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Review

Control and energy management of standalone microgrids in remote areas: A review of recent advances, challenges, and opportunities for future research

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ABSTRACT

While standalone microgrids are an essential means of electrifying remote communities, high renewable penetration poses significant problems with power sharing, voltage/frequency stability, and optimal dispatch in low-inertia, communication-constrained scenarios. Using structured analysis across control methodologies, optimization techniques, and validation platforms, this paper synthesizes emerging paradigms in hierarchical control and energy management systems (EMS) through a systematic review of studies conducted in 2025. The following key findings show clear shifts: (i) adaptive droop and event-triggered consensus reduce communication overhead by 80% while maintaining voltage accuracy within ±2%; (ii) super-twisting sliding mode control shows chattering-free operation with 98% cyber-attack detection capability; (iii) hybrid model predictive control frameworks enable real-time execution on embedded hardware with 25%–40% cost reduction; and (iv) deep reinforcement learning-based EMS shows 12% cost improvement and 97.8% reduction in computational load. There are still significant gaps: 68% of studies do not have hardware validation, 78% do not integrate cyber-security, power-sharing errors surpass 5% when there is an impedance mismatch, and there are no standardized benchmarking protocols. The review offers practical suggestions covering lifecycle-aware battery management, distributionally robust optimization (DRO) for renewable uncertainty, edge-computing architectures for communication-light operation, and cooperative cyber–physical testbeds for field validation. This synthesis provides a well-organized road map for developing technically demanding, financially feasible, and operationally robust microgrids that can provide sustainable access to electricity in underserved areas.

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List of abbreviations

Abbrev.	Definition	Abbrev.	Definition
AC	Alternating current	MGs	Microgrids
ACO	Ant colony optimization	MPC	Model predictive control
AI	Artificial intelligence	MPPT	Maximum power point tracking
ANFIS	Adaptive neuro-fuzzy inference system	OPF	Optimal power flow
ANN	Artificial neural network	PCC	Point of common coupling
DC	Direct current	PEMFC	Proton exchange membrane fuel cell
DERs	Distributed energy resources	PI	Proportional integral
DG	Distributed generation	PID	Proportional integral derivative
DRL	Deep reinforcement learning	PSO	Particle swarm optimization
EMS	Energy management systems	PV	Photovoltaic
ESS	Energy storage systems	RCP	Rapid control prototyping
FLC	Fuzzy logic control	RESs	Renewable energy sources
FNNs	Feed-forward neural networks	SCU	Secondary control unit
FQB	Frequency–reactive power boost	SI	Swarm intelligence
GA	Genetic algorithm	SMC	Sliding mode control
HIL	Hardware-in-the-loop	SoC	State of charge
IoT	Internet of things	STC	Super-twisting control
LFC	Load frequency control	VPD	Voltage–real power droop
MAS	Multi-agent system	VSC	Voltage source converter
MILP	Mixed-integer linear programming	MINLP	Mixed-integer nonlinear programming

1. Introduction

1.1. Background and motivation

For many isolated and remote communities, where traditional grid extension is economically prohibitive due to low load density, terrain, and capital costs, reliable, affordable, and sustainable electricity access is still elusive [1,2]. One viable path to quality supply, resilience, and faster access to energy in this regard is *standalone microgrids* – localized networks of distributed energy resources (DERs), energy storage systems (ESS), and controllable loads [3–5]. The growth of the electric vehicle (EV) adoption only highlights the necessity of the strong charging facility, which could be coupled with standalone microgrids to offer sustainable transportation systems in isolated locations [6,7]. Although such systems may have few infrastructures, hierarchical control and power-electronic interfaces enable these systems to operate alone and meet some of the tightest quality-of-supply demands due to their limited infrastructure base [8,9]. The decarbonization of such microgrids is being hastened by the rapid adoption of renewable energy sources (RESs) especially wind and photovoltaic, but instability, reduced apparent inertia, and vulnerability to disturbances make voltage and frequency regulation more difficult [10,11]. These challenges are exacerbated by the absence of a rigid upstream reference in islanded mode; only local controllers and an Energy Management System (EMS) can ensure stability, power sharing, and optimal dispatch [12,13]. Existing studies on isolated power systems have shown that conventional frequency regulation and inertia-support mechanisms face inherent limitations under uncertainty and renewable variability, motivating the exploration of more adaptive coordination strategies [14].

Hybrid photovoltaic–thermoelectric systems with innovative ventilation schemes in distributed and residential microgrids have been shown to improve energy utilization and operational resilience [15].

1.2. Technical difficulties in standalone microgrids

Power flow and inverter dynamics are the two main factors that control how standalone microgrids operate. Despite varying generation and demand, real-time voltage and frequency stability must be preserved. A three-layer hierarchy is commonly used to organize control [16]:

- *Primary control* allows for decentralized power sharing without communication when it is implemented locally using virtual impedance loops or droop control. Nevertheless, under impedance mismatch, conventional droop control has slow transient response, frequency deviations, and power-sharing errors [11,17,18].
- *Secondary control* uses distributed consensus-based techniques or centralized supervisory controllers to return voltage and frequency to nominal values [19,20].
- *Tertiary control* uses forecasts and multi-objective criteria like cost, emissions, and reliability to perform cost-effective and constraint-aware coordination (e.g., optimal power flow, setpoint scheduling) [3,10].

Adaptive, communication-light, and disturbance-resilient solutions are required for these hierarchical layers to function in harmony in isolated environments with limited communication infrastructure and high control hardware costs. Autonomy, robustness, and graceful degradation are especially important because these requirements are heightened by communication sparsity [3], cost constraints [11,13,21], and harsh environments [22].

1.3. Emerging paradigms in 2020–2026

The year 2020 to early 2026 landscape shows a decisive shift toward adaptive, intelligent, and resilient solutions:

- *Adaptive droop and virtual impedance*, including SoC-aware and nonlinear gains, to improve power sharing and voltage support across changing network conditions [11,17,19,23].
- *Robust nonlinear control*, particularly Sliding Mode Control (SMC) and super-twisting control (STC) variants [18,19,24–26], which provide strong disturbance rejection and finite-time convergence; event-triggered designs further minimize computation and bandwidth.
- *Model Predictive Control (MPC)* for multi-objective, constraint-handling operation and predictive coordination of DERs and ESS under high RES penetration [3,4,10,27–34].
- *Distributed and multi-agent systems (MAS)* enabling consensus-based secondary control and plug-and-play scalability without single points of failure [27,35–40].

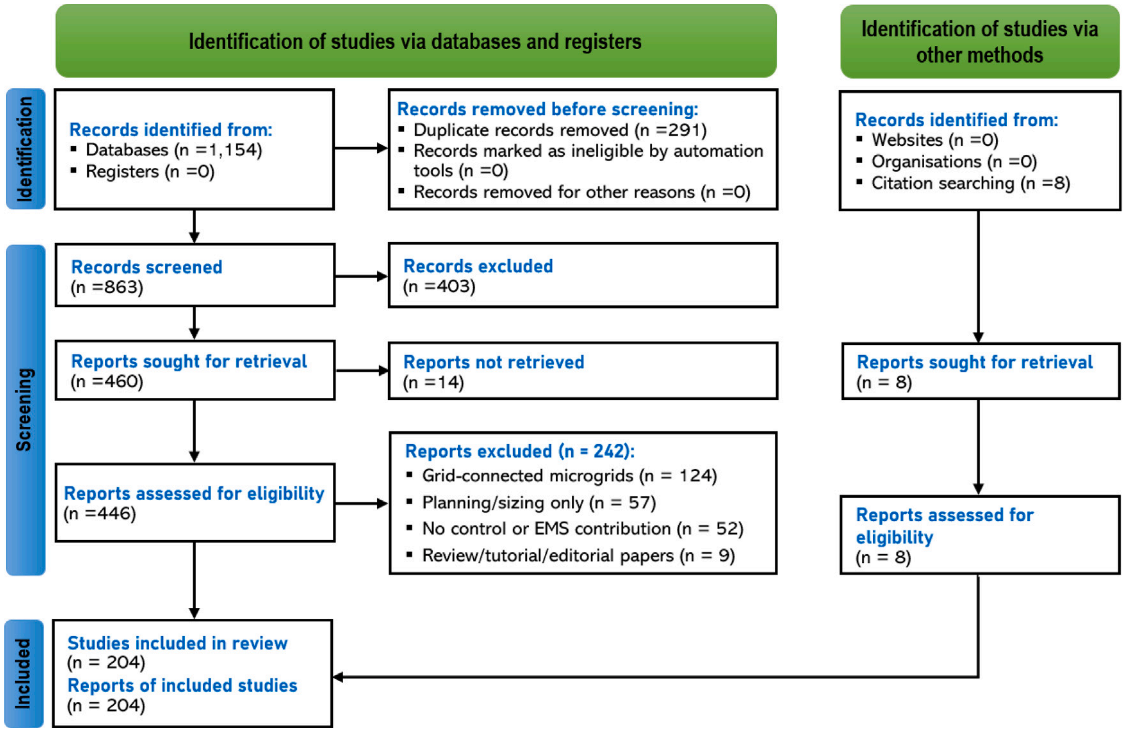

Fig. 1. PRISMA 2020 flow diagram illustrating the identification, screening, eligibility, and inclusion of studies for the systematic review.

- *AI-driven control and EMS* (e.g., neural networks, RL/DRL) that improve fault tolerance, forecasting, and predictive scheduling; hybrid AI–optimization schemes are being reported more frequently [41–44].

These trends motivate the need for an integrated analytical framework that jointly considers control, energy management, communication constraints, and validation practices, which forms the basis of the present review.

1.4. Energy management system (EMS) advances

Modern EMS techniques balance cost, reliability, emissions, and asset health through *multi-objective* optimization, which goes beyond simple scheduling. The reported formulations include learning-based policies (RL/DRL), metaheuristics Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant-Colony Optimization (ACO), and classical mathematical programming (e.g., MILP), frequently in hybrid day-ahead plus real-time corrective layers [45–47]. Resilience and cybersecurity (anomaly detection, secure communications) are now top design priorities due to increased digitalization [33,48–50]. Recent work has shown that predictive energy management strategies can leverage battery energy storage systems to actively mitigate load-altering attacks in islanded microgrids, using fast corrective dispatch to prevent instability and potential blackouts [51]. Hybrid EMS frameworks that integrate real-time corrective control and predictive optimization are becoming more and more popular because they allow microgrids to dynamically adjust to load and renewable generation uncertainty.

1.5. Review methodology

This review follows the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020)* guidelines for methodological transparency, rigor, and reproducibility, with literature selection conducted in four stages (identification, screening, eligibility assessment, and inclusion) as depicted in the PRISMA flow diagram (Fig. 1).

1.5.1. Identification of studies

A systematic literature search was conducted using the *Scopus* and *Web of Science* databases. To improve search precision and reduce the inclusion of marginally relevant studies, the search was restricted to the *title field*. This decision is justified by the highly specific scope of the review as "control and energy management of standalone" or "islanded microgrids", where core technical contributions almost always explicitly state these concepts in the title.

The search was limited to English-language journal articles and conference papers published between 2020 and 2026. Subject areas unrelated to power and energy systems were excluded to further reduce noise. The Scopus search string used in this study is reported below to ensure full reproducibility:

```
TITLE ( ( "standalone microgrid*" OR "islanded microgrid*" OR "isolated
microgrid*" OR "off-grid microgrid*" OR "remote microgrid*" OR
"isolated power system*" OR "autonomous power system*" ) AND ( control OR
"control strategy*" OR "control scheme*" OR "energy management" OR
"energy management system*" OR "power management" OR EMS OR dispatch OR
scheduling OR optimization ) ) AND ( PUBYEAR > 2019 AND PUBYEAR < 2027 )
AND ( LIMIT-TO ( DOCTYPE , "ar" ) OR LIMIT-TO ( DOCTYPE , "cp" ) ) AND
( LIMIT-TO ( LANGUAGE , "English" ) ) AND ( EXCLUDE ( SUBJAREA , "AGRI" )
OR EXCLUDE ( SUBJAREA , "MULT" ) OR EXCLUDE ( SUBJAREA , "NEUR" ) OR
EXCLUDE ( SUBJAREA , "BIOC" ) OR EXCLUDE ( SUBJAREA , "BUSI" ) OR
EXCLUDE ( SUBJAREA , "EART" ) OR EXCLUDE ( SUBJAREA , "CHEM" ) OR EXCLUDE
( SUBJAREA , "ECON" ) OR EXCLUDE ( SUBJAREA , "MEDI" ) OR EXCLUDE
( SUBJAREA , "SOCI" ) OR EXCLUDE ( SUBJAREA , "DECI" ) OR EXCLUDE
( SUBJAREA , "ENVI" ) OR EXCLUDE ( SUBJAREA , "PHYS" ) OR EXCLUDE
( SUBJAREA , "MATE" ) )
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Equivalent keyword logic was applied in the Web of Science database.

1.5.2. Screening and eligibility assessment

A total of 1154 records were obtained through the search in the database. Following duplicates removal, 863 records had been retained to undergo title and abstract screening. At this stage, studies based on grid-connected microgrids with no control or energy management components, planning, sizing, or non-technical contributions were not included.

Full-text eligibility assessment was thereafter done for 446 reports according to predefined inclusion and exclusion criteria. Studies were excluded if they only addressed grid-connected operation, lacked explicit control or energy management contributions, or were review papers, tutorial papers, or editorial papers.

1.5.3. Inclusion and data synthesis

Sequel to the eligibility check, a total of 204 studies were included in the final review. Besides searching databases, snowballing (backward citation screening) was carried out to mitigate the risk of missing important studies. Citation searching identified eight studies, which were deduplicated and added with the database results prior to eligibility assessment and are included within the final total, according to PRISMA 2020 guidelines.

For each included study, relevant information was extracted systematically and synthesized, including control or energy management methodology, system configuration, validation approach, and key findings. This organized synthesis made it possible to compare the work, identification of dominant trends, and recognition of open research questions in standalone microgrid control and energy management.

1.6. Objectives and scientific contributions

Though this is a review article, its contribution extends past the descriptive overview of previous research. Instead of listing control and energy management methods separately, the paper presents a systematic analytical framework, combining control hierarchies, energy management structures, communications constraints and validation practices, in standalone microgrids. The novelty of this review lies in three interrelated dimensions:

1. First, the paper provides a cross-layer synthesis of control and energy management evolution, explicitly linking advances at the primary and secondary control levels (e.g., adaptive droop, sliding-mode control, distributed MPC, and event-triggered consensus) to their implications for tertiary energy management systems. This unified viewpoint shows how controller-level assumptions constrain or enable EMS optimization, which is quite disjointed in current surveys.
2. Second, by restricting the scope to 2020–2026 period, the review captures emerging paradigm shifts that are not visible in broader multi-year surveys. These include the transition toward communication-light and event-triggered control, hybrid model-based/model-free methods, edge-deployable predictive control, and learning-driven EMS architectures. The analysis thus functions as a time-resolved snapshot of the state-of-the-art, rather than a historical aggregation.
3. Third, the paper presents a thematic methodological taxonomy, which linkd bibliometric trends with technical characteristics like control structure, optimization strategy, cyber-resilience, and validation platform. This interconnection reveals systematic misalignments between theoretical developments, cybersecurity integration, and experimental validation and thus identifying structural research gaps rather than isolated open problems.

According to this paradigm, the contributions to this review, in particular, are:

1. A unified analytical framework that collectively examines hierarchical control methods, EMS formulations, communication architectures, and validation platforms for standalone microgrids.
2. A 2020–2026-focused paradigm analysis that identifies dominant methodological shifts toward adaptive, learning-based, and communication-efficient control and energy management.
3. A thematic taxonomy based on bibliometric and technical synthesis, which allows making objective comparisons between control and EMS approaches on the basis of the algorithm level.
4. A systemic research gap diagnosis, such as lack of hardware-in-the-loop (HIL) verification, cyber–physical security integration, and a lack of standard benchmarking protocols were identified.
5. An actionable research roadmap detailing future directions in edge-AI deployment, distributionally robust optimization, lifecycle-aware energy storage management, and cooperative cyber–physical testbeds tailored to remote and resource-constrained environments.

By these contributions, the paper provides not only a consolidated view of recent advances but also a conceptual and methodological foundation for future research on resilient, scalable, and practically deployable standalone microgrids.

1.7. Paper organization

The paper is organized as follows. Section 2 introduces microgrid fundamentals and hierarchical control. Section 3 covers the different control strategies. EMS optimization: deterministic, stochastic/robust, metaheuristics, AI-driven, demand response, and cyber-security are discussed in Section 4. Section 5 analyzes publication trends and thematic evolution. Section 6 identifies research gaps and recommendations. Section 7 synthesizes findings and future directions.

2. Microgrid fundamentals and control hierarchies

2.1. Standalone microgrid architecture overview

As shown in Fig. 2, the microgrids mostly comprise photovoltaic arrays, wind turbines, and distributed generators (DGs) connected to ESS and power converters to supply local loads in a low- or medium-voltage network [3,10,52]. The main functional goals are to: (i) guarantee power quality (voltage and frequency within legal bounds); (ii) give DERs plug-and-play capability; (iii) facilitate smooth islanding and reconnection; and (iv) reduce losses and emissions [53].

2.2. Hierarchical control concept

In accordance with the ANSI/ISA-95 automation pyramid, microgrid control is typically arranged into three levels, namely primary, secondary, and tertiary to coordinate a variety of resources [8,9,54–58]. Stable, scalable, and cost-effective operation is guaranteed by this hierarchy:

- *Primary control* eliminates the need for communication links by offering quick local voltage/frequency regulation and power sharing through virtual impedance loops or droop characteristics [11,22,59–63].
- *secondary control* restores bus voltage and frequency to their nominal values in order to compensate for steady-state deviations. Different communication overheads are associated with centralized, distributed, and event-triggered variants [18–20,37,49,64–66].
- *Tertiary control* performs optimization of power flow and dispatch, considering economic and environmental criteria. It typically runs at a slower timescale (minutes) and may leverage forecast data and market signals [3,25,67–69].

A summary of the typical objectives, timescales, and representative control actions at each layer is provided in Table 1. The hierarchical structure of microgrid control is conventionally represented as a three-layer pyramid, where each layer addresses distinct timescales and objectives whereby primary control ensures fast local regulation through droop or virtual impedance loops, secondary control restores nominal voltage and frequency using regulators or distributed consensus schemes, and tertiary control optimizes power flow and dispatch over minutes to hours by leveraging methods such as economic load dispatch, optimal power flow (OPF), or MPC.

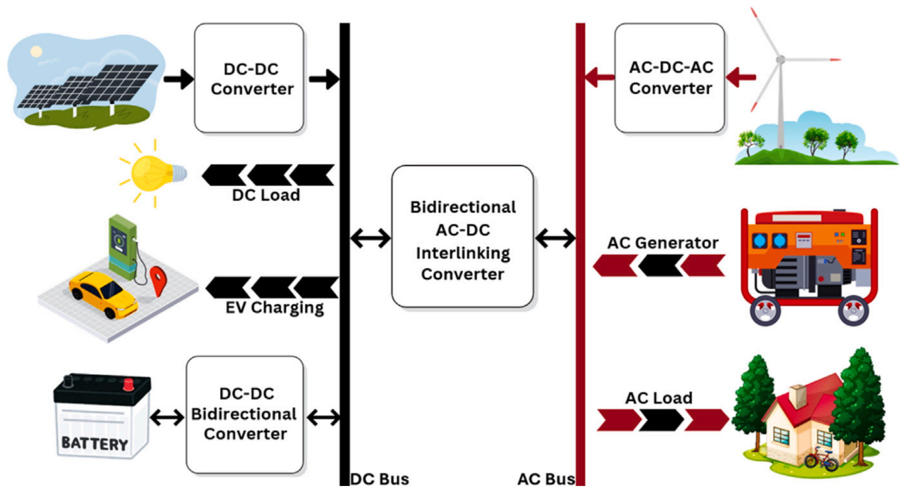

Fig. 2. Generic architecture of an AC/DC standalone microgrid, showing DERs, ESS, PCC, and various loads.

Table 1
Typical objectives, timescales, and control actions of hierarchical control layers.

Layer	Main objective	Typical timescale	Example control actions
Primary	Local stabilization, power sharing	ms–hundreds of ms	Droop control, virtual impedance, inner current/voltage loops
Secondary	Restore nominal voltage and frequency	seconds	PI/PID regulators, consensus algorithms, event-triggered restoration
Tertiary	Optimal dispatch, cost and emission minimization	minutes–hours	Economic load dispatch, OPF, MPC-based optimization

2.3. Communication and coordination issues

Although hierarchical control is well established, its dependence on reliable communication links can be a vulnerability in remote microgrids. Packet delays or losses may lead to oscillations, degraded dynamic response, or even system collapse if unmitigated [70–72]. Research in 2025 has emphasized communication-light strategies such as distributed consensus control, event-triggered updates, and resilient cooperative protocols that continue operating during partial communication outages [73,74].

2.4. Converter types and roles

Usually, three primary converter control modes are used:

- **Grid-forming converters**, which set the islanded network's voltage and frequency reference.
- **Grid-supporting converters**, which use virtual impedance or droop to share power.
- **Grid-feeding converters**, which supply the grid with a predetermined power reference or current.

Maintaining stability under changing DER mix and load conditions requires the proper distribution of converter roles.

2.5. Key insights

Although the 2020–2026 literature emphasizes moving towards (i) adaptive and communication-resilient implementations; (ii) integration with energy management optimization to provide multi-objective performance guarantees; and (iii) embedding cyber-security and fault-tolerance features at every layer, hierarchical control is still the foundation of microgrid operation. The thorough analysis of control strategies in Section 3 is motivated by these observations.

Throughout this review, control and energy management solutions are organized not only by algorithmic approach, but also by system characteristics such as microgrid topology (AC, DC, and hybrid AC–DC), system scale, load types, and DER configurations. This broader perspective supports consistent comparison of performance and applicability across diverse standalone microgrid deployments.

3. Control strategies for standalone microgrids

The proposed control strategies in the literature are summarized and classified in this section using a unified taxonomy based on control hierarchy, algorithmic paradigm, design objectives, and validation characteristics. The reviewed methods are organized into coherent methodological clusters to enable structured comparison across robust, predictive, distributed, and data-driven control approaches. For each cluster, we discuss the underlying control mechanisms, typical performance trade-offs, and representative studies.

3.1. Conventional droop control (P–f / Q–V)

The simplicity, locality, and plug-and-play nature of droop make it the most widely used primary-control method for grid-forming and grid-supporting inverters [11,17,22,60,75]. It permits decentralized power sharing without fast communication links by establishing proportional relationships between frequency and active power (P–f) and between voltage and reactive power (Q–V) [11]. Droop control has been shown to effectively coordinate decentrally over a wide variety of operating conditions. Multi-converter coordination is made better with multifrequency power management and hierarchical droop schemes [54,76], and with adaptive droop, fuzzy logic and neural networks, power-sharing accuracy in multi-DG DC microgrids is improved [61]. Another study further verifies the droop performance robustness of averaged converter model in a relaxing operating environment [77]. The control formulation is given by:

$$\omega = \omega_{\mathrm{ref}} - K_p^{\mathrm{droop}}(P - P_{\mathrm{ref}}) \tag{1}$$

$$V = V_{\mathrm{ref}} - K_d^{\mathrm{droop}}(Q - Q_{\mathrm{ref}}) \tag{2}$$

In Eqs. (1) and (2) ω and V represent the angular frequency and voltage magnitude of the inverter output, respectively; ω_{ref} and V_{ref} are their nominal reference values; P and Q stand for the measured active and reactive power outputs; P_{ref} and Q_{ref} are the corresponding reference (setpoint) powers; K_p^{droop} and K_d^{droop} are the active- and reactive-power droop coefficients that define the frequency and voltage deviations per unit power variation.

Persistent problems still exist despite the observed improvement in control quality: steady-state frequency/voltage offsets, slower transients under heavy load steps, and power-sharing errors under line impedance mismatch. To overcome these without relying on communication links, nonlinear neural-network-assisted droop strategies based on NARX models have been introduced to adapt droop behavior online, significantly improving active and reactive power sharing accuracy under feeder impedance mismatch and load variability [78]. At harmonic frequencies introduced by nonlinear loads, adaptive virtual harmonic impedance schemes regulated via distributed consensus have been proposed to correct harmonic power sharing errors among DGs without requiring prior knowledge of line impedance, thereby reducing voltage distortion at the PCC [79]. In hybrid PV–battery–diesel islanded microgrids, droop-based voltage and frequency control has also been extended to coordinate energy exchange among DERs, enabling synthetic inertia support and improved frequency nadir during active power transients while preserving stable islanded operation [80]. Complementary to learning-based and harmonic compensation approaches, optimization-driven droop tuning has also been investigated using multi-objective metaheuristic algorithms combined with fuzzy decision-making to balance voltage profile enhancement, stability margins, and convergence performance in islanded microgrids [81]. By employing differential evolution algorithms to optimize the selection of droop parameters and validating the results through HIL testing, recent work has addressed these limitations [82]. To enhance damping and lessen noise sensitivity, practical implementations use low-pass filtered power measurements and inner current/voltage loops [83].

3.2. Adaptive and nonlinear droop

In *adaptive droop*, K_p and K_q are functions of measurable parameters (e.g., SoC, impedance). Typical formulation:

$$\omega = \omega_{\mathrm{ref}} - K_p^{\mathrm{droop}}(x)(P - P_{\mathrm{ref}}), \tag{3}$$

$$V = V_{\mathrm{ref}} - K_q^{\mathrm{droop}}(x)(Q - Q_{\mathrm{ref}}), \tag{4}$$

where x may represent a *state variable* such as SoC, bus voltage, or line impedance. For example:

$$K_p^{\mathrm{droop}}(x) = K_{p0}\left(1 + \alpha f_{\mathrm{SoC}}\right), \tag{5}$$

$$K_q^{\mathrm{droop}}(x) = K_{q0}\left(1 + \beta f_Z\right), \tag{6}$$

This enables *dynamic adaptation*, whereby the droop gains automatically adapt to maintain stable power sharing and bus voltage when the SoC is low or impedance increases.

State of charge (SoC)-based droop techniques with variable-frequency low-pass filters are essential in terms of battery life and stability of DC bus voltages [84]. Nonlinear droop laws decrease the voltage sag and enhance the accuracy of sharing under reactive dynamic variations of power [85]. A 300% rise time of the battery and a 10-fold decrease in overshoot of voltage have been obtained with SoC-conscious power allocation in hybrid energy storage systems [84]. SoC-aware droop favors ESS protection and lifetime by biasing the actual sharing of power to healthier units, but keeping the frequency within reasonable bounds. Other options like voltage real power droop (VPD) and frequency real power boost (FQB) further improve transient assistance in extreme disturbance [86].

3.3. Virtual impedance and circulating current mitigation

Virtual output impedance is widely used to decouple active/reactive power control, suppress cross-coupling, and mitigate circulating currents among parallel inverters [87]. The technique emulates resistive and inductive elements in software by modifying the inverter voltage reference as

$$V^* = V_{\mathrm{ref}} - Z_v i_o = v_{\mathrm{ref}} - (R_v + j\omega L_v)i_o, \tag{7}$$

where V^* is the commanded output voltage, V_{ref} the nominal reference, $Z_v = R_v + j\omega L_v$ the virtual impedance, and i_o the inverter output current. This formulation effectively increases the output impedance and suppresses circulating currents, improving stability in weak grids.

Current technologies involve event-triggered virtual impedance techniques which minimize communication needs and yet hold stability [70,72]. Distributed control with virtual impedance has been resilient to communication outages and cyber-attacks as well [19,49,88]. Moreover, adaptive virtual impedance (i.e. where Z_v changes with frequency or current magnitude) boosts damping and current sharing in the imbalanced or harmonic-rich scenarios [64,89–91]. Constant-switching-frequency MPC has been reported to enhance the quality of power using harmonic compensation with virtual impedance [92].

Limitations: Excessive virtual impedance causes voltage drops and efficiency losses; frequency-selective designs (e.g., virtual RC at harmonic orders) balance harmonic suppression with fundamental performance.

3.4. Model predictive control (MPC)

MPC is employed at both converter-level control and tertiary dispatch to solve finite-horizon optimal control problems subject to state and input constraints [3,4,10,23,28–34,64]. At the secondary control layer, feedback linearization-based distributed MPC explicitly addresses nonlinear DG dynamics, enabling fully distributed voltage and frequency regulation using only local and neighboring information while preserving plug-and-play capability [93]. At the converter level, predictive deadbeat and finite-control-set MPC schemes regulate output current and voltage while enforcing saturation and grid-code constraints [94], with active damping extensions further improving transient performance. Stochastic MPC formulations have also been shown to outperform deterministic and robust counterparts in isolated power systems by explicitly accounting for renewable and load uncertainty while preserving frequency regulation and energy storage objectives [95].

The standard discrete-time MPC formulation is given by:

$$\min_{u(k),\ldots,u(k+N-1)} \sum_{i=0}^{N-1} \left[\|x(k+i+1) - x_{\mathrm{ref}}\|_Q^2 + \|u(k+i)\|_R^2 \right] \tag{8}$$

subject to system dynamics $x(k+1) = Ax(k) + Bu(k)$ and operational constraints on states and inputs. Here, x and u denote the state and control vectors, x_{ref} is the reference trajectory, and Q and R are weighting matrices. Rather than reiterating formulation details, the following discussion emphasizes comparative computational complexity, communication requirements, and real-time feasibility across MPC variants.

At the supervisory level, MPC has evolved into an energy management framework integrating renewable forecasts to co-optimize generator dispatch, ESS, and deferrable loads [4,28,96]. Reduced-order and move-blocking formulations enable real-time implementation on low-cost hardware [48], while hybrid and two-step MPC–MINLP designs enhance resilience under uncertainty and support multi-objective optimization of cost, emissions, and reliability [3]. Learning-driven MPC approaches, including neural-network- and reinforcement-learning-enhanced variants, further improve prediction accuracy and energy sharing under high renewable penetration [30,39,97]. Hybrid intelligent MPC frameworks combining fuzzy logic, type-2 fuzzy sets, or restricted Boltzmann machines enhance robustness against modeling uncertainties and power-quality disturbances [62,98]. GA–MPC integrated with ARIMA–LSTM forecasting further optimizes battery life-cycle performance and system stability in hybrid energy storage systems [65]. Practical feasibility has been demonstrated through MATLAB/Simulink and HIL validations in hybrid microgrids [10,29,31].

3.4.1. Strengths and challenges

MPC offers explicit constraint handling and multi-objective coordination, making it suitable for complex microgrids. Yet, its computational demand limits embedded use. Recent studies mitigate this through reduced-order modeling, move-blocking, and warm-starting, with HIL validations confirming feasibility despite complexity constraints.

3.5. Distributed and multi-agent control (Consensus-based)

Multi-agent systems (MAS) and distributed secondary control have grown to be scalable solutions to frequency-voltage restoration, with robust power sharing and negligible dependence on centralized control. Multi-agent control using inverter-based power regulation and real-time validation has been shown to be highly scalable and resilient using a decentralized approach to the control of hybrid AC/DC microgrids [37]. Agents in these frameworks communicate local estimates along sparse communication graphs (e.g. ring, line or small-world) and agree on terms of correction.

In contrast to traditional secondary controllers which will not start until primary stabilization has been achieved, D-PMU-based strategies to control secondary frequency have been shown to run simultaneously with primary control in such a way that overall frequency recovery is achieved faster without destabilizing primary droop behavior [99].

To deal with the practical problem of adjusting the large number of parameters in the consensus based secondary control, experimental design methods have been used to systematically search near optimal controller settings with a small number of experiments, which is better than trial-and-error methods [100].

The generic consensus law among N agents is expressed as

$$\dot{x}_i = -\sum_{j=1}^{N} a_{ij}(x_i - x_j), \tag{9}$$

where x_i is the control variable of agent i, and a_{ij} is the communication adjacency weights defining the graph topology.

Recent advances span many directions. While fixed-time distributed methods guarantee convergence regardless of initial conditions [67], event-triggered consensus improves fault tolerance and reduces eavesdropping risks [101]. Under dynamic conditions, learning-driven controls, e.g. GNN–LSTM designs, offer spatiotemporal adaptability [38,102]. Cyber-resilient distributed MPC prevents denial-of-service (DoS) and false-data injection attacks, while robust distributed control with SMC secondary controllers allows frequency and voltage recovery in the event of packet loss [19,103,104]. Beyond communication-related disruptions, fault-tolerant consensus-based secondary control strategies have been developed to explicitly address actuator faults and disturbances, ensuring reliable voltage and frequency restoration with accurate power sharing under partial loss of effectiveness and biased actuator failures [105]. Iterative learning control improves secondary accuracy over cycles, and multi-agent learning methods like MADRL with temporal modeling and action masking improve coordination in extreme weather [40]. Also, plug-and-play operation and stable operations in remote areas are made possible by hierarchical distributed architectures with dynamic mode-switching that strike a balance between autonomy and coordination across interconnected microgrids [106].

3.5.1. Practicalities

Consensus-based distributed secondary control in practice needs to be resilient to cyber–physical threats as well as communication failures. Observer-based techniques are required to filter noisy measurements and account for time-varying delays because latency and additive noise impair synchronization accuracy, prolong convergence, and destabilize voltage restoration [106]. By incorporating encryption-decryption schemes into intermittent communication, event-triggered privacy-consensus mechanisms minimize bandwidth consumption while protecting exchanged states from eavesdropping [107]. Compound sensor and actuator faults are further mitigated by fault-tolerant observers, which guarantee safe and robust coordination even in the event of network and device degradation [107].

3.6. Sliding mode control (SMC)

Sliding mode control is still widely used in 2025 because of its resilience to external disturbances, parameter uncertainties, and finite-time convergence [19,24–26,59,60,108–111]. These properties are essential during the unfavorable conditions of microgrids. Specifically, the super-twisting algorithm enhances current sharing and frequency restoration in the presence of major disturbances at the cost of minimal chattering and with strong robustness. Distributed sliding mode control has also been utilized at the secondary level of control together with the consensus mechanism to provide a robust reactive power sharing in case of line impedance differences and load changes [112].

3.6.1. Advanced SMC variants and applications

Prescribed performance SMC enforces transient and steady-state bounds in isolated DC microgrids [18]. Also, modified backstepping SMC with observer-less rejection improves robustness without added complexity [113]. Event-triggered distributed SMC lowers communication load by up to 80% while preserving stability under sources intermittency [109], and hybrid fixed-time terminal SMC ensures rapid convergence with predefined settling time [108]. Recent formulations embedding composite nonlinear feedback and adaptive reaching laws improve convergence and oscillation damping [114,115], with predictive SMC further optimizing transient performance and power quality [116]. Beyond sliding-mode-based designs, prescribed-time secondary control strategies combined with adaptive dynamic event-triggered mechanisms have been shown to guarantee user-defined convergence times while significantly reducing communication burden in islanded microgrids [117].

3.6.2. Super-twisting and higher-order SMC

Adaptive STC dynamically tunes gains for finite-time restoration under uncertainties, outperforming fixed-gain schemes [19,24], with self-tuning mechanisms removing dependence on disturbance bounds [24]. Exact-time convergent SMC achieves network-size-independent restoration [20], while integral sliding–composite strategies extend robustness with reduced effort [114]. The STC enhances DC microgrid stability under grid disturbances [118].

3.6.3. Cybersecurity and fault-tolerant SMC

SMC is increasingly applied to secure microgrids against cyber–physical threats. Distributed SMC with unknown input observers detects attacks [49], while finite-time SMC with barrier functions ensures frequency stability under false data injection (FDI) and DoS [119]. From a communication-efficiency perspective, distributed secondary voltage recovery has also been achieved using dynamic event-triggered control schemes with artificial delays, which significantly reduce communication frequency while guaranteeing exponential stability through LMI-based conditions [120]. Resilient distributed SMC maintains restoration despite packet loss and unforeseen disruptions [19], and fault-tolerant observers further mitigate compound sensor/actuator faults.

3.6.4. Model-free SMC

Robust control without detailed models is made possible by model-free adaptive SMC with prescribed performance [121]. While DI-SMC + I-BSC hybrids enhance nonlinear restoration under uncertainty, disturbance-observer SMC increases hybrid AC/DC resilience [122]. Adaptability under high renewable penetration and mode switching is improved by intelligent fuzzy approaches, such as type-3 fuzzy SMC with barrier functions [119].

3.6.5. Implementation aspects

Boundary-layer smoothing and adaptive gain tuning are used in the implementation to reduce chattering and converter stress. Experimental studies validate the real-time feasibility of self-tuning adaptive super-twisting controllers, while hybrid SMC–MPC frameworks combine robustness and constraint handling for better transients.

3.7. Fuzzy logic and neuro-Fuzzy control

Fuzzy controllers (FCs) encode heuristic rules for voltage and frequency regulation, while adaptive variants such as ANFIS and fuzzy–neural (FN) automatically tune parameters from data. In remote microgrid applications with inverter-interfaced PV and battery support, adaptive fuzzy PID-based decentralized voltage control has been applied to maintain stable three-phase voltage under irradiance variability and storage operating constraints, without requiring fixed adaptation gains or detailed system model [123]. Reported 2025 implementations show superior disturbance rejection, reduced overshoot, and lower operating cost compared to PI/PID or optimization-only EMS, with modest computational demand. Decentralized FC remains popular, where price-signaling fuzzy schemes enable multi-prosumer coordination without communication [124], and fuzzy–incremental conductance MPPT improves renewable integration and power quality in isolated DC microgrids, with HIL validation confirming practical feasibility [125–127]. Neuro-fuzzy and ANFIS systems, including GA-optimized MANFIS, enhance scheduling and stability [128], while two-layer FN networks regulate droop parameters for multi-DG DC microgrids, improving voltage stability and power sharing [61]. Real-time FN EMS methods further achieve near-optimal scheduling with interpretable parameters and rapid response [129]. Hybrid fuzzy methods also show strong results. For instance, a GA-Grey Wolf Optimizer (GWO)-optimized TSK fuzzy controller unified converter and inverter management in hydrogen fuel-cell microgrids, achieving 97.58% PV, 98.56% wind, and 98.88% fuel-cell tracking efficiency while minimizing PCC power exchange and enhancing frequency regulation under both grid-connected and islanded modes [130]. Similarly, a type-3 fuzzy MPC combined with a disturbance observer and square-root cubature Kalman filter stabilized CPL-fed DC microgrids, reducing voltage fluctuations by 20% and improving dynamic response and efficiency [131].

3.7.1. Strengths and challenges

Fuzzy and neuro-fuzzy systems provide adaptability, resilience, and low computational cost, making them well suited for embedded microgrid controllers. Their main limitations remain reliance on expert rule design and sensitivity to membership tuning, but hybridization with metaheuristics, MPC, and neural networks mitigates these drawbacks and enhances scalability under uncertain renewable conditions.

3.8. Neural network and deep learning controllers

For secondary restoration and control, neural networks (NN) approximate nonlinear mappings. Deep architectures like deep neural networks (DNN), CNN, and LSTM are being utilized more and more for forecasting, fault detection, and anomaly recognition in control loops [97,132–135]. While robust data-driven predictive control (DDPC) methods use DNN to approximate nonlinear MPC laws for high-speed, automated power management in DC microgrids, CNN-based methods improve dispatch accuracy for PV–battery coordination [132]. Real-time stability restoration under load surges, cyberattacks, and stochastic disturbances is made possible by the proposed DDPC, which reduces computational load by 97.8%, has a smoother control response by 31%, and converges 50% faster than PI control [135]. In order to improve communication efficiency and dynamic stability, decentralized GNN–LSTM event-triggered controllers have been introduced. They have been shown to improve voltage stability indices, reduce frequency regulation error, and achieve 55% lower communication overhead, 45% higher voltage regulation accuracy, and 35% better frequency regulation performance [38]. CMPA–PINN hierarchical control improves islanding detection and reduces total harmonic distortion (2%) in grid-connected and islanded modes, according to recent advancements in physics-informed and IoT-augmented intelligence [133]. For microgrid anti-islanding protection, a complementary strategy uses a hybrid unscented Kalman filter–deep neural network (UKF–DNN) method, in which the UKF serves as a state observer and DNN residual indices facilitate quick and precise islanding detection. The method's low computational cost and 98.5% accuracy have been validated on IEEE UL174 test systems [136].

3.9. Reinforcement learning/deep reinforcement learning

For microgrid supervisory control and energy management under uncertainty, Reinforcement Learning (RL) and Deep RL (DRL) offer model-free adaptability [137]. At the frequency control level, data-driven DRL methods have been used to treat the microgrid controller as an intelligent agent that autonomously balances frequency regulation and generation cost, using priority experience replay and entropy-based exploration to enhance robustness under disturbances [138]. Recent work has further shown that RL-enhanced hybrid optimization methods, in which RL dynamically regulates multi-strategy metaheuristic search and algorithm parameters, can significantly improve the economic performance and robustness of islanded microgrid scheduling under renewable generation and load uncertainty [139]. In a related work, in remote islanded microgrids where accurate models and reliable terrestrial communication are difficult to guarantee, data-driven predictive control was combined with wideband LEO satellite communication to enable coordinated, system-level stability enhancement under severe disturbances [140].

Algorithms comparisons show that Pursuit Algorithm-driven Q-learning improves cost-reliability metrics by 8% [141], while Deep Q-Network (DQN) was superior, achieving 12% less cost over Q-learning [27]. Secured residential systems [142] and the RL-based MPC are examples of advanced solutions that greatly improve power quality and adaptive control in microgrids [39]. For EV integration and renewable microgrids, Soft Actor-Critic (SAC) performs excellently in stochastic environments [36]. Using DE-PSO optimization, hybrid methods combine DRL and MPC, achieving up to 40% energy savings and 25% more comfort [143]. Elsewhere, stochastic optimization uses Dynamic Programming with quadratic programming for forecast uncertainty [144], while DQN-tuned PSO was employed in [145], where results indicated that, across standard daily, high-volatility, and low-load conditions, the proposed DQN-PSO technique enhances renewable energy usage by 3.2%, 4.5%, and 10.9%, respectively, relative to traditional PSO methods, while lowering power supply reliability risk to just 0.70%, 1.04%, and 0.30% in those scenarios.

The conceptual interaction between the RL agent and the standalone microgrid is illustrated in Fig. 3. The agent observes system states such as frequency/voltage deviations and SoC variations, executes control actions through learned policies, and receives reward signals that guide its optimization toward cost-effective and stable operation.

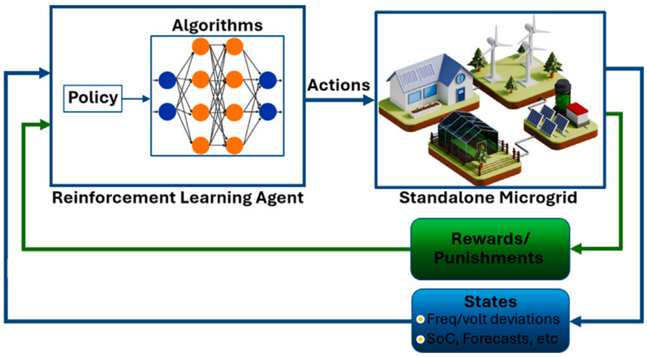

Fig. 3. Microgrid control integration with deep reinforcement learning.

3.10. Metaheuristic optimization for controller tuning

In 2025, metaheuristic algorithms have become popular for fine-tuning independent controllers, with GA–GWO frameworks showing significant performance improvements. Grey Wolf-optimized TSK fuzzy controllers, for instance, minimize power exchange and improve frequency regulation while achieving over 97% tracking efficiency for PV and wind sources and 98.9% for hydrogen fuel cells [130]. Hybrid fuzzy–MPC schemes [131] use Type-3 fuzzy systems with disturbance observers and cubature Kalman filters to reduce voltage fluctuations by 20% and speed up dynamic response under constant power loads. A PSO–SFLA hybrid offers faster convergence, higher accuracy, and improved cost-effectiveness for hybrid PV–wind–battery microgrids, according to recent hybrid optimization studies that combine Political Optimization, Artificial Electric Field, and Shuffled Frog Leaping algorithms. These findings were confirmed using real-time meteorological data from remote Egyptian regions [146].

Intelligent load frequency control of isolated microgrids has been addressed using hybrid metaheuristic approaches, where PSO–GWO-based tuning of PI–PD controllers significantly improves frequency regulation performance under load variations and external disturbances compared to conventional PI/PID schemes [147]. Hybrid metaheuristic frameworks combining multiple bio-inspired algorithms have also emerged as effective tools for multi-objective microgrid optimization under renewable uncertainty [148]

3.11. Advanced novel control methods

In order to improve the stability, adaptability, and resilience of microgrids, recent studies from 2025 highlight the convergence of sophisticated computation, power electronics, and control techniques. By combining Zeta and Ćuk converter structures, single-stage converter–inverter designs like the Integrated Zeta–Ćuk Inverter (IZCI) make DC/AC conversion for DC microgrids easier. IZCI is appealing for small standalone applications because it operates in discontinuous conduction mode and creates a linear duty–voltage relationship that streamlines the control strategy, reduces sensing requirements, and achieves high conversion efficiency with low total harmonic distortion (THD) [149]. Coordinated inverter and MPPT controllers have been developed for wind-hydrogen-battery microgrids in order to preserve voltage and frequency stability in the event of distribution line failures. MATLAB/Simulink and RTDS testing have validated the suggested fault-tolerant control, which reduces current stress and improves reliability [150]. Under normal and faulted operating conditions, coordinated V–f and constant-power inverter control schemes have also been applied in PV-integrated islanded microgrids to maintain voltage and frequency stability while enabling low-voltage ride-through through prioritized reactive power support [151].

A coordinated reserve-energy management strategy that combines battery and supercapacitor storage enhances DC-link voltage stability and lowers capacitor stress for voltage regulation under renewable intermittency. The method increases inverter lifespan and reliability while stabilizing voltage across various operating modes, such as irradiance and load intermittencies [152]. Additionally, frameworks for integrated co-simulation and HIL testing that combine RTDS environments with FPGA controllers have surfaced for the experimental validation of advanced synchronization control. The grid-forming battery converter control and modified phase-locked loop (PLL)-based synchronization showed fault resilience and stable standalone operation under load disturbances [153].

Moreover, hybrid adaptive control techniques are recent developments that improve harmonic suppression and synchronization even more. To enhance frequency estimation, dynamic response, and power balance in hybrid wind-PV-BESS microgrids, the FANF–EMOGI–FLL approach combines a frequency-adaptive notch filter with a generalized integrator [154]. Similar to this, fuel-cell/aqua-electrolyzer converters are used in PV–wind–SMES–FC–AE–battery systems as dual-purpose DC regulators and MPPT controllers, resulting in stable DC-link voltage and enhanced power quality in both steady-state and transient scenarios [155].

These advancements are complemented by optimization-driven control techniques. For smooth diesel generator engagement and harmonic mitigation, an optimized multi-source hybrid standalone microgrid combines wind, PV, and diesel units with adaptive synchronization control and a variable-size perturb-and-observe MPPT scheme [156]. Lastly, to enhance dynamic performance in systems that are penetrated by renewable energy sources, intelligent optimization and frequency control techniques are being implemented. A recent study uses a two-DoF controller tuned by the Sine Cosine Algorithm (SCA) to stabilize frequency in AC microgrids that include wind, solar PV, and thermoelectric power plants. By effectively modifying controller gains to suppress oscillations brought on by load variations and renewable intermittency, the SCA outperforms conventional PI and PID controllers in terms of transient recovery and steady-state precision. Under stochastic operating conditions, the method's superior robustness and faster frequency restoration validate its potential for high-performance standalone microgrid applications [157].

3.12. DC and hybrid AC–DC microgrid considerations

Recent studies from 2025 demonstrate notable advancements in hybrid AC–DC microgrid control, with the goal of improving efficiency, voltage stability, and adaptability for remote communities. Adaptive PV array reconfiguration between series–parallel and parallel modes reduces partial shading and increases power by up to 53% when compared to traditional arrays [158]. Interval load flow modeling enables uncertainty-aware analysis of islanded systems by combining droop-controlled DGs and interlinking converter dynamics for accurate probabilistic load flow solutions [68]. Coordinated control with battery-supercapacitor storage improves DC-link voltage regulation and inverter reliability under changing irradiance [159]. In order to stabilize microgrid transients, virtual-interface control introduces dual-side virtual capacitances to provide inertia on AC and DC buses [63]. Furthermore, integrated Zeta–Ćuk inverter topologies offer low harmonic distortion, high efficiency, and linear duty–voltage operation with fewer sensors for standalone DC microgrids [149]. Together, these advancements give hybrid microgrid designs flexibility and resilience.

3.13. Special topics for microgrids

3.13.1. Cyber-resilient control architectures

Through anomaly detection and mitigation, Bayesian learning and data-driven frameworks are used to enhance microgrid cyber resilience

Table 2
Capabilities, risks, and deployment implications of cyber–physical enablers in standalone microgrids.

Enabler	Primary Capability	Key Risks and Limitations	Deployment Implications
Cybersecurity	Protection from false data injection, denial-of-service attacks, and unauthorized access; improved data integrity and communication resilience	Added computational and communication overhead; reliance on key management; potential latency in real-time control loops	Essential for distributed microgrids but requires co-design with control and EMS to balance security and real-time performance
Digital Twins	Improved system visibility, predictive analysis, controller testing, and validation under diverse scenarios	Model fidelity limits; high data dependency; increased computational burden for real-time synchronization	Effective for design, tuning, and supervisory EMS, but limited for fast primary control without model reduction
Edge Computing	Lower latency, localized decision-making, improved scalability, and reduced reliance on centralized cloud infrastructure	Expanded cyber-attack surface; limited edge-node resources; increased system integration complexity	Well suited for real-time control and distributed EMS in remote microgrids, provided security and resource limits are addressed

[160]. Combining BiLSTM neural networks with whale-optimized detection results in 98% accuracy against false-data injection attacks [161]. Robustness against model uncertainties and communication delays is ensured by multi-objective optimization with distributed sliding-mode observers [162].

Beyond conceptual schemes, recent research emphasizes real-time cyber-resilience via HIL and cyber–physical testbeds. These platforms assess attack impacts under realistic latency, packet loss, and encryption overhead-factors critical for remote microgrids using embedded edge devices. Consequently, lightweight encryption and resource-aware, timing-constrained security are essential to ensure that resilience does not compromise real-time control performance.

3.13.2. Digital twin-enabled energy management

Digital twins allow dynamic microgrid modeling by combining machine learning, physics-based models, and real-time sensor data [163]. IoT-based physics-informed NN enhances harmonic suppression and islanding detection [164].

3.13.3. Edge computing integration

Compared to centralized schemes, edge architectures reduce communication latency by half by executing control locally on smart meters [165]. Event-triggered updates reduce overhead without compromising stability because they only happen in response to major state changes. By combining edge cloud computing with IEC 62264 standards, a new three-layer architecture based on Open Platform Communications Unified Architecture (OPC UA) tackles interoperability issues in aggregated microgrids [166]. It facilitates secure TLS/AES256 communication, adaptive semantic modeling, and smooth data exchange by dividing operations into three layers: Microgrid Aggregation, Communication, and Distributed Microgrid. Tested on a testbed with a 17.86-fold latency reduction, OPC UA provides faster real-time coordination and wider interoperability than IEC 61850. For cloud-integrated edge control in contemporary microgrids, this architecture provides a scalable, secure, and responsive basis.

To synthesize the distinct capabilities, risks, and deployment implications of cybersecurity mechanisms, digital twins, and edge computing in standalone microgrids, a comparative assessment is summarized in Table 2.

3.13.4. Quantum-enhanced security

Achieving key generation rates above 1 Mbps over 50 km fibre links, dynamic quantum key distribution protocols with distributed error correction dynamically modify photon encoding rates to optimize secure key output under changing channel conditions [167]. Quantum-inspired optimization improved uncertainty handling and control [168].

3.13.5. Bio-inspired control algorithms

According to recent research, virtual synchronous generator parameters can be efficiently adjusted for frequency regulation in islanded microgrids using ant colony optimization (ACO). In [169], the authors used ACO to modify virtual inertia and damping, which improved recovery time by 30% and decreased frequency deviations by 40% under high renewable variability. Also, energy storage and inverter dispatch have been coordinated using multi-objective optimization based on swarm intelligence. In order to minimize cost, emissions, and frequency deviation within 5% of nominal values across a range of load scenarios, Rochd et al. [170] combined enhanced PSO with demand-response constraints.

3.14. Summary of control techniques

The main control strategies examined in the literature are summarized in Table 3, which shows a clear shift away from traditional robust and predictive techniques and towards intelligent, model-free, and communication-resilient frameworks. Even though each paradigm has unique benefits in terms of coordination, stability, and adaptability, the majority are still limited by the computational requirements, insufficient experimental validation, and scalability issues in actual microgrid deployments.

Across the reviewed paradigms, the manuscript explicitly examines computational complexity, convergence behavior, cyber–physical resilience, and hardware readiness, highlighting how these factors constrain real-time deployment in remote standalone microgrids.

To avoid redundancy, variant-level descriptions of adaptive droop, virtual impedance, and MPC have been consolidated into Table 3, with the main text emphasizing comparative insights, deployment constraints, and system-level trade-offs.

3.15. Quantitative performance trends and comparative metrics

Despite diverse study setups, we can compare control paradigms through metrics like stability bounds, power-sharing accuracy, resource loads, costs, and validation levels. Trends show that adaptive and event-triggered methods cut communication by 50%–80% while staying within ±2% voltage limits. Conversely, robust and predictive controllers trade higher computational demand for better disturbance rejection, while learning-based EMS offers top efficiency but lacks experimental proof. These trade-offs highlight the clear need for standardized benchmarking protocols.

To support a quantitative comparison, key performance indicators repeatedly reported across the literature were extracted and synthesized. Table 4 summarizes the most common metrics, their typical ranges, and the paradigms in which they are most frequently evaluated.

Since reported improvements stem from diverse test systems and baseline assumptions, these values are not directly comparable. Instead, they should be viewed as indicative performance trends relative to each study's internal setup rather than as normalized benchmarks.

Table 3
Comprehensive summary of control strategies identified in the literature.

Strategy	Algorithm/Variant	Key Objectives/Features	Limitations/Gaps	Representative Works
Adaptive/ Nonlinear Droop (incl. SoC-aware, VPD/FQB)	Virtual impedance; Consensus; Super-twisting; Fixed-time; ANFIS	Power sharing; voltage regulation; frequency restoration; SoC-balancing; transient response enhancement; stability under impedance mismatch	Limited validation beyond DC microgrids; narrow SoC operating ranges; real-world implementation challenges; reliance on simulation; insufficient grid-connected scenario coverage	[11,14,17,19,23,44,61, 78,79,84,85,89]
Model Predictive Control (MPC)	Quadratic MPC; Nonlinear MPC; Economic MPC; Distributed MPC; Hybrid MPC-RL	Multi-objective optimization; explicit constraint handling; coordinated DER dispatch; voltage/frequency restoration; renewable uncertainty management	High computational burden; model dependency; real-time embedded deployment challenges; limited robustness under communication delays; scalability constraints	[3,4,10,23,28–34,48,62, 64,65,93,94,98,171–173]
Distributed/Consensus/ MAS	Average consensus; Leader–follower; Event-triggered; GNN-LSTM; Dynamic weight adjustment	Decentralized coordination; plug-and-play scalability; communication overhead reduction; voltage/frequency synchronization; fault tolerance	Vulnerability to cyber-attacks; packet loss sensitivity; communication delay impact; limited topology reconfiguration adaptability; convergence speed constraints	[19,37,38,40,65,67,101, 103,105,106,174,175]
Sliding Mode Control (SMC)/Super-Twisting (STC)	Conventional SMC; Integral SMC; Super-twisting; Adaptive STC; Finite-time SMC; Prescribed performance SMC	Robustness to uncertainties; finite-time convergence; chattering reduction; disturbance rejection; parameter variation tolerance	Residual chattering; fixed-gain limitations; limited nonlinear dynamics adaptation; insufficient experimental validation; tuning complexity	[18–20,24–26,49,59,60, 104,108–116,118,119, 121,122,176,177]
Reinforcement Learning (RL/DRL)	Q-learning; Deep Q-network (DQN); PPO; DDPG; SAC; Actor–critic; Multi-agent DRL	Data-driven optimization; model-free adaptability; autonomous regulation; policy generalization; online learning capability	Training instability; sample inefficiency; interpretability deficit; high computational cost; safety guarantee absence; exploration risks	[27,36,39,40,73,102, 137–139,141–145]
DC or Hybrid AC–DC Microgrid Control	Hierarchical control; Bidirectional converter; Virtual interface; Hybrid bus optimization; Energy routing	Improved efficiency; flexible AC-DC power exchange; topology coordination; SoC balancing; DC bus ripple reduction; enhanced resilience	Converter nonlinearity not addressed; weak-grid interaction neglected; hardware validation gap; limited AC–DC transition studies; complexity in hybrid topologies	[63,149,158–160]
Adaptive/Intelligent Control	Fuzzy logic; Neuro–fuzzy; ANFIS; Adaptive law; Self-tuning; GA-optimized controllers	Parameter auto-adjustment; unknown disturbance handling; load/generation adaptability; robustness enhancement without full modeling	Slow adaptation; high tuning complexity; local minima risk; HIL validation absence; membership function sensitivity	[61,123–131,147,178]
Event-Triggered/ Communication-Aware Control	Event-triggered; Self-triggered; Asynchronous update; Adaptive threshold; Distributed event-based	Communication reduction (up to 80%); network efficiency; stability preservation with sparse updates; cyber-aware consensus	Threshold design complexity; Zeno behavior risk; update synchronization delays; scalability under realistic networks; triggering condition tuning	[70,72–74,101,109,120, 175]
Hybrid Model-Free/Data-Driven Control	Model-free adaptive control (MFAC); RLS-based; Online identification; Hybrid adaptive–STC; Deep neural network predictive	Explicit model elimination; nonlinearity adaptability; real-time learning; disturbance rejection; reduced tuning burden	Data dependency; noise sensitivity; convergence guarantee limitations; validation insufficiency; overfitting potential; computational overhead	[38,121,133,135,136]

Table 4
Common performance metrics reported in the literature on standalone microgrid control and EMS studies.

Performance Metric	Description	Typical Reported Range	Commonly Evaluated In
Frequency deviation	Maximum steady-state or transient frequency error	±0.1–0.5 Hz	SMC, MPC, Distributed control
Voltage deviation	Bus voltage deviation from nominal value	±1%–2%	Droop, MPC, Fuzzy control
Power-sharing error	Mismatch in active/reactive power sharing among DGs	1%–5%	Droop-based, SMC, MAS
Communication overhead	Reduction in data exchange compared to periodic updates	50%–80% reduction	Event-triggered, MAS
Computational burden	Execution time or controller complexity	Up to 97% reduction	DRL-based EMS
Economic cost reduction	Operational cost savings relative to baseline EMS	10%–40%	MPC, RL/DRL-based EMS
Renewable tracking efficiency	Accuracy of RES power utilization or MPPT performance	>95%	Fuzzy, Metaheuristic EMS
Validation level	Extent of experimental verification	Mostly simulation; limited HIL/experimental	All paradigms

3.16. Hardware validation and deployment readiness across control paradigms

Simulation dominates the literature, but with 68% of studies lacking hardware evaluation, validation maturity remains highly paradigm-dependent. MPC-based controllers mostly reach HIL and field testing due to their deterministic structure and real-time feasibility. Conversely, SMC is often restricted to simulation or HIL by chattering issues and actuator stress. Meanwhile, learning-based and DRL methods remain almost exclusively simulation-bound, hindered by safety risks and a lack of convergence guarantees. These discrepancies underscore the need for standardized simulation–HIL–field deployment pipelines to ensure reliable transitions from theory to practice.

4. Energy management systems and optimization

Energy Management Systems (EMS) orchestrate generation, storage, and controllable loads for reliable, economic, and sustainable operation of standalone microgrids. By 2025, EMS design has evolved beyond simple scheduling into a multi-layered, multi-objective decision-making process that accounts for uncertainty, nonlinearity, and resilience.

4.1. EMS architecture and functional layers

Day-ahead scheduling, intra-day or hour-ahead rescheduling, and real-time corrective dispatch are the three primary elements of modern EMS frameworks [179]. The day-ahead layer relies on renewable forecasts and load profiles to minimize operating costs while satisfying constraints such as generator ramp limits, ESS SoC bounds, and reserve requirements [178]. Deep learning-based forecasting models, particularly LSTM recurrent neural networks, have been employed to capture the stochastic behavior of solar irradiance and wind speed, enabling more accurate anticipation of renewable power variations and improved frequency regulation in isolated microgrids [180]. In diesel-dominated standalone microgrids operating under uncertain electricity prices, risk-aware self-scheduling formulations based on mixed-integer nonlinear optimization have been employed to jointly coordinate PV, wind, and diesel units, balancing fuel cost and market revenue without requiring probabilistic price models [181]. Complementary cost-effective EMS approaches have also been developed for islanded hybrid microgrids by integrating day-ahead photovoltaic power forecasting with cost-function-based optimization, enabling coordinated scheduling of renewable resources and battery storage to minimize operating costs under uncertain weather conditions [182]. A year 2025 distributed EMS formulations have further shown that explicitly accounting for correlated uncertainties between renewable generation and load demand enables more consistent resource coordination and improved economic performance in isolated microgrids [174]. Intra-day rescheduling controls forecast errors by recalculating setpoints on a regular basis, while real-time dispatch manages frequency regulation and final power balancing. Fig. 4 displays a generic EMS architecture with forecasting, optimization, and dispatch modules.

4.2. Deterministic optimization (DO) approaches

For scheduling, dispatch, and protection in standalone and hybrid microgrids, deterministic techniques like Mixed-Integer Linear Programming (MILP) and Mixed-Integer Nonlinear Programming (MINLP) continue to be essential. While protection-oriented MILP formulations integrating IEC/IEEE relay characteristics minimize tripping time and enhance selectivity, unified MILP-based models allow for precise power scheduling, overload mitigation, and a smooth mode transition in home DC microgrids [183]. Through joint placement and operation planning, BONMIN-based MINLP optimization for Na–$NiCl_2$ systems achieves over 30% cost reduction and increased hosting capacity [184]. In multi-microgrid settings, rolling-horizon and hierarchical MILP schemes further enhance scalability and coordination [185]. Deterministic models are still susceptible to forecast errors despite their interpretability and global optimality, which is why reserve margins and strong constraints are used to increase reliability in the face of renewable uncertainty. In addition to operational optimization, microgrid component sizing problems have been successfully solved using linear programming. Recent hybrid approaches that combine linear search and LP have achieved notable computational speedups while preserving solution accuracy [186].

4.3. Stochastic and robust optimization

These techniques use complementary strategies to address microgrid uncertainty. Using Markov decision processes for 95% reliability in standalone PV microgrids [171] and Advanced Dynamic Programming for forecast uncertainty [144], stochastic programming minimizes expected cost under various renewable and load scenarios with chance constraints. For DC microgrid variability, robust counterparts use interval optimization with convex relaxation [46], and for the worst-case situations, hierarchical MPC with robust constraints [31]. In home energy management systems, adaptive load grouping and time-varying tariffs enhance operational efficiency, lower costs, and balance supply and demand in residential microgrids. More recently, dynamic pricing and clustering-based optimization have been further integrated to manage demand uncertainty [53].

4.4. Metaheuristic-based EMS solutions

Metaheuristic algorithms like PSO, GA, ACO, GWO, and NSGA-II efficiently handle nonconvex and nonlinear EMS optimization problems. For example, a recent work has explored intelligent spider monkey algorithm applications that address uncertainties in wind generation and EV charging/discharging dynamics, demonstrating enhanced operational reliability and cost-effectiveness [187].

Through the integration of evolutionary optimization and probabilistic forecasting, a two-stage GA–ELM hierarchical EMS enhances flexibility and cost efficiency in interconnected microgrids [188]. In PV-wind-fuel-cell systems, GA-GWO frameworks achieve robust frequency regulation and over 97% renewable tracking efficiency [189]. By lowering frequency deviation by 28% and accelerating recovery, chaotic swarm-based optimizers, such as the Chaotic African Vulture Optimizer (CAVO), perform better than PSO and WOA [190]. Similarly, using real meteorological data, hybrid PSO–SFLA and GA–ACO methods improve convergence and cost-effectiveness in PV–wind–battery scheduling [191]. The value of these hybrid and chaos-enhanced metaheuristics for independent and networked microgrid energy management is further supported by the faster convergence, increased renewable utilization, and stronger stability they provide when combined. Applications for 2025 have been reported to include:

- Multi-objective economic–environmental dispatch (cost vs. CO_2 emissions),
- SoC-aware charging/discharging of ESS for lifecycle extension,
- Joint optimization of power flow and demand response participation.

4.5. AI-driven EMS: Reinforcement learning and predictive scheduling

Model-free EMS design without explicit system modeling is becoming more and more possible thanks to deep reinforcement learning techniques like DQN, PPO, DDPG, and SAC [27,36]. In-depth analyses examine AI applications throughout the microgrid lifecycle [137]. ML-IoT EMS for AC microgrids using sensor networks [192] and smart city implementations combining IoT, AI, and GANs [193] are examples of IoT and digitalization advancements. High-quality predictions are fed into optimization layers by neural network forecasting modules that use CNN, FNN, LSTM, and Transformer architectures [194–197].

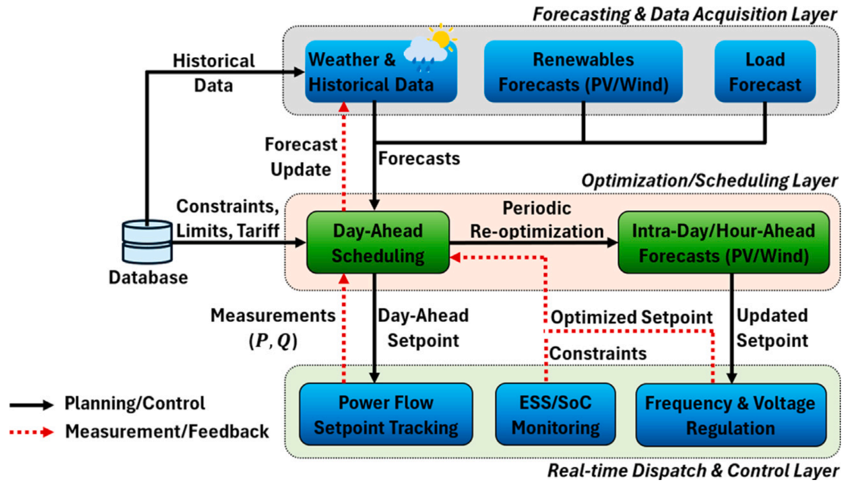

Fig. 4. Generic architecture of an Energy Management System (EMS) for a standalone microgrid, illustrating the forecasting, day-ahead scheduling, intra-day rescheduling, and real-time dispatch layers.

4.6. Demand response and flexible loads

To improve renewable usage and smooth out peaks, the DR schemes make use of the controllable loads flexibility. Taking price-based and incentive-based DR schemes into EMS frameworks allows load shifting and shedding based on system conditions [28,198]. Although transactive energy mechanisms are studied for peer-to-peer microgrids [199], game-theoretic models are reported for fair and cost-effective DER allocation [200]. Achieving coordination without centralized control, Pursuit Algorithm-driven Q-learning has optimized energy management with flexible loads [141].

4.7. Cyber-resilience and security

As EMS depend more and more on communication networks, cybersecurity has become crucial. Distributed SMC with unknown input observers achieves 98% accuracy for intrusion detection against FDI attacks [49]. While distributed predictive control with sliding mode observers provides security during DoS attacks [64], cyber-resilient distributed MPC uses residual-based observation to continue operating during coordinated attacks [201]. Adaptive finite-time sliding mode with barrier functions countering FDI while maintaining frequency stability [110] and DRL integrating intrusion detection with control policies for residential microgrids [143] are examples of secure implementations. In order to create multi-layered defence mechanisms for microgrid infrastructures, emerging approaches use machine learning for anomaly detection, packet encryption, and resilient scheduling during communication loss [19,64,201].

4.8. Summary of EMS and optimization techniques

The main EMS approaches discussed in the 2025 literature are summarized in Table 5, which includes objective functions, solution methodologies, validation platforms, and performance indicators. In order to handle renewable uncertainty, computational limitations, and scalability requirements in isolated microgrids, the taxonomy shows how deterministic optimization gave way to hybrid, learning-driven, and cyber–physical frameworks.

From a system-level perspective, hierarchical control and energy management strategies operate as tightly coupled layers rather than independent modules. Primary and secondary control layers are responsible for fast voltage and frequency regulation and disturbance rejection, while supervisory EMS operates on slower time scales to optimize economic performance, resource utilization, and operational constraints. Recent studies increasingly adopt integrated architectures in which predictive, distributed, or learning-based approaches span multiple layers, enabling coordinated decision-making between real-time control and supervisory optimization. This cross-layer perspective highlights the need for unified control–EMS frameworks that explicitly account for communication constraints, computational burden, and real-time feasibility in standalone microgrids.

Hierarchical control and EMS work on coupled but distinct time scales: fast primary and secondary layers regulate voltage and frequency in real time, while EMS performs slower supervisory optimization of power dispatch and storage. Their interaction is mediated by setpoints and state feedback, whereby EMS decisions define feasible operating trajectories, and real-time responses inform subsequent optimization. This cross-timescale coupling forms an implicit interaction model that is increasingly central to predictive, distributed, and learning-based microgrid architectures.

5. Bibliometric analysis

Unlike conventional bibliometric surveys, this analysis is explicitly coupled with the technical taxonomy developed in Sections 2–4, enabling interpretation of publication trends in terms of control philosophy, EMS architecture, and validation maturity.

5.1. Publication landscape and source influence

The source distribution (Table 6) reveals not only publication volume but also thematic orientation and methodological emphasis within the standalone microgrid literature. High-output journals such as *Scientific Reports, Results in Engineering,* and *IEEE Access* collectively indicate a strong preference for methodologically exploratory and interdisciplinary work, where novel control and EMS paradigms are often validated through simulation-heavy or hybrid analytical–computational approaches.

In contrast, the sustained presence of domain-specific outlets such as *Electric Power Systems Research, IEEE Transactions on Industry Applications, IEEE Transactions on Smart Grid,* and *Renewable Energy* reflects a parallel stream of theory-driven and system-level studies, typically characterized by rigorous control design, stability analysis, and grid-oriented performance metrics. This split suggests an emerging divide in the literature between **innovation-driven algorithm development** and **power-system-grounded validation**, highlighting a disconnect between bibliometric trends and technical depth in some studies.

Importantly, the rise of open-access journals coincides with the rapid growth of AI-driven control, distributed MPC, and hybrid EMS

Table 5
Comprehensive summary of the reported EMS and optimization approaches.

Approach	Optimization/Algorithm	Key Objectives/Features	Limitations/Gaps	Representative Works
Rule-Based EMS	Heuristic logic; Priority scheduling; If-then rules	Simplified energy scheduling; low computational overhead; real-time feasibility; suitable for low-complexity standalone systems	Lack of optimality; poor scalability for multi-agent networks; inflexible to dynamic pricing; absence of learning capability	[124,160,200]
Optimization-Based EMS	MILP; MINLP; Linear programming; Convex optimization; BONMIN solver	Cost minimization; emission reduction; energy balance; protection coordination; precise scheduling under operational constraints	Requires accurate models; computationally expensive for nonlinear/stochastic problems; forecast error sensitivity; limited scalability for high-dimensional systems	[66,184,185,188,202]
Metaheuristic Optimization	PSO; GA; DE; ACO; WOA; GWO; Hybrid PSO–GA; Chaotic swarm-based optimizers; Harris hawks optimization	Multi-objective scheduling (cost, emissions, reliability); robustness to nonlinearities; global search capability; renewable uncertainty handling	High iteration count; no guaranteed global optimality; parameter sensitivity; longer convergence in large-scale systems; tuning complexity	[45–47,56,130,146,189–192,203]
Stochastic/Robust Optimization	Chance-constrained programming; Robust convex optimization; Two-stage stochastic; Markov decision processes	Renewable uncertainty management; reliability under forecast errors; worst-case scenario handling; feasibility guarantees across multiple scenarios	Over-conservatism leading to suboptimal dispatch; scenario explosion; high computational burden; extensive historical data requirements	[31,46,53,144,171]
Model Predictive Control (MPC)-Based EMS	Deterministic MPC; Stochastic MPC; Economic MPC; Hierarchical MPC; Rolling-horizon MPC	Predictive DER coordination; explicit constraint handling; real-time disturbance adaptability; multi-objective optimization; renewable forecast integration	Accurate model and forecast dependency; computationally intensive for large-scale real-time deployment; limited robustness under communication delays	[3,4,10,28–34,48]
Reinforcement Learning (RL/DRL)-Based EMS	Q-learning; DQN; DDPG; PPO; SAC; Multi-agent DRL; Hierarchical RL	Model-free adaptability; dynamic decision-making; autonomous learning; scalability for multi-agent systems; online policy improvement	Training instability; sample inefficiency; large state/action space complexity; reward shaping difficulty; interpretability deficit; safety guarantee absence	[27,36,39,40,73,137,141–145]
Hybrid and Data-Driven EMS	Hybrid MPC–RL; Fuzzy–GA; ANN–PSO; CNN-based dispatch; LSTM forecasting; Data-driven predictive control	Combines optimization rigor with learning adaptability; enhanced uncertainty robustness; data-driven forecasting; reduced model dependency	Integration complexity; limited real-time hardware validation; overfitting risk to training datasets; historical data quality dependency; computational overhead	[30,39,42,97,132,135,180,189,195–198]
Blockchain/ Transactive EMS	Smart contracts; Distributed ledger; Game-theoretic pricing; Peer-to-peer energy trading; Auction	Transparency; decentralized energy markets; trust and traceability enhancement; autonomous transaction execution; prosumer participation	High computational and communication overhead; scalability constraints; latency issues; regulatory uncertainties; interoperability challenges	[199,201,204]
Edge/Cloud-Based EMS	Fog computing; Edge intelligence; Federated learning; Cloud-integrated EMS; OPC UA-based	Real-time computation at network edge; latency reduction (sub-100 ms); privacy preservation; scalable data aggregation; distributed processing	Security vulnerabilities; communication infrastructure dependence; node synchronization inconsistency; limited validation in realistic networks	[53,166,167,193,194]

Table 6
Top 20 most relevant sources.

S/N	Sources	Articles
1	Scientific Reports	12
2	Results in Engineering	10
3	IEEE Access	8
4	Electric Power Systems Research	6
5	Energies	6
6	IEEE Transactions on Industry Applications	6
7	Renewable Energy	6
8	Energy	5
9	IEEE Transactions on Smart Grid	5
10	International Journal of Electrical Power and Energy Systems	5
11	Journal of Energy Storage	5
12	Applied Energy	3
13	Computers and Electrical Engineering	3
14	Electronics (Switzerland)	3
15	IEEE Transactions on Industrial Informatics	3
16	IEEE Transactions on Power Systems	3
17	IET Renewable Power Generation	3
18	2025 International Conference on Computing Technologies	2
19	Conference Record – IAS Annual Meeting (IEEE Industry Applications Society)	2
20	Energy Reports	2

Table 7
Top 20 most relevant authors.

S/N	Authors	Articles
1	Fernández-Ramírez, Luis M.	4
2	Horrillo-Quintero, Pablo	4
3	Mahdian Dehkordi, Nima	4
4	Carrasco-González, David	3
5	García-Triviño, Pablo	3
6	Su, Chun Lien	3
7	Abdelbasset, Krama	2
8	Aguilera, Ricardo P.	2
9	Ahmad, Noor Syafawati	2
10	Ahmad, Saghir	2
11	Ali, Saima	2
12	Andújar Márquez, José Manuel	2
13	Azmi, Azralmukmin Bin	2
14	Baali, El Houssain	2
15	Babayomi, Oluleke	2
16	Bansal, Ramesh C.	2
17	Blasco, X.	2
18	Bouziane, Khalid	2
19	Chen, Hao	2
20	Dey, Rajdip	2

Table 8
Top 20 most relevant affiliations.

S/N	Affiliation	Articles
1	Islamic Azad University	22
2	Universidad de Cádiz	19
3	Shanghai Jiao Tong University	13
4	Tianjin University	13
5	Universiti Malaysia Perlis	12
6	Central South University	11
7	Hassan II University of Casablanca	11
8	Hunan University	11
9	Wuhan University of Technology	11
10	Huazhong University of Science and Technology	10
11	School of Electrical Engineering	9
12	National Institute of Technology Rourkela	8
13	Universitat Politècnica de València	8
14	University of Technology Sydney	8
15	Henan Polytechnic University	7
16	Institut de Recherche en Energie Electrique de Nantes Atlantique	7
17	Norges Teknisk-Naturvitenskapelige Universitet	7
18	Qilu University of Technology	7
19	Shahid Rajaee Teacher Training University	7
20	Amrita Vishwa Vidyapeetham University	6

frameworks, implying that fast dissemination venues are currently shaping early-stage methodological exploration, while archival IEEE journals remain the primary channels for mature and validated contributions.

5.2. Author productivity, research clusters, and thematic leadership

The most prolific authors (Table 7) form clearly identifiable thematic clusters, rather than isolated contributors. Authors with the highest publication counts are predominantly associated with: (i) distributed secondary control and consensus-based regulation, (ii) nonlinear and sliding-mode-based control frameworks, and (iii) AI-enhanced EMS and predictive optimization.

This clustering shows that research leadership in microgrids is method-centric rather than application-centric. That is, leading authors tend to specialize deeply in specific control paradigms (e.g., SMC, MPC, DRL), extending them incrementally across different microgrid configurations, rather than proposing entirely new system architectures.

At the same time, the long tail of authors with two publications reflects broad but shallow participation, often driven by case-study-based EMS optimization or algorithm benchmarking. While publication volume is increasing, conceptual consolidation and cross-paradigm synthesis remain limited, particularly between control-theoretic and data-driven communities.

5.3. Institutional contributions and geographic research priorities

The affiliation analysis (Table 8) reveals a geographically diverse but strategically concentrated research ecosystem. High-output institutions from Asia, the Middle East, and Southern Europe dominate the dataset, regions that are simultaneously: (i) Highly exposed to remote electrification challenges and (ii) Actively investing in renewable-dominated standalone systems. Institutions with the highest publication counts tend to focus on algorithmic robustness and EMS optimization, whereas institutions with moderate output but high citation impact often emphasize converter-level control, hardware-aware modeling, and experimental validation. This asymmetry suggests that quantity-driven publication strategies are not necessarily aligned with technical influence, reinforcing the need for stronger integration between bibliometric productivity and engineering relevance.

5.4. Citation structure and technical impact of foundational works

The global citation analysis (Table 9) shows a highly skewed citation distribution, where a small subset of papers accounts for a disproportionate share of total citations. These highly cited works consistently address fundamental technical bottlenecks, including: (i) frequency and voltage stability in low-inertia systems, (ii) distributed secondary control under communication constraints, and (iii) robust control formulations resilient to uncertainty and disturbances.

Notably, many recent AI- and DRL-based EMS papers exhibit lower citation counts despite methodological novelty, reflecting both their recency and unresolved concerns related to interpretability, safety guarantees, and hardware feasibility. This contrast indicates that technical depth and problem relevance, rather than algorithmic sophistication alone, remain the dominant drivers of long-term impact in this field.

5.5. Thematic evolution and methodological gaps

By jointly interpreting the co-occurrence networks shown in Figs. 5–7 and bibliometric tables presented above, a clear thematic evolution emerges:

- Droop-based control enhancements and deterministic EMS optimization dominated early work (2020–2022).
- Recent studies (2023–2025) increasingly emphasize distributed control, event-triggered communication, MPC variants, and AI-driven EMS.

However, this evolution is largely horizontal rather than integrative. Few studies explicitly bridge:

- Converter-level nonlinear control with system-level EMS decisions,
- Learning-based EMS with formal stability guarantees, or
- Bibliometrically dominant methods with large-scale experimental validation.

While the bibliometric growth is evident, the lack of cross-layer and cross-method synthesis limits the translation of research volume into deployable microgrid solutions.

Table 9
Top 20 most globally cited documents.

S/N	Paper	DOI	Total citations
1	Shahab, 2020, IEEE Trans. Smart Grid	10.1109/TSG.2019.2916727	123
2	Kumar, 2021, Int. J. Model. Simul.	10.1080/02286203.2020.1767840	104
3	Bidram, 2020, IEEE Trans. Ind. Informatics	10.1109/TII.2019.2941748	104
4	Yan, 2022, IEEE Trans. Control Netw. Syst.	10.1109/TCNS.2022.3140702	66
5	Cecilia, 2020, Energies	10.3390/en13061454	54
6	Wang, 2023, Prot. Control Mod. Power Syst.	10.1186/s41601-023-00284-z	43
7	Rodrigues, 2020, IEEE Trans. Smart Grid	10.1109/TSG.2019.2919123	40
8	Guo, 2020, Asian J. Control	10.1002/asjc.1906	35
9	Gurugubelli, 2022, Prot. Control Mod. Power Syst.	10.1186/s41601-022-00248-9	31
10	Wang, 2025, Energy	10.1016/j.energy.2024.134165	27
11	Chang, 2021, IEEE Trans. Sustain. Energy	10.1109/TSTE.2021.3095928	26
12	Andreotti, 2024, IEEE Trans. Cybern.	10.1109/TCYB.2024.3364820	25
13	Kumar, 2024, IEEE Trans. Ind. Appl.	10.1109/TIA.2024.3350577	24
14	Szilagyi, 2023, Energy Reports	10.1016/j.egyr.2023.10.088	23
15	Sahoo, 2025, Results Eng.	10.1016/j.rineng.2025.104010	19
16	Silva Ramkumar, 2025, Sci. Reports	10.1038/s41598-025-90062-8	16
17	Ndeh, 2024, E-Prime Adv. Electr. Eng. Electron. Energy	10.1016/j.prime.2024.100433	13
18	Rochd, 2025, Results Eng.	10.1016/j.rineng.2025.104400	12
19	Ramesh, 2025, Sci. Reports	10.1038/s41598-024-83625-8	10
20	Sandeep, 2025, Results Eng.	10.1016/j.rineng.2025.105479	10

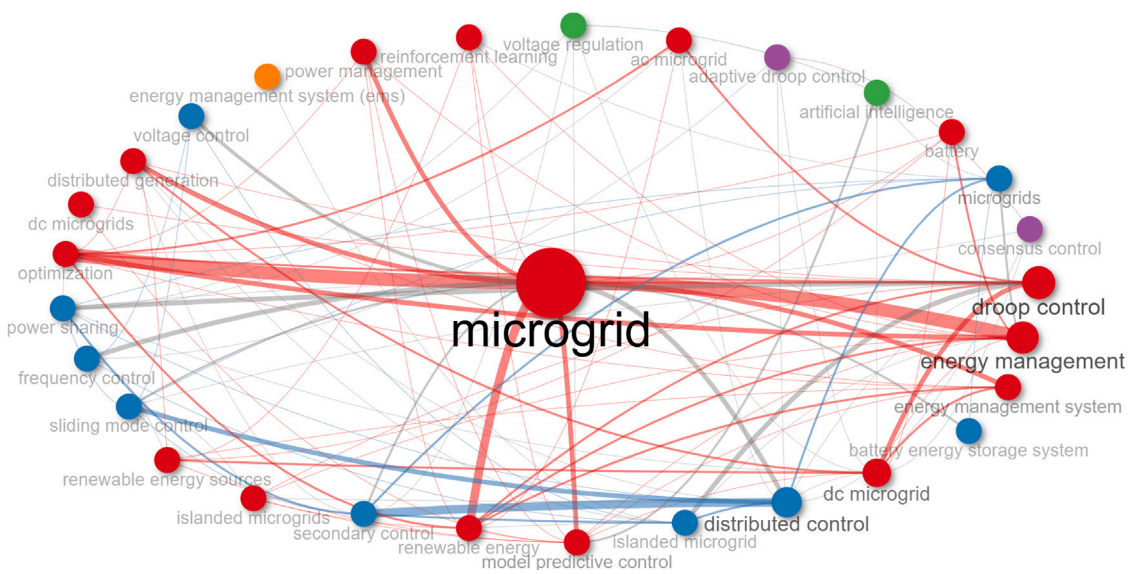

Fig. 5. Keywords co-occurrence network revealing the conceptual architecture and thematic clusters in microgrid research.

5.6. Synthesis: From bibliometrics to technical insight

To address the identified disconnect, this review explicitly uses bibliometric evidence to motivate the technical discussions in Sections 3 and 4. The dominance of certain sources, authors, and highly cited works is not treated as an endpoint, but as quantitative justification for focusing on robustness, scalability, and validation gaps in standalone microgrid control and EMS design. Accordingly, the bibliometric findings directly inform the research gaps and future directions outlined in Section 6, particularly the need for:

- Benchmarking frameworks that unify control and EMS evaluation,
- Hybrid model-based and data-driven methods with provable guarantees, and
- Experimental and cyber–physical validation beyond simulation-centric studies.

6. Structural research challenges and design recommendations

Rather than cataloging isolated open problems, this section synthesizes recurring challenges across control, energy management, communication, and validation into a set of structural research challenges. These challenges emerge from cross-analysis of the literature and highlight systemic limitations affecting the real-world deployment of standalone microgrids. The resulting recommendations are thus positioned at the design level, rather than as incremental algorithmic improvements. Collectively, these design-level recommendations constitute a deployment-oriented methodological framework for addressing cybersecurity integration, hardware validation, and benchmarking gaps in standalone microgrid control and energy management.

A major barrier to rigorous quantitative benchmarking is the lack of standardized test systems, operating scenarios, and evaluation metrics, which motivates the need for a common, metric-driven benchmarking framework to enable reproducible and fair comparison across studies.

6.1. Challenge 1: Power-sharing accuracy and stability under weak and heterogeneous networks

Low-inertia conditions, nonlinear load scenarios, and line impedance mismatch all continue to cause errors in droop and virtual impedance methods [19,22,90]. Circulating currents, variations in bus voltage, and possible synchronization loss are caused by these errors.

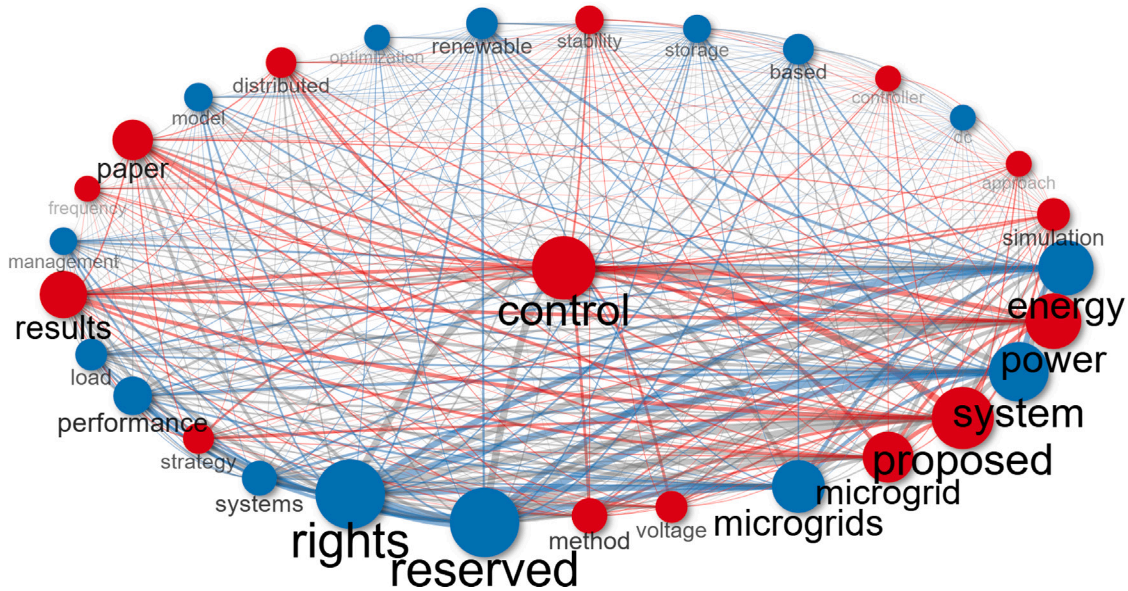

Fig. 6. Abstract co-occurrence network showing methodological emphasis and integration of research concepts.

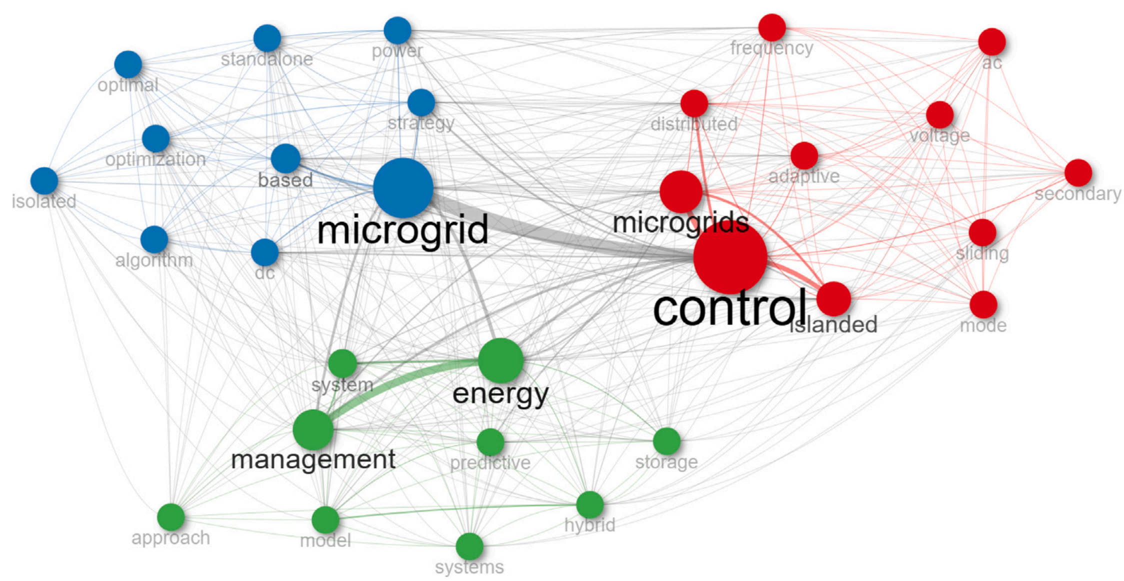

Fig. 7. Title co-occurrence network displaying research positioning and conceptual framing in publication titles.

Recommendation: Future research should study adaptive impedance estimation, data-driven droop tuning, and schemes that combine droop with distributed secondary controllers for real-time compensation. HIL testing under high-penetration renewable conditions is encouraged to validate small- and large-signal stability margins.

6.2 Challenge 2: Communication dependence and resilience

Distributed and hierarchical controls rely on communication links that may be unreliable or expensive in remote locations. Delays, packet loss, and cyber-attacks can degrade performance or even cause instability [8,19,30,179].

Recommendation: Prioritize event-triggered, communication-light consensus stable under asynchronous updates [72,109]. Edge frameworks enable local intelligence during communication failures, while lightweight encryption and anomaly detection should be protocol-embedded.

6.3 Challenge 3: Computational complexity of MPC and DRL

While MPC methods like those proposed by [4,23,28,30–34,42] and DRL methods by [36,39,40,43,73,142,143] provide multi-objective optimality and adaptability, their computational demands remain a barrier for real-time deployment on embedded hardware. Training RL agents online can be risky in safety-critical environments.

Recommendation: Future work should focus on reduced-order modeling, move-blocking MPC, and surrogate modeling for computationally efficient optimization. For DRL, offline training using high-fidelity simulators, combined with safety filters (e.g., Lyapunov-constrained critics), should be standardized. Transfer learning approaches may reduce retraining effort when microgrid configurations are changed.

6.4 Challenge 4: Uncertainty and forecast error handling

Scheduling reliability is weakened by forecast errors in demand profiles and renewable generation. These effects are lessened by stochastic and robust optimization, but they are still computationally demanding and often conservative [4,12,53,56,111,128,129,143,194]. Although there is currently little integration with stochastic EMS frameworks, recent dynamic pricing and user clustering techniques increase adaptability and lessen forecast-driven imbalance.

Recommendation: To balance performance and conservatism, future works should focus on probabilistic forecasting and distributionally robust optimization (DRO). Response to changing uncertainties can be improved by combining adaptive chance constraints with multi-stage stochastic MPC. Also, scalable decomposition or surrogate methods combined with data-driven uncertainty modeling may greatly lower the real-time scheduling computational cost.

6.5 Challenge 5: Cybersecurity and privacy

The digitalization of microgrid control and communication layers has increased vulnerability to cyberthreats like DoS, FDI, and data leaks [19,49,64,65,68,110]. Many EMS frameworks in use today are susceptible to coordinated attacks and compromised nodes because they continue to function under idealized, trusted-network assumptions.

Recommendation: Systems must be cyber-resilient, integrating fault tolerance, authentication, and anomaly detection. Additionally, federated learning and privacy-preserving optimization are essential for secure, collaborative intelligence and merit further focus.

6.6 Challenge 6: Lack of benchmarking and standardized validation

Non-uniform performance metrics, different load scenarios, and inconsistent test conditions make it difficult to compare control and optimization strategies. The lack of standardized benchmarks restricts the application of research findings in industry and compromises reproducibility.

Recommendation: It is crucial to create transparent and uniform benchmarking plans that include representative models, load and generation profiles, and disruption scenarios. Shared real-time simulation platforms (like OPAL-RT and Typhoon HIL) and publicly available datasets would encourage equitable performance comparison, ease validation, and support the convergence towards generally recognized best practices.

6.7 Challenge 7: Integration of demand response and energy market signals

In standalone microgrid EMS research, where loads are frequently regarded as passive consumers, demand response (DR) and transactive energy mechanisms are still scarce. Flexibility and economic optimization are limited by the absence of dynamic pricing and user participation models.

Recommendation: Active demand-side involvement should be incorporated into EMS architectures using incentive-compatible, game-theoretic, or auction-based control frameworks. To assess user acceptability, market responsiveness, and practical cost-benefit performance, documented pilot implementations with community involvement are required.

6.8 Challenge 8: Lifecycle-aware and sustainable operation

The majority of EMS frameworks prioritize short-term economic dispatch over long-term sustainability considerations like cumulative emissions, battery degradation, and fuel supply logistics. This opportunistic optimization may result in hidden lifecycle costs and early component ageing.

Recommendation: Future studies should use multi-horizon EMS formulations that include full lifecycle cost analysis, CO_2 pricing, and ESS ageing models. Carbon-neutral, policy-aligned microgrid operation will be made possible by coupling with Life Cycle Assessment (LCA)-based sustainability metrics.

6.9 Challenge 9: Validation in real-world deployments

Despite growing algorithmic sophistication, most 2025 studies remain limited to simulation-based evaluations, with only a small number progressing to HIL or field implementations. Extensive validation under real-world operating conditions is still lacking, despite promising experimental attempts on low-cost computing platforms such as Raspberry Pi [10,13] and embedded controllers [133].

Recommendation: It is crucial for academia, industry, and utilities to establish cooperative cyber–physical testbeds. To find hidden failure modes, evaluate scalability, and build confidence for large-scale deployment, field-scale trials should include realistic grid disturbances, communication outages, and renewable intermittency.

6.10 Challenge 10: Human-centric and dynamic pricing participation models

The majority of EMS prioritize technical optimization at the expense of equity, human behavior, and adaptive demand response. Less participation and market inefficiency result from the current dynamic-pricing and clustering frameworks' infrequent modeling of user preferences or socioeconomic diversity [53]. For community-scale microgrids, integrating behavioral adaptability, transparency, and fairness is still a challenge.

Recommendation: Behavioral modeling and incentive-compatible pricing should be incorporated into multi-agent frameworks in future EMS research. Demand-side strategies can be made more equitable, transparent, and responsive to real-world preferences and sustainable energy transition objectives by implementing community-driven dynamic tariffs, privacy-preserving analytics, and social welfare metrics.

7. Conclusion

This systematic review created a thorough taxonomy of control and energy management techniques for standalone microgrids in remote communities by synthesizing publications from 2020–2026. By means of methodical examination of hierarchical control layers, algorithmic paradigms, and validation techniques, the review pinpoints groundbreaking developments and crucial research gaps.

Key technical advances

Four paradigm shifts are illustrated in the literature. First, event-triggered virtual impedance lowers communication overhead by 80%, while adaptive droop control with SoC-aware gains reduces voltage overshoot by 10× and improves battery lifetime by 300% compared to fixed-gain methods. Secondly, chattering-free operation with 98% cyber-attack detection accuracy and finite-time convergence independent of initial conditions is made possible by super-twisting sliding mode controllers. Third, model predictive control has developed into tractable hierarchical implementations that run on embedded platforms in 50–100 ms. Hybrid MPC-RL architectures have been shown to reduce costs by 25%–40%. Fourth, when combined with data-driven predictive control, deep reinforcement learning techniques (DQN, PPO, and SAC) show 97.8% increases in computational efficiency and a 12% cost improvement over classical methods.

Persistent research gaps

Despite these advances, deployment is still limited by critical flaws: (i) power-sharing errors of 3%–8% persist under line impedance mismatch; (ii) only 12% of studies validate on hardware, with 68% limited to simulation; (iii) 78% of EMS frameworks lack cyber-security integration despite demonstrated vulnerabilities; (iv) computational complexity limits real-time MPC/DRL deployment on low-cost platforms; and (v) absence of standardized benchmarking protocols undermines reproducibility and comparative assessment.

Strategic recommendations

Addressing these gaps requires coordinated action across three dimensions:

1. **Embedded Deployment**: To enable sub-100 ms control execution on ARM Cortex-M and FPGA platforms for communication-light operation, priority should be given to reduced-order modeling, move-blocking MPC, and edge computing architectures.
2. **Cyber-Physical Security**: Shift from reactive anomaly detection to secure-by-construction frameworks that incorporate quantum key distribution, federated learning, blockchain-based transactive energy, and multi-layered defence that has been verified under coordinated attack scenarios.
3. **Lifecycle-Aware Validation**: With utility and industry partnerships, create multi-horizon EMS that includes battery ageing models and full lifecycle costs in addition to open standardized benchmarks (network topologies, DER scenarios, and disturbance sequences) hosted on cooperative testbeds (OPAL-RT, Typhoon HIL).

Closing perspective

The technical frameworks for reliable, intelligent standalone microgrids are defined in 2025 literature. High-performance operation under renewable uncertainty and cyber–physical threats is made possible by combining adaptive control, predictive optimization, and learning-driven dispatch. But putting these developments into practice calls for a strong dedication to lifecycle-aware design, standardized benchmarking, and embedded validation. Standardization must now take precedence over proliferation, deployment over simulation, and validation over novelty in the research community. Standalone microgrids have the potential to advance global decarbonization and provide energy to 733 million people if they are rigorously pursued.

CRediT authorship contribution statement

Muhammad Auwal Shehu: Writing – original draft, Data curation, Conceptualization. **Kulash Talapiden:** Software, Methodology, Formal analysis. **Tin Trung Chau:** Validation, Investigation, Data curation. **Auwal Haruna:** Writing – review & editing, Validation, Investigation. **Mokhtar Aly:** Validation, Methodology, Data curation. **Vijayakumar Gali:** Writing – review & editing, Visualization, Resources. **Ton Duc Do:** Writing – review & editing, Supervision, Methodology. **Ahmad Bala Alhassan:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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