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A Survey of Control and Energy Management in Hydrogen Production Systems

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ABSTRACT This article provides a comprehensive review of power electronics converter control and energy management for hydrogen production systems through water electrolysis. Hydrogen production from renewable energy sources is a key pathway toward decarbonizing energy systems and enabling large-scale energy storage. Efficient and dependable operation necessitates addressing the dynamic properties of electrolyzers, the intermittent nature of renewable sources, and the coordination among numerous power electronic interfaces. Unlike earlier studies that addressed these aspects separately, this review systematically connects electrolyzer modeling, converter design, control architectures, and energy management to reveal their critical interdependence. By examining these connections, the analysis reveals critical research gaps in real-time coordination, parameter adaptation, and scalable architectures, outlining pathways toward intelligent and grid-independent hydrogen production systems. This review integrates electrolyzer modeling, power converter control algorithms, AC and DC energy hub architectures, hierarchical control schemes, and energy management systems from classical to advanced methods.

INDEX TERMS Electrolyzer modeling, energy hub, energy management, green hydrogen production, hierarchical control.

I. INTRODUCTION

Hydrogen has emerged as a critical enabler for decarbonizing hard-to-electrify sectors and providing large-scale energy storage in renewable-dominated power systems [1], [2]. Global hydrogen demand is projected to increase nearly eightfold by 2050, driven primarily by renewable-powered electrolysis (green hydrogen) [3]. This growth necessitates efficient, controllable hydrogen production systems capable of reliable operation under fluctuating renewable energy sources (RESs), requiring advanced control and energy management frameworks to ensure operational stability, power quality, and optimal energy utilization [4], [5].

Hydrogen's unique ability to interconnect the electricity, transportation, and industrial sectors positions it as a critical enabler of deep decarbonization. In renewable-dominated power systems, electrolyzers serve a pivotal function by converting excess renewable electricity into hydrogen, which can subsequently be reconverted into electricity or utilized as an industrial feedstock [6]. This power-to-hydrogen pathway not only mitigates renewable energy curtailment but also enhances grid flexibility and enables long-term, large-scale energy storage. However, the inherent variability of solar and wind generation creates operational challenges: renewable intermittency conflicts with electrolyzers' requirement for stable operating conditions to maintain efficiency and longevity.

While technical performance indicators like as efficiency, dynamic responsiveness, and dependability are important, the ultimate success of green hydrogen systems is determined by their economic competitiveness. The fundamental motivation for next-generation hydrogen systems is still cost reduction. Advanced control and energy management strategies must exhibit quantifiable effects on the levelized cost of hydrogen (LCOH) by the following:

1) improved capacity factor by enabling stable operation under variable renewable power;

2) extending equipment lifespan through degradation-aware control methods; and
3) increasing revenue through participation in grid services.

Currently, global hydrogen production is 98% reliant on fossil-based processes, producing approximately 900 Mt CO_2/year. In contrast, water electrolysis powered by renewable energy offers a carbon-neutral and sustainable pathway for hydrogen generation [3]. This process utilizes electrical energy to decompose water into hydrogen and oxygen and is primarily implemented through three commercially established technologies: alkaline water electrolyzers (AWE), proton exchange membrane (PEM) electrolyzers, anion exchange membrane (AEM), and solid oxide electrolysis cells (SOEC) [7]. Each of these technologies exhibits distinct electrical and dynamic behaviors, thereby requiring specifically tailored power conversion and control architectures [7], [8].

Integrating electrolyzers with variable RESs introduces technical and economic challenges. Rapid fluctuations in voltage, current, and power adversely impact electrolyzer durability and efficiency. Power quality concerns and the lack of standardized control methodologies further hinder large-scale deployment [9], highlighting the need for coordinated control and energy management frameworks.

Power electronic converters serve as the primary interface between renewable generators and electrolyzer units, performing hierarchical control from fast current regulation to power quality management and voltage stabilization [10]. The design of AC–DC and DC–DC converter topologies with appropriate modulation strategies is essential for stable operation under renewable intermittency.

To address these challenges, hierarchical control and energy management architectures are required to coordinate power electronic converters, renewable sources, energy storage systems, and electrolyzer units across multiple timescales. These architectures must integrate device-level control (current/voltage regulation) with system-level energy management (power dispatch, storage coordination) to ensure both fast dynamic response and optimal long-term operation [11].

While several reviews have addressed electrolyzer technologies, renewable integration, or control methods independently, a unified treatment covering the complete chain from electrolyzer modeling to device-level control and system-level energy management remains limited. Existing works often focus on isolated aspects without addressing the interplay between electrolyzer characteristics, power electronic interfaces, hierarchical control, and energy management strategies.

This review provides a systematic treatment spanning electrolyzer modeling, power electronic interfacing, hierarchical control, and system-level energy management. Section II establishes modeling foundations for AWE, PEM, AEM, and SOEC technologies. Section III presents energy hub architecture integrating renewable sources, storage systems, and converters. Section IV examines control frameworks from classical to advanced methods. Section V explores energy management architectures and optimization strategies. Section VI discusses emerging technologies and deployment challenges. Finally, Section VII concludes this article.

II. WATER ELECTROLYSIS: FUNDAMENTALS AND MODELING

Water electrolysis decomposes water into hydrogen and oxygen using DC electrical energy, forming the basis for green hydrogen production. The design of power electronic interfaces for electrolyzers must address the control challenges inherent to water electrolysis, including precise regulation of voltage and current, dynamic compensation for nonlinear and time-varying load behavior, and robust performance under fluctuating or intermittent power conditions [12].

A. ELECTROCHEMICAL REACTIONS AND THERMODYNAMICS

The water electrolysis process involves oxidation and reduction reactions occurring at two electrodes immersed in an electrolyte medium. The overall water electrolysis reaction is [7]

$$H_2O(l) \rightarrow H_2(g) + \frac{1}{2}O_2(g). \tag{1}$$

From an electrical standpoint, this decomposition is initiated by applying a DC voltage across the electrodes that exceeds the thermodynamic minimum of 1.23 V (the reversible voltage E_{rev} at standard conditions) [13]. The applied current drives electrochemical reactions at each electrode: reduction of water at the cathode liberates hydrogen gas, while oxidation at the anode produces oxygen. According to Faraday's law, the hydrogen production rate is directly proportional to the applied current, a relationship that forms the basis for current-based control of electrolyzer output [14]. However, practical cells require substantially higher voltages (typically 1.8–2.2 V) due to overpotentials arising from activation kinetics, ohmic resistance, and mass transport limitations [15].

From a thermal control perspective, electrolyzer operation is characterized by a thermoneutral voltage of 1.48 V. Operation above this voltage, typical of industrial systems, generates excess heat, making temperature regulation a critical control objective to maintain stable performance and prevent degradation [15]. These electrochemical and thermal characteristics translate into specific control and energy management requirements. Industrial systems operate with high currents (hundreds to thousands of amperes) at low cell voltages (1.2–2.5 V per cell), resulting in nonlinear voltage–current (V–I) relationships that vary with operating conditions, such as temperature, pressure, and current density [16]. The electrolyzer's electrical impedance changes dynamically during transient operation due to electrochemical double-layer charging, gas bubble formation, and concentration gradients, creating control challenges absent in resistive loads [17]. These time-dependent characteristics necessitate advanced control strategies capable of handling nonlinear dynamics and coordinating power regulation with thermal

TABLE 1. Comparison of Electrolyzer Technologies

Characteristics	Electrolyzer Technology AWE	PEM	AEM	SOEC
Electrochemical Characteristics				
Electrolyte	25–30% KOH (liquid)	Solid polymer (Nafion)	Alkali solution, pure water	Solid oxide (ceramic)
Operating Temperature (°C)	60–70	50–80	40–90	600–800
Pressure (bar)	1–30	1–30	1–30	1–25
Current Density (mA/cm²)	200–400	400–2000	200–1000	300–2000
Cell Voltage (V)	1.8–2.4	1.5–2.0	1.4–2.0	0.7–1.5
Performance				
Electrical Efficiency(%)	60–70	65–75	60–70	80–90
Dynamic Characteristics				
Cold Start-up Time	>15 min	<15 min	5–15 min	-
Response Time (operating)	Seconds	Milliseconds	Seconds	Minutes
Ramp-up Rate (%/s)	0.3–17	10–80	Not reported	Slow (thermally limited)
Power Electronics & Control				
Typical DC-DC Topology	Buck	Interleaved Buck	Buck/Boost	Isolated DC–DC
Control Complexity	Low	High	Medium	Very High
Thermal Management	Simple	Moderate	Moderate	Critical
System-Level Considerations				
Technology Maturity	Commercial	Commercial	Emerging	Pilot / early commercial
Relative Capital Cost USD/kW	Low (880–1650)	High (1540–2550)	Medium (Not reported)	Very High (>2000)
References	[29]	[29], [30]	[31], [32]	[21], [23], [26], [29]

management and hydrogen production requirements as discussed in Section IV.

B. ELECTROLYZER TECHNOLOGIES

Four electrolyzer technologies exist, each exhibiting distinct electrical and dynamic characteristics that influence converter design and control requirements, as summarized in Table 1.

1) *AWE* represent the most mature and cost-effective technology, utilizing liquid KOH electrolyte [16]. Their slow dynamic response (minutes) and relatively lower sensitivity to current ripple compared to membrane-based technologies make them compatible with simpler converter topologies, particularly suited for steady-state base-load hydrogen production where operational flexibility is less critical [15].
2) *PEM electrolyzers* provide superior dynamic response capabilities (milliseconds), rendering them optimal for renewable energy integration and grid service applications [15]. The solid polymer electrolyte eliminates liquid management challenges but necessitates precious metal catalysts and sophisticated multiphase converter architectures to minimize current ripple effects on membrane degradation [18].
3) *AEM electrolyzers* represent an emerging technology combining benefits of both AWE and PEM systems [19]. By employing solid membrane structures with nonprecious metal catalysts, AEM systems offer a promising pathway toward cost-effective renewable hydrogen production with moderate dynamic performance [20].
4) *SOEC* operate at elevated temperatures, achieving the highest electrical efficiency (80% –90% , Table 1) among water electrolysis technologies. Commercial planar cells from leading manufacturers, such as Elcogen and SolydEra typically operate at 600–800 °C [21], [22], [23], while metal-supported variants enable lower temperatures (450–630 °C) [24], and laboratory studies report operation up to 900 °C [23], [25]. However, high operating temperatures introduce several challenges, including thermal inertia (multihour startup times), thermal stress induced by cycling, and limitations in startup and shutdown operation [26]. In addition, SOECs currently suffer from relatively fast degradation rates and high stack and balance-of-plant costs compared to low-temperature electrolysis technologies [23], [27], mainly due to stringent material and thermal management requirements.

Table 1 provides a comprehensive comparison of these technologies, including electrochemical characteristics, dynamic response, and power electronics requirements.

C. CONTROL-ORIENTED TECHNOLOGY COMPARISON

From a control perspective, the characteristics summarized in Table 1 translate into distinct control design requirements across these technologies. AWE exhibit relatively slow dynamic behavior and relatively lower sensitivity to current ripple compared to membrane-based technologies [28], which makes them well suited for low-bandwidth regulation and simple converter-level control strategies [16], as discussed in Section IV.In contrast, PEM systems are capable of millisecond-scale electrochemical response, with operational current densities reaching up to 1–2 A/cm^2. This allows for a quick dynamic response that is appropriate for the integration of RESs [15]. However, this necessitates careful regulation to prevent membrane degradation from current fluctuations and thermal variations [33]. PEM systems can operate at elevated pressures up to 30 bar, requiring careful management of differential pressure to prevent excessive hydrogen crossover.

Positioned between these extremes, AEM electrolyzer technology typically operates at intermediate current densities, generally in the range of 0.2–1.0 A/cm^2 [34], with recent laboratory-scale demonstrations approaching 1.0 A/cm^2 [19]. This operating regime suggests a moderate dynamic behavior compared to both AWE and PEM systems, which can influence the design and bandwidth requirements of associated power converters and control loops. However, AEM membranes suffer from lower chemical stability, particularly in highly alkaline environments and at elevated temperatures, which presents challenges for long-term durability and necessitates careful thermal and degradation management strategies [19].

From a control design perspective, these technology differences manifest as distinct control objectives and constraints. PEM systems require controllers capable of fast power tracking (millisecond response) to follow renewable energy variations while simultaneously enforcing constraints on current ripple (for membrane protection), differential pressure (to prevent gas crossover), and thermal gradients (to avoid hot spots). AEM systems, while benefiting from simplified water management and potentially lower cost, demand careful constraint handling to accommodate their lower chemical stability, with control objectives emphasizing long-term durability over aggressive dynamic performance. AWE systems prioritize robustness and simplicity given their industrial maturity and tolerance to variations, while SOEC systems require coordinated thermal-electrical control objectives to maintain high efficiency within strict temperature operating windows. These V–I characteristics and their implications for converter design are illustrated in detail in Fig. 3 (see Section II-D).

Among the four technologies, SOEC systems present the most demanding control requirements due to their pronounced thermal-electrical coupling. Unlike low-temperature electrolyzers where electrical dynamics dominate converter control, SOEC operation requires careful coordination between electrical power input and thermal management to maintain efficiency within strict temperature operating windows. This distinction has direct implications for electrical modeling approaches, as discussed in Section II-D.

D. ELECTRICAL MODELING APPROACHES

Although all electrolyzer technologies follow the same fundamental voltage equation, the underlying physical mechanisms and parameter dependencies differ significantly between technologies. The general structure of the cell voltage is

$$U_{\text{cell}} = E_{\text{rev}} + \eta_{\text{act}} + \eta_{\text{ohm}} + \eta_{\text{conc}} \tag{2}$$

where E_{rev} [1.229 V at standard temperature and pressure (STP)] is the reversible voltage, representing the thermodynamic minimum potential required for water splitting [13]. For high-temperature SOEC systems, the relative contribution of each overpotential term differs significantly from low-temperature electrolyzers due to enhanced reaction kinetics and ionic conductivity. In particular, activation and concentration overpotentials are generally reduced at elevated operating temperatures. While these overpotential components can be identified across all electrolyzer technologies, their associated electrical time constants and impact on system-level dynamics

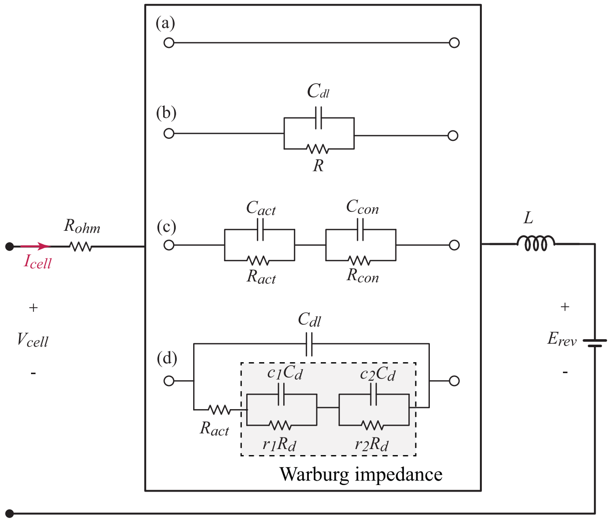

FIGURE 1. Equivalent electrical circuit models for electrolyzer systems. (a) Static model. (b) Medium-dynamic with single RC. (c) Low-dynamic with dual RC branches. (d) High-dynamic with Warburg impedance.

vary substantially, particularly for high-temperature SOEC operation [35], [36].

The overpotential components vary among technologies: the activation overpotential (η_{act}) depends on electrode reaction kinetics, which differ between alkaline and acidic environments [37]. This component dominates at low current densities and accounting for the initial voltage rise in polarization curve. In addition, the ohmic overpotential (η_{ohm}) reflects ionic transport resistance, differing between liquid electrolytes (AWE) and solid membranes (PEM/AEM), typically within 0.1 to 0.3 Ω·cm^2 [38]. The concentration overpotential (η_{conc}) arises from mass transport limitations, such as gas bubble formation in alkaline systems and gas permeation in membrane-based cells, becoming significant at high current densities [9].

1) MODEL CLASSIFICATION AND PARAMETER ANALYSIS

Electrolyzer electrical behavior is captured through equivalent circuit models of varying complexity. For low-temperature electrolyzers (AWE, PEM, AEM), reduced-order models (see Fig. 1) provide sufficient accuracy for real-time power converter control. For high-temperature SOEC systems, detailed electrochemical impedance spectroscopy (EIS) models (see Fig. 2) enable diagnostic analysis of individual processes.

All models incorporate reversible voltage (E_{rev}) and ohmic resistance (R_{ohm}), with RC networks representing charge accumulation dynamics. Model selection depends on current density and dynamic requirements, as summarized in Table 2. The time constants listed in Table 2 represent distinct physical processes: at low current densities, activation ($\tau_1 \equiv \tau_{\text{act}}$) and concentration ($\tau_2 \equiv \tau_{\text{conc}}$) dynamics are modeled separately using dual RC branches; at medium current densities, an effective time constant (τ_{eff}) captures the combined dynamics through a single RC branch; at high current densities,

TABLE 2. Classification of Electrolyzer Electrical Models for Power Electronics Applications

Model Type	Current Density	Time Constant	Circuit Elements	Applications
Static	All ranges	0	$V_{DC} + R_{ohm}$	Grid-tied systems, efficiency analysis
Low-Current Dynamic	< 200 mA/cm^2	τ_1, τ_2	Two RC branches	Renewable integration, slow dynamics
Medium-Current Dynamic	200–800 mA/cm^2	τ_{eff}	Single RC branch	Hybrid microgrid, islanded operation
High-Current Dynamic	> 800 mA/cm^2	τ_{act}, τ_{diff}	RC + Warburg impedance	Grid services, fast frequency response

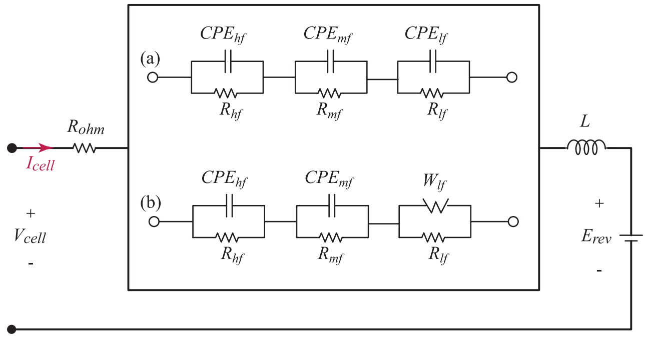

FIGURE 2. EIS-based equivalent circuit models for SOEC systems. (a) Three *R* ∥ CPE branches for high-, mid-, and low-frequency processes. (b) Warburg element replacing the low-frequency branch for gas-phase diffusion.

activation (τ_{act}), and diffusion (τ_{diff}) processes are explicitly separated due to significant Warburg impedance effects.

In Fig. 2, the series ohmic resistance R_{ohm} represents the combined ionic resistance of the electrolyte and electronic/contact resistances within the cell, while the inductance L accounts for high-frequency (hf) parasitic effects introduced by the measurement setup and interconnections. The impedance response is decomposed into three parallel R∥ CPE branches corresponding to distinct frequency domains: hf processes associated with charge-transfer reactions at the triple-phase boundaries, mid-frequency electrochemical processes within the porous electrodes involving coupled charge transfer and transport phenomena, and low-frequency (lf) contributions related to gas conversion and mass-transport limitations. In model (b), the lf R∥ CPE element is replaced by a finite-length Warburg element W_{lf} to explicitly capture gas-phase diffusion effects in the porous electrode support and flow channels. Such multielement EIS-based models, typically comprising three to five dynamic components, are essential for detailed electrochemical diagnostics and degradation analysis of SOEC systems [35], [36].

Static models: For steady-state analysis and grid-connected applications where dynamic response is not a primary concern, static models are commonly employed. These models are based on the simplified linear relationship

$$V_{cell}(s) = E_{rev} + R_{ohm} \cdot I_{cell}(s). \tag{3}$$

By maintaining computational simplicity, static models offer adequate accuracy for evaluating system efficiency and performing thermal management studies. They are particularly suitable for applications operating under relatively constant load conditions, such as base-load hydrogen production facilities, where the electrolyzer functions close to steady-state for extended periods.

Dynamic models: Dynamic models extend the static representation by incorporating capacitive effects through transfer function formulations, making them suitable for applications requiring fast response, such as grid-support services and renewable energy integration [39]

$$V_{cell}(s) = E_{rev} + I_{cell}(s)\left[R_{ohm} + \frac{R_{act}}{1+\tau_{act}s} + \frac{R_{conc}}{1+\tau_{conc}s}\right] \tag{4}$$

where τ_{act} and τ_{conc} represent activation and concentration time constants, respectively. The activation time constant (τ_{act}), typically ranging from milliseconds to seconds, governs charge-transfer dynamics at electrode surfaces and directly determines the achievable control bandwidth of power converters [40]. The concentration time constant (τ_{conc}), typically larger (seconds to tens of seconds), reflects mass-transport limitations and becomes dominant at high current densities [41].

The model parameters in (4) are assumed constant at the nominal operating temperature. This assumption is commonly adopted for the analysis of fast electrical transients, where thermal time constants are significantly larger than electrical time constants. However, for applications involving pronounced thermal dynamics, such as start-up and shutdown transients in SOEC systems or operating conditions with varying thermal loads in PEM electrolyzers, temperature-dependent parameters ($E_{rev}(T)$, $R_{ohm}(T)$, and $R_{act}(T)$) should be incorporated through coupled thermal–electrical models [41], [42].

Circuit parameter values vary significantly by technology, reflecting fundamental differences in electrochemical processes. AWE typically exhibit higher area-specific ohmic resistance (approximately 0.3–0.5 $\Omega \cdot$ cm^2) and a larger effective double-layer capacitance, mainly associated with the liquid electrolyte and extended electrode–electrolyte interfaces [15], [43]. PEM electrolyzers generally exhibit lower area-specific ohmic resistance (approximately 0.1–0.2 $\Omega \cdot$ cm^2) due to the solid polymer membrane and efficient proton transport, while inductive effects are typically negligible in equivalent circuit representations [18]. AEM systems show intermediate characteristics between AWE and PEM in terms of both resistance and capacitance, while SOEC achieves ultra-low resistance (0.01–0.1 $\Omega \cdot$ cm^2) at elevated temperatures [44].

For SOEC systems, the dominant system dynamics are governed by thermal processes with time constants ranging from minutes to hours, particularly during load variations and start-up/shut-down transients [26], necessitating coupled thermal–electrical modeling frameworks for accurate system-level analysis.

Model complexity selection involves tradeoffs between computational burden and accuracy. For hybrid microgrids with moderate dynamics, single-RC models [see Fig. 1(b)] or dual-RC models [see Fig. 1(c)] provide sufficient accuracy while maintaining computational simplicity. For high-current grid services requiring fast frequency response, full RC–Warburg models [see Fig. 1(d)] are necessary to accurately capture diffusion-related impedance and concentration polarization effects at elevated current densities [45].

2) NONLINEAR CHARACTERISTICS AND POWER ELECTRONICS IMPLICATIONS

The V–I characteristics of electrolyzer technologies represent one of the most critical factors in power electronics design. They directly influence the selection of the converter topology, the implementation of the control strategy, and the requirements for the integration of the grid. Building upon the technology comparison in Table 1 and Section II-B, Fig. 3 illustrates the V–I polarization curves for all four electrolyzer technologies under various operating conditions, based on electrochemical parameters from the literature [15], [18], [19], [26]. A clear understanding of these electrochemical behaviors is essential for maximizing power conversion efficiency and ensuring operational stability under fluctuating renewable energy situations.

The polarization behavior of electrolyzers follows the general voltage relationship in (2), where each over potential component exhibits distinct technology-specific characteristics. As demonstrated in Fig. 3(a) and (b), temperature significantly affects operating voltage, with cell voltage decreasing as temperature increases for both AWE and PEM systems. The activation overpotential, which dominates at low current densities, significantly affects the converter's control bandwidth and operational range [39].

The ohmic overpotential region typically defines the main operating range for industrial systems, where the linear V–I relationship enables predictable converter performance. Fig. 3(c) demonstrates that SOEC technology achieves substantially lower operating voltages (0.9–1.3 V at 650–750 °C) compared to low-temperature systems (1.8–2.4 V), due to favorable ionic conductivity at high temperatures [47].

At high current densities, concentration overpotentials become increasingly significant, causing exponential voltage rises that limit converter power-handling capability. AEM electrolyzers have recently demonstrated promising advances, achieving improved dynamic performance while maintaining cost-effectiveness through the use of nonprecious metal catalysts [48].

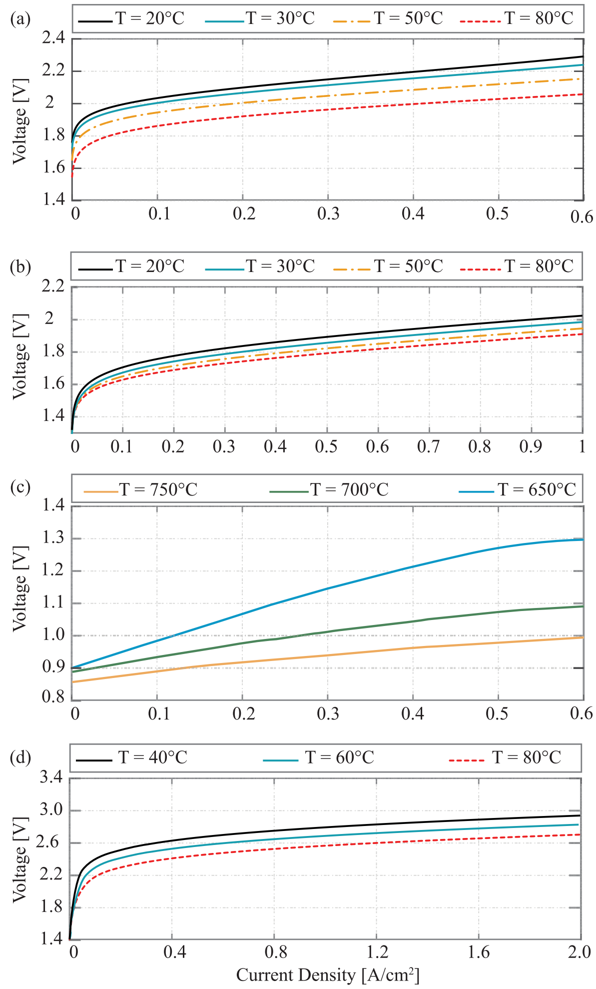

FIGURE 3. V–I density curves for (a) AWE [29], (b) PEM [46], (c) SOEC [21], and (d) AEM [32] at various operating temperatures.

III. ENERGY HUB ARCHITECTURE AND SYSTEM CONFIGURATION

A hydrogen production energy hub integrates multiple RESs, energy storage systems, and power electronic interfaces to enable reliable green hydrogen generation under fluctuating renewable supply. The architecture must coordinate these heterogeneous components while managing power quality, system stability, and operational efficiency. This section examines each component's characteristics and modeling approaches, followed by system-level integration considerations. Fig. 4 illustrates the complete energy hub architecture, showing the transition from current AC bus-based systems (gray paths) toward future DC bus configurations (green paths) driven by efficiency improvements.

A. MULTISOURCE RENEWABLE ENERGY INTEGRATION

1) PHOTOVOLTAIC (PV) SYSTEMS

PV systems exhibit significant variability due to diurnal and seasonal patterns, with typical capacity factors of 15% –25% [49]. Cloud transients introduce rapid power fluctuations, with

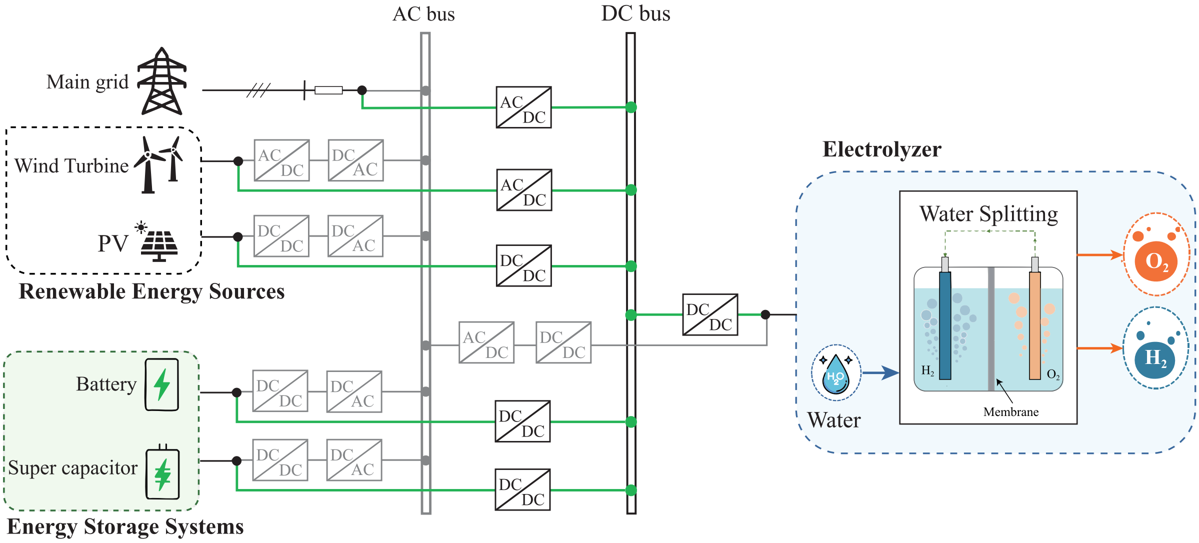

FIGURE 4. **Energy hub architecture showing the transition from current AC bus-based systems (gray paths) to emerging DC bus configurations (green paths).**

ramp rates reaching 70% –80% of rated capacity within minutes [50]. This variability necessitates coordinated operation between energy storage and electrolyzer power management to maintain stable hydrogen production while preventing frequent start-stop cycles that degrade electrolyzer lifetime.

Temperature-dependent efficiency losses (approximately 0.4% –0.5% per °C above 25°C) introduce predictable power derating that must be incorporated into energy management strategies [51]. In high-temperature climates, this can reduce annual energy yield by 10% –15% , directly impacting hydrogen production economics. To maximize energy extraction under varying conditions, continuous maximum power point tracking (MPPT) control is essential, with modern algorithms achieving tracking efficiencies up to 98% [52]. Advanced predictive MPPT techniques that anticipate electrolyzer load requirements enable smoother power transitions and improved system efficiency [53].

The inherent modularity of PV systems (scalable from kW to GW) and their configurable DC voltage levels (typically 400–1000 V, aligning with electrolyzer input requirements) simplify system integration by minimizing power conversion stages, thereby reducing losses and control complexity [54].

2) WIND ENERGY SYSTEMS

Wind turbines provide complementary generation profiles to PV systems [55], with capacity factors typically ranging from 33% to 38% for onshore and 40% to 50% for offshore installations [56]. Modern multimegawatt turbines offer cost-effective solutions for large-scale hydrogen production [57]. However, the cubic dependence of power output on wind speed ($P \propto v^3$) introduces substantial fluctuations that require robust energy management and control strategies [58]. Turbines typically cut-in at 3–4 m/s, reach rated power at 12–16 m/s, and cut-out above 25 m/s. This wide operating range necessitates advanced control mechanisms to ensure stable electrolyzer operation and prevent degradation from frequent start-stop cycles.

For dedicated hydrogen applications, wind turbines can operate independently of traditional grid constraints [59], eliminating concerns related to reactive power compensation and grid stability that typically affect grid-connected configurations [60]. The generation profiles of hybrid PV-wind systems work together to balance the fluctuation of the solar radiation and the wind's more unpredictable patterns, resulting in more consistent aggregate power production and better use of the electrolyzer.

3) BATTERY ENERGY STORAGE SYSTEMS (BESS)

Modern lithium-ion BESS provide essential fast-response capabilities for renewable power smoothing and electrolyzer protection, characterized by high round-trip efficiency and subsecond response times [61]. However, battery lifetime depends heavily on control strategy, maintaining operation within a narrow state-of-charge (SOC) window (typically 20% –80%) is crucial for ensuring long cycle life, as deviations accelerate capacity degradation [62]. Consequently, energy management algorithms must carefully balance short-term power demands with long-term aging considerations.

In hydrogen production systems, BESS mitigates short-term renewable variability and sustains electrolyzer operation within optimal ranges [63]. The power-to-energy ratio (C-rate) represents a fundamental design tradeoff: higher C-rates enable faster transient response but increase both capital costs and thermal stress. Coordinated thermal and power management is, therefore, vital to preserve performance and extend system lifespan [61].

4) SUPERCAPACITORS

Supercapacitors complement batteries through ultra-fast response and exceptional cycle life (often exceeding one million

TABLE 3. Comparison of Energy Storage Technologies for Hydrogen Systems

Characteristic	Li-ion BESS	Supercapacitor	Hydrogen
Energy Density (Wh/kg)	150–250	5–15	3.3×10^4
Power Density (W/kg)	$0.5–2\times10^3$	$5–15\times10^3$	$0.5–2\times10^3$
Response Time	0.1–0.5 s	<1 ms	1–30 s
Round-trip Efficiency (%)	85–95	90–98	30–45
Cycle Life	$3–5\times10^3$	$>10^6$	$1–4\times10^4$ h
Calendar Life (yr)	10–15	15–20	10–20
Self-discharge	2–5%/mo	10–40%/2wk	≈0
Capital Cost ($/kWh)	300–400	$1–5\times10^3$	2–35
Reference	[62], [67]	[49]	[68]

cycles), making them particularly effective for mitigating hf transients from cloud passages and wind gusts [64]. However, their low energy density and relatively high self-discharge limit practical applications to short-duration peak power support, typically ranging from seconds to tens of seconds.

In hybrid battery-supercapacitor configurations, frequency-based power allocation assigns fast transients to supercapacitors while batteries handle slower variations [65]. This complementary operation significantly extends battery lifetime by reducing cycling stress and preventing exposure to high-rate charge/discharge events [66]. However, the added system complexity and cost must be justified by substantial improvements in battery longevity and performance, particularly in highly intermittent renewable environments.

5) STORAGE TECHNOLOGY COMPARISON

Table 3 compares key performance metrics of energy storage technologies relevant to hydrogen production systems, including lithium-ion BESS, supercapacitors, and hydrogen storage itself. The comparison highlights the fundamental tradeoffs between energy density, power density, response time, efficiency, and lifetime characteristics that govern storage technology selection.

The selection of storage technology depends primarily on application timescale: supercapacitors excel at short-duration transients (milliseconds to seconds), batteries provide intermediate buffering (minutes to hours), and hydrogen storage enables long-term energy shifting (hours to seasons). Each technology occupies a distinct operational niche, and hybrid configurations can combine their complementary strengths to optimize overall system performance.

B. POWER ELECTRONIC INTERFACES

1) DC–DC CONVERTER TECHNOLOGIES

Bidirectional DC–DC converters form the critical interface between RESs, storage systems, and electrolyzer loads. Buck–boost topologies typically achieve efficiencies exceeding 95% at rated power and must accommodate wide voltage ranges as battery SOC and electrolyzer operating points vary [10].

For high-power applications (>100 kW), interleaved multiphase configurations are preferred due to their reduced current ripple, modular scalability, and improved reliability through phase redundancy [69]. When galvanic isolation is required for safety or ground loop prevention, dual-active-bridge (DAB) converters provide bidirectional power flow with 93% –97% efficiency through soft-switching operation [70].

These converters require fast current control loops (2–5 kHz bandwidth) to maintain stability, particularly given the constant-power load behavior of electrolyzers which can destabilize DC buses through negative incremental impedance [71].

2) DC–AC INVERTERS

Three-phase inverters interface RESs with AC grids, achieving 97% –98% efficiency in modern implementations [72]. For strong grid connections, inverters typically operate in grid-following mode, enabling active/reactive power control and ancillary grid support functions [73]. In islanded or weak-grid hydrogen facilities, grid-forming operation is essential to establish stable AC voltage and frequency, requiring sufficient energy storage or controllable generation to maintain power balance. *LCL* filters are commonly employed to attenuate harmonics while minimizing filter size and cost [74]. Large-scale hydrogen plants generally use medium-voltage inverters (2.3–4.16 kV) with modular parallel-connected units to allow redundancy and staged commissioning.

3) AC–DC RECTIFIERS

Active front-end (AFE) rectifiers enable bidirectional power flow between AC grids and DC buses, providing grid support capabilities unavailable in passive diode rectifiers [72]. AFE rectifiers achieve power factors exceeding 0.99 and maintain total harmonic distortion below 5% , meeting grid code requirements for renewable energy integration. These converters support regenerative operation, allowing excess hydrogen production capacity or stored energy to be exported back to the grid during high electricity prices. For grid-connected hydrogen facilities, AFE rectifiers with integrated grid synchronization and fault ride-through capabilities ensure robust operation during grid disturbances while maintaining compliance with interconnection standards.

4) BUS SELECTION

The choice of DC, AC, or hybrid architectures has a major impact on system efficiency, cost, and flexibility. DC bus systems are increasingly favored for dedicated hydrogen facilities, as they directly connect DC sources (PV, batteries) with DC loads (electrolyzers), eliminating AC–DC–AC conversion stages, reducing losses, and simplifying system design [10].

As illustrated in Fig. 4, the hydrogen production industry is transitioning from AC-based to DC-based configurations. AC bus systems (gray paths) dominate existing hydrogen facilities due to established grid infrastructure and mature protection equipment. However, these systems require multiple conversion stages, like AC–DC for electrolyzers and DC–AC for PV/battery systems, with each stage introducing 2% –4% efficiency losses. However, DC bus systems (green paths,

Fig. 4, 600–1500 V) represent the optimized architecture for dedicated hydrogen facilities [10]. By directly connecting DC sources (PV, batteries) with DC loads (electrolyzers), this configuration eliminates intermediate conversions, reducing cumulative losses and simplifying control. The industry is increasingly adopting DC-coupled architectures in new installations, driven by demonstrated efficiency improvements of 3% –6% and reduced system complexity.

C. SYSTEM-LEVEL INTEGRATION

Successful integration of renewable sources, storage systems, and electrolyzers requires coordination across multiple spatial and temporal scales. System-level design must address both steady-state power flow management and dynamic stability under disturbances. This section examines the hierarchical control architecture for power flow coordination and the stability challenges inherent to DC-coupled and AC-coupled hydrogen production systems.

1) POWER FLOW COORDINATION

Green hydrogen production systems require advanced power management to coordinate RESs, battery storage, and electrolyzer loads while maintaining system stability. Hierarchical control architectures address this challenge through three temporal layers [75]: primary control (milliseconds to seconds) stabilizes voltage and frequency through fast feedback loops; secondary control (seconds to minutes) manages power sharing among renewable sources and battery SOC to smooth fluctuations; and tertiary control (minutes to hours) optimizes economic operation based on electricity prices, hydrogen demand forecasts, and maintenance schedules [12]. This multitimescale approach enables the system to respond effectively to both rapid power transients and longer-term operational objectives.

Renewable energy forecasting plays a critical role in predictive energy management for hydrogen systems. Short-term forecasts spanning one to six hours guide real-time dispatch decisions, determining when to produce hydrogen directly from renewables versus drawing from battery storage or grid power. Day-ahead forecasts support optimal scheduling of electrolyzer operation, battery charging profiles, and grid interactions to minimize costs while meeting hydrogen production targets. The operational strategy must balance load-following modes that maximize renewable utilization against baseload operation, which simplifies downstream hydrogen compression and storage but increases grid dependency [76].

2) SYSTEM STABILITY

DC-coupled hydrogen systems face unique stability challenges due to the constant-power load behavior of electrolyzers. Tightly regulated electrolyzer power control creates negative incremental impedance: when bus voltage drops, the electrolyzer draws more current to maintain constant power, potentially triggering voltage oscillations or collapse [77]. Active damping techniques implemented through converter control loops and carefully designed input filters mitigate this instability by modifying the apparent impedance seen by the DC bus.

For islanded AC microgrids, frequency stability requires sufficient system inertia to limit rate of change during power imbalances. Traditional rotating generators provide physical inertia, but renewable-dominated systems rely on grid-forming inverters that synthesize virtual inertia through control algorithms emulating synchronous machine dynamics [78]. The energy storage system capacity and control bandwidth determine the system's ability to ride through sudden changes in renewable generation or electrolyzer load, making proper sizing and control design essential for stable off-grid hydrogen production [79].

IV. CONTROL STRATEGIES AND ARCHITECTURES FOR GREEN HYDROGEN PRODUCTION SYSTEMS

Green hydrogen production systems require sophisticated control architectures and strategies to effectively integrate RESs with hydrogen energy storage. Unlike conventional electrolysis systems operating at constant power, renewable-coupled electrolyzers face the following three fundamental control challenges:

1) *fast power transients* from intermittent PV/wind sources requiring response times from microseconds (power electronics switching) to seconds (thermal dynamics), spanning over six orders of magnitude;
2) *strong operational nonlinearities* in the V–I characteristic, temperature-dependent kinetics, and gas crossover phenomena that invalidate linear control assumptions;
3) *conflicting operational objectives* between maximizing hydrogen production, minimizing degradation from cycling, and providing grid ancillary services [80].

This section focuses on device-level and supervisory control, including power converter regulation and local coordination strategies. System-level energy management and multienergy optimization are addressed in Section V. The section begins with the hierarchical control framework that provides temporal decomposition across multiple time scales (see Section IV-A), followed by control objectives and operational requirements (see Section IV-B), and concludes with controller design methodologies from classical proportional-integral-derivative (PID) approaches (see Section IV-C) to advanced nonlinear techniques (see Section IV-D).

A. HIERARCHICAL CONTROL FRAMEWORK

Hierarchical control has emerged as the predominant paradigm for managing electrolyzer-integrated energy systems, drawing from established practices in power systems and microgrid operations [81]. This design disaggregated the control issue through temporal stratification, with each layer functioning on different time scales and targeting unique operational goals [82]. As illustrated in Fig. 5, the framework comprises the following three principal levels [81].

1) *Primary control (microseconds):* Provides fast device-level regulation of power converters and electrolyzer

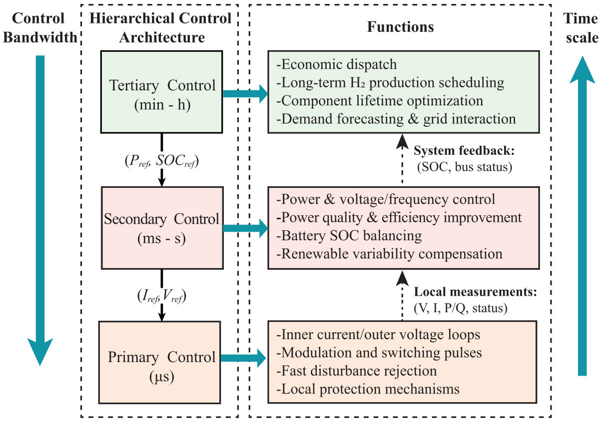

FIGURE 5. Hierarchical control architecture with three layers: primary (μs–s), secondary (ms–s), and tertiary (min–h) control with decreasing bandwidth and increasing time scale.

stacks through local controllers operating autonomously without communication infrastructure. Local measurements (voltage, current, power, reactive power, and device status) enable fast feedback control [83].

2) *Secondary control (milliseconds to seconds):* Coordinates multiple system components and compensates for primary control deviations using advanced methods, such as MPC, sliding-mode control (SMC), and adaptive techniques. This layer receives local measurements from the primary level and provides current and voltage references (I_{ref}, V_{ref}) for tracking [84].
3) *Tertiary control (minutes to hours):* Optimizes long-term economic operation, component lifetime, and market participation through centralized energy management systems (EMSs). System-level feedback including SOC and DC bus status enables the tertiary layer to dispatch optimal power references (P_{ref}, SOC_{ref}) to lower control layers [85].

B. CONTROL OBJECTIVES AND REQUIREMENTS

Building on the hierarchical framework presented in Fig. 5, the control of hydrogen production systems must fulfill several interrelated and often conflicting objectives [86]. These objectives span multiple operational layers and time scales, requiring careful coordination to achieve optimal system performance. These objectives are summarized as follows.

Hydrogen production objectives:

1) *Production maximization:* Optimal utilization of available renewable energy to maximize hydrogen output while respecting electrolyzer operating constraints.
2) *Production stability:* Maintenance of consistent hydrogen production rates despite renewable source variability, critical for downstream applications with steady hydrogen demand.
3) *Purity requirements:* Control of hydrogen-to-oxygen crossover impurity levels to meet safety standards, particularly relevant for alkaline electrolyzers where impurity accumulation affects the lower load limit [87].

Operational constraints:

1) *Safe operating area:* Enforcement of current, voltage, temperature, and pressure limits to prevent stack damage and ensure personnel safety.
2) *Dynamic limitations:* Adherence to maximum ramp rates during load changes to avoid thermal stress and degradation. Alkaline electrolyzers typically exhibit slower dynamic response compared to PEM systems, necessitating careful transient management [88].
3) *Start-stop cycles:* Minimization of frequent start-stop events, which accelerate electrolyzer degradation and reduce lifetime [87].

System-level requirements:

1) *Power quality:* Maintenance of acceptable voltage and current harmonics, particularly important given the nonlinear V–I characteristics of electrolyzer stacks [89].
2) *Grid support:* For grid-connected systems, provision of ancillary services including frequency regulation and voltage support through controlled load modulation.
3) *Economic operation:* Minimization of energy costs through intelligent scheduling while maximizing component lifetime and hydrogen production revenue [90].

C. LINEAR CONTROL DESIGN: PID CONTROLLERS

Despite the nonlinear dynamics and multiobjective requirements outlined in Section IV-B, PID controllers remain the dominant choice for primary-level electrolyzer regulation in industrial practice due to their simplicity, proven reliability, and minimal computational requirements [91]. Within the hierarchical control framework (see Fig. 5), PID loops typically implement the fastest primary control layer: inner current regulation within power electronic converters (operating at kHz switching frequencies) and outer voltage or power tracking loops [92].

Industrial implementations commonly employ cascaded PI structures (omitting derivative action to avoid noise amplification), with inner current loops achieving 100–500 Hz bandwidth and outer power/voltage loops operating at 1–10 Hz [93].

Although PID control applications in electrolyzer systems have been widely adopted and have been proven effective, they are still subject to several fundamental limitations that necessitate the development of advanced control strategies. The main difficulties consist of the following.

1) *Nonlinearity compensation:* Electrolyzer systems exhibit strong nonlinear behavior across the activation, ohmic, and concentration polarization regions, which limits the effectiveness of conventional linear PID controllers designed around a single operating point [94]. According to [92], PID performance significantly decreases when used throughout high current density variations, especially when powered by RESs that introduce frequent input and load fluctuations.
2) *Parameter variation:* Electrolyzer characteristics change significantly due to temperature variations, aging effects, and membrane degradation, requiring

TABLE 4. Control Implementations for Electrolyzer Systems: Comparison of Linear and Advanced Methods

Ref	Control Method	Control Objective	Electrolyzer Technology	Key Innovation	Limitations	Validation
Linear Controllers (PID/PI)						
[98]	PI-controlled synchronous buck	Voltage regulation	AWE	Synchronous buck for high efficiency at low voltage, high current	Simplified model; no transient analysis	Lab
[99]	Dual-loop PI (MPPT + current)	Power & current regulation	AWE	Auto mode-switching: MPPT current control via P&O	PV-only; residual P&O ripple	Lab
[100]	Single-loop PI	Current control	PEM	Model-based design for high voltage-ratio buck-full bridge	No voltage loop; limited coordination	Lab
[101]	PI (RTDT-based)	Stack current	AWE	Real-time DT integration; DAB converter (10 kW)	Fixed gains; no adaptation	HIL
[102]	Frequency-domain PID	Thermal control	AWE	Delay-aware tuning via frequency-domain thermal model	Limited stability under full range	Lab
[103]	Three-level interleaved PI	Voltage control	PEM	Multi-phase interleaving for ripple reduction	Complex switching; topology-specific	Lab
[104]	Frequency-domain PID	Temperature regulation	AWE	Multi-objective optimization with time-delay consideration	Scale-dependent tuning; delay-sensitive	Lab
[105]	Cascade PI	Hydrogen flow	AWE	Two-layer cascade for direct gas flow regulation	Flow nonlinearity; measurement delay	Lab
[106]	PI + slew-rate limiting	Power tracking (thermal-constrained)	SOEC	Model-derived current limits; feed-forward for hot-standby	Model-dependent; module-level validation	Sim.
Advanced Control Methods						
[107]	SMC	Current control	PEM	Indirectly coupled PV-EL; buck vs. quadratic buck	No electrolyzer constraints; no voltage regulation; no chattering mitigation;	Sim.
[108]	Adaptive SMC	Voltage & current balancing	PEM	Adaptive scheme for interleaved converter robustness	Simplified PEM model (ohmic only); chattering not addressed	HIL
[109]	BISMC	MPPT + voltage regulation	PEM	Backstepping + integral SMC for two-stage boost-buck; solar variability robustness	Simplified PEM model; no degradation/start-up constraints; chattering reduction unclear	Sim.
[110]	PINN-Adaptive Terminal SMC	Voltage tracking	PEM	PINN for uncertainty estimation; adaptive backstepping terminal SMC	Offline PINN training; high computational cost; trial-and-error design	HIL
[111]	H_2/H_∞ (IMC-based)	DC-DC voltage regulation	PEM	Internal model control + loop-shaping; robustness to DC-link variations	High-order compensator; conservative design	Sim.
[112]	Fuzzy PI	Voltage regulation	PEM	Fuzzy-based adaptive gain tuning for PV-PEM buck converter	Single converter; no coordination	Sim.
[113]	Type-2 FLC	MPPT + converter control	PEM	Type-2 membership for uncertainty; primary-level MPPT	Single converter; no coordination	Sim.
[114]	Adaptive FLC + PID (GA-optimized)	Grid-side P-Q decoupling; DC bus regulation; MPPT	AWE	Adaptive FLC for grid P/Q control; offline GA tuning of FLC and PID	Offline GA (no real-time adaptation); simplified electrolyzer model	Sim.
[115]	FLC + LSTM	Temperature regulation	AEM	LSTM for valve delay compensation; $\pm 1^\circ$C stability at 10 kW	Fixed power; single cooling loop	Lab

continuous controller retuning to maintain performance [95]. Traditional fixed-parameter PID controllers become suboptimal over time, which might raise safety issues when used for extended periods of time.

3) *Multiphysics coupling:* The strong coupling between electrical, thermal, and fluidic dynamics in electrolyzer systems creates complex interactions that single-variable PID controllers cannot effectively address [96]. This coupling happens when disturbances spread between control loops, which is undesirable for the general performance of the system, especially under transient situations.
4) *Safety constraints:* To avoid membrane degradation and guarantee safe operation, electrolyzer operation requires rigorous adherence to current, voltage, temperature, and pressure limitations [95]. Due to their inability to handle constraints naturally, conventional PID controllers need extra safeguards that could interfere with control goals in crucial operational situations.

These fundamental limitations have motivated extensive research into improved PI/PID implementations and alternative control approaches [97]. Table 4 provides a comprehensive overview of PI/PID controller implementations in electrolyzer systems, documenting the evolution from basic current regulation to advanced multiloop and thermal control strategies, along with their key achievements and remaining limitations.

Overall, PID implementations have progressively evolved from simple single-loop voltage or current regulation toward multiloop cascaded architectures addressing thermal dynamics and hydrogen flow control. Despite these advances, fundamental challenges persist: fixed-gain structures struggle with wide operating ranges, single-variable designs inadequately address multiphysics coupling, and explicit constraint handling remains absent. These limitations become particularly critical in large-scale renewable-powered systems where operating conditions are highly variable and component protection is paramount, motivating the development of advanced nonlinear control methods examined in Section IV-D.

D. ADVANCED CONTROL METHODS

While PID controllers remain prevalent for primary-level control due to their simplicity, the nonlinear characteristics of electrolyzer V–I relationships, coupled with parameter variations and renewable energy fluctuations, have motivated the development of advanced nonlinear control strategies. This section reviews the advanced control methods specifically applied to the primary level in the hierarchical control strategy for hydrogen production systems.

1) ROBUST CONTROL METHODS

Robust control techniques address parameter uncertainties and external disturbances inherent in electrolyzer systems operating under variable renewable inputs. Two principal approaches, SMC, and H_∞ control, offer distinct tradeoffs between performance guarantees and implementation complexity.

SMC provides robust voltage and current regulation for electrolyzers through its inherent insensitivity to parameter uncertainties and external disturbances—characteristics critical for systems operating under variable renewable inputs and changing electrochemical conditions. El Fadil et al. [116] applied super-twisting sliding-mode control (ST-SMC) with adaptive extended Kalman filter to an interleaved buck converter feeding a PEM electrolyzer. The ST-SMC achieved tight voltage regulation, equal current sharing between converter legs, and finite-time convergence while maintaining asymptotic stability under measurement noise and unknown electrolyzer parameters. Building on this, Koundi et al. [108] introduced an adaptive sliding-mode scheme for similar interleaved converter topology, ensuring accurate voltage regulation and balanced current distribution while maintaining robustness against system parameter variations and operating condition changes.

For PV-electrolyzer integration, Bekki et al. [109] implemented backstepping integral sliding-mode control (BISMC) through two-stage DC–DC converters. Combining backstepping and sliding mode with integral action, the controller achieved robust voltage regulation under variable solar irradiance. More recently, Baraean et al. [110] developed physics-informed neural network-based adaptive backstepping terminal SMC, where neural networks estimate system uncertainties while terminal sliding-mode guarantees finite-time convergence. Hardware-in-the-loop validation confirmed superior dynamic response and robustness compared to conventional sliding mode approaches.

While SMC performs reliably, it still encounters challenges in green hydrogen systems. The chattering effect generates hf current ripples that wear down the membrane over time, ultimately shortening the electrolyzer's lifespan and affecting long-term reliability. SMC design requires explicit uncertainty bounds, difficult to characterize given time-varying electrolyzer parameters from temperature fluctuations, aging effects, and renewable energy variability. In addition, state measurement or observer requirements add computational overhead and sensor costs. These constraints have motivated investigation of frequency-domain robust control methods, such as H-infinity control, offering systematic design with guaranteed stability under less restrictive uncertainty assumptions.

H_∞ control provides a systematic frequency-domain framework for designing controllers with guaranteed robust stability, particularly valuable for electrolyzer systems supplied by intermittent renewable sources. In [111], an H_2/H_∞ robust controller is designed for DC–DC converter-electrolyzer systems supplied by microwind energy conversion systems. The controller was synthesized using internal model control structure with loop-shaping to guarantee stability under parametric variations and unmodeled dynamics. Theoretical verification confirmed robustness to DC-link voltage variations and input inductance uncertainties. However, this control method typically results in high-order compensators and exhibit conservative performance due to worst-case optimization criteria.

2) FUZZY LOGIC CONTROL

Fuzzy logic control (FLC) offers a practical alternative for electrolyzer systems where nonlinear dynamics, thermal constraints, and uncertain renewable inputs make precise model-based control challenging. Unlike conventional controllers requiring exact mathematical models, FLC operates through linguistic rules and expert knowledge, making it particularly suitable for PEM electrolyzers with complex electrochemical behavior [117].

Early applications focused on local converter control. Han et al. [112] applied Fuzzy PI at the buck converter level in a PV–PEM system, adaptively tuning PI gains to regulate voltage and current, achieving lower ripple (0.005 versus 0.0207) and faster settling time (0.1 s versus 0.5 s) compared to classical PI. Barhoumi et al. [113] extended this approach with Type-2 FLC at the primary converter level, improving transient response under irradiance fluctuations and achieving higher power transfer efficiency than both perturb and observe (P&O) and Type-1 FLC methods. However, both approaches remained confined to single-converter regulation without system-wide coordination.

More recent work has extended FLC to system and grid interface levels. Abadlia et al. [114] proposed an adaptive FLC scheme for a grid-connected PV-hydrogen hybrid system, enabling decoupled active and reactive power regulation at the grid interface. Offline genetic algorithms were used to tune FLC scaling factors and PI gains, improving DC bus voltage regulation and power factor. Nevertheless, the study relies on simplified electrolyzer modeling and simulation-only validation, without considering higher level energy management or real-time operational constraints. Moreover, in [115], an FLC with long short-term memory (LSTM) neural networks is combined for temperature regulation, maintaining stack temperature within $\pm 1^\circ$C and stable 10 kW power output. The LSTM prediction compensated for valve actuation delays and system nonlinearities, though validation was limited to a fixed 10 kW laboratory setup with single cooling loop.

Despite practical success, FLC faces fundamental limitations. The absence of formal stability guarantees is critical for electrolyzer systems with nonlinear I–V characteristics and thermal dynamics. While fuzzy controllers show the robust performance across operating ranges, stability analysis remains complex. Computational burden increases significantly when coordinating multiple electrolyzer stacks with varying operational constraints and hydrogen production targets, affecting real-time performance in large-scale applications. Dynamic requirements during startup, shutdown, and load-following operations further complicate rule design and membership function optimization. In addition, effective controller design demands deep understanding of electrolysis parameters—gas bubble dynamics, electrode kinetics, thermal management—making initial structure design and rule formulation heavily dependent on electrochemical engineering expertise, even when optimization algorithms assist parameter tuning.

E. COMPARATIVE ASSESSMENT AND PRACTICAL CONSIDERATIONS

Overall, the comparative assessment reveals a clear tradeoff between control performance and implementation complexity. Conventional PID/PI controllers remain the dominant choice in industrial electrolyzer applications due to their simplicity, low computational cost, proven reliability, and straightforward tuning procedures. However, their performance degrades under wide operating ranges, nonlinear V–I characteristics, and time-varying parameters associated with temperature changes and aging effects.

Advanced nonlinear control methods offer improved capability in addressing these challenges. SMC provides fast dynamic response and strong robustness against parameter variations, making it attractive for applications requiring rapid power tracking under renewable fluctuations. Nevertheless, chattering-induced hf current ripple, increased switching stress, and the need for bounded uncertainty characterization limit its practical adoption without additional mitigation techniques. FLC enables intuitive rule-based implementation and adaptive behavior without requiring precise electrolyzer models, offering smoother control action and reduced stress on electrochemical components. At the same time, the lack of formal stability guarantees and the need for electrochemical expertise in membership function design pose challenges for systematic deployment.

As highlighted in Table 4, despite the theoretical advantages of advanced control approaches, most reported implementations remain at the simulation or laboratory-validation level, with relatively few industrial demonstrations. This gap reflects practical constraints related to controller complexity, tuning effort, robustness certification, and cost sensitivity in large-scale electrolyzer systems. Consequently, while advanced control methods show strong potential for enhancing dynamic performance and robustness, further research is needed to simplify controller structures, develop systematic tuning methodologies, and validate performance under realistic operating conditions.

Moreover, it is important to note that all control strategies reviewed in this section primarily address local, converter-level regulation of individual electrolyzer units. Coordinated operation of multiple electrolyzers within renewable-powered hydrogen production systems requires higher level energy management and supervisory control architectures, which extend beyond primary-level control techniques and are discussed in Section V.

V. ENERGY MANAGEMENT STRATEGIES FOR HYDROGEN-BASED ENERGY HUBS

According to the hierarchical control framework established in Section IV, this section addresses system-level energy management for hydrogen-integrated energy hubs. While Section IV focused on device-level control (primary layer), this section examines coordination and optimization at secondary and tertiary levels. The operational complexity extends beyond device-level challenges: renewable sources exhibit rapid power variations and batteries respond within milliseconds, while electrolyzers require seconds to minutes for stable operation [118]. This temporal mismatch, coupled with competing objectives of efficiency, cost, and component lifetime, demands advanced coordination strategies.

This section examines two complementary aspects: 1) spatial coordination architectures that determine how control authority is distributed across physically distributed components (see Section V-A), and 2) optimization methodologies employed at different hierarchical levels (see Section V-B).

A. ENERGY MANAGEMENT ARCHITECTURE

Energy management architecture defines how control authority is spatially distributed across physically separated components within the hierarchical framework. Two primary coordination approaches exist: centralized and decentralized structures [119], [120].

1) CENTRALIZED (TWO-LAYER) CONTROL ARCHITECTURE

Centralized architectures employ an upper level EMS that collects system-wide data through communication networks and dispatches optimized control commands to local controllers, as illustrated in Fig. 6 [119], [121]. The EMS continuously monitors measurements from all components—renewable sources (PV, wind), energy storage (battery, supercapacitor), grid connection, and electrolyzer units—via bidirectional information flow (dashed lines). Based on this global information, the EMS computes optimal power references and sends control commands to regulate power flow through each converter.

This hierarchical structure enables global optimization across multiple operational time scales, from real-time dispatch to long-term economic planning [119]. Centralized decision-making achieves coordinated operation of diverse

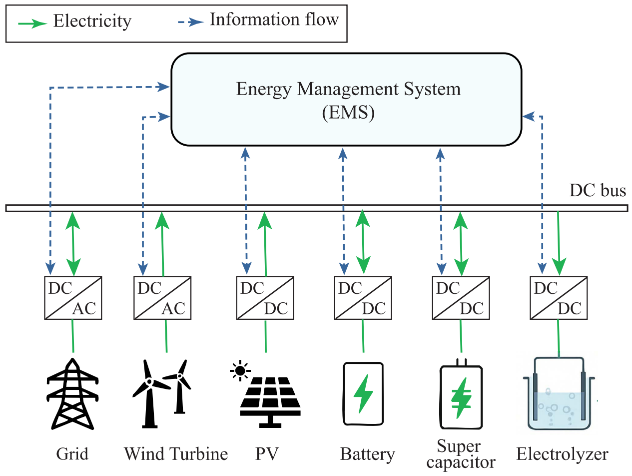

FIGURE 6. **Centralized control architecture showing EMS coordination via communication network (dashed lines) and power flow through DC bus (solid lines).**

generation and storage units, enabling efficient power sharing and resource allocation [120]. For instance, the EMS can simultaneously optimize battery charging/discharging, electrolyzer load management, and grid import/export to minimize operational costs while meeting hydrogen production targets. Furthermore, computationally intensive optimization algorithms can be executed at the EMS level without overloading local controllers [121].

However, this architecture introduces critical dependency on communication infrastructure. Network failures or latency can compromise supervisory control, potentially leading to suboptimal operation or loss of coordination between subsystems [122]. In addition, the single point of failure at the EMS level raises reliability concerns for mission-critical or islanded applications.

2) DECENTRALIZED CONTROL ARCHITECTURE

Decentralized architectures eliminate the centralized EMS and communication infrastructure shown in Fig. 6, maintaining the same physical topology but with each converter making autonomous decisions based on local measurements [123]. This approach addresses critical limitations of centralized systems: enhanced reliability without communication dependency, elimination of single-point-of-failure at the EMS level, and reduced infrastructure requirements [122], [123].

However, decentralized control achieves suboptimal performance due to lack of global information. Local controllers cannot consider system-wide objectives, renewable generation forecasts, or coupling constraints between components, resulting in higher operational costs and reduced efficiency compared to centralized optimization [122], [124]. The fundamental tradeoff is reliability versus economic performance.

B. ENERGY MANAGEMENT METHODOLOGIES

Effective energy management in hydrogen-based microgrids requires advanced control strategies capable of balancing multiple objectives: operational efficiency, economic performance, equipment longevity, and system reliability. Contemporary implementations employ hybrid approaches, combining centralized optimization methods (MPC, fuzzy logic, AI) at secondary and tertiary levels with decentralized droop control at the primary level, as detailed in the hierarchical framework (see Section IV-A). This section reviews the primary optimization methodologies, highlighting their respective advantages, limitations, and application contexts.

1) MODEL PREDICTIVE CONTROL

MPC offers advantages for multiparameter systems by explicitly handling uncertainties and constraints. The MPC optimization framework enables flexible management of hydrogen energy storage and battery systems by optimizing control actions through a cost function with adjustable weighting factors [125]. Kibidi et al. [126] developed a distributed explicit MPC considering current ramp rate constraints to better match the dynamic characteristics of fuel cells and electrolyzers. The main challenges in MPC implementation involve determining appropriate multiobjective weight coefficients and computational complexity [127]. However, MPC remains attractive for systems requiring explicit constraint satisfaction and where computational resources are adequate [126].

2) FUZZY LOGIC CONTROL

FLC provides an effective approach for managing nonlinear and uncertain systems without requiring accurate mathematical models [128]. The method demonstrates strong robustness to parameter variations and can be constructed using simple linguistic rules. Garcia et al. [129] proposed an adaptive neuro-fuzzy inference system that combines artificial neural networks with fuzzy logic to train membership functions using experimental data, thereby optimizing power sharing between battery and hydrogen storage systems, while maintaining both SOC and hydrogen levels within desired limits.

Multiple fuzzy logic controllers can be coordinated for hierarchical decision-making. Vivas et al. [130] developed a multi-FLC system where FLC1 manages grid interaction decisions while FLC2 distributes power between battery and hydrogen storage, simultaneously considering technical and economic objectives.

Despite its practical advantages, FLC faces several inherent limitations in energy management applications.

1) *Empirical rule design*: Construction of fuzzy rule bases relies heavily on expert knowledge and heuristic approaches, lacking systematic design methodologies [128]
2) *Scalability challenges*: Rule complexity increases exponentially with the number of input variables, limiting applicability to large-scale systems
3) *Suboptimal performance*: Unlike optimization-based methods, FLC cannot guarantee global optimality or theoretical performance bounds

4) *Membership function tuning*: Parameter selection for membership functions remains largely trial-and-error, impacting control quality

Nevertheless, FLC remains particularly valuable in scenarios with substantial model uncertainty, offering computational simplicity, adaptability, and resilience under fluctuating renewable power conditions.

3) ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML) METHODS

AI and ML techniques have emerged as transformative approaches for energy management in hydrogen-integrated microgrids, addressing system uncertainties, nonlinearities, and dynamic operational conditions that challenge conventional methods [131].

Deep reinforcement learning (DRL) provides model-free learning capabilities, enabling systems to learn optimal operational policies through continuous interaction without requiring explicit mathematical models. Recent studies has demonstrated DRL's performance comparable to MPC while eliminating dependency on forecasts and real-time optimization computations [132], [133]. This adaptability allows robust performance under varying renewable inputs and unforeseen disturbances.

ML methods including support vector machines, random forests, and neural networks have been successfully deployed for predictive control and thermal management in PEM electrolyzer systems [134], [135]. Data-driven optimization of operating parameters has demonstrated measurable efficiency improvements in experimental setups, and PV–battery–electrolyzer microgrid prototypes have validated the practical feasibility of ML-based energy management under laboratory conditions [136], [137].

Despite promising results, several critical barriers persist for industrial-scale deployment.

1) *Limited validation*: Most of the experimental studies remain confined to laboratory environments. Industrial-scale demonstrations are insufficient to validate the approaches for real-world deployment [136].
2) *Degradation modeling*: Learning algorithms inadequately incorporate long-term equipment degradation effects. Current models fail to account for performance deterioration over extended operational periods.
3) *Computational requirements*: Real-time implementation in multimegawatt systems demands substantial processing resources. The computational burden poses practical challenges for large-scale hydrogen production facilities.
4) *Robustness concerns*: System behavior during rare or extreme conditions remains insufficiently characterized, raising concerns over operational resilience [131].

To mitigate these issues, hybrid hierarchical architectures have been proposed, integrating MPC or FLC for real-time control with offline ML modules for degradation prediction, parameter adaptation, and long-term planning optimization [138]. This integrated approach bridges data-driven intelligence with control reliability, paving the way for adaptive and self-optimizing hydrogen energy hubs.

VI. ADVANCED TOPICS AND FUTURE RESEARCH DIRECTIONS

The integration of hydrogen energy storage in microgrids represents a rapidly evolving field with significant opportunities for advancement. This section examines emerging technologies and research directions that will shape the future of operational control and energy management strategies for electric-hydrogen hybrid systems. Based on recent developments in industry and academia, we identify three critical research frontiers: modular electrolyzer architectures, AI-driven control systems, and digital-twin (DT) technologies for real-time monitoring and optimization.

A. MODULAR AND SCALABLE ELECTROLYZER SYSTEMS

The hydrogen production industry is transitioning from single-stack installations toward modular designs to meet gigawatt-scale production demands. Modular configurations offer the following three key advantages:

1) extended operational flexibility by reducing minimum system load to approximately 1/N of rated capacity while maintaining individual module constraints [139];
2) improved availability through redundancy, enabling partial shutdowns for maintenance without compromising overall operation [140]; and
3) enhanced annual hydrogen production—comparative studies demonstrate over 33% production increase while reducing degradation compared to single-stack systems [141].

Table 5 summarizes representative industrial implementations demonstrating the transition toward standardized, mass-producible systems. These developments range from 10 MW PEM building blocks to 100 MW containerized units, with facilities such as Hamburg's 5 GW Gigahub enabling serial production from 2025.

B. AI AND ML INTEGRATION

AI and ML techniques are transforming energy management in hydrogen systems, with documented applications in over 200 cases spanning prediction, fault detection, and optimization [150]. ML algorithms (SVM, MLP, random forest) effectively predict electrolyzer performance parameters with mean absolute errors below 0.07, providing significantly higher computational efficiency than CFD models [151]. Reinforcement learning-driven energy management demonstrates 8% –10% cost savings under demand variability [152], while AI-driven optimization enables potential energy savings up to 20% –24% through intelligent operational strategies [153].

Despite progress, critical research gaps remain. DRL shows promise for adaptive control but requires extensive validation in real hydrogen systems. LSTM networks demonstrate effectiveness in forecasting renewable generation and preregulating electrolyzer power to prevent fluctuations [154], suggesting

TABLE 5. Industrial Implementations of Modular Electrolyzers and DT-Enabled Hydrogen Systems

Project / Developer	Scale & Type	Key Technical Features
(A) Modular Electrolyzer Systems		
Quest One Gigahub, Hamburg [142]	10 MW PEM modules, 5 GW facility	Integrated skids enabling serial production from 2025; scalable >100 MW
Electric Hydrogen—Infinium Project, Texas [143]	100 MW modular PEM	DNV-validated containerized units; prefabricated for high availability
Plug Power – Galp Sines, Portugal [144]	100 MW (10 MW modules)	Produces 15,000 t/y H_2; modular layout enables phased expansion
Accelera (Cummins)—Quebec, Canada [145]	90 MW PEM	Four 25 MW units enabling redundancy and grid-responsive operation
(B) DT –Enabled Projects		
HyNetherlands (ENGIE) [146]	100 MW PEM	Real-time DT for monitoring and performance optimization; GW-scalable
EPHYRA – Corinth Refinery, Greece [147]	30 MW AEL	DT with automated control for hydrogen-refinery integration
Hyundai Rotem H_2 System, Korea [148]	Industrial infrastructure	Real-time DT for control, predictive maintenance, and optimization
MW-scale AEL Study [149]	MW-class alkaline	Validated DT for real-time simulation and efficiency optimization

that integrating DRL for adaptive control with deep learning for temporal modeling could significantly enhance system intelligence and robustness.

C. DT TECHNOLOGY FOR HYDROGEN SYSTEMS

DT technology enables real-time monitoring, control, and optimization of hydrogen production systems by maintaining adaptive virtual models synchronized with physical assets [155], [156]. Recent frameworks establish comprehensive methodologies spanning system definition, modeling, data selection, knowledge extraction, and DT design. Table 5 presents industrial DT implementations ranging from 30 to 100 MW systems, demonstrating applications in performance optimization, predictive maintenance, and hydrogen-refinery integration.

Literature analysis reveals that actual industrial implementations remain limited, with most published works relying on simulation data rather than real-time operational information [156]. This gap represents a critical opportunity for advancing practical DT deployment in large-scale hydrogen facilities.

D. CRITICAL CHALLENGES AND FUTURE OUTLOOK

Despite significant progress, the following three critical challenges must be addressed for widespread deployment of intelligent hydrogen energy hubs.

1) *Data Infrastructure and standardization:* The effectiveness of AI/ML models and DTs critically depends on high-quality data. Major barriers include synchronization errors, data loss, and latency in real-time monitoring systems [157]. Standardized communication protocols (IEC 61850, OpenADR) and robust cybersecurity frameworks for hydrogen systems remain urgent priorities.
2) *Multiscale modeling integration:* Current approaches often address either cell/stack-level or system-level optimization in isolation. Comprehensive solutions require multiscale frameworks linking molecular electrochemistry to system-level energy management, achieved through hybrid physics-informed ML models that maintain computational efficiency for real-time control.
3) *Economic viability and cost competitiveness:* Despite technical progress, cost remains the primary barrier to green hydrogen adoption. Recent project-based estimates indicate that installed electrolyzer CAPEX in 2023 ranged from approximately \$2000/kW for alkaline systems to \$2450/kW for PEM systems (including balance of plant, engineering, procurement, construction, and contingencies) [1]. SOEC systems, while offering the highest theoretical efficiency (80% –90% , Table 1), remain at pilot/early commercial stages with limited cost data for large-scale deployments. The IEA attributes recent cost increases to inflation in materials and labor, higher interest rates, with 2023 values revised upward by approximately 20% compared to previous estimates [1]. However, mass manufacturing and scale-up could reduce installed CAPEX by 40% –55% by 2030 across all technologies [1].
4) *Control-economics integration gap:* Operational challenges persist—some large plants underperform at low part-load operation, directly impacting capacity factor and LCOH. Advanced control strategies contribute to cost reduction through the following:
   1) improved capacity factor by enabling wider load range operation;
   2) extended equipment lifetime through degradation-aware management;
   3) revenue enhancement through grid service participation.

   However, quantitative techno-economic analysis comparing different control strategies remains limited. While LCOH is site-specific and depends on electricity prices, capacity factors, and policy support, systematic cost-benefit analysis of advanced control methods represents a critical research gap requiring connection of control performance metrics to economic indicators for data-driven deployment decisions.

As the hydrogen economy continues to expand toward the 10 GW production capacity targets set by various governments for 2030 [80], these advanced control and management technologies will play an increasingly critical role in ensuring efficient, reliable, and economically viable operation of green hydrogen production systems.

VII. CONCLUSION

This article has provided a comprehensive review of control and energy management strategies for renewable hydrogen production systems, integrating electrolyzer modeling, power converter design, hierarchical control, and system-level optimization into a unified perspective. Unlike earlier studies that addressed these aspects in isolation, this review demonstrates that electrolyzer electrochemical dynamics, converter control bandwidth, control architectures, and energy management strategies constitute a tightly coupled design chain. In particular, electrochemical time constants directly constrain achievable converter control bandwidth, which in turn limits feasible control strategies and system-level energy management flexibility under renewable intermittency.

This coupling clarifies the limitations of conventional PI-based control, which remains dominant in industrial practice but struggles to maintain performance across wide operating ranges and variable renewable conditions. Advanced predictive, adaptive, and robust control strategies, together with emerging AI-assisted and DT-supported energy management frameworks, represent promising pathways to enhance dynamic stability, operational efficiency, and component lifetime when appropriately integrated within multiscale hierarchical architectures.

Future research should focus on multiphysics modeling that explicitly links electrochemical, electrical, and thermal dynamics across timescales, as well as degradation-aware energy management strategies capable of extending electrolyzer lifetime under frequent power variations. Addressing these challenges is essential to bridge the gap between laboratory-scale demonstrations and industrial deployment. Ultimately, the development of resilient, modular, and intelligently coordinated green hydrogen energy hubs will depend on the coherent integration of control intelligence across device, system, and energy management layers.

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