controllable power exchange between medium-voltage AC networks, low-voltage AC loads, DC buses, renewable energy sources, and energy storage systems. Unlike conventional low-frequency transformers, solid-state transformers integrate power electronic conversion stages, enabling voltage regulation, bidirectional power flow, reactive power support, power quality improvement, and coordinated AC and DC link control. These capabilities make solid-state transformers relevant for hybrid AC and DC microgrids where renewable generation, battery energy storage systems, electric vehicle charging, and flexible loads require dynamic management.

From a control perspective, solid-state transformers can support multiport energy routing, DC bus regulation, grid-forming or grid-supporting operation, and fast disturbance response. They can also improve the coordination between distributed energy resources and storage devices by providing a flexible interface between AC and DC subsystems. However, the literature notes that these devices remain less commercially mature and can involve high capital cost variability. In addition, their implementation introduces protection challenges, semiconductor reliability concerns, and advanced supervisory control requirements. Nevertheless, solid-state transformers can simplify power routing at the system level by enabling direct interaction between AC and DC links, reducing reactive power flow issues, and improving energy management flexibility. Therefore, their application is most suitable for advanced microgrid systems where improved controllability, higher power quality, flexible energy routing, and compact design can justify the additional cost and implementation complexity.

2.3. Implications of Integration Topology for Energy Management Systems

Advanced energy management systems are constrained in their design and performance by the selection of energy storage technology and integration topology. Control methodologies, ranging from rule-based approaches to deterministic and optimization-driven techniques such as PSO and GWO, operate within the physical and electrical limitations defined by the selected architecture [23]. Therefore, the integration topology directly affects the achievable control bandwidth, optimization timeframe, and system responsiveness to dynamic disturbances [24].

For instance, DC-coupled autonomous microgrids can use direct DC-bus signalling to balance power between PV arrays, wind turbines, and batteries without the latency associated with multiple DC-AC conversion stages. In contrast, AC-coupled systems often require more sophisticated synchronization and frequency regulation protocols to maintain stability between distributed resources [25]. In addition to conventional AC-coupled and DC-coupled converter-based architectures, solid state transformers represent an advanced interface for future hybrid AC and DC microgrids. They offer enhanced controllability, coordinated AC and DC link operation, and flexible power routing, but at the expense of higher cost, increased protection complexity, and implementation challenges.

It is therefore essential to explicitly define system boundaries, power flow pathways, and converter interfaces to ensure consistency in future analyses involving economic modelling, deterministic load and generation modelling, and optimization-based energy management system design [26]. The technological and architectural considerations outlined in this section establish the foundation for the economic, deterministic, and control frameworks examined through offline simulation in the subsequent sections.

3. Economic Constraints and Optimization Strategies

The integration of ESS into modern power grids is not merely a technical challenge of voltage regulation and frequency control; it is fundamentally an economic optimization problem. The decision to deploy storage depends heavily on the trade-off between high upfront Capital Expenditures (CAPEX) and the long-term Operational Expenditures (OPEX), driven by efficiency losses, fuel costs, and component degradation. While technical feasibility is a prerequisite, the ultimate deployment of hybrid systems is governed by the minimization of the Net Present Cost (NPC) and the Levelized Cost of Energy (LCOE) over the project's lifetime.

3.1. Tariff Structures and Optimization Objectives

It is important to note that this review emphasizes a structural methodology of economic optimization, rather than a focus on specific monetary values or fixed rates of tariffs. Electricity prices are highly volatile, dependent on location and subject to rapid regulatory changes. Therefore, the dependence on static price inputs limits the durability and applicability of the review. Instead, this paper assesses optimization frameworks on their ability to manage dynamic price structures, such as time-of-use (TOU) ratios and peak demand penalties, rather than evaluating their efficiency at a specific, transitory price point. Currently, current literature recognizes HOMER Pro as the primary tool for modelling these complex economic constraints. The primary objective of optimization in these frameworks is to minimize the NPC, which represents the total lifetime cost adjusted to the present year and is usually expressed as the total annualized cost divided by the capital recovery factor [27].

However, static cost analysis often proves insufficient due to market fluctuations. A recent study [28] highlights that investor choice is particularly sensitive to the difference between electricity buying and selling prices. This research confirmed that advantageous feed-in tariffs are often a key factor in determining the economic viability of battery deployment, suggesting that deterministic optimization algorithms should account for tariff sensitivity rather than relying on fixed inputs.

3.2. Levelized Cost of Energy and Feasibility Across Diverse Applications

The versatility of the NPC and LCOE optimization framework is demonstrated across various scales and applications in recent literature. In the context of rural electrification, hybrid PV–battery systems have been shown to significantly undercut fossil-fuel generation costs; specifically, the optimization of groundwater pumping systems in Ecuador reveals a substantial reduction in the LCOE compared to diesel-only alternatives [29]. This highlights the economic dominance of storage in remote areas without relying on fixed price points that are vulnerable to market fluctuations. Transitioning to urban and campus microgrids, optimizing solar and wind capacities can achieve renewable fractions up to 72% while maintaining an LCOE competitive with grid tariffs [30,31].

This economic advantage extends to transportation infrastructure as well. Research into AC microgrids integrated with Electric Vehicle (EV) fleets suggests that treating EVs as flexible loads through Demand-Side Management (DSM) reduces the required stationary battery capacity, thereby lowering the overall NPC [32,33]. Furthermore, sensitivity analysis demonstrates that while hydrogen fuel cells provide reliable backup, their high LCOE currently limits them to niche applications compared to standard battery systems [34].

3.3. Site-Specific Constraints and Hybridization

To minimize the high costs of energy storage, recent literature has advocated for the diversification of energy sources and the careful choice of location to improve economic returns. Ong et al. [35] used Geographic Information Systems (GIS) alongside HOMER to assess the integration of solar and wind into an existing hydroelectric power plant. They found that, due to resource complementarity, hybridization reduces diesel dependency more efficiently than standalone solar. Similarly, Nguyen et al. [36] evaluated a solar–biogas–BESS system in Vietnam; their work demonstrated that including biogas as a dispatchable renewable energy source stabilized solar variability and allowed for a smaller, more cost-efficient battery bank in line with net-zero targets.

The importance of spatial–economic links is further strengthened by Karadeniz et al. [37] and Lauro et al. [38], who used multi-criteria decision-making and GIS to optimize the physical location of offshore wind and onshore solar assets, ensuring that LCOE calculations account for real-world resource availability constraints.

3.4. The Sizing–Dispatch Optimization Trade-Off

The critical limitation of conventional techno-economic simulation tools is the inherent contradiction between optimal system size in the planning phase and optimal dispatching in the operating phase. Although HOMER Pro is widely recognized for its robust capacity allocation, its internal dispatch strategies, specifically cycle charging and load following, are often considered too rigid for modern energy systems characterized by dynamic tariffs and high penetration of renewables. This mismatch between planning and performing has prompted researchers to explore alternative routes to optimization.

There are two primary approaches to solving this conflict: external sizing optimization and external dispatch control logic. Wahid et al. [39] noted that the proprietary derivative-free optimization algorithm used in HOMER is prone to converge to local optima, often missing the global minimum cost configuration. To address this, they utilized an external algorithm to independently optimize the capacity of PV, diesel, and battery components; this resulted in a significant reduction in the LCOE compared to native optimization. Conversely, Pontes et al. [40] asserted that the main limitation of HOMER is not in sizing accuracy, but in operational flexibility. They used MATLAB Link to replace HOMER's built-in dispatch strategies with a custom peak-aware control algorithm capable of reacting to complex tariff structures; this led to a significant reduction in grid peak demand costs without altering the underlying component sizes. The core distinctions and economic benefits of these two methodologies are concisely contrasted in Table 3.

Table 3. Comparative analysis of optimization approaches: sizing vs. dispatch.

Feature	**External Sizing Optimization [39]**	**External Dispatch Control [40]**
Primary Focus	Component capacity (CAPEX)	Operational logic (OPEX)
Critique of HOMER	Prone to local optima traps	Built-in strategies lack dynamic flexibility
Integration Insight	Achieves a lower global LCOE	Actively reduces peak demand charges

While Table 3 summarizes the fundamental distinctions between these methodologies, their practical superiority depends strongly on the specific operational environment. External sizing optimization significantly outperforms dispatch control in isolated networks, where high initial capital expenditures determine project feasibility and tariff volatility is absent. In such static environments, avoiding local optima during component selection is critical for achieving the minimum Levelized Cost of Energy. In contrast, external dispatch control is more effective in grid-integrated systems exposed to highly dynamic pricing structures and substantial peak demand penalties. Under these volatile operating conditions, the ability to actively shift loads and manage battery state of charge in real time provides significantly greater economic benefits than optimizing physical equipment capacity alone.

3.5. Integration with Physical Modelling Tools

Although HOMER provides a reliable macroeconomic view, it lacks the physical fidelity to model accurately complex shading, thermal losses, and electrochemical degradation. A meso-scale integration strategy is being adopted to address this constraint, using tools such as Helioscope or PVsyst. This integration is explicitly demonstrated in building-integrated photovoltaic (BIPV) applications [41], where the specific energy yield (kWh/kWp) is maximized by using the Helioscope to model physical constraints such as roof geometry, barrier shading, and string mismatch. This high-fidelity generation profile is then imported into the HOMER system. This smooth transmission of data ensures that the economic model is based on realistic yield data and not theoretical capacity estimates. Such a layered methodology is essential; accurate estimates of renewable energy penetration require reliable physical modelling to validate the underlying economic assumptions made in the HOMER Pro 3.18.4 techno-economic software [42].

In addition, meso-scale platforms such as PVsyst are used to perform detailed electrochemical modelling of the battery cells, which provides an accurate rate of degradation over time and allows HOMER to plan realistic costs for the replacement of batteries. Table 4 shows the specific relationship between these layers of physical and economic optimization.

3.6. Battery Degradation and Operational Trade-Offs

The oversimplification of battery ageing remains a primary limitation in standard techno-economic modelling. Optimization frameworks must distinguish between calendar ageing and cycle ageing to provide accurate estimations of life-cycle costs. Lithium-ion batteries often face significant utility challenges in 100% renewable scenarios; low utilization in seasonal roles can severely undermine their economic feasibility [43]. Flow batteries provide a robust alternative for grid integration because they typically exhibit superior cycle life compared to solid-state variants [44]. However, in hydrogen-based systems, the finite lifespans of electrolysers and fuel cells impose strict constraints on operational scheduling [45]. The penetration of rooftop solar and electric vehicle charging infrastructure creates rapid fluctuations that increase the stress on storage assets, leading to power quality issues and accelerated capacity fade [46,47]. Operational strategies must reconcile the conflict between short-term demand response and the long-term preservation of component health [48].

Table 4. Alignment of physical and economic optimization tools.

Feature	(PVsyst and Helioscope)	Macro-Scale Tool (HOMER Pro 3.18.4)	Integration Advantage
Primary Function	Physical modelling (e.g., shading, string layout).	Economic dispatch modelling focused on energy balancing and cost optimization.	Ensures that economic models are based on realistic energy yield rather than theoretically installed capacity.
Battery Modelling	Electrochemical cell degradation analysis.	System autonomy and replacement forecasting.	PVsyst provides effective battery capacity degradation over time, which allows HOMER to schedule realistic replacement costs
Optimization Goal	Maximize physical energy yield.	Minimize Net Present Cost (NPC).	Links physical yield directly to economic savings.

Improper management can lead to inconsistent performance and increased operational expenses, particularly when the system is subjected to high-frequency charge–discharge transitions [49]. These factors necessitate a health-aware control strategy, assessed through offline simulation, to balance AC-microgrid stability against the high replacement costs of storage assets [50].

4. State of the Art in Hybrid Renewable Energy Systems and Forecasting

While the selection of appropriate energy storage technologies and integration topologies establishes the physical capabilities of a modern power system, the operational efficiency of these assets is fundamentally governed by the cyber layer of the EMS. The stochastic variability of RES, particularly solar and wind, introduces complexities that traditional deterministic control models struggle to manage effectively [51,52]. Consequently, the state of the art has migrated toward advanced co-simulation integration. These leverage structured text automation and hybrid metaheuristic frameworks capable of handling non-linear dependencies and complex operational constraints [53,54]. This section critically reviews the current landscape of automated control architectures, hybrid optimization strategies for system stability, and the requisite operational frameworks that underpin these advanced techniques.

4.1. Advanced Load and Distribution Forecasting

Accurate load and distribution forecasting serves as the fundamental prerequisite for reliable microgrid operation and optimal energy dispatch. As modern power networks transition toward high renewable penetration, advanced predictive frameworks have become essential for managing the complex variability inherent in smart grids and decentralized energy systems [55,56]. Traditional deterministic approaches often fail to capture the highly non-linear nature of modern electrical loads; consequently, stochastic modelling architectures have emerged as the standard for extracting complex temporal patterns from historical operational data. On the generation side, profiling the exact output of renewable resources is vital to maintain AC-microgrid stability and minimize reliance on expensive spinning reserves. Advanced forecasting architectures are highly effective at predicting solar radiation and wind availability; they reliably model both power consumption and generation profiles over varying time horizons [57,58]. By capturing the complex dependencies of meteorological variables, these robust mathematical frameworks provide grid operators with the precise generation estimates necessary to schedule energy storage dispatch effectively. On the demand side, predicting load consumption requires sophisticated techniques to account for heterogeneous consumer behaviour and shifting daily schedules. Structured load models enhanced by data clustering techniques significantly improve short-term forecasting accuracy across diverse multi-type buildings and commercial facilities. This highly granular approach to load profiling directly empowers advanced anomaly detection and automated demand response mechanisms [59–61]. Ultimately, integrating these robust forecasting methods is critical for the effective management of variable renewable energy systems. It ensures that the overarching energy management system operates with exceptionally reliable power estimations to minimize levelized costs and preserve overall grid stability [61,62].

The efficacy of these predictive models is best evaluated through standardized error metrics, primarily the Mean Absolute Percentage Error and Root Mean Square Error. Table 4 provides a comparative quantitative synthesis of recent artificial intelligence-driven forecasting models. The data illustrates that integrating advanced clustering and deep learning algorithms significantly reduces error margins, which directly dictates the efficiency of battery dispatch and overall grid economics.

As shown in Table 5, recent forecasting methodologies substantially enhance the operational efficiency and economic performance of Distributed Energy (DE) systems. The quantitative evidence indicates that advanced machine learning and statistical models applied to historical consumption data significantly reduce prediction uncertainty, thereby improving demand estimation and dispatch scheduling accuracy. These improvements facilitate enhanced battery utilization, reduced renewable curtailment, and more effective demand response strategies for end-use consumers. Furthermore, the comparative analysis highlights that forecasting accuracy plays a pivotal role in addressing seasonal consumption variability and peak demand events, thereby strengthening system reliability, and improving overall cost effectiveness. Overall, the synthesis demonstrates that high-precision load forecasting is a critical enabler for economically optimal and operationally resilient microgrid energy management frameworks.

Table 5. Comparative analysis of forecasting accuracy and dispatch.

Reference	Forecasting Method	Accuracy Metric	Dispatch and Economic Impact
[62]	Hybrid Ensemble Learning	Predictability coefficient of 0.9821 for renewable forecasting.	Reduced renewable uncertainty and improved decentralized system operation.
[61]	Comprehensive Artificial Intelligence Review	Improved predictive accuracy using multimodal weather and generation data.	Optimized storage scheduling and reduced power curtailment.
[59]	Clustering Enhanced Deep Learning	Reduced MAE by 14.00 percent during variable conditions.	Improved load balancing and forecasting stability.
[58]	Hybrid Deep Learning	Reduced MSE to 0.012 for household demand and 0.045 for solar generation.	Improved smart grid balancing in net zero buildings.

4.2. Hybrid Metaheuristic Optimization for Control

Beyond advanced predictive frameworks, the optimal control and sizing of Hybrid Renewable Energy Systems (HRES) represent a complex multi-objective optimization problem. A critical challenge here is the "exploration vs. exploitation" dilemma; single algorithms often fail to balance searching the entire solution space against refining a specific local solution. To address this, hybrid metaheuristic algorithms have emerged as a dominant methodology. A prominent example is the hybridization of GWO and PSO. In this dual-strategy approach, GWO is utilized for its superior exploration capabilities to locate promising regions of the solution space; meanwhile, PSO is employed to exploit the specific optimal solution within that region [63]. As illustrated in Figure 6, recent research demonstrates that the GWO-PSO hybrid significantly outperforms standalone algorithms in the optimal management of grid-connected PV–battery systems; it effectively balances technical constraints with economic targets.

To employ hybrid metaheuristic algorithms effectively, the optimization objectives must be mathematically defined. In renewable-integrated microgrids, common objective functions include emission minimization, network loss minimization, autonomy maximization, and total cost minimization.

The emissions minimization objective can be expressed as

$$F_{emissions} = \sum (t=1)^{T} \sum (g=1)^{G} P_g(t) EF_g \tag{1}$$

where $P_g(t)$ is the power generated by source g at time t, and EF_g is the emission factor of that generation source.

The network power-loss minimization objective can be expressed as

$$F_{losses} = \sum (t=1)^{T} \sum ((i,j) \in \Omega_l) I_i j^2(t) R_i j \tag{2}$$

where $I_i j(t)$ is the current magnitude in the distribution branch between nodes i and j at time t, and $R_i j$ is the branch resistance.

System autonomy can be improved by minimizing the loss of power supply probability:

$$F_{autonomy} = LPSP = \frac{(\sum (t=1)^{T} L_{unmet}(t))}{\sum (t=1)^{T} L_{demand}(t)} \tag{3}$$

where $L_{unmet}(t)$ is the unmet load at time t, and $L_{demand}(t)$ is the total load demand. A lower LPSP value indicates higher autonomy and improved local supply reliability.

The total cost minimization objective can be expressed as

$$F_{cost} = C_{cap} + C_{op} + C_{maint} + C_{deg} + C_{grid} \tag{4}$$

where C_{cap}, C_{op}, C_{maint}, C_{deg} and C_{grid} represent capital, operating, maintenance, degradation, and grid-interaction costs, respectively.

These individual objectives can be combined into a weighted multi-objective function:

$$F_{total} = w_1 F_{cost} + w_2 F_{emissions} + w_3 F_{losses} + w_4 F_{autonomy} \tag{5}$$

where w_1, w_2, w_3, and w_4 are weighting coefficients selected according to the economic, environmental, technical, and reliability priorities of the microgrid. This formulation enables hybrid optimization algorithms to balance economic performance, environmental impact, network efficiency, and energy autonomy.

Equations (1)–(5) define the main objective functions used to guide optimization-based energy management in renewable-integrated microgrids. Equation (1) represents emission minimization by reducing the contribution of generation sources with higher emission factors and encouraging greater utilization of renewable generation and storage dispatch. Equation (2) targets network loss minimization by reducing branch current-related losses across the distribution network, which improves technical efficiency and reduces unnecessary energy dissipation. Equation (3) supports autonomy maximization by minimizing the loss of power supply probability, where a lower LPSP value indicates greater local supply reliability and reduced dependence on external grid support. Equation (4) represents total cost minimization by combining capital, operating, maintenance, degradation, and grid-interaction costs, thereby linking operational dispatch decisions with long-term economic feasibility. Finally, Equation (5) combines these objectives into a weighted multi-objective function, allowing hybrid metaheuristic algorithms to balance economic, environmental, technical, and reliability priorities according to the specific requirements of the AC microgrid.

This formulation is important because energy storage operation is not governed by a single objective. For example, a dispatch strategy that minimizes cost may increase battery degradation, while a strategy that maximizes autonomy may require additional cycling or higher storage capacity. Similarly, reducing emissions and network losses may require different dispatch priorities depending on renewable availability, load demand, and grid conditions. Therefore, the weighted formulation in Equation (5) provides a flexible structure for hybrid algorithms such as GWO-PSO to search for a balanced solution rather than optimizing one performance indicator in isolation. By adjusting the weighting coefficients, the energy management system can prioritize cost reduction, reliability, emission reduction, or technical efficiency depending on the operational goals of the microgrid.

Other evolutionary approaches, such as the Slime Mould Algorithm and Genetic Algorithms (GA), are also being deployed to solve multi-objective problems related to the energy trilemma [16]. However, translating these complex algorithms into reliable field operations using structured text and Programmable Logic Controllers (PLCs) remains essential for managing the stochastic nature of distributed energy resources (DERs) and ensuring grid stability.

4.3. Data Preprocessing and Feature Extraction

The accuracy of advanced predictive and control algorithms is heavily dependent on the quality of data input. Raw renewable energy data is often non-stationary and contains noise due to sensor errors, environmental interference, or transmission failures [64]. Therefore, robust pre-processing frameworks are essential for reliable algorithm execution. Signal decomposition strategies, such as Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), and Wavelet Decomposition (WD), are widely employed to handle the severe volatility of wind and solar data. These methods break down complex, non-stationary time series into simpler sub-signals or Intrinsic Mode Functions (IMFs). This "divide and conquer" strategy allows forecasting frameworks to calculate individual components separately, significantly improving overall operational reliability [64,65].

Additionally, data normalization techniques, such as Min–Max scaling, are standard practice to accelerate algorithm convergence by scaling inputs to a specific range. Furthermore, addressing missing data through advanced imputation methods rather than simple deletion is crucial for maintaining the integrity of time-series datasets used in executing hybrid control strategies. Table 6 describes the core pre-processing techniques needed to prepare raw, unstable AC-microgrid data for accurate forecasting and optimal control.

Simple scaling methods such as Min–Max and Z-score standardization are essential to accelerate the convergence of hybrid algorithms. Meanwhile, complex decomposition strategies, such as EMD, VMD, and WT, are required to isolate underlying trends from severe signal noise. Ultimately, selecting the right technique based on the specific characteristics of the dataset enables the energy management system to effectively mitigate the unpredictability of renewable energy production.

Table 6. Comparative analysis of data preprocessing techniques.

Technique	Primary Function	Best Use Case
Min–Max Normalization	Scales features to a fixed range (e.g., 0 to 1)	Accelerating algorithm convergence (e.g., GWO-PSO)
Z-Score Standardization	Transforms data to mean 0 and standard deviation 1	Handling datasets with significant, unpredictable outliers.
Empirical Mode Decomposition (EMD)	Breaks non-linear signals into Intrinsic Mode Functions	Processing highly volatile renewable data (e.g., wind speed)
Variational Mode Decomposition (VMD)	Separates signals into band-limited modes	Isolating true signal trends from severe weather noise
Wavelet Transform (WT)	Multi-resolution time–frequency domain decomposition.	Denoising sudden transient events or severe weather spikes.
Principal Component Analysis (PCA)	Transform correlated variables into uncorrelated components.	Reducing feature redundancy in high-dimensional weather data
Seasonal-Trend Decomposition (STL)	Separates seasonal, trend, and residual components	Load forecasting scenarios with strong seasonal fluctuations

4.4. System Integration and Techno-Economic Modelling

The integration of advanced co-simulation automation strategies into practical power systems requires robust simulation tools to validate their economic and technical viability. In the existing literature, tools such as HOMER Pro are widely used to design and optimize HRES configurations at a macro-economic level; however, traditional feasibility studies often simplify microgrids as balanced single-phase systems to reduce computational load [66]. Recent techno-economic modelling has addressed the severe complexities of unbalanced three-phase AC networks [67]. This paradigm shift is critically important because modern energy management systems must accurately reflect the physical realities of low-voltage distribution grids where phase asymmetries and volatile load imbalances are highly prevalent. To bridge the critical gap between static capacity planning and dynamic control, emerging techno-economic frameworks now couple macro-scale sizing software with high-fidelity dynamic simulators. Researchers increasingly incorporate optimization models such as Mixed-Integer Linear Programming (MILP) and MATLAB-based environments to perform joint optimal sizing and transient operational analysis [68]. This integrated approach explicitly accounts for the physical power quality challenges that static economic models traditionally overlook. By validating rigorous operational constraints against long-term economic targets, such coupled models ensure that infrastructure investment decisions remain resilient to both financial uncertainty and severe physical grid disturbances.

Moreover, the current frontier of system integration in the literature emphasizes the necessary transition from isolated software models to advanced co-simulation validation. Advanced studies now utilize dynamic simulation environments, such as MATLAB/Simulink, to execute complex control programming. This enables offline simulation of hybrid metaheuristic algorithms such as GWO-PSO. This layered approach combines deterministic time-series forecasting, hybrid optimization, and high-fidelity three-phase simulation, forming a comprehensive basis for modern EMS. Such rigorous validation frameworks are essential to advance these control strategies from theoretical academic research into highly reliable NNS for AC microgrids.

5. Hybrid Control Strategies

The integration of renewable energy sources requires advanced management to maintain the balance between supply and demand; current literature indicates that metaheuristic optimization algorithms provide a reliable mechanism for hybrid systems [67]. Studies show that approaches such as the GWO effectively determine the optimal sizing and control of energy storage systems to minimize the error between the initial and final state of charge [67]. Building directly upon these optimization strategies, recent research highlights that the optimal integration of battery storage serves as a highly efficient non-network solution for expanding AC-microgrid capacity. While traditional grid planning relies heavily on capital-intensive infrastructure improvements, modern frameworks prioritize smart investment options to defer these massive costs [68]. Furthermore, utilizing techno-economic modelling tools enables researchers to rigorously verify the financial and technical feasibility of deploying non-network solutions under varying load conditions and generation uncertainties [69]. A summary of key NNS solution integration for AC microgrids is shown in Table 7.

Table 7. Key non-network solution integration factors for AC microgrids.

Factor	Description	Related Framework
Techno-Economic Feasibility	Validating smart investments against traditional infrastructure upgrades.	Links to the techno-economic models discussed in Section 3.
System Health Index	Incorporating physical asset condition to defer equipment replacements.	Expands on the physical constraints mapped in Figure 2.
Voltage Stability	Coordinating NNS to ensure grid reliability in renewable-heavy systems.	Builds upon the energy management workflow in Figure 7.
Metaheuristic Optimization	Utilizing algorithms like GWO for near-optimal sizing and control.	Extends the traditional predictive strategies evaluated in Section 4.
Cost-Reflective Pricing	Accurately modelling network costs when integrating distributed energy.	Addresses the economic gaps identified in the literature.

The strategic placement and sizing of distributed renewable energy within AC microgrids fundamentally alter how network costs are estimated and modelled for cost-reflective pricing [70].

Furthermore, multi-stage integrated planning models leverage these energy storage solutions alongside scenario reasoning to enhance overall equipment selection and capacity optimization [71]. To clearly identify existing gaps in the literature, Table 8 summarizes selected planning studies. This demonstrates that while algorithms such as GWO successfully reduce installation costs and grid dependence, a substantial research opportunity remains to combine these algorithms with physical AC-microgrid constraints. Furthermore, incorporating the health index of existing physical assets into this expansion planning justifies deploying energy storage to postpone expensive equipment replacements and preserve overall grid reliability [72].

The wider implementation of non-network solutions must take AC-microgrid stability and spatial constraints into consideration, following the evaluations shown in the tables. To maximize the capacity of an AC microgrid, distributed renewable energy must be placed and sized optimally [73]. To achieve this mathematically, planners typically utilize an objective function to minimize the total expansion cost; this balances traditional infrastructure upgrades against smart NNS investments:

$$min\ C_{total} = \sum_{t=1}^{T} (C_{network}(t) + C_{NNS}(t) + C_{operation}(t) + C_{loss}(t)) \tag{6}$$

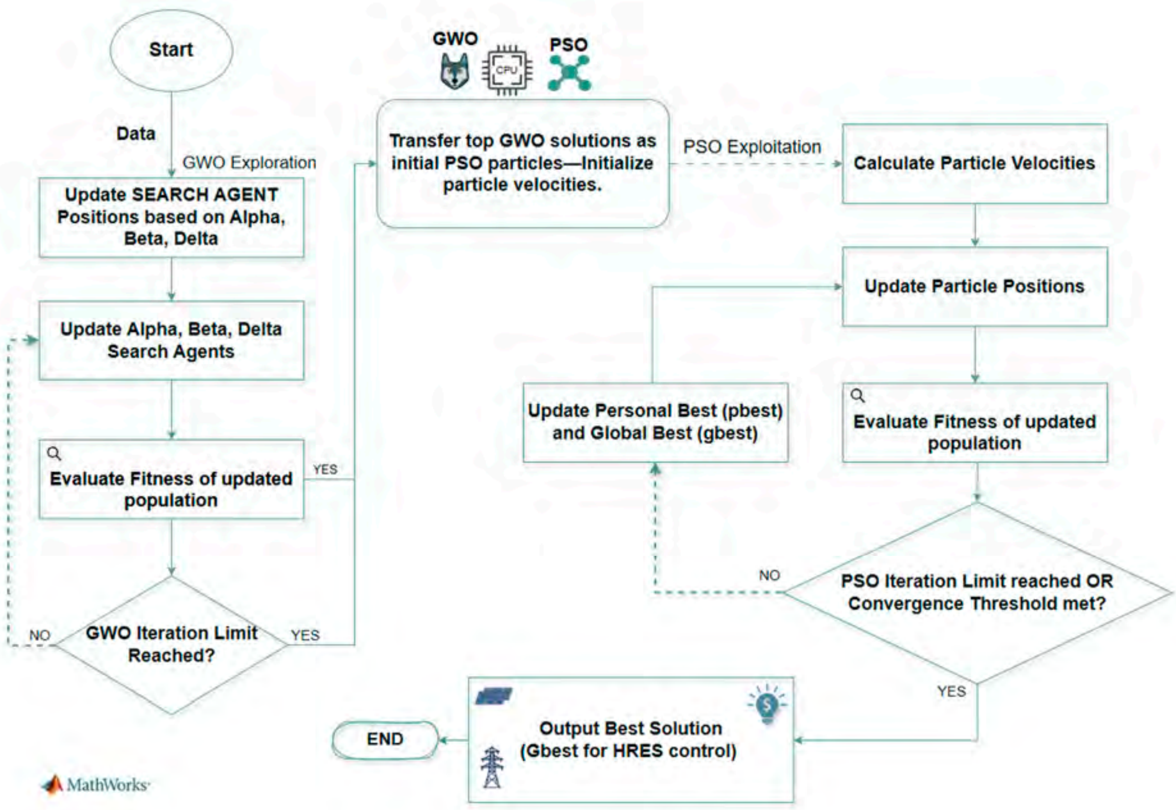

Figure 7. Schematic workflow of the hybrid GWO-PSO algorithm, detailing the HRES control calculation.

Table 8. Summary of advanced planning and control studies for hybrid microgrids.

Reference	Approach	Key Objectives	NNS Type	Benefits Highlighted
[66]	Grey Wolf Optimizer	Minimize state of charge error.	Lead–acid and lithium-ion batteries.	Reduced grid dependence and lower installation costs.
[67]	Expansion planning review	Evaluate new market designs.	Distributed energy resources.	Identifies pathways for modern grid market integration.
[68]	Multi-stage planning	Optimize transmission and distribution.	Smart investment options.	Manages load uncertainties and defers capital expenditure.
[69]	Cost-reflective modelling	Estimate and model network costs.	Distributed renewable energy.	Establishes fairer pricing schemes and accurate cost allocation.
[70]	Multi-level planning	Optimize equipment capacity.	Integrated energy systems.	Enhances scenario reasoning for precise component selection.
[71]	Health index incorporation	Delay physical equipment replacement.	Battery energy storage systems.	Optimize capital allocation and extends physical asset lifespan.

Beyond economic sizing, these non-network solutions must be coordinated with dynamic reactive power compensators, such as Static Synchronous Compensators (STATCOMs), to ensure voltage stability during transient events in wind-penetrated AC microgrids [74].

This dynamic support principle extends even to complex offshore networks, where planners evaluate the feasibility of AC versus DC connection options [75]. Furthermore, putting strong group key management protocols in place is crucial to safeguarding the communication frameworks controlling these vital non-network assets as these decentralized energy storage systems become increasingly digitalized and integrated into the smart grid [76]. To fully realize these stability objectives, the physical infrastructure must be governed by advanced hybrid control strategies. Decentralized approaches such as droop control and active power–frequency control are essential for ensuring equitable load sharing and mitigating transient stability issues within AC microgrids. By integrating these primary control mechanisms with battery energy storage systems, the network can autonomously regulate voltage and frequency deviations without relying entirely on potentially vulnerable communication links.

Battery Management Systems and State Estimation in AC Microgrids

In NNS-like islanded AC microgrids, the BMS acts as the central intelligence unit, ensuring safe, optimized energy dispatch [77–80]. It continuously monitors internal cell parameters to safeguard the physical asset while coordinating with overarching energy production systems [81,82]. When integrated with renewable generation, the BMS governs bidirectional DC-DC converters to align battery output safely with highly variable solar or wind resources [83,84]. By strictly monitoring operational limits, it protects the system against severe hazards like thermal runaway and deep discharging [85,86]. It actively or passively redistributes energy to equalize charge levels across varying cells, ensuring no single cell limits the usable energy range during peak production cycles [87,88]. To execute these production and protection strategies effectively, the NNS-integrated BMS must manage two distinct but correlated metrics: the SoC and the SoE [89,90]. In advanced academic modelling, these metrics are primarily defined using standard continuous-time integral equations. SoC quantifies the remaining available charge using Coulomb counting [91,92]. However, it possesses a significant limitation because it does not account for the nonlinear terminal voltage dynamics during operation [50]. It is defined mathematically as

$$SoC_t = SoC_0 - \frac{\int_0^t i(\xi)\, d\xi}{C_n} \tag{7}$$

where C_n represents the nominal capacity. Similarly, SoE incorporates real-time voltage variations by integrating power over time [93,94], because useful battery capacity varies nonlinearly with terminal voltage, internal parameters, and temperature. SoE provides a much more direct and accurate representation of the actual energy an NNS can produce and supply to the grid [95]; it is formally defined as

$$SoE_t = SoE_0 - \frac{\int_0^t i(\xi) u(\xi)\, d\xi}{E_n} \tag{8}$$

where E_n is the nominal energy and $u(\xi)$ is the terminal voltage.

While these continuous-time integral formulas form the rigorous computational foundation for a deterministic BMS, they are practically interpreted through simplified operational ratios for system monitoring under offline simulation. For SoC, this ratio is explicitly defined as

$$SoC = \frac{Remaining\ Charge\ (\mathrm{Ah})}{Nominal\ Capacity\ (\mathrm{Ah})} \times 100 \tag{9}$$

Similarly, the operational ratio for the State of Energy is defined as

$$SoE = \frac{Remaining\ Energy\ (\mathrm{KWh})}{Nominal\ Capacity\ (\mathrm{KWh})} \times 100 \tag{10}$$

Furthermore, research demonstrates a highly stable positive correlation between SoC and SoE, which can be mathematically modelled using a quadratic polynomial [92]:

$$SoE = \ a \cdot Soc^2(k) \ + \ b \cdot \mathrm{SOC}(k) \ + \ c \tag{11}$$

Because directly measuring these states is impossible, a smart BMS utilizes advanced algorithms to process current, voltage, and temperature data under offline simulation to co-estimate both metrics [95–97]. This co-estimation allows the BMS to correct sensor noise and cumulative errors by cross-referencing their strong positive correlation [98–100]. For islanded AC microgrids, the BMS must prioritize SoE over SoC for load distribution and energy production decisions [101,102]. While SoC indicates the charge percentage required for internal cell balancing, SoE accurately quantifies the actual releasable energy, preventing the BMS from overestimating available capacity and causing unexpected power shortages during dispatch [102]. Collectively, Equations (6)–(11) provide the mathematical foundation for battery state estimation and dispatch coordination within AC microgrids. These equations define the continuous-time and operational forms of SoC and SoE, as well as their polynomial relationship, which supports degradation-aware battery operation and grid-aware energy management under offline simulation. When combined with the objective functions in Equations (1)–(5), these state-estimation equations help link optimization targets, battery health constraints, and dispatch decisions within a unified AC-microgrid energy management framework. Table 9 summarizes the operational comparison of SoC and SoE in Battery Management Systems.

Table 9. Quantitative improvements in state tracking and economic operation.

Parameter/Algorithm	Quantitative Tracking Improvement	Direct Economic and Operational Effect	Reference
SoC	Improved tracking performance by 3.1 percent.	Prevented saturation; reduced required battery cell count.	[66]
SoE	Reduced capacity estimation error by 5 percent.	Prevented capacity overestimation; prevented unexpected power shortages.	[99]
Hybrid GWO-PSO	Precise offline time-domain state tracking.	Lowered Total Net Present Cost; reduced expensive grid energy imports.	[63]

This table synthesizes the quantifiable improvements in state estimation and their direct economic impacts when managed by advanced hybrid control algorithms. The data illustrates that precise tracking of the State of Charge improves operational performance by 3.1 percent, which directly reduces the required number of battery cells and lowers capital costs. Furthermore, prioritizing State of Energy reduces capacity estimation errors by 5 percent, preventing the system from overestimating available energy and avoiding costly power shortages. By integrating these precise state estimations, algorithms like the Grey Wolf Optimizer and Particle Swarm Optimization successfully balance transient technical constraints with macro-economic targets, ultimately lowering the Total Net Present Cost and reducing reliance on expensive grid imports.

The successful deployment of non-network solutions depends heavily on the sophisticated capabilities of the BMS. By accurately monitoring the internal charge state health limits through the State of Charge, alongside the grid-aware operational performance represented by the State of Energy, the system bridges the critical gap between battery protection and economically efficient grid operation. This dual-state estimation ensures that distributed energy storage assets can reliably deliver the precise amount of energy required to defer costly infrastructure upgrades without unintentionally accelerating battery degradation or causing premature decommissioning.

Quantitatively, improved SoE estimation directly influences economic outcomes by mitigating battery degradation costs. Accurate SoE tracking prevents the system from overcommitting storage resources, thereby avoiding unnecessary charging and discharging cycles as well as excessive depth-of-discharge events. Since cycle ageing is proportional to both the total energy exchanged and the depth of discharge, minimizing these unnecessary cycles reduces the degradation cost per kilowatt-hour. Consequently, this precise operational control extends battery cycle life, delays significant capital replacement expenditures, and lowers the overall Levelized Cost of Storage. Furthermore, achieving comprehensive dynamic stability requires these non-network solutions to operate in coordination with primary network support technologies such as STATCOMs. A STATCOM is a power-electronics-based device that provides dynamic reactive power support to maintain short-term voltage stability during transient grid disturbances. While relying solely on conventional network reinforcement solutions is both expensive and operationally inflexible, coordinating STATCOMs with distributed battery energy storage systems maximizes voltage stability enhancement at a fixed investment cost.

The reviewed literature demonstrates that integrating advanced deterministic energy management frameworks with coordinated reactive power compensation is not merely a complementary operational strategy. Rather, it is a fundamental requirement for ensuring the long-term techno-economic viability and dynamic stability of modern low-inertia power systems.

6. Conclusions and Future Trends

As modern energy systems continue to decentralize, future research must increasingly address the inherent conflict between macro-scale economic planning and micro-scale dynamic stability. The next generation of advanced deterministic energy management systems will need to rely on highly advanced, adaptive control strategies to achieve unprecedented accuracy in the face of extreme renewable variability. This will enable a critical shift from reactive fault mitigation to proactive, grid-aware energy planning. Future frameworks must optimize droop controls to precisely manage active power sharing and maintain strict frequency stability in low-inertia environments. Moreover, the continuous development of hybrid metaheuristic algorithms, such as the GWO-PSO framework, must transition from theoretical software simulations to real-time industrial automation applications. Validating these complex control logics through real-time Power Hardware-in-the-Loop (HIL) platforms, such as OPAL-RT, alongside standard industrial protocols like ST, will be vital for active distribution network management. Crucially, the success of this instantaneous adaptive control over bidirectional energy flows will depend heavily on next-generation BMS utilizing rigorous co-estimation algorithms to provide flawless real-time SoE boundary conditions.

Finally, the transition to a decarbonized energy landscape requires a fundamental paradigm shift from traditional, capital-intensive pole-and-wire upgrades to smart, highly responsive Non-Network Solutions. The reviewed literature demonstrates that BESS can fulfil this critical infrastructure deferral role only if their integration is treated as a tightly coupled, multi-dimensional optimization problem rather than a simple hardware installation. By seamlessly linking degradation-aware economic modelling in tools such as HOMER Pro to high-fidelity physical generation data from PVsyst and dynamic transient control in MATLAB/Simulink, network operators can successfully bridge the critical optimization gap identified in contemporary studies. This holistic, multi-scale framework ensures that the strategic deployment of energy storage not only preserves grid stability in the absence of rotational inertia but also minimizes LCOE over the project lifecycle. Consequently, it delivers the secure, equitable, and sustainable infrastructure required to solve the modern energy trilemma.

Author Contributions: Y.I.R.A. managed the conceptualization, methodology, investigation, and writing of the original draft. K.P. contributed to the conceptualization and methods, and reviewed and edited the manuscript. J.K. reviewed and edited the manuscript. Both K.P. and J.K. supervised the PhD student Y.I.R.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Oladigbolu, J.; Bakare, M.S.; Motlagh, S.G.; Mujeeb, A.; Li, L. A review on transport and power systems planning-operation integrating electric vehicles, energy storage, and other distributed energy resources. *J. Energy Storage* **2025**, *135*, 118419. [CrossRef]
2. Zhang, J.; Zhang, Y.; Shuai, X.; Wang, X.; Zhang, L.; Xin, C.; Wang, Z. Power Planning Analysis for High Proportion of Renewable Energy with Multiple Flexible Resources. In *Proceedings of the 2024 6th Asia Energy and Electrical Engineering Symposium, AEEES 2024*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2024; pp. 1250–1254. [CrossRef]
3. Liu, J.H.; Chu Tsai, C.; Wu, C.C.; Wu, G.B.; Chen, K.L. Integration and Implementation of Distributed Battery Energy Storage for Grid Support Technology. In *Proceedings of the 2025 IEEE Industry Applications Society Annual Meeting (IAS)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–8. [CrossRef]
4. Galea, S.; Licari, J.; Micallef, A. Mitigating Power Quality Issues Due to Renewable Energy in Maltese LV Distribution Networks with Battery Energy Storage Systems. In *Proceedings of the EUROCON 2025: 21st International Conference on Smart Technologies*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025. [CrossRef]
5. Vaziri Rad, M.A.; Kasaeian, A.; Niu, X.; Zhang, K.; Mahian, O. Excess electricity problem in off-grid hybrid renewable energy systems: A comprehensive review from challenges to prevalent solutions. *Renew. Energy* **2023**, *212*, 538–560. [CrossRef]
6. Zhao, B.; Ren, J.; Chen, J.; Lin, D.; Qin, R. Tri-level robust planning-operation co-optimization of distributed energy storage in distribution networks with high PV penetration. *Appl. Energy* **2020**, *279*, 115768. [CrossRef]
7. Al-Ismail, F.S. DC Microgrid Planning, Operation, and Control: A Comprehensive Review. *IEEE Access* **2021**, *9*, 36154–36172. [CrossRef]
8. Supian, M.F.I.M.; Redzuan, S.M.; Halim, F.H.A.; Talim, M.A.; Idros, M.F.M.; Razak, A.H.A.; Abdin, A.F.; Al Junid, S.A.M. *A Science Mapping Review of Energy Storage Systems Enabling Resilient Grid Stability in the Renewable Era*; Institute of Electrical and Electronics Engineers (IEEE): Piscataway, NJ, USA, 2025; pp. 1–12. [CrossRef]
9. Naima, B.; Belkacem, B.; Ahmed, T.; Benbouhenni, H.; Riyadh, B.; Samira, H.; El-Barbari, Z.M.S.; Mohammed, S.A. Enhancing MPPT optimization with hybrid predictive control and adaptive P&O for better efficiency and power quality in PV systems. *Sci. Rep.* **2025**, *15*, 24559. [CrossRef] [PubMed]
10. Kalaivani, C.; Subramanyam, M.V.; Singaram, G.; Udhaya Kumar, A.; Mohanraj, K.; Saravanakumar, R. Review of Hybrid Microgrid Power Management Using Renewable Energy Sources. In *Proceedings of the 2023 9th International Conference on Advanced Computing and Communication Systems, ICACCS 2023*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2023; pp. 1491–1496. [CrossRef]
11. Undre, V.; Mohale, V.; Chelliah, T.R.; Hote, Y.V. Synchronization Circuit Design for Battery Energy Storage Integration in DFIM-Based Hydro Power Systems. In *Proceedings of the 2024 IEEE 15th International Symposium on Power Electronics for Distributed Generation Systems (PEDG)*; IEEE: Piscataway, NJ, USA, 2024; pp. 1–6. [CrossRef]
12. Hirsch, A.; Parag, Y.; Guerrero, J. Microgrids: A Review of Technologies, Key Drivers, and Outstanding Issues. *Renew. Sustain. Energy Rev.* **2018**, *90*, 402–411. [CrossRef]
13. Ghosh, A.; Mitra, S.; Yemula, P.K. Degradation Aware Optimal Allocation of Battery Energy Storage System for Unbalanced Active Distribution Network. In *Proceedings of the Conference Record—IAS Annual Meeting (IEEE Industry Applications Society)*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025. [CrossRef]

14. Lampsidis Tompros, G.; Kontargyri, V.T.; Fotopoulou, M.; Rakopoulos, D.; Malamaki, K.-N.; Christopoulos, S.; Karafotis, P.; Moraitis, I.; Kaousias, K. The Opportunities and Limitations of the Green Energy Transition to European Networks: A Perspective Paper Focusing on the European Union and Greece. *Energies* **2026**, *19*, 1400. [CrossRef]
15. Zahari, N.E.M.; Mokhlis, H.; Mubarak, H.; Mansor, N.N.; Sulaima, M.F.; Ramasamy, A.K.; Zulkapli, M.F.; Ja'Apar, M.A.B.; Jaafar, M.; Marsadek, M.B. Integrating Solar PV, Battery Storage, and Demand Response for Industrial Peak Shaving: A Systematic Review on Strategy, Challenges and Case Study in Malaysian Food Manufacturing. *IEEE Access* **2024**, *12*, 106832–106856. [CrossRef]
16. Shrivastav, A.K.; Dutta, S. Multi-objective optimization of hybrid microgrid for energy trilemma goals using slime mould algorithm. *Sci. Rep.* **2025**, *15*, 29242. [CrossRef]
17. Jain, A.; Nagar, S.; Singh, P.K.; Dhar, J. A hybrid learning-based genetic and grey-wolf optimizer for global optimization. *Soft Comput.* **2023**, *27*, 4713–4759. [CrossRef]
18. Assaad, C.; Das, K.; Ghazouani, S. Optimizing Utility-Scale Hybrid Power Plants: Technology Mixes and Methodologies. In *Proceedings of the 2025 IEEE PES 35th Australasian Universities Power Engineering Conference (AUPEC)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–5. [CrossRef]
19. Benitez, I.B.; Cuizon, E.C.; Dizon, J.C.R.; Varela, D.A.B. Artificial intelligence for optimizing renewable energy systems: Techniques, applications, and future directions. *Int. J. Appl. Power Eng. (IJAPE)* **2026**, *15*, 275–288. [CrossRef]
20. Benosenko, E.; Vitols, K.; Avotins, A. Prospect Analysis of DC Coupled Energy Storage for PV Park. In *Proceedings of the 2025 IEEE 12th Workshop on Advances in Information, Electronic and Electrical Engineering, AIEEE 2025*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025. [CrossRef]
21. Wang, X.; Mohamed, A.A.S.; Rehman, W.u.; Bhavaraju, V. A Comprehensive Technoeconomic Evaluation of DC vs. AC-Coupled Fast Charging Solutions for Commercial Electric Vehicle Fleets. In *Proceedings of the 2025 IEEE Energy Conversion Conference Congress and Exposition (ECCE)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–7. [CrossRef]
22. Sharida, A.; Bayindir, A.B.; Bayhan, S.; Abu-Rub, H. Hierarchical Control of DC Coupled Fast EV Charging Station. *IEEE Trans. Power Electron.* **2025**, *40*, 11690–11700. [CrossRef]
23. Nguyen, T.L.; Nguyen, Q.A. A Multi-Objective PSO-GWO Approach for Smart Grid Reconfiguration with Renewable Energy and Electric Vehicles. *Energies* **2025**, *18*, 2020. [CrossRef]
24. Ibrahim, A.W.; Xu, J.; Al-Shamma'a, A.A.; Farh, H.M.H.; Aboudrar, I.; Oubail, Y.; Alaql, F.; Alfraidi, W. Optimized Energy Management Strategy for an Autonomous DC Microgrid Integrating PV/Wind/Battery/Diesel-Based Hybrid PSO-GA-LADRC Through SAPF. *Technologies* **2024**, *12*, 226. [CrossRef]
25. Rathod, A.A.; Subramanian, B. Design and optimization of various hybrid renewable energy systems using advanced algorithms for powering rural areas. *J. Clean. Prod.* **2025**, *501*, 145199. [CrossRef]
26. Yang, Y.; Bremner, S.; Menictas, C.; Kay, M. Battery energy storage system size determination in renewable energy systems: A review. *Renew. Sustain. Energy Rev.* **2018**, *91*, 109–125. [CrossRef]
27. Kumar, K.K.; Singh, S.; Kundu, S.; Saraswat, S.; Manita. Optimizing Green Energy Technologies and Energy Storage Solutions using HOMER Pro software. In *Proceedings of the 2025 IEEE Madhya Pradesh Section Conference (MPCON)*; IEEE: Piscataway, NJ, USA, 2025. [CrossRef]
28. Halmous, A.; Oubbati, Y.; Lahdeb, M. Techno-Economic Study of Grid-Connected Hybrid Renewable Energy Systems Optimized by Homer Pro. In *Proceedings of the 2024 2nd International Conference on Electrical Engineering and Automatic Control, ICEEAC 2024*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2024. [CrossRef]
29. Alvarez, D.I.; Rojas Espinoza, J.; Flores-Vázquez, C.; Cárdenas, A. A Hybrid System That Integrates Renewable Energy for Groundwater Pumping with Battery Storage, Innovative in Rural Communities. *Energies* **2025**, *18*, 5976. [CrossRef]
30. Kumar, S.; Maity, A.; Veeranjaneyulu, V.I.; Harini, M.; Melviah, G.; Vishnupriya, B. *Multi-Source Hybrid Microgrid Optimization Using HOMER Pro: A Case Study for Campus-Scale Energy Sustainability*; Institute of Electrical and Electronics Engineers (IEEE): Piscataway, NJ, USA, 2025; pp. 59–64. [CrossRef]
31. Shaswati, C.; Vandana, K.S.; Kumar, P.H.; Kumar, P.S.; Divya, K.; Rashmi, G. Design of Hybrid Renewable Energy Systems for Sustainable Power Solutions Using Homer Pro. In *Proceedings of the 7th International Conference on Energy, Power and Environment, ICEPE 2025*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025. [CrossRef]
32. Yasmeena; Lakshmi, S.; Mahto, T.; Tewari, S.V. Planning of an Electric Vehicle Fleet-Integrated Microgrid for a University Campus by Using HOMER. In *Proceedings of the 2024 IEEE 21st India Council International Conference, INDICON 2024*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2024. [CrossRef]
33. Sun, S.; Yang, F.; Lu, J. Modelling of Hybrid Microgrid with EV Charging Station Using HOMER Pro. In *Proceedings of the 2025 IEEE Region 10 Symposium: Innovations in Technology: Shaping the Future, TENSYMP 2025*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025. [CrossRef]

34. Swain, R.; Sarkar, I.; Pattnaik, M. Techno Economic Assessment and Sizing Analysis of PV, Fuel Cell and Battery Microgrid Using HOMER Pro. In *Proceedings of the 2025 IEEE North-East India International Energy Conversion Conference and Exhibition, NE-IECCE 2025*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025. [CrossRef]
35. Ong, E.I.C.; Damian, A.N.B.; Jimenez, A.P.; Ignacio, C.H.; De Ramos, L.M.; Tubola, O.D. Techno-Economic Assessment of Integrating Solar and Wind Energy to Existing Hydropower Plant in Catanduanes Island Using HOMER and GIS. In *Proceedings of the 2025 IEEE 5th International Conference on Power Engineering Applications: Engineering the Future: Smart Solutions for Sustainable Power Systems, ICPEA 2025*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025; pp. 1–6. [CrossRef]
36. Nguyen, T.P.; Nguyen, Q.H.; Hoang, A.; Cao, T.T.; Nguyen, H.N.; Trinh, V.C. Optimization and Techno-Economic Analysis of An On-Grid Hybrid Energy System for Electrification using Solar, Biogas, and BESS via HOMER Pro: A Case Study in Vietnam. In *Proceedings of the 2025 10th International Conference on Applying New Technology in Green Buildings, ATiGB 2025*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025; pp. 124–130. [CrossRef]
37. Karadeniz, A.; Naetiladdanon, S.; Sangswang, A.; Konghirun, M. Multi-Criteria Site Selection for Offshore Wind Energy Deployment in Southern Thailand Using HOMER Simulation. In *Proceedings of the 2025 12th International Conference on Electrical and Electronics Engineering (ICEEE)*; IEEE: Piscataway, NJ, USA, 2025; pp. 339–343. [CrossRef]
38. Lauredo, J.D.; Bongalon, J.R.A.; Ejanda, M.S.L.; Pamittan, M.A.L.; Tubola, O.D. Simulation of GIS-Based Distributed Rooftop Solar PV for Power Crisis Mitigation in Occidental Mindoro Using HOMER. In *Proceedings of the 2025 IEEE 5th International Conference on Power Engineering Applications: Engineering the Future: Smart Solutions for Sustainable Power Systems, ICPEA 2025*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025; pp. 152–157. [CrossRef]
39. Wahid, M.; El Rahman, M.A.E.A.H.A.; Helmy, S. Optimal Sizing of Hybrid Microgrids Using Weighted Average Algorithm and HOMER. In *Proceedings of the 2025 15th International Conference on Electrical Engineering, ICEENG 2025*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2025. [CrossRef]
40. Pontes, L.; Costa, T.S.; Lima, M.C.C.; Chalegre, R.; Leon, R.; Quicu, S.; Marinhoe, M. Customized Dispatch Strategies for Hybrid Energy Systems Using HOMER Pro and MATLAB Link: A Comprehensive Review and Case Study. In *Proceedings of the 2025 16th IEEE International Conference on Industry Applications (INDUSCON)*; IEEE: Piscataway, NJ, USA, 2025; pp. 109–114. [CrossRef]
41. Arnoos, H.; Kamel, S.; Jurado, F.; Yaqoob, S.J. Optimizing Photovoltaic Systems in Building Applications: Environmental and Economic Benefits with Helioscope and HOMER Pro Analysis. In *Proceedings of the International Conference on Electrical, Computer, and Energy Technologies, ICECET 2024*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2024. [CrossRef]
42. Sulistyono, S.; Pamuji, F.A.; Suryoatmojo, H. *Optimization of Hybrid Renewable Energy Potential in Southeast Sulawesi Using HOMER PRO*; Institute of Electrical and Electronics Engineers (IEEE): Piscataway, NJ, USA, 2025; pp. 1–6. [CrossRef]
43. Gumbrell, I.C. Electricity Storage in 100% Renewable Markets: The Case of New Zealand in 2050. Master's Thesis, University of Auckland, Auckland, New Zealand, 2020. [CrossRef]
44. Boretti, A. Flow batteries for net zero in New Zealand. *Energy Storage* **2023**, *5*, e513. [CrossRef]
45. Mcintosh, L.C. Design of a Hydrogen Energy Storage System for Renewable New Zealand Micro-Grids. Master's Thesis, University of Canterbury, Christchurch, New Zealand, 2025. [CrossRef]
46. Vaidya, S.; Prasad, K.; Kilby, J. To Study the Impact of Rooftop Solar-Powered EV Charging Stations on Distribution Network Efficiency: Challenges and Solutions. In *Proceedings of the 2025 IEEE Region 10 Symposium (TENSYMP)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–8. [CrossRef]
47. Cavus, M.; Jiang, J.; Allahham, A. Deep Multi-Task Forecasting of Net-Load and EV Charging with a Residual-Normalised GRU in IoT-Enabled Microgrids. *Energies* **2026**, *19*, 311. [CrossRef]
48. Wamalwa, F.; Ishimwe, A. Optimal energy management in a grid-tied solar PV-battery microgrid for a public building under demand response. *Energy Rep.* **2024**, *12*, 3718–3731. [CrossRef]
49. Chakir, A.; Tabaa, M.; Moutaouakkil, F.; Medromi, H.; Julien-Salame, M.; Dandache, A.; Alami, K. Optimal energy management for a grid connected PV-battery system. *Energy Rep.* **2020**, *6*, 218–231. [CrossRef]
50. Liu, T.; Liu, Y.; Peng, Q.; Meng, J.; Gao, F. State of Energy Recovery of Battery Energy Storage System With Primary Frequency Control for Battery Aging Mitigation. *IEEE Trans. Transp. Electrif.* **2024**, *11*, 5276–5287. [CrossRef]
51. Wang, H.; Lei, Z.; Zhang, X.; Zhou, B.; Peng, J. A review of deep learning for renewable energy forecasting. *Energy Convers. Manag.* **2019**, *198*, 111799. [CrossRef]
52. Benti, N.E.; Chaka, M.D.; Semie, A.G. Forecasting Renewable Energy Generation with Machine Learning and Deep Learning: Current Advances and Future Prospects. *Sustainability* **2023**, *15*, 7087. [CrossRef]
53. Devaraj, J.; Madurai Elavarasan, R.; Shafiullah, G.M.; Jamal, T.; Khan, I. A holistic review on energy forecasting using big data and deep learning models. *Int. J. Energy Res.* **2021**, *45*, 13489–13530. [CrossRef]
54. Ukoba, K.; Olatunji, K.O.; Adeoye, E.; Jen, T.C.; Madyira, D.M. Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy Environ.* **2024**, *35*, 3833–3879. [CrossRef]
55. Aslam, S.; Herodotou, H.; Mohsin, S.M.; Javaid, N.; Ashraf, N.; Aslam, S. A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. *Renew. Sustain. Energy Rev.* **2021**, *144*, 110992. [CrossRef]

56. Habbak, H.; Mahmoud, M.; Metwally, K.; Fouda, M.M.; Ibrahem, M.I. Load Forecasting Techniques and Their Applications in Smart Grids. *Energies* **2023**, *16*, 1480. [CrossRef]
57. Alkahtani, H.; Aldhyani, T.H.H.; Alsubari, S.N. Application of Artificial Intelligence Model Solar Radiation Prediction for Renewable Energy Systems. *Sustainability* **2023**, *15*, 6973. [CrossRef]
58. Khan, S.U.; Khan, N.; Ullah, F.U.M.; Kim, M.J.; Lee, M.Y.; Baik, S.W. Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting. *Energy Build.* **2023**, *279*, 112705. [CrossRef]
59. Hu, Y.S.; Lo, K.Y.; Hsieh, I.Y.L. AI-driven short-term load forecasting enhanced by clustering in multi-type university buildings: Insights across building types and pandemic phases. *J. Build. Eng.* **2025**, *104*, 112417. [CrossRef]
60. Wang, X.; Wang, H.; Bhandari, B.; Cheng, L. AI-Empowered Methods for Smart Energy Consumption: A Review of Load Forecasting, Anomaly Detection and Demand Response. *Int. J. Precis. Eng. Manuf.* **2024**, *11*, 963–993. [CrossRef]
61. Yousef, L.A.; Yousef, H.; Rocha-Meneses, L. Artificial Intelligence for Management of Variable Renewable Energy Systems: A Review of Current Status and Future Directions. *Energies* **2023**, *16*, 8057. [CrossRef]
62. Baseer, M.A.; Almunif, A.; Alsaduni, I.; Tazeen, N. Electrical Power Generation Forecasting from Renewable Energy Systems Using Artificial Intelligence Techniques. *Energies* **2023**, *16*, 6414. [CrossRef]
63. Alshdaifat, Y.I.R.; Prasad, K.; Al-Tameemi, Z.H.A.; Kilby, J.; Lie, T.T. Optimal Energy Storage Management in Grid-Connected PV-Battery Systems Based on GWO-PSO. *Energies* **2025**, *18*, 6036. [CrossRef]
64. Liu, H.; Chen, C. Data processing strategies in wind energy forecasting models and applications: A comprehensive review. *Appl. Energy* **2019**, *249*, 392–408. [CrossRef]
65. Mawson, V.J.; Hughes, B.R. Deep learning techniques for energy forecasting and condition monitoring in the manufacturing sector. *Energy Build.* **2020**, *217*, 109966. [CrossRef]
66. Santos, L.H.S.; Silva, J.A.A.; López, J.C.; Rider, M.J.; da Silva, L.C.P. Joint Optimal Sizing and Operation of Unbalanced Three-Phase AC Microgrids Using HOMER Pro and Mixed-Integer Linear Programming. *J. Control Autom. Electr. Syst.* **2024**, *35*, 346–360. [CrossRef]
67. Ramadan, H.S.; Alhelou, H.H.; Ahmed, A.A. Impartial near-optimal control and sizing for battery hybrid energy system balance via grey wolf optimizers: Lead acid and lithium-ion technologies. *IET Renew. Power Gener.* **2025**, *19*, e12423. [CrossRef]
68. de Lima, T.D.; Lezama, F.; Soares, J.; Franco, J.F.; Vale, Z. Modern distribution system expansion planning considering new market designs: Review and future directions. *Renew. Sustain. Energy Rev.* **2024**, *204*, 114709. [CrossRef]
69. Borozan, S.; Strbac, G. Multi-Stage Integrated Transmission and Distribution Expansion Planning Under Uncertainties With Smart Investment Options. *IEEE Trans. Sustain. Energy* **2025**, *16*, 546–559. [CrossRef]
70. Abeygunawardana, A.K.; Arefi, A.; Ledwich, G. Estimating and modeling of distribution network costs for designing cost-reflective network pricing schemes. In Proceedings of the 2015 IEEE Power & Energy Society General Meeting, Denver, CO, USA, 26–30 July 2015; pp. 1–5. [CrossRef]
71. Wang, Y.; Zhang, D.; Zhou, M.; Song, F.; Liu, L.; Liu, Y.; Zhu, J. Integrated energy system multi-level planning model based on scenario reasoning, equipment selection, and capacity optimization. *Int. J. Green Energy* **2022**, *19*, 1512–1530. [CrossRef]
72. Zhou, L.; Sheng, W.; Liu, W.; Ma, Z. An optimal expansion planning of electric distribution network incorporating health index and non-network solutions. *CSEE J. Power Energy Syst.* **2020**, *6*, 681–692. [CrossRef]
73. Xing, H.; Fan, H.; Sun, X.; Hong, S.; Cheng, H. Optimal siting and sizing of distributed renewable energy in an active distribution network. *CSEE J. Power Energy Syst.* **2018**, *4*, 380–387. [CrossRef]
74. Liu, J.; Xu, Y.; Qiu, J.; Dong, Z.Y.; Wong, K.P. Non-Network Solution Coordinated Voltage Stability Enhancement with STATCOM and UVLS for Wind-Penetrated Power System. *IEEE Trans. Sustain. Energy* **2020**, *11*, 1559–1568. [CrossRef]
75. Meng, K.; Zhang, W.; Qiu, J.; Zheng, Y.; Dong, Z.Y. Offshore Transmission Network Planning for Wind Integration Considering AC and DC Transmission Options. *IEEE Trans. Power Syst.* **2019**, *34*, 4258–4268. [CrossRef]
76. Jain, R.; Varshney, M. Group Key Management Protocols for Non-Network: A Survey. *Iraqi J. Electr. Electron. Eng.* **2024**, *20*, 214–225. [CrossRef]
77. Gabbar, H.A.; Othman, A.M.; Abdussami, M.R. Review of Battery Management Systems (BMS) Development and Industrial Standards. *Technologies* **2021**, *9*, 28. [CrossRef]
78. Sagar, B.S.; Hampannavar, S.; Deepa, B.; Bairwa, B. Applications of Battery Management System (BMS) in Sustainable Transportation: A Comprehensive Approach from Battery Modeling to Battery Integration to the Power Grid. *World Electr. Veh. J.* **2022**, *13*, 80. [CrossRef]
79. Krishna, T.N.V.; Kumar, S.V.S.V.P.D.; Srinivasa Rao, S.; Chang, L. Powering the Future: Advanced Battery Management Systems (BMS) for Electric Vehicles. *Energies* **2024**, *17*, 3360. [CrossRef]
80. Stecca, M.; Elizondo, L.R.; Soeiro, T.B.; Bauer, P.; Palensky, P. A Comprehensive Review of the Integration of Battery Energy Storage Systems Into Distribution Networks. *IEEE Open J. Ind. Electron. Soc.* **2020**, *1*, 46–65. [CrossRef]

81. Hu, Y. Research on the Construction of Battery System Simulation Platform Based on Computer BMS Algorithm. In *Proceedings of the 2024 IEEE 2nd International Conference on Control, Electronics and Computer Technology (ICCECT)*; IEEE: Piscataway, NJ, USA, 2024; pp. 1280–1285. [CrossRef]
82. Jayasekara, N.; Wolfs, P.; Masoum, M.A.S. An optimal management strategy for distributed storages in distribution networks with high penetrations of PV. *Electr. Power Syst. Res.* **2014**, *116*, 147–157. [CrossRef]
83. Raj, P.J.; Prabhu, V.V.; Krishnakumar, V.; Anand, M.C.J. Solar Powered Charging of Fuzzy Logic Controller (FLC) Strategy with Battery Management System (BMS) Method Used for Electric Vehicle (EV). *Int. J. Fuzzy Syst.* **2023**, *25*, 2876–2888. [CrossRef]
84. Saidulu, I.; Manimaraboopathy, M.; Monda, K.; Purushotham, S.; Kumar, K.S.; Lydia, J. A Smart Battery Management System (BMS) Development for Electric Vehicles to Improve Energy and Power Management Structure. In *Proceedings of the 2024 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)*; IEEE: Piscataway, NJ, USA, 2024; pp. 1–6. [CrossRef]
85. Fan, X.; Zhang, W.; Sun, B.; Zhang, J.; He, X. Battery pack consistency modeling based on generative adversarial networks. *Energy* **2022**, *239*, 122419. [CrossRef]
86. Bhuvaneswari, S.; Mohan, A.; Sundaram, A. Improved BMS: A Smart Electric Vehicle Design based on an Intelligent Battery Management System. In *Proceedings of the 2024 International Conference on Inventive Computation Technologies (ICICT)*; IEEE: Piscataway, NJ, USA, 2024; pp. 1999–2006. [CrossRef]
87. Vanlalchhuanawmi, C.; Deb, S.; Onen, A.; Ustun, T.S. Energy management strategies in distribution system integrating electric vehicle and battery energy storage system: A review. *Energy Storage* **2024**, *6*, e682. [CrossRef]
88. Sarda, J.; Patel, H.; Popat, Y.; Hui, K.L.; Sain, M. Review of Management System and State-of-Charge Estimation Methods for Electric Vehicles. *World Electr. Veh. J.* **2023**, *14*, 325. [CrossRef]
89. Bhattacharya, S.; Bauer, P. Requirements for charging of an electric vehicle system based on state of power (SoP) and state of energy (SoE). In *Proceedings of The 7th International Power Electronics and Motion Control Conference*; IEEE: Piscataway, NJ, USA, 2012; pp. 434–438. [CrossRef]
90. Geetha, A.; Suprakash, S.; Lim, S.J. Sensor based Battery Management System in Electric Vehicle using IoT with Optimized Routing. *Mob. Netw. Appl.* **2024**, *29*, 349–372. [CrossRef]
91. Feng, Y.; Wang, Y.; Bai, F.; Cao, Z.; Han, F. Estimating State of Energy in Lithium-ion Batteries Using a Super-Twisting Algorithm-Based Sliding Mode Observer. In *Proceedings of the IECON Proceedings (Industrial Electronics Conference)*; IEEE: Piscataway, NJ, USA, 2024. [CrossRef]
92. Chen, L.; Ma, H.; Song, Y.; Lopes, A.M.; Bao, X.; Yen, L.; Liu, A. State-of-Charge and State-of-Energy Estimation for Lithium-Ion Batteries Based on Meta-Learning and Square-Root Unscented Kalman Filter. *IEEE Trans. Transp. Electrif.* **2025**, *11*, 12472–12483. [CrossRef]
93. Sharma, S.; Panigrahi, B.K. Lithium-Ion Battery State-of-Charge and State-of-Energy Simultaneous Estimation via Sparse-Quasi Recurrent Neural Networks(S-QRNN). *IEEE Trans. Ind. Appl.* **2025**, *61*, 774–783. [CrossRef]
94. Liu, G.; Li, D.; Wang, W.; Sun, C.; Cheng, J.; Wang, J.; Liu, B. Joint Estimation of SOC and SOE for Energy Storage Lithium-ion Batteries Based on KNN Algorithm. In *Proceedings of the 2024 5th International Conference on Power Engineering (ICPE)*; IEEE: Piscataway, NJ, USA, 2024; pp. 501–505. [CrossRef]
95. Zheng, X.; Li, Q.; Liu, Z.; Zhi, J. Lithium-ion Battery SoC and SoE Sliding Mode Observation for Energy Storage System. In *Proceedings of the IECON 2024—50th Annual Conference of the IEEE Industrial Electronics Society*; IEEE: Piscataway, NJ, USA, 2024; pp. 1–5. [CrossRef]
96. Chen, L.; Song, Y.; Lopes, A.M.; Bao, X.; Zhang, Z.; Lin, Y. Joint Estimation of State of Charge and State of Energy of Lithium-Ion Batteries Based on Optimized Bidirectional Gated Recurrent Neural Network. *IEEE Trans. Transp. Electrif.* **2024**, *10*, 1605–1616. [CrossRef]
97. He, Z.; Wang, H.; Liu, H.; Chen, C. Joint Estimation of SOC and SOE in Lithium-Ion Batteries Using TimesNet with Mixture of Experts. In *Proceedings of the 2025 IEEE 2nd International Conference on Big Data Science and Engineering (ICBDSE)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–6. [CrossRef]
98. Zeng, X.; Guo, X.; Zhu, J.; Cai, Z. State of Charge and State of Energy Co-estimation for Lithium-ion Battery Based on PatchTST Model. In *Proceedings of the 2024 4th Power System and Green Energy Conference (PSGEC)*; IEEE: Piscataway, NJ, USA, 2024; pp. 1205–1209. [CrossRef]
99. Sharma, S.; Achlerkar, P.D.; Shrivastava, P.; Garg, A.; Panigrahi, B.K. Combined SoC and SoE Estimation of Lithium-ion Battery using Multi-layer Feedforward Neural Network. In *Proceedings of the 2022 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*; IEEE: Piscataway, NJ, USA, 2022; pp. 1–6. [CrossRef]
100. Safder, M.U.; Sanjari, M.; Garmabdari, R.; Lu, J. Energy Management in Islanded DC Grid via SOE Estimation of Storage. In *Proceedings of the 2022 IEEE PES 14th Asia-Pacific Power and Energy Engineering Conference (APPEEC)*; IEEE: Piscataway, NJ, USA, 2022; pp. 1–5. [CrossRef]

101. Naseri, F.; Farjah, E.; Ghanbari, T.; Kazemi, Z.; Schaltz, E.; Schanen, J.-L. Online Parameter Estimation for Supercapacitor State-of-Energy and State-of-Health Determination in Vehicular Applications. *IEEE Trans. Ind. Electron.* **2020**, *67*, 7963–7972. [CrossRef]
102. Gupta, R.; Zecchino, A.; Yi, J.-H.; Paolone, M. Reliable Dispatch of Active Distribution Networks via a Two-Layer Grid-Aware Model Predictive Control: Theory and Experimental Validation. *IEEE Open Access J. Power Energy* **2022**, *9*, 465–478. [CrossRef]