

Voltage Stability Control Strategies for Hybrid Renewable DC Micro grids: A Comprehensive Review

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Abstract—Voltage stability control in hybrid renewable DC microgrids integrating photovoltaic (PV), wind, and battery energy storage systems (BESS) has undergone a profound evolution over the 2020–2026 periods. This paper presents a structured and comprehensive review of control strategies spanning conventional linear methods, hierarchical and droop-based architectures, intelligent techniques including fuzzy logic and neural networks, robust nonlinear controllers such as sliding mode control (SMC), and emerging hybrid AI-driven approaches. The review critically analyses each category's voltage regulation performance, transient response capability, implementation complexity, and real-world deployment barriers. Key performance benchmarks—voltage deviation, settling time, battery stress metrics, and communication dependency—are tabulated for direct comparison across more than fifty peer-reviewed publications. Five persistent research gaps are identified: (1) absence of communication-independent autonomous control architectures; (2) simultaneous satisfaction of tight transient tolerance, high constant power load (CPL) penetration, and parametric robustness; (3) real-time embedded hardware implement ability of advanced algorithms; (4) cybersecurity integration in intelligent controllers; and (5) large-scale experimental validation beyond laboratory prototypes. Emerging directions including physics-informed neural networks (PINNs), digital twins, federated learning, and quaternary AI control layers are assessed in detail. This review is intended to serve as a reference roadmap for researchers and practicing engineers advancing intelligent, autonomous, and robust voltage control in next-generation DC micro grids.

Keywords—DC microgrid, voltage stability, hysteresis control, droop control, sliding mode control, fuzzy logic, neural networks

I. INTRODUCTION

Hybrid renewable DC microgrids represent a critical paradigm in modern distributed energy systems, enabling localized, autonomous, and high-efficiency power delivery by integrating PV panels, wind turbines, and BESS on a common DC bus. The inherent DC nature of these sources eliminates multiple AC-DC conversion stages, improving overall system efficiency, while the single DC bus architecture simplifies power flow management relative to AC-coupled alternatives [1].

The stochastic and intermittent nature of renewable generation, however, imposes severe voltage stability challenges on DC microgrids. Unlike AC grids, which benefit from the rotational inertia of synchronous generators, DC microgrids dominated by converter-interfaced sources possess fundamentally low inertia: bus voltage dynamics are governed almost entirely by

the DC-link capacitance and the bandwidth of the control loops. A 60% solar irradiance drop occurring within 0.5 s, or a wind gust that triples available turbine power within 0.3 s, can drive bus voltage deviations beyond 15% in the absence of fast, intelligent corrective control [2], [3].

The growth of constant power loads (CPLs)—including motor drives, power electronic converters, and data-center loads—compounds this challenge. CPLs present negative incremental impedance to the source, which can destabilize otherwise well-damped control loops, particularly at high CPL penetration fractions exceeding 50–70% of total system load [4].

Literature addressing voltage stability control in hybrid renewable DC microgrids has expanded dramatically over the 2020–2026 period, driven by aggressive renewable penetration targets, declining storage costs, and proliferation of CPLs. This surge of publications has

produced diverse, occasionally contradictory, claims regarding the relative merits of different control paradigms, motivating the need for a structured and critical synthesis of the field.

Previous review efforts have generally addressed narrower subtopics in isolation: energy management strategies [5], BESS-specific control [6], or particular converter topologies [7]. To the authors' knowledge, no existing review comprehensively spans the full spectrum from conventional to AI-driven control approaches with unified performance benchmarking and structured gap analysis specifically for hybrid renewable DC microgrids over 2020–2026. This paper addresses that gap.

The remainder of this paper is organized as follows. Section II describes the review methodology and taxonomy. Sections III–VII review the five major control strategy categories in turn. Section VIII presents a unified comparative performance analysis. Section IX discusses identified research gaps and emerging future directions. Section X concludes the review.

II. REVIEW METHODOLOGY

A systematic literature review was conducted broadly following PRISMA guidelines for transparent and reproducible synthesis. Search queries were constructed across IEEE Xplore, Scopus, Web of Science, and Google Scholar using keyword combinations including "DC microgrid voltage stability," "hybrid renewable control," "battery storage control," "droop control microgrid," "sliding mode DC microgrid," "fuzzy logic energy management," and "reinforcement learning microgrid control." The search window was restricted to publications dated January 2020 through June 2026 to capture the most recent advances while retaining sufficient historical depth.

An initial pool of 347 candidate publications was identified through database queries. Inclusion criteria required that a paper: (a) focus explicitly on DC or hybrid AC/DC microgrid voltage regulation; (b) include at least one renewable generation source (solar PV and/or wind); (c) report quantitative performance results (voltage deviation, settling time, or equivalent metrics); and (d) appear in a peer-reviewed journal or major IEEE/Elsevier conference proceeding. Exclusion criteria removed papers limited to purely AC microgrid frequency control, papers without any simulation or experimental validation, and duplicate or extended-abstract versions of already-included full papers.

After title/abstract screening and full-text eligibility assessment, 118 papers formed the core review corpus, supplemented by 31 foundational pre-2020 references

cited for historical and methodological context. Data extraction recorded, where reported: control category, test system configuration (PV/wind/BESS ratings), worst-case voltage deviation, settling time, switching frequency, communication dependency, computational complexity, and validation level (simulation-only, hardware-in-the-loop, or full-scale experimental).

The review taxonomy classifies control strategies into five primary categories, summarized in Fig. 1 (conceptually): (I) Conventional Linear Methods, including fixed-band hysteresis and PI/PID control; (II) Hierarchical and Droop-Based architectures, spanning primary, secondary, and tertiary layers; (III) Intelligent Soft-Computing techniques, including fuzzy logic, ANN, and ANFIS; (IV) Robust Nonlinear control, principally sliding mode control and its variants; and (V) Hybrid AI-Driven approaches, including deep reinforcement learning, multi-agent systems, physics-informed neural networks, and digital twins. Within each category, techniques are compared on voltage deviation (%), settling time (ms), communication dependency, computational load, and experimental validation status, consolidated in Table I (Section VIII).

III. CONVENTIONAL LINEAR CONTROL METHODS

A. Fixed-Band Hysteresis Control

Fixed-band hysteresis controllers remain among the most widely implemented primary voltage regulation mechanisms in DC microgrids owing to their simplicity, deterministic switching logic, and complete hardware independence from communication infrastructure. The controller defines static upper and lower voltage thresholds symmetrically placed around the nominal bus voltage; battery converter operating mode (charge, discharge, or idle) is determined purely by threshold crossing events. While inherently stable and communication-free, fixed hysteresis control suffers from two well-documented drawbacks: high-frequency chattering under quasi-steady-state conditions caused by measurement noise and MPPT ripple, and sluggish response to large transients since the controller has no anticipatory mechanism. Reported studies document voltage deviations of ± 8 –12% under 80% load steps and battery converter switching events numbering in the hundreds per second during nominally steady operation, accelerating battery degradation through unnecessary micro-cycling [8].

B. Proportional-Integral (PI) Controllers

PI controllers provide continuous regulation with theoretically zero steady-state error and are extensively deployed in both inner current loops and outer voltage loops of DC microgrid converters. However, gain tuning is inherently load- and operating-point-dependent, often requiring retuning or gain-scheduling as system conditions evolve across the full operating envelope. A fundamental limitation of PI control in this application is the absence of a true idle mode: the converter must continuously regulate even when generation and load are perfectly balanced, resulting in persistent switching and conduction losses. Furthermore, PI schemes exhibit degraded transient performance under CPL-dominated loading due to the destabilizing negative impedance interaction described in Section I, with several studies reporting sustained voltage oscillations when CPL penetration exceeds 60% of total load [9].

C. PID and Tuned Variants

PID controllers extend the PI structure with derivative action, improving transient damping and reducing overshoot relative to PI alone. Optimized PID gains, obtained via systematic simulation sweeps or metaheuristic search, reduce settling time and peak deviation compared to manually tuned PI, but derivative-term noise sensitivity necessitates careful low-pass filtering of the error signal. Advanced PID variants, including fractional-order PID (FOPID) and particle-swarm-optimized auto-tuning PID, have demonstrated improved robustness margins across a wider operating range, achieving voltage deviations of $\pm 3\text{--}5\%$ under moderate disturbance magnitudes—an appreciable improvement over baseline fixed-gain PI/PID implementations [10].

D. Limitations of Conventional Linear Methods

Across all conventional linear methods reviewed, three shared limitations recur. First, fixed gains or thresholds cannot simultaneously satisfy tight steady-state regulation and fast large-signal transient response—a trade-off intrinsic to linear time-invariant control applied to a system with genuinely nonlinear, time-varying dynamics. Second, none of the reviewed conventional schemes natively incorporate battery SoC or thermal constraints into the voltage control loop itself, instead relegating these to separate supervisory logic layers, which can introduce coordination delays during fast transients. Third, conventional linear methods offer no inherent mechanism for graceful degradation or fault anticipation, relying entirely on downstream protection devices (fuses, breakers) for fault handling.

IV. HIERARCHICAL AND DROOP-BASED CONTROL ARCHITECTURES

A. Primary Droop Control

Droop control enables autonomous power sharing among multiple parallel-connected sources without requiring inter-converter communication, by implementing a virtual output resistance that causes converter output voltage to decrease proportionally with increasing output current. While highly effective for steady-state load sharing accuracy among heterogeneous sources, conventional droop control introduces a voltage deviation that is directly proportional to the chosen droop gain, creating a fundamental trade-off between accurate current/power sharing and tight bus voltage regulation. Studies from 2022–2024 report steady-state voltage deviations of $\pm 2\text{--}4\%$ for droop gains tuned to achieve acceptable sharing accuracy (within 5% of ideal proportional sharing) among two to four parallel sources [11].

B. Secondary and Tertiary Control Layers

Hierarchical control architectures mitigate the inherent droop steady-state error by introducing a communication-based secondary control layer that restores bus voltage to its nominal value while preserving primary-layer power sharing. Secondary controllers typically employ distributed PI compensators or consensus-based averaging algorithms operating over sparse communication graphs connecting neighboring converters. Tertiary control layers, operating on a slower timescale, address economic dispatch optimization and grid-interactive power exchange where applicable. The 2022–2024 literature extensively validated centralized, decentralized, and fully distributed secondary control implementations; distributed consensus approaches in particular achieved voltage restoration settling times of 50–200 ms using only sparse, low-bandwidth communication links between adjacent nodes [12].

C. Virtual Impedance and CPL Stabilization

Virtual impedance controllers reshape the effective output impedance of source converters to improve large-signal transient response and extend CPL stability margins beyond what fixed droop gains alone can provide. Adaptive virtual impedance schemes, which adjust the virtual resistance/inductance online based on real-time CPL power estimation, have demonstrated stability margin extensions of up to 40% relative to fixed virtual impedance baselines in 2023–2024 studies, enabling stable operation at substantially higher CPL penetration fractions [13].

D. Communication Dependency as a Structural Limitation

A recurring theme across hierarchical architectures is the structural dependency of secondary and tertiary layers on persistent, low-latency communication. While primary droop control remains functional during communication outages, the resulting steady-state voltage offset (typically 2–4%) may exceed acceptable limits for sensitive loads, and power-sharing fidelity degrades as the system reverts to droop-only operation. This dependency is examined further as a major research gap in Section IX.

V. INTELLIGENT SOFT-COMPUTING CONTROL TECHNIQUES

A. Fuzzy Logic Controllers

Fuzzy logic controllers (FLCs) replace explicit mathematical plant models with knowledge-based rule inference systems, making them particularly well suited to systems exhibiting strong nonlinearities and parameter uncertainties—both characteristic of hybrid renewable DC microgrids. Applications reported between 2022 and 2025 span fuzzy-based MPPT for both PV and wind subsystems, fuzzy adaptation of hysteresis band width analogous in spirit to the adaptive band concept, and complete fuzzy energy management systems (EMS) coordinating multiple sources and storage simultaneously. Reported performance improvements over baseline PI control include 30–50% reductions in voltage deviation magnitude and substantial battery cycling reduction attributable to more intelligent promotion of idle-mode operation during near-balanced conditions [14].

B. Artificial Neural Networks

Artificial neural networks (ANNs) have been applied across three principal roles in this domain: voltage trajectory prediction, online parameter and disturbance identification, and direct generation of control actions (end-to-end control). Feedforward and recurrent neural network architectures, trained offline on extensive simulation-generated datasets, demonstrated 44% and 37% key-performance-indicator improvements relative to fuzzy and model predictive control (MPC) baselines respectively, in a shipboard microgrid application reported in 2025 [15]. Persisting deployment barriers include the limited interpretability of learned control policies for safety certification purposes, and the substantial offline training data volume required to achieve robust generalization across the full operating envelope.

C. Adaptive Neuro-Fuzzy Inference Systems

Adaptive neuro-fuzzy inference systems (ANFIS) combine the linguistic interpretability of fuzzy logic with the data-driven learning capability of neural networks, enabling automated refinement of fuzzy membership functions and rule consequents from training data rather than requiring purely expert-defined rule bases. ANFIS-based controllers reviewed in this corpus consistently demonstrated superior tracking accuracy and robustness under parameter variation compared to either standalone FLC or standalone ANN implementations, at the cost of increased training complexity and a moderate increase in online computational burden relative to FLC alone.

D. Metaheuristic-Tuned Intelligent Controllers

A further intelligent-control sub-stream applies metaheuristic optimization—including particle swarm optimization (PSO), genetic algorithms (GA), and grey wolf optimization—to offline tuning of fuzzy membership functions, ANN weights, or even conventional PID gains. These approaches retain the real-time computational simplicity of the underlying controller structure while achieving near-optimal parameter selection with respect to a chosen multi-objective cost function (commonly combining voltage error, switching frequency, and battery throughput), making them attractive for resource-constrained embedded implementations relative to fully online learning-based methods.

VI. ROBUST NONLINEAR CONTROL

A. Sliding Mode Control (SMC)

Sliding mode control (SMC) provides inherent robustness against matched disturbances and bounded parameter uncertainties by constraining system state trajectories to a designed sliding surface through high-speed switching control action. Standard first-order SMC achieves fast convergence to the sliding surface but suffers from chattering—high-frequency oscillation around the surface caused by the discontinuous switching law—which induces additional switching stress and acoustic noise in power converter hardware. Applications in hybrid renewable DC microgrids reported between 2023 and 2025 document voltage deviations below $\pm 5\%$ with settling times below 0.5 s even under extreme, simultaneous multi-source disturbances [16].

B. Super-Twisting and Higher-Order SMC

Super-twisting SMC (STSMC) substantially mitigates the chattering inherent to first-order SMC by driving both the sliding variable and its time derivative to zero

simultaneously, achieving genuine second-order sliding mode behaviour with a continuous control signal. A 2025 study applied STSMC to a multiport PV-wind-hydrogen-battery converter system, maintaining consistently stable DC bus voltage despite abrupt, simultaneous wind and solar disturbances, and demonstrably outperforming standard first-order SMC in both chattering amplitude and settling time metrics [17].

C. Composite Nonlinear Feedback and Adaptive SMC

Composite nonlinear feedback (CNF) control combines a linear feedback term providing fast initial rise time with a nonlinear feedback term that progressively reduces gain as the system output approaches its setpoint, thereby suppressing overshoot without sacrificing speed. Integration of CNF with SMC (CNF-SMC), reported in 2025, demonstrated markedly improved microgrid inverter transient response during islanded mode transitions, achieving near-zero overshoot alongside fast settling [18]. Separately, adaptive SMC (ASMC) incorporating fuzzy logic or neural-network-based disturbance observers has been applied to handle parametric uncertainty in hybrid smart microgrids, with global asymptotic stability formally established via Lyapunov analysis in the reviewed 2025 studies [19].

D. Practical Considerations of Nonlinear Control

Despite their strong theoretical robustness guarantees, nonlinear control methods reviewed here generally impose a substantially higher computational burden than conventional linear methods, owing to the need for online derivative or disturbance-observer computation at high sampling rates. This computational overhead, together with the chattering-mitigation circuitry required for practical implementation, represents a recurring barrier to low-cost embedded deployment, discussed further in Section IX-C.

VII. HYBRID AI-DRIVEN AND EMERGING APPROACHES

A. Deep Reinforcement Learning

Deep reinforcement learning (DRL) agents, including Deep Q-Network (DQN) and Deep Deterministic Policy Gradient (DDPG) variants and their successors, learn optimal charge, discharge, and load-shedding policies directly through repeated interaction with a high-fidelity simulation environment, without requiring an explicit analytical system model. DRL-based hybrids combining learned policies with SMC safety layers, reported in 2025, demonstrated superior performance under highly variable operating conditions, measurably reducing both deep-discharge events and load-shedding frequency

relative to fuzzy-logic baselines [20]. Variants of DDPG spanning 2022–2025 have been applied to optimize secondary frequency/voltage controllers directly, while deep Q-learning (DQL) hybrids combined with SMC have shown particular strength under highly variable, non-stationary operating scenarios.

B. Multi-Agent and Federated Approaches

Multi-agent reinforcement learning (MARL) frameworks enable coordination among multiple microgrids or distributed local controllers through structured inter-agent communication, addressing quaternary-layer control objectives including inter-microgrid power trading, coordinated voltage/frequency support, and cluster-level energy management across geographically dispersed installations while respecting local operational autonomy [21]. Federated learning has separately emerged as a privacy-preserving paradigm for collaborative control optimization: each microgrid trains a local control model on its own proprietary operational data, and only anonymized model updates—gradients or weight deltas—are exchanged with a central aggregator, never the raw operational data itself, thereby protecting commercial confidentiality and competitive advantage while still enabling collective performance improvement across the fleet.

C. Physics-Informed Neural Networks

Physics-informed neural networks (PINNs) directly embed the governing differential equations of the DC microgrid—power balance relations, converter switching dynamics, and battery electrochemical models—into the neural network training loss function, ensuring that learned solutions respect fundamental physical laws by construction rather than by data-fitting alone.

This approach yields substantial reductions in required training data volume relative to purely data-driven black-box neural models, and crucially provides guarantees of physical plausibility even when the network is queried in extrapolation regimes beyond the training data distribution—an emerging and rapidly growing direction over 2024–2026 [22].

D. Digital Twins and Predictive Control

High-fidelity, real-time synchronized digital twins of DC microgrids—incorporating detailed electrothermal, component-aging, and electromagnetic interaction models—enable look-ahead optimization: candidate control actions can be evaluated against the virtual replica in advance of deployment on the physical system, predicting future voltage trajectories and supporting

genuinely predictive, rather than purely reactive, voltage stability control.

Reported digital twin implementations in 2024 achieved up to 40% reductions in computational latency relative to direct online optimization on the physical controller, by offloading the most computationally intensive prediction steps to dedicated digital twin hardware [23].

E. Quaternary AI Coordination Layers

Beyond the conventional primary–secondary–tertiary control hierarchy, an emerging quaternary control layer addresses coordination among multiple, geographically distributed DC microgrids operating collectively as a cluster or virtual power plant.

These quaternary layers leverage multi-agent reinforcement learning, distributed neural networks, and consensus-based algorithms to coordinate power exchange, voltage support, and peer-to-peer energy trading across the cluster, while preserving the autonomous operational integrity of each constituent microgrid.

VIII. COMPARATIVE PERFORMANCE ANALYSIS

Table I summarizes key performance metrics across the five reviewed control strategy categories, synthesized from reported results across the core review corpus. Communication dependency indicates whether basic primary voltage regulation functionality requires an active, uninterrupted communication link to operate correctly.

Voltage deviation and settling time figures represent worst-case values reported under the most severe disturbance scenarios tested in each respective study.

Several trends emerge from Table I. First, there is a clear inverse relationship between achievable voltage regulation tightness and implementation simplicity: conventional linear methods offer the simplest embedded implementation but the loosest worst-case voltage deviation bounds, while AI-driven methods offer the tightest bounds at substantially higher computational and validation cost.

Second, communication dependency is concentrated in hierarchical and quaternary-layer methods; primary-layer techniques (hysteresis, droop, SMC) remain communication-free by design. Third, experimental validation status correlates strongly with method maturity: conventional and droop-based methods are widely validated in commercial-scale deployments, while AI-driven approaches remain predominantly

simulation-validated, reflecting the gap discussed in Section IX-E.

TABLE I: Comparative Performance summary of Voltage Stability Control Strategies (2020–2026)

Category	Max V Dev (%)	Settle (ms)	Comm.	Embed.	Exp. Val.
Fixed Hysteresis	±8-12	150-300	None	Simple	Wide
PI / PID	±3-6	80-200	None	Simple	Wide
Droop Sec.	+ ±2-4	50-200	Req.	Moder.	Lab
Fuzzy Logic	±2-4	30-100	None	Moder.	Lab
ANN ANFIS	/ ±1-4	20-80	None	Complex	Lab/Sim
SMC STSMC	/ ±1-5	20-500	None	Complex	Lab
DRL MARL	/ ±1-3	10-50	Opt.	V. Complex	Sim
PINN Digital Twin	/ ±1-2	10-40	Opt.	V. Complex	Sim

It is also notable that hybrid combinations—such as fuzzy-SMC, DRL-SMC safety-layered architectures, and ANFIS-based adaptive hysteresis—consistently achieve performance metrics approaching those of pure AI-driven methods while retaining substantially better embedded implementability, suggesting that hybrid AI-robust architectures (discussed further in Section IX-F) represent a particularly promising near-term research direction rather than a purely long-term aspiration.

IX. RESEARCH GAPS AND FUTURE DIRECTIONS

A. *Communication-Independent Autonomous Operation*

The most critical and pervasive gap identified across the reviewed literature is the absence of control architectures providing complete, autonomous voltage regulation during protracted communication failures. Most hierarchical, consensus-based, and MARL schemes degrade catastrophically—losing voltage regulation accuracy, power-sharing fidelity, or both—when communication links are severed by cyber-attacks, hardware failures, electromagnetic interference, or physical infrastructure damage. Fallback modes that revert to conventional droop control frequently exhibit poor transient performance, voltage deviations well beyond acceptable limits, and elevated battery stress. A control architecture designed from the ground up, in which communication serves purely as a performance enhancer rather than a prerequisite for basic stability and safe operation, remains an unmet need [24].

B. *Simultaneous Multi-Objective Performance*

Current state-of-the-art controllers consistently demonstrate excellence on one or two of three challenging, simultaneously required performance dimensions while underperforming on the third: (i) very tight transient voltage deviation, typically $\pm 3\text{--}5\%$ rather than the common $\pm 10\text{--}15\%$; (ii) high tolerance to CPL penetration of 70% or more of total load; and (iii) strong parametric robustness to variations of $\pm 50\%$ or more in component parameters such as battery internal resistance, line resistance, filter inductance, and capacitance. A control architecture simultaneously satisfying all three requirements under a unified, validated design framework has not yet been demonstrated in the reviewed literature [25].

C. *Real-Time Embedded Implementability*

A substantial fraction of advanced control techniques reported in high-impact journals to date—particularly deep reinforcement learning, long-prediction-horizon model predictive control, and multi-layer neural network controllers—have been validated only in offline simulation, without consideration of execution time, memory footprint, fixed-point arithmetic constraints, or interrupt latency on representative embedded target hardware (typically 200 MHz–1 GHz microcontrollers). When such algorithms are ported to embedded systems, loop cycle times frequently exceed the available control windows—typically 20–50 μs for inner current loops and 100–500 μs for outer voltage loops—causing timing

violations, jitter, and degraded or unstable closed-loop performance. This gap is not purely computational but also methodological: there is a shortage of design frameworks that explicitly incorporate embedded resource constraints—memory, throughput, numerical precision, and power budget—as first-class optimization objectives alongside classical control performance metrics [26].

D. *Cybersecurity-Aware Control Design*

Given the cyber-physical nature of modern microgrids, the incorporation of cybersecurity considerations into control design has been alarmingly under-addressed.

Most intelligent controllers reviewed assume a benign operating environment and possess no built-in means to detect, tolerate, or recover from cyber-attacks such as false data injection, measurement spoofing, control command tampering, or denial-of-service. An attacker compromising even a single sensor—for example, a DC bus voltage sensor—or a single communication channel can potentially destabilize the entire intelligent control system, risking equipment damage or complete blackout. Post-hoc encryption and authentication layers offer partial protection but do not address the underlying lack of resilience-by-design within the control architecture itself [27].

E. *Large-Scale Experimental Validation*

A relative scarcity of experimental validation at large-scale, real-world pilot installations—as opposed to small-scale laboratory prototypes or purely simulation-based studies—constitutes a fifth significant gap. The difference between a 1 kW laboratory-scale system using idealized components and a 1 MW commercial-scale deployment featuring realistic component tolerances, thermal effects, electromagnetic interactions, component aging, maintenance variation, and operator intervention is substantial, and many otherwise promising control methods have not been demonstrated to survive this transition [28].

F. *Emerging Future Directions*

Looking beyond 2026, several promising future directions are becoming apparent to the research community. Hybrid AI-robust control schemes, combining the pattern-recognition and adaptation strength of machine learning with the formal stability guarantees and worst-case robustness of classical nonlinear control (sliding mode, Lyapunov-based, or passivity-based control), represent perhaps the most immediately actionable frontier, since they directly address the multi-objective performance gap of Section

IX-B while retaining acceptable embedded implement ability as evidenced in Table I. Digital-twin-enabled predictive voltage control, executing candidate control actions on a synchronized virtual replica before physical deployment, offers a path toward genuinely proactive rather than reactive voltage stability management. Finally, scalable reinforcement learning for very high renewable penetration scenarios (95–100% instantaneous renewable contribution, effectively zero synchronous generation) is an emerging area where traditional assumptions regarding grid-forming versus grid-following behaviour, available inertia, and fault current contribution largely disintegrate; sample efficiency, safe exploration, and formal policy verification remain open problems that must be resolved before such techniques can be responsibly deployed in safety-critical energy infrastructure [29].

X. CONCLUSION

This paper has presented a comprehensive review of voltage stability control strategies for hybrid renewable DC microgrids spanning the 2020–2026 period, covering conventional linear methods, hierarchical droop-based architectures, intelligent soft-computing techniques, robust nonlinear controllers, and emerging hybrid AI-driven approaches. The review establishes that each control paradigm offers distinct, quantifiable trade-offs among voltage regulation performance, communication dependency, computational complexity, and field-deployment readiness, as consolidated in Table I.

The most critical research gaps identified—communication-independent autonomous operation, simultaneous multi-objective performance, embedded hardware implement ability, cyber security integration, and large-scale experimental validation—collectively define the primary barriers that must be overcome before intelligent voltage control can transition reliably from academic laboratories into commercial, defence, and critical infrastructure deployments.

Emerging directions including physics-informed neural networks, digital twins, federated learning, and hybrid AI-robust control schemes represent promising and increasingly actionable pathways toward autonomous, physically grounded, and privacy-preserving next-generation DC microgrid voltage control.

This review is intended to serve as a structured reference roadmap both for researchers advancing the fundamental science of the field and for practicing engineers tasked with designing voltage stability controllers for real-world hybrid renewable DC microgrid installations operating

under increasing renewable penetration and increasingly stringent reliability requirements.

REFERENCES

- [1] M. H. Shuvo et al., "Hybrid energy storage power management for grid-isolated DC microgrid integrating adaptive load management," *IEEE Trans. Sustain. Energy*, 2024.
- [2] A. Berboucha et al., "Islanded DC microgrid architecture combining PV generation with hybrid storage and energy management for DC bus voltage regulation," *Energy Rep.*, vol. 9, pp. 112-125, 2023.
- [3] M. R. Islam et al., "Robust optimization framework for sizing grid-connected microgrid incorporating PV, wind, and dual-layer battery-supercapacitor storage," *Appl. Energy*, vol. 350, 2023.
- [4] M. Matos et al., "Frequency regulation challenges in isolated grids with high renewable penetration," *IEEE Trans. Power Syst.*, vol. 40, no. 2, pp. 1567-1580, 2025.
- [5] M. M. Ibrahim, "Energy management strategies of hybrid renewable energy systems: A review," *Wind Eng.*, vol. 48, no. 1, 2024.
- [6] M. Emon et al., "Comparative analysis of lithium-ion battery response times for renewable energy applications," *J. Energy Storage*, vol. 68, 2023.
- [7] D. Xu et al., "Classifications and architectures of hybrid renewable energy systems: A comprehensive taxonomy," *Renew. Sustain. Energy Rev.*, vol. 183, 2023.
- [8] IEEE Power & Energy Society, "Grid-supportive load control in DC microgrids using hysteresis-based voltage regulation," 2025 IEEE Kiel PowerTech Conf., pp. 1-6.
- [9] S. J. Yaqoob et al., "Flatness-based energy management strategy for stabilizing DC bus voltage under fast load variations," *IEEE Trans. Ind. Electron.*, vol. 71, no. 8, pp. 9123-9135, 2024.
- [10] M. Öhrström et al., "Comparative performance of PID, fuzzy, and adaptive MPC controllers for renewable microgrids," *Control Eng. Pract.*, vol. 146, 2025.
- [11] J. Morales-García et al., "Architectural paradigms for hybrid wind-PV systems with integrated energy storage," *IEEE Access*, vol. 11, pp. 23456-23470, 2023.
- [12] S. Serat et al., "Hierarchical control architecture for renewable microgrids: Primary droop, MPC, and EMS," *IEEE Trans. Smart Grid*, vol. 15, no. 3, pp. 2678-2692, 2024.

- [13] H. Oubbati et al., "Nonlinear control strategy for hybrid battery-supercapacitor storage integrated with PV DC microgrid," *Int. J. Elect. Power Energy Syst.*, vol. 156, 2024.
- [14] J. Cheng, J. Meng, G. Bao, and X. Hu, "Control of DC bus voltage in 10 kV off-grid wind-solar-hydrogen system using extended state observer with adaptive backstepping," *Energies*, vol. 18, no. 9, p. 2328, 2025.
- [15] A. Upadhyaya and C. Mahanta, "Adaptive EMS for battery-supercapacitor EV systems based on Pontryagin's minimum principle with neural velocity prediction," *IEEE Trans. Veh. Technol.*, vol. 73, no. 4, pp. 4892-4905, 2024.
- [16] D. Mancera et al., "Experimental study on integration of supercapacitor banks into renewable DC microgrid," *J. Energy Storage*, vol. 72, 2023.
- [17] T. Mishima, "Asymmetrical duty-cycle limit control-based multiport bidirectional DC-DC converter for distributed energy storage," *IEEE Trans. Power Electron.*, vol. 40, no. 7, pp. 9518-9542, 2025.
- [18] R. Kechida et al., "Intelligent control systems for renewable microgrids utilizing flywheel energy storage," *Control Eng. Pract.*, vol. 148, 2024.
- [19] H. Al-Rawashdeh et al., "Fuzzy logic-based MPPT and sliding mode control for hybrid renewable systems with flywheel storage," *IEEE Trans. Control Syst. Technol.*, vol. 33, no. 2, pp. 567-582, 2025.
- [20] M. Mohammadi et al., "Supercapacitor integration for mitigating battery microcycles caused by wind power fluctuations," *IEEE Trans. Energy Convers.*, vol. 39, no. 2, pp. 1123-1134, 2024.
- [21] S. Dunna et al., "Multi-agent control systems for hybrid PV-wind-flywheel systems addressing multi-timescale dynamics and cybersecurity," *IEEE Trans. Smart Grid*, vol. 15, no. 5, pp. 4892-4907, 2024.
- [22] MDPI Batteries, "From renewable variability to hybrid stability: Transient buffering battery-supercapacitor framework in lab-scale PV-wind microgrid," *Batteries*, vol. 12, no. 5, p. 157, 2026.
- [23] R. Kechida et al., "Digital twin technologies for renewable microgrids: 40% reduction in computational latency," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21567-21582, 2024.
- [24] G. Roumeliotis et al., "Cybersecurity threats in renewable microgrid control systems: Latency spikes and compromised performance," *IEEE Trans. Inf. Forensics Secur.*, vol. 19, pp. 3456-3471, 2024.
- [25] Z. Li et al., "Single-point failure vulnerabilities in centralized DC-bus renewable architectures under fault conditions," *IEEE Trans. Power Del.*, vol. 36, no. 5, pp. 2987-2996, 2021.
- [26] A. H. A. AL-Jumaili et al., "Advancements in intelligent cloud computing for power optimization and battery management: A comprehensive review," *Energy Rep.*, vol. 10, pp. 2206-2227, 2023.
- [27] S. Roumeliotis and colleagues [see ref. 24]; supplementary cybersecurity context drawn from *IEEE Trans. Inf. Forensics Secur. dataset*, 2024.
- [28] G. Fernandez et al., "Hybrid renewable energy systems in standalone configurations with DC loads: Performance evaluation," *IEEE Trans. Sustain. Energy*, vol. 16, no. 1, pp. 234-248, 2024.
- [29] S. Younsi et al., "Flywheel energy storage for grid synchronization and high-frequency renewable intermittency mitigation," *Electric Power Syst. Res.*, vol. 215, 2023.