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A Modular Intelligent Control Framework for Scalable Biohydrogen Production in Microbial Electrolysis Cells

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The global energy transition requires technologies that can be scaled rapidly to decarbonise both power and chemical production. Microbial electrolysis cells (MECs) convert wastewater into renewable hydrogen; however, their commercial adoption is hindered by highly nonlinear dynamics, complex microbial interactions, and inadequate process control. This review traces the evolution of five control paradigms, including voltage/proportional-integral-derivative (PID), model-based, adaptive, fuzzy logic, and artificial-intelligence (AI) systems, as well as hybrid intelligent controllers, and benchmarks each against scalability, dynamic responsiveness, and energy-recovery performance. Recent hybrid approaches that embed AI learners within mechanistic-based models and real-time feedback loops show the greatest gains in predictive accuracy and robustness. To translate these advances beyond laboratory volumes, a modular design framework is introduced that (i) separates sensing, decision-making, and actuation into plug-and-play units; (ii) supports incremental scale-up from bench reactors to pilot-scale stacks without re-engineering the core algorithms; and (iii) leverages distributed edge-computing hardware to execute computationally intensive tasks close to the reactor, reducing latency and cloud-dependence. By directly targeting the bottlenecks of controller portability, computational load, and integration with industrial supervisory systems, this framework provides a practical roadmap for deploying intelligent MEC control across large-scale wastewater-to-hydrogen facilities.

1. Introduction

Over the past two decades, microbial electrochemical systems (MESs), including microbial electrolysis cells (MECs), microbial fuel cells (MFCs), microbial desalination cells (MDCs), and hybrid MEC–anaerobic digestion (AD) systems, have emerged as promising platforms for sustainable biohydrogen production and wastewater valorization (Kadier et al., 2020). In parallel, MES review literature has grown, addressing microbial dynamics, electrochemical performance, reactor design, modeling, and process control. However, unified syntheses of control strategies for biohydrogen-focused MECs remain scarce. Early reviews laid foundational insights: Kadier et al. (2016) discussed reactor configurations and influencing factors (e.g., biofilm growth, voltage losses) but lacked adaptive control frameworks. Luo et al. (2016) reviewed engineering/statistical models (e.g., Monod kinetics, Nernst–Planck transport) and emerging data-driven methods, yet noted limited real-time integration. Gadkari et al. (2018) emphasized the need to link models with automated control, while Deb et al. (2020) introduced nonlinear controllers through bioelectrochemical MFC models. Recio-Garrido et al. (2016) advocated model-based dynamic frameworks to optimize hydrogen production and improve system stability in MFCs and MECs. Recent literature reveals a shift toward artificial intelligence (AI)-enabled control strategies, although critical reviews highlight major limitations in their practical deployment. Li et al. (2023) catalogued various AI tools in MECs, including artificial neural network (ANN), genetic programming (GP), Support Vector Machine (SVM), Support Vector Regression (SVR), and Adaptive Neuro-Fuzzy Inference System (ANFIS), but noted that most remain limited to offline simulations, hindered by sparse, non-standardized datasets and absent benchmarking essential for scale-up. Similarly, Pandey et al. (2023) advocated for the use of deep reinforcement learning in biohydrogen production. Yet, they cited unresolved challenges in terms of real-time adaptability and safety constraints under dynamic conditions. Sanghvi et al. (2024) advocated for AI-driven optimization from a techno-economic perspective. Still, they lacked a quantitative comparison with conventional strategies (e.g., model predictive control (MPC),

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proportional-integral-derivative (PID)), casting doubt on the claimed scalability. Hybrid modelling has emerged to address interpretability challenges of data-driven methods, though its real-time effectiveness varies. Yao et al. (2022) showed improved dynamic prediction with AI-mechanistic hybrids, yet reported trade-offs between interpretability and data demands. Jadhav et al. (2021) reviewed ANN–fuzzy hybrids for MFCs but noted <0.1 % of studies were validated at industrial scale. Jadhav et al. (2024) proposed a fuzzy-supervised adaptive PID for MEC–AD systems, primarily using surrogate metrics such as coulombic efficiency, with limited evidence of operational robustness. Cross-disciplinary evidence echoes these gaps. Dutta and Upreti (2021) found <50 % of AI-based biochemical controllers underwent real-time experimental validation, revealing weak benchmarking in hybrid approaches. Asrul et al. (2022) demonstrated promising ANN predictions for fermentative hydrogen production but warned of overfitting from small datasets and a lack of feedback tests. Broader insights into renewable energy by Jha et al. (2017) highlight computational methods and predictive control; however, their application to microbial-electrochemical systems remains speculative. Wang et al. (2015) detailed advanced power electronics (e.g., Maximum Power Point Tracking (MPPT)) for MFCs but excluded microbial–electrode dynamics, limiting MEC relevance. Sewsynker-Sukai et al. (2017) endorsed ANN for biofuels but acknowledged real-time hybrid AI–physics architectures remain largely theoretical. Despite this growing body of work, key gaps remain. Real-time, closed-loop validations of adaptive control frameworks are scarce, whereas most reported schemes still operate only in simulated environments. In parallel, microbial kinetics, electrode electrochemistry, and advanced control theory are often examined in isolation, resulting in existing syntheses that fail to capture the coupled microbe–electrode dynamics governing hydrogen yield. Overcoming these shortcomings is pivotal for developing AI-enabled, scalable control architectures that can accelerate the industrial deployment of MEC-based biohydrogen production. This review addresses these gaps by delivering a focused synthesis of process control strategies for biohydrogen production in MECs. It traces the evolution of control paradigms from voltage regulation to hybrid AI-driven architectures, offering a comparative performance analysis to inform the design of next-generation intelligent MEC controllers. In doing so, it presents a unified perspective on how dynamic, scalable, and adaptive control strategies can accelerate the industrial viability of MEC-based biohydrogen production.

2. Evolution and Performance of Process Controllers in MECs for Biohydrogen Production

The evolution of process control strategies in MECs for biohydrogen production has followed distinct paradigms, as illustrated in Figure 1, mapping this progression from basic voltage control to advanced hybrid and intelligent systems over time. Each transition demonstrates an increase in complexity in system objectives, reactor environments, and computational capabilities. Complementing this timeline, each control strategy is benchmarked against five performance criteria, including prediction accuracy, robustness, real-time feasibility, scalability, and computational efficiency, which are scored on a 1-to-5 rubric. Together, this timeline clarifies the progression and supports the benchmarking analysis that follows. The full dataset used to derive the performance scores and the relative emphasis data in Figure 1 is available as Supplementary Data (Asrul, 2025). The earliest efforts in MEC control strategy development were grounded in direct voltage manipulation and basic mechanistic modelling under static laboratory conditions. These approaches focused on a period when the primary aim was to establish feasibility and maximise hydrogen production under predictable input regimes. However, fixed-parameter methods could not handle system variability, revealing bottlenecks, prompting a shift to closed-loop designs. Applying its minimal-resistance-tracking (MRT) algorithm, Tartakovsky et al. (2011) lowered the apparent internal resistance of a 50 mL membraneless chamber; however, the closed-loop response remained moderate with $R^2 \approx 0.85$ with ±0.05 V excursions and 73–92 % hydrogen recovery, so the method scores just 1/5 for scalability and 2/5 for robustness. This shift was soon accompanied by mechanistic population models, which introduced biochemical realism and enabled the interpretation of substrate-level processes. These models, although computationally lightweight and biologically meaningful, lacked dynamic tuning mechanisms, rendering them increasingly inadequate as substrate complexity and performance demands increased. Operated on a 50 mL dual-chamber, membraneless MEC fed with acetate, which is small enough to place at the bottom of the scalability scale (equal to 1/5), the multi-population mechanistic models of Pinto et al. (2011) reproduced current and hydrogen-flow profiles with adjusted $R^2 \approx 0.80$ and about 80 % theoretical hydrogen yield, pushing coulombic efficiency to 70–82 % which justifies prediction scores 3/5 and robustness scores 2/5 because disturbance tests were limited. Pinto et al. (2012) applied the same framework to complex wastewater, where the coulombic efficiency declined to the mid-50 % range, confirming sensitivity to substrates. In both studies, optimisation and tuning remained offline, so real-time feasibility and scalability each scored 1/5, while algebraic solutions maintained computational efficiency at a score of 4/5. Subsequent studies explored digital environments for responsive control. Adaptive feedback and neural approximators marked a shift to adaptability. Azwar et al. (2015) first applied adaptive-gain PID in a 10 L fed-batch, dual-chamber model, reducing integral-absolute error (IAE) up to 36 % from 1.75 to 1.12, raising hydrogen rate to 1.17 L/day, and shortening settling time from 110 s to 45 s, indicating scores for prediction/robustness of 3/5, scalability of 2/5, real-time feasibility of 2/5, and computational of 5/5. Using the same reactor model, Azwar et al. (2018) replaced the PID with an inverse ANN, where the mean square error (MSE) fell to 0.0348 (training) and 0.0625 (testing), and the overshoot dropped from 10 % to 2 %, lifting the prediction score to 4/5 and maintaining a robustness score of 3/5. However, the training load pushed the computational score to 3/5. Later, in Azwar et al.

(2020), an internal-model-control neural network (IMC-NN) scheme on the same 10 L platform achieved $R^2 = 0.915$ and superior noise rejection, with a score of robustness nudging at 4/5 and computational recovery at 4/5. However, the real-time feasibility score remained at 1/5 and the scalability score at 2/5, as validation was limited to simulation-only. Rule-based systems were introduced to simplify implementation and enable real-time responsiveness without extensive training. The Mamdani-inference fuzzy-logic controller (FLC) by Hong et al. (2021) achieved the MEC at 2.14 L-H_2/day while driving the IAE from 0.090 (proportional–integral (PI) baseline) to 5×10^{-4}, which is over two orders of magnitude better, justifying a robustness score of 4/5. However, it remains at bench scale (scalability score of 2/5). Hybrid strategies were followed, combining fuzzy inference with evolutionary and neural-based predictors. In a 500 mL single-chamber, membraneless MEC with graphite anode and Nickel-mesh cathode (scalability score at 2/5), Fathy et al. (2023) coupled an ANFIS predictor with a Jellyfish optimiser (ANFIS-JO), with moderate training overhead (score of computational at 4/5). This achieved root MSE (RMSE) = 0.0302, $R^2 = 0.963$, reduced oscillations warranted robustness with a score of 3/5, and boosted hydrogen by 6.7 % to 1.252 m^3-H_2/m^3/day, though it remained offline (as real-time feasibility score at 1/5).

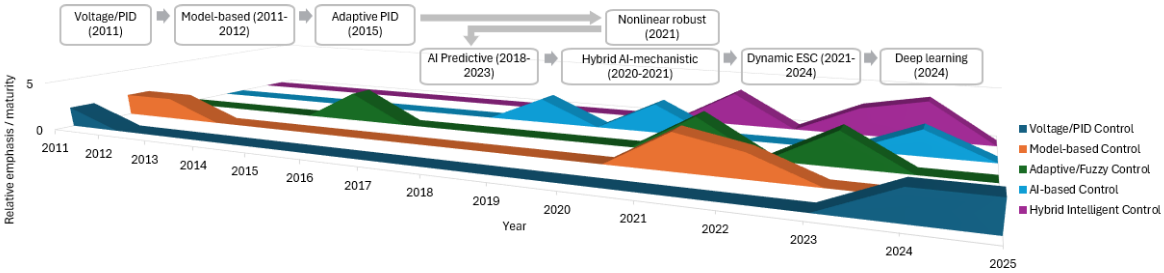

Figure 1: Evolution of process control strategies for MECs in biohydrogen production

Cheng et al. (2021) employed a three-population mechanistic core with Bayesian learning on 77 runs from 13 studies, spanning setups ranging from bench-scale MFCs to pilot MEC stacks (scalability score at 3/5). Their hybrid model achieved an RMSE of approximately 0.8 and matched microbial composition (approximately 72 % Bray–Curtis similarity), indicating high prediction accuracy and robustness (both scores at 4/5). However, offline updates compromised real-time feasibility (score at 3/5). Alcaraz-González et al. (2021) implemented a Lyapunov-based adaptive-robust controller in a 1 L continuous-flow dual-chamber MEC treating synthetic wastewater (scalability score at 3/5), keeping anodic current near 256 mA and hydrogen rate at 2.5 L/day. The responses showed negligible overshoot and fast disturbance recovery, justifying a score of robustness of 5/5, with closed-form control maintaining a computational score of 4/5. Rahman et al. (2022) implemented a fractional-order $H\infty$ controller on a simulated continuous-flow MEC, achieving zero overshoot, zero steady-state error, and 0.02 day settling time (scores for robustness of 5/5 and prediction of 3/5), but as it was simulation-only, scalability and real-time feasibility were scored at 1/5, and relatively high computational (score at 2/5) due to the intensive optimisation routines. In Rahman et al. (2023), the same control architecture with anti-windup and optimal linearization was used, but for a fed-batch condition, maintaining zero overshoot/offset under ±30 % uncertainty and achieving 15 % faster settling, thereby reinforcing the robustness score to 5/5, while leaving the other scores unchanged. Torres-Zúñiga et al. (2021) applied super-twisting extremum-seeking control (ST-ESC) on a 2 L, three-cell MEC stack, eliminating steady-state error and reducing tracking integral-square error (ISE) by 8× over PI, yielding scores for robustness at 4/5, real-time feasibility at 3/5, scalability at 4/5, and computational at 3/5. In a follow-up, Torres-Zúñiga et al. (2024) integrated Internet-of-Things (IoT)-based remote monitoring and edge computing into the ESC framework, enabling cloud-based updates and real-time logging, which reduced convergence time by 25 %. These enhancements raised scores for real-time feasibility to 4/5 and scalability to 5/5, while robustness and computational efficiency remained constant. Wang et al. (2024) used a Golden-Sine-enhanced particle swarm optimisation (GS-PSO) to tune PID in a 0.8 L single-MEC. This controller reduced overshoot to 6.6 %, stabilized the substrate within 44 s, and outperformed back-stepping, sliding-mode control (SMC), and fuzzy-SMC controllers. Thus, the scores for robustness are 4/5, prediction is 3/5, real-time feasibility is 1/5 due to offline tuning, and computational efficiency is 4/5. Venkatesh et al. (2025) implemented a bi-LSTM controller on simulated data from a 250 mL anode compartment MEC model. Test RMSE approximately 7.8×10^{-3} and ISEs for set-point and disturbance dropped by 8.5× and 2.6× versus internal-model PI; thus, robustness and prediction scores at 4/5. Real-time feasibility remained low at 1/5 due to moderate computational requirements at 3/5, primarily attributed to the size and complexity of the neural network training. Despite adaptive and hybrid advances, voltage-only strategies remain a focus of exploration. Marchetti et al. (2025) employed a bench-scale setup of a 0.86 L two-chamber MEC with a fixed potential of +0.3 V vs. the standard hydrogen electrode (SHE), achieving energy efficiencies of 81–85 % and a hydrogen production rate of 1.28 m^3-H_2/m^3/day. The system demonstrated resilience, recovering from a pH of 7.5 to 4.5 with minimal current output loss (robustness score of 3/5, real-time feasibility score of 4/5 due to simple, low-latency control logic). Still, this potentiostatic approach offered limited adaptability (prediction score at 1/5) and scalability (score at 1/5) due to manual catholyte replacement and offline tuning, while the computational cost remained negligible, thus earning a score of 5/5. This reinforces the limitations of fixed-parameter methods in dynamic or scaled environments.

3. Design Guideline: A Modular Intelligent Control Framework

The reviewed studies reveal a convergence in hardware design and reactor conditions among MECs for hydrogen production. Most MEC configurations fall within 50–500 mL volumes, either single- or dual-chamber, operating under batch or semi-continuous flow. A smaller but growing set of studies utilise 0.5–2 L systems, some of which incorporate edge computing and telemetry for pilot-scale adaptability. Anodes are typically carbon-based (such as cloth or felt), while cathodes are predominantly nickel- or platinum-coated. Electrochemical environments range from 25 to 37 °C, with membrane-less single-chamber setups or dual-chamber configurations featuring cation-exchange membranes. These commonalities in hardware minimise structural variability, enabling control algorithm performance to emerge as the primary differentiator. Building on these established conditions, a stepwise control development methodology is proposed, explicitly tailored for MEC applications in biohydrogen production. This methodology is informed by empirical gaps and performance trade-offs identified in prior control schemes. The process begins by specifying key experimental parameters, including reactor type and configuration (single- or dual-chamber, membrane type), working volume and scale (bench or pilot), electrode materials and positioning, flow mode (batch, semi-batch, or continuous), and substrate and temperature conditions. This step ensures alignment with literature-based conditions and contextualises the scale of control complexity. Next, the target control outcomes must be clearly defined. These typically include maximizing biohydrogen yield, suppressing methanogenesis, optimizing chemical oxygen demand (COD) removal, and minimizing overshoot, settling time, and disturbance rejection metrics. These objectives dictate subsequent strategy selection and variable prioritisation. A decision node is then introduced to identify the suitable domain based on the defined objectives and operational constraints. Traditional control methods (e.g., PID, voltage tracking) are preferred when simplicity, interpretability, or limited data are present. AI-based control (e.g., ANN, bi-LSTM) is more suitable for highly dynamic systems or datasets with rich information. Hybrid control (e.g., IMC–ANN, ST-ESC) is adopted when high adaptability, prediction accuracy, and robustness are simultaneously required. This selection is informed by performance benchmarks, particularly in terms of scalability, robustness, and computational feasibility. The model must next specify the manipulated variables (voltage input, flow rate, pH adjustment) and the controlled variables or outputs (current density, hydrogen production rate, COD removal efficiency). Additionally, disturbances such as substrate variability, temperature shifts, and microbial imbalance must be considered. This step ensures that the simulation or algorithm structure reflects real process disturbances. Architecture design then proceeds through simulation-based development. This involves initial testing of the selected control law (e.g., ANFIS, fuzzy-MPC, PID-ANN), tuning based on dynamic criteria such as IAE, ISE, RMSE, MSE, and overshoot, and adjustment for system-specific conditions, including substrate complexity or noise filtering. A critical checkpoint follows to assess control performance across benchmark indicators derived from the literature. These include prediction accuracy (e.g., $R^2 > 0.9$, RMSE < 0.05), robustness under disturbance or uncertainty (e.g., stable control under ±30 % uncertainty), real-time feasibility (e.g., latency, onboard computation constraints), computational cost (based on training burden or controller complexity), and scalability (validation beyond 500 mL scale or in stack-based systems). Validation methods may include Monte Carlo simulations, disturbance injection, or dataset cross-validation. Upon reaching the validation stage, the methodology forks into four distinct pathways depending on the original objective. In the case of finalised implementation, the system is deemed validated and ready for operational deployment. Where scaling is the objective, the control strategy proceeds to pilot or stack-scale adaptation. Benchmark comparison involves evaluating a controller against established methods for performance ranking. Finally, for monitoring integration, the controller is interfaced with IoT or edge computing platforms to provide real-time feedback and facilitate remote updates. This algorithmic methodology synthesises over a decade of process control studies in MECs and offers a formalised pathway for designing next-generation controllers tailored to hydrogen production (see Figure 2).

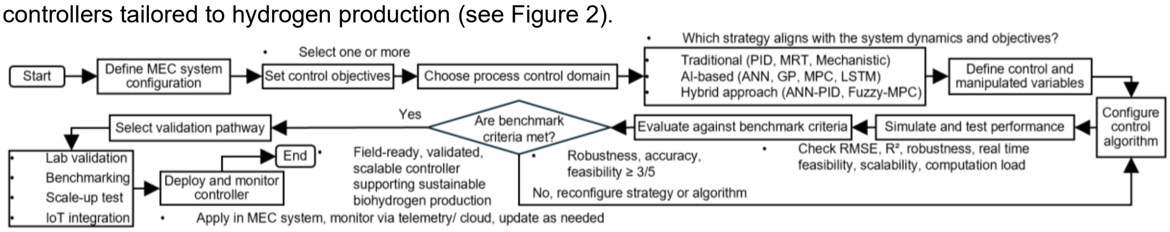

Figure 2: Framework flowchart for the design and validation of hybrid MEC control systems

Each step, rooted in published experimental data, ensures traceability, adaptability, and performance optimizationgrounded in published experimental data, ensures traceability, adaptability, and optimized performance. Rather than adopting a one-size-fits-all model, the framework supports modular branching based on system goals, technical constraints, and available computational resources.

4. Conclusions

This review systematically evaluated process control development for biohydrogen-producing MECs by analyzing five major strategies including voltage/PID, model-based, adaptive/fuzzy logic, AI-based, and hybrid intelligent controllers, against five quantitative performance metrics: prediction accuracy, robustness, real-time applicability, scalability, and computational efficiency. In the 50 mL–H_2/L systems most commonly reported, voltage/PID control remains a standard reference; however, it plateaus at approximately 4.6–5.3 L-H_2/L/day and lacks robustness under variable conditions. Model-based controllers enhance electron conversion ($R^2 \approx 0.92$, >60 % efficiency), but are sensitive to microbial shifts. Adaptive and fuzzy logic controllers yield 2–5× IAE reductions and maintain ≈approximately 2 L-H_2/day output, yet offer limited long-term prediction capabilities. AI-based approaches (e.g., ANN, bi-LSTM) achieve R^2 values exceeding 0.95 and reduce ISE by up to 8 times, but often require extensive training and face real-time limitations. Hybrid controllers that combine mechanistic models with AI consistently outperform others, supporting hydrogen production rates of ≥2.5 L/day, currents of up to 255 mA, and a 25–30 % faster response under IoT-enhanced setups, while keeping computational costs acceptable. These results suggest that hybrid approaches, balancing model transparency and data-driven adaptability, are best suited for scaling MEC technology. The design guideline developed provides a structured pathway spanning goal setting, variable selection, simulation, validation, and scaling, supporting the transition from lab-scale MECs to reliable, high-efficiency practical applications.

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