



Predictive Control and Artificial Neural Networks For Energy Optimization in Microbial Fuel Cells: A Critical Review

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Abstract

Microbial fuel cells (MFCs) combine wastewater treatment with direct bioelectrochemical energy recovery, but their practical deployment remains constrained by low and variable power density, nonlinear dynamics, biological uncertainty, and sensitivity to substrate and load disturbances. This critical narrative review examines how predictive control and artificial intelligence can improve MFC energy performance. A structured, non-exhaustive search of DOI-indexed records and publisher platforms was updated through August 2026 using combinations of terms related to MFCs, predictive control, neural networks, machine learning, voltage regulation, power prediction, and adaptive control. Eligible studies were critically compared by model structure, manipulated and controlled variables, constraint handling, data requirements, validation maturity, interpretability, and deployment readiness. Mechanistic models remain essential for interpreting mass transfer, microbial kinetics, charge balance, and electrode overpotentials; however, parameter uncertainty and scale dependence can limit real-time use. Proportional-integral-derivative controllers provide transparent regulation near nominal conditions but lose effectiveness under strong coupling and regime shifts. Model predictive control can explicitly handle constraints and multivariable interactions, although its performance depends on model fidelity and online optimization. Artificial neural networks offer flexible nonlinear approximation, but they require representative data and rigorous external validation. The principal contribution is a cross-framework assessment showing that the most defensible architecture is hybrid: physical balances define feasible behavior, neural models compensate for residual nonlinearities, and predictive control coordinates feed, load, and operating constraints. Five evidence gaps persist: weak cross-reactor transferability, inadequate uncertainty treatment, limited closed-loop experimental validation, non-standardized comparisons, and incomplete scale-up economics. Progress therefore requires reproducible, constraint-aware systems tested under common disturbances and long-duration operation.

Keywords: bioelectrochemical systems; wastewater valorization; nonlinear modeling; data-driven operation; intelligent automation.

1. Introduction

Microbial fuel cells convert the chemical energy of biodegradable substrates into electricity through the catalytic activity of electroactive microorganisms. In a conventional two-chamber configuration, microorganisms oxidize organic matter in the anode, electrons flow through an external circuit, and ions migrate through a separator to sustain the cathodic reaction. This architecture is attractive because it links renewable electricity generation with wastewater treatment and resource recovery (He et al., 2017; Rahimnejad et al., 2012; Wang et al., 2022). Nevertheless, laboratory demonstrations have not yet translated into broad industrial deployment. Power output is often low, internal resistance is high, and performance changes with microbial community composition, substrate availability, temperature, pH, ionic strength, electrode condition, membrane fouling, and external load.

These interacting influences make MFCs nonlinear, time varying, and strongly coupled systems. A change in feed flow can modify substrate concentration and microbial growth, while a change in external resistance alters current, overpotentials, and apparent conversion efficiency. Consequently,

optimization cannot be reduced to selecting a single electrode material or tuning one operating variable. It requires a coordinated strategy that observes system states, anticipates disturbances, respects biological and electrochemical constraints, and balances power generation against treatment performance and long-term stability (Jadhav & Ghangrekar, 2009; Xia et al., 2017).

Control research has therefore progressed from fixed-gain proportional-integral-derivative (PID) regulation toward model predictive control, adaptive nonlinear control, artificial neural networks (ANNs), support vector regression, fuzzy systems, and hybrid optimization. Model predictive control is particularly relevant because it predicts future trajectories and can optimize multiple manipulated variables within explicit constraints. ANNs complement this approach by approximating complex input-output relations that are difficult to derive from first principles. Evidence already shows that data-driven models can predict MFC biofilm communities and performance, while hybrid machine-learning methods can estimate power generation with high statistical accuracy (Hossain et al., 2023; Lesnik & Liu, 2017).

The rapid expansion of intelligent methods has also created a methodological risk. High coefficients of determination obtained from small or narrowly distributed datasets do not guarantee robust closed-loop control. Training-test leakage, lack of temporal validation, insufficient disturbance testing, and absence of uncertainty estimates can produce optimistic conclusions. Moreover, simulated improvements are not directly comparable when studies use different reactor geometries, substrates, power normalizations, sampling rates, and controller objectives. A critical synthesis is therefore needed to distinguish prediction from control, model fit from operational reliability, and laboratory optimization from scalable deployment.

This review evaluates the roles of control-oriented mechanistic models, PID regulation, predictive control, multilayer perceptrons, neuro-fuzzy approaches, and hybrid physics-data architectures in MFC energy optimization. It addresses three questions: which variables and constraints define the MFC control problem; what advantages and limitations characterize the principal controller and predictor families; and what validation practices are required before intelligent control can support reliable scale-up?

Its original contribution is a control-readiness framework that evaluates each approach beyond predictive accuracy. The framework links reactor and electrode characteristics to controllability, distinguishes prediction from closed-loop decision making, and judges the evidence according to constraint handling, disturbance rejection, uncertainty management, experimental maturity, computational feasibility, and transferability. This cross-framework perspective is intended to identify not only which methods perform well under reported conditions, but also what must be demonstrated before they can be considered credible for continuous or scaled MFC operation.

2. Materials and methods

2.1. Review design and scope

A critical narrative review design was selected because the objective was to integrate heterogeneous evidence from electrochemistry, environmental engineering, process control, and machine learning rather than estimate a pooled effect size. The review focused on peer-reviewed studies that addressed at least one of the following: MFC dynamic or control-oriented modeling; regulation of output voltage or power; prediction of MFC performance using ANN or other machine-learning models; optimization of operating parameters; or the interaction between reactor design and controllability. Studies devoted exclusively to unrelated fuel-cell chemistries, batteries, photovoltaic systems, or wind-energy optimization were excluded.

2.2. Source identification and eligibility

The reference corpus embedded in the original manuscript was first audited for topical relevance, bibliographic completeness, and DOI availability. Targeted searches of publisher platforms and DOI-indexed records, including journal landing pages discoverable through Crossref and publisher search services, were then used to update the synthesis through August 2026. Search strings combined the core concept ('microbial fuel cell' OR 'bioelectrochemical system') with control and prediction terms ('model predictive control' OR 'predictive control' OR 'PID' OR 'adaptive control' OR 'neural network' OR 'machine learning' OR 'neuro-fuzzy') and performance terms ('voltage control' OR 'power prediction' OR 'energy optimization' OR 'COD removal'). Backward checking of relevant review and primary-study reference lists was used to identify foundational evidence.

Records were considered eligible when they were peer reviewed, directly addressed MFC operation or modeling, and reported information relevant to at least one prespecified domain: dynamic model formulation; manipulated or controlled variables; controller design; data-driven prediction;

disturbance or constraint treatment; experimental or simulation validation; or reactor factors affecting controllability. Studies of unrelated fuel-cell chemistries and papers without sufficient technical detail to support comparison were excluded. Priority was given to full-text studies with explicit model definitions, identifiable input-output variables, reported training and test procedures, experimental validation, or reproducible control metrics. Foundational studies were retained when they clarified reactor behavior, material effects, or control-oriented equations. Because this was a critical narrative review, not a systematic review, no claim of exhaustive database coverage or PRISMA-compliant study enumeration is made.

2.3. Synthesis procedure

Evidence was organized into five analytical domains: physical and biological state variables; manipulated variables and disturbances; model structure; controller or predictor family; and validation maturity. For cross-framework comparison, each approach was examined against eight criteria: intended operational role, model assumptions, constraint handling, data requirements, computational burden, interpretability, uncertainty treatment, and readiness for experimental deployment. Reported performance was interpreted using the original units and reactor context. Because configurations, substrates, normalization conventions, controller objectives, and evaluation metrics varied substantially, numerical results were not pooled. The synthesis therefore used structured thematic comparison rather than effect-size aggregation.

2.4. Critical appraisal and methodological limitations

Evidence strength was judged qualitatively from the transparency of the model and dataset, separation of training and testing, temporal or external validation, use of common baselines, disturbance testing, reporting of constraints, computational feasibility, and experimental duration. Greater weight was assigned to evidence validated on measured time-series data or real reactors than to single-trajectory simulations. The review did not apply a formal risk-of-bias instrument because the included evidence spans mechanistic modeling, controller simulation, materials studies, and machine-learning prediction, for which no single appraisal scale is appropriate. Its conclusions should therefore be interpreted as a critical engineering synthesis rather than an exhaustive systematic estimate.

3. Control-oriented dynamics of microbial fuel cells

3.1. Coupled biological and electrochemical processes

A control-oriented representation must capture enough of the MFC mechanism to predict the variables that matter for operation. The anode is commonly represented by substrate consumption and microbial growth kinetics, often through Monod-type expressions. Electrochemical rates are linked to activation overpotentials through Butler-Volmer relationships, while mass balances describe substrate, biomass, dissolved species, and ionic transport. Charge balances and ohmic losses connect these states to current and cell voltage. Detailed mechanistic models improve interpretability, but every additional state introduces parameters that may be difficult to identify from routine measurements (Xia et al., 2017).

The central control challenge is partial observability. Voltage and current are inexpensive to measure, whereas biofilm activity, local pH, dissolved metabolites, and electrode surface conditions are not continuously available in most reactors. A controller may therefore act on a reduced-order model or a soft sensor that infers unmeasured states from accessible signals. The quality of those estimates is decisive: a predictor that tracks nominal data but fails during biofilm maturation, substrate shock, or membrane fouling can destabilize the closed loop.

3.2. Inputs, outputs, disturbances, and constraints

Typical manipulated variables include anode feed flow, substrate loading, external resistance, recirculation, catholyte aeration, temperature conditioning, and switching among cells in a stack. Controlled outputs may include voltage, current, power density, chemical oxygen demand removal, coulombic efficiency, or a weighted combination of energy and treatment objectives. Disturbances arise from influent composition, microbial succession, temperature, ionic conductivity, load demand, and sensor noise. Operational constraints include acceptable pH, substrate washout limits, current and voltage bounds, pump capacity, aeration energy, and maximum rates of change.

The choice of objective function shapes the resulting controller. Maximizing instantaneous power can increase oscillation, accelerate substrate depletion, or reduce treatment stability. Conversely, a conservative voltage-tracking objective may underuse available substrate. Multi-objective control should therefore penalize tracking error, rapid input movement, energy consumed by pumps or

aeration, and violations of biological constraints. This formulation makes MPC conceptually attractive, while also clarifying why a neural predictor alone is not a controller.

3.3. Materials, reactor architecture, and controllability

Controllability is partly designed into the reactor before any algorithm is selected. Electrode spacing and anode placement modify ionic resistance, mass-transfer paths, and the spatial distribution of electroactive biofilms; consequently, identical control laws can produce different responses in geometrically distinct cells (Prakash et al., 2018; Raman & Lan, 2012). Reactor configuration should therefore be treated as a structural factor in model identification, not as background information that can be omitted from a controller study.

Electrode composition also changes the plant dynamics seen by the controller. Porous carbon, nitrogen-doped nanotubes, metal-oxide nanocomposites, and low-cost carbon catalysts can alter effective surface area, charge-transfer resistance, microbial attachment, and oxygen-reduction kinetics (Chen et al., 2015; Ci et al., 2012; Mateo et al., 2018; Mehdinia et al., 2014; Singh et al., 2018; Yang et al., 2020). Conductive hydrogel bioanodes further illustrate how material selection can simultaneously influence power output and chemical oxygen demand removal (Wang et al., 2020). These effects imply that a data-driven model trained on one electrode system should not be transferred to another without recalibration or external validation.

Feed composition, temperature, organic loading, and microbial adaptation create slower biological changes that can resemble model drift. Studies using sludge, solid potato waste, cellulose, and controlled changes in chemical oxygen demand or temperature show that substrate characteristics and acclimation materially affect electrical response (Cai et al., 2018; Du & Li, 2017; Gonzalez del Campo et al., 2013; Kim et al., 2011; Ren et al., 2008). For predictive control, these variables should be measured as disturbances, represented through scheduling variables, or incorporated into periodic model updating.

4. Classical and predictive control strategies

4.1. PID control as an operational baseline

PID control remains useful because it is transparent, inexpensive, and easily implemented on industrial hardware. When the MFC operates near a stable regime and one manipulated variable primarily affects one output, a tuned PID loop can reduce steady-state error and smooth voltage response. It is also a valuable benchmark for judging whether a more complex controller delivers a meaningful improvement rather than merely fitting a simulation.

Its limitations become apparent when gains change with operating point, delays are long, or constraints are active. Fixed gains cannot anticipate future substrate depletion or coordinate competing objectives. Aggressive tuning may produce overshoot, while conservative tuning may respond too slowly to influent or load disturbances. Fuzzy gain scheduling and adaptive PID variants address some of these weaknesses, but they still require a principled rule base and disturbance testing.

4.2. Model predictive control

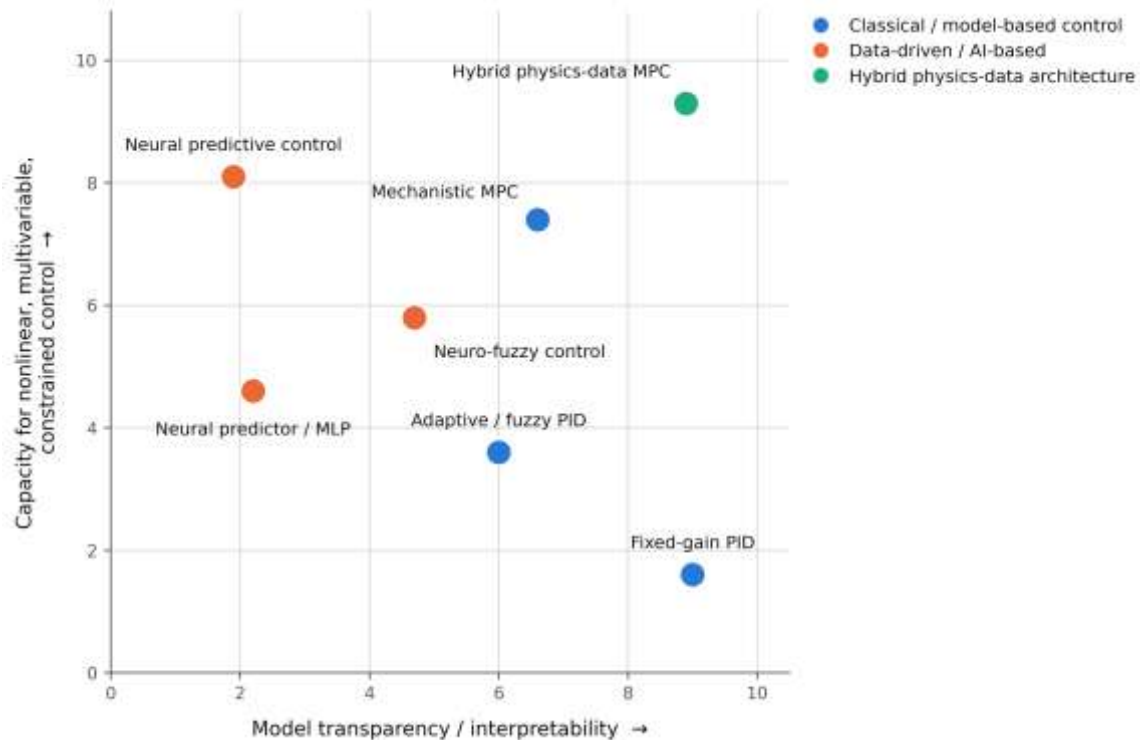
MPC repeatedly predicts future system behavior over a finite horizon, selects a sequence of control actions that minimizes an objective, applies the first action, and updates the optimization when new measurements arrive. This receding-horizon structure allows explicit treatment of input, state, and output constraints. Fan et al. (2015) showed that predictive strategies can improve MFC dynamic and steady-state behavior in simulation, and later work has extended the concept through receding-horizon and adaptive formulations (Gao et al., 2022).

MPC performance depends on the quality of the prediction model, state estimation, horizon selection, weighting matrices, and numerical solver. Mechanistic nonlinear MPC can preserve physical meaning but may be computationally demanding. Linear MPC is faster but may fail across broad operating ranges. Reduced-order, gain-scheduled, or data-driven prediction models can reduce computational burden. An effective implementation must report sample time, solver convergence, constraint handling, and computation time relative to the control interval.

Figure 1 synthesizes this trade-off across the approaches introduced above and the artificial-intelligence-based strategies discussed next, positioning each one according to the transparency and the capacity for nonlinear, multivariable, constrained control described qualitatively in Table 1.

Figure 1. Conceptual positioning of control and prediction approaches for microbial fuel cells, synthesized from the qualitative comparison in Table 1. Approaches are grouped by family (classical/model-based control, data-driven/AI-based, and hybrid physics-data architectures) and

positioned according to their reported transparency and their capacity to handle nonlinear, multivariable, and constrained operation.



5. Artificial intelligence for prediction and control

5.1. Multilayer perceptrons and surrogate models

Multilayer perceptrons learn nonlinear mappings between operational variables and outputs. In MFC applications, inputs may include substrate concentration, temperature, pH, external resistance, electrode area, membrane thickness, aeration, and time, while outputs may include voltage, power density, chemical oxygen demand removal, or coulombic efficiency. Lesnik and Liu (2017) demonstrated that ANN models can connect microbial community information with bioreactor performance, illustrating the value of biological features that are often omitted from purely electrochemical models.

Recent studies have broadened the data-driven toolkit. Ghasemi et al. (2023) compared MLP and support vector regression for MFC behavior, while Hossain et al. (2023) combined Bayesian hyperparameter optimization with support vector regression and boosted regression trees. These studies show that nonlinear learners can outperform simpler response-surface models when the dataset is informative. However, a high coefficient of determination is insufficient evidence for control use. Temporal holdout tests, repeated training, uncertainty intervals, robustness to noise, and validation on a different reactor are needed to establish generalizability.

5.2. Neural predictive and neuro-fuzzy control

A neural network can support control in several ways. It may act as a soft sensor, approximate an unknown plant model inside MPC, estimate residual dynamics left unexplained by a mechanistic model, or approximate the optimizer itself for faster online execution. Neural network predictive control is especially attractive for MFCs because it can represent nonlinear input-output behavior without solving all biological mechanisms explicitly. The risk is extrapolation: control actions can drive the plant outside the training domain, where the network has no physical guarantee.

Neuro-fuzzy control combines adaptive learning with rule-based interpretation. Demir and Eren (2022) used optimization-based adaptive neuro-fuzzy controllers for voltage tracking in a nonlinear two-chamber model and reported improved disturbance rejection. Such approaches can capture uncertainty and nonlinearities, but the number of rules, membership functions, optimizer settings, and stability conditions must be reported. Comparative studies should use identical reference trajectories and disturbances across PID, MPC, and intelligent controllers.

5.3. Hybrid physics-data architectures

The most defensible architecture combines mechanistic constraints with data-driven flexibility. Mass and charge balances can define feasible state transitions, while a neural network estimates kinetic

residuals, unmeasured states, or slowly varying parameters. The resulting hybrid model can be embedded in MPC so that optimization respects operational limits. This structure also supports monitoring: large residuals between the physical model and measured behavior can signal sensor faults, biofilm drift, or an operating regime absent from the training data.

Hybridization should not be treated as an automatic guarantee of accuracy. It requires identifiability analysis, careful normalization, avoidance of information leakage, and explicit uncertainty management. Physics-informed penalties can improve plausibility, but they must be evaluated against a purely mechanistic model and a purely data-driven baseline. The benefit should be demonstrated on experimental time-series data rather than inferred from a single simulated trajectory.

6. Comparative synthesis

Table 1. Comparative characteristics of control and prediction approaches for microbial fuel cells.

Approach	Principal strength	Main limitation	Recommended role
Fixed-gain PID	Simple, transparent, and inexpensive	Sensitive to operating-point changes and delays	Baseline regulation near a nominal regime
Adaptive or fuzzy PID	Adjusts gains under changing conditions	Rule design and stability verification can be difficult	Intermediate-complexity voltage regulation
Mechanistic MPC	Handles constraints and multivariable objectives	Parameter uncertainty and online computation	Constraint-aware optimization with validated models
Neural predictor or MLP	Flexible nonlinear approximation	Requires representative data and can extrapolate poorly	Soft sensing, forecasting, and residual modeling
Neural predictive control	Combines nonlinear prediction with online optimization	Limited physical guarantees outside training data	Rapid control when domain coverage is demonstrated
Neuro-fuzzy control	Adaptive behavior with interpretable rules	Many tuning choices and limited cross-reactor validation	Robust tracking under modeled uncertainty
Hybrid physics-data MPC	Balances feasibility, interpretability, and flexibility	Highest integration and validation burden	Long-term target architecture for real reactors

The comparison indicates that intelligent methods should be evaluated as components of an operational architecture rather than as isolated predictors. PID remains valuable as a transparent baseline. MPC contributes constraint handling and anticipatory action. Neural networks contribute representation of residual nonlinearities and inaccessible states. A hybrid system is therefore attractive when its additional complexity is justified by experimentally demonstrated gains in robustness, energy recovery, or treatment stability.

7. Validation and implementation challenges

7.1. Data quality and transferability

MFC datasets are typically small and heterogeneous. Measurements may be collected at different sampling intervals and under different reactor geometries, substrates, inocula, and normalization conventions. Random train-test splits can leak temporal information and exaggerate predictive performance. Time-blocked validation, leave-one-reactor-out testing, and external datasets are more informative for deployment. Metadata should document electrode area, reactor volume, temperature, pH, hydraulic retention time, external load, and sensor calibration.

7.2. Uncertainty, drift, and explainability

Microbial communities evolve and electrode surfaces age, so a model trained during start-up may not remain valid during mature operation. Drift detection should monitor residual distributions and trigger recalibration only when sufficient new data are available. Prediction intervals or ensemble disagreement can inform safe fallback behavior. Explainability methods may identify dominant variables, but causal interpretation should be avoided unless supported by the experimental design.

7.3. Fair controller comparison

Controller studies should report identical initial conditions, disturbance profiles, constraints, simulation horizons, and measurement noise for all methods. Relevant metrics include integrated absolute error, overshoot, settling time, input movement, constraint violations, computation time, net recovered energy, and treatment efficiency. Peak power alone is inadequate because it ignores oscillation, actuator energy, and long-term stability. Where possible, results should be confirmed in hardware-in-the-loop experiments and then in continuously operated reactors.

7.4. Scale-up and operational economics

Scale-up changes hydrodynamics, internal resistance, mass-transfer gradients, and the spatial distribution of biofilms. A controller validated on a laboratory cell may therefore fail on a stack. The energy required for pumping, recirculation, aeration, sensing, and computation should be included in the net-energy objective. Control performance must also be considered alongside material durability, membrane fouling, maintenance, and capital cost. Intelligent control is most valuable when it reduces experimentation, stabilizes operation, and extends useful service rather than only increasing simulated peak output.

7.5. Five critical evidence gaps

Gap 1 - Cross-reactor transferability: most models are calibrated for one geometry, substrate, inoculum, or electrode system, and their validity after a change in reactor configuration remains uncertain. Gap 2 - Uncertainty and drift: few studies quantify prediction intervals, parameter uncertainty, biofilm evolution, or safe behavior outside the training domain. Gap 3 - Closed-loop experimental maturity: simulation remains more common than long-duration validation on continuously operated reactors or stacks. Gap 4 - Comparability and reproducibility: inconsistent disturbances, objectives, normalizations, sampling rates, and baselines prevent reliable ranking of controllers. Gap 5 - Scale-up economics: reported power improvements seldom account for pumping, aeration, sensing, computation, maintenance, material degradation, and net recovered energy. These gaps define the minimum evidence needed for future claims of operational readiness.

8. Research Agenda

Future research should establish shared, machine-readable MFC benchmark datasets with raw time-series signals, operational metadata, and clearly separated training and external test reactors. Benchmark scenarios should include substrate shocks, load changes, temperature variation, sensor noise, biofilm maturation, and fouling. This would allow meaningful comparison of PID, MPC, ANN, support vector regression, neuro-fuzzy control, and hybrid models.

Control development should move from one-step prediction toward closed-loop decision quality. Models need calibrated uncertainty, safe operating envelopes, and fallback strategies. Digital twins can combine real-time measurements with mechanistic states, but they should be continuously checked against material and energy balances. Online learning should be constrained to prevent unsafe actions during distribution shifts.

The most useful objective is likely multi-objective: stable voltage or power, high chemical oxygen demand removal, acceptable coulombic efficiency, low auxiliary energy, and minimal actuator movement. Pareto-based optimization can make trade-offs visible to operators. Finally, long-duration experiments and independent replication are essential. The field should distinguish statistical prediction accuracy from control robustness and should treat reproducibility, not isolated peak performance, as the principal evidence of readiness.

A staged validation pathway is recommended. First, models should be tested with time-blocked and external-reactor data. Second, controllers should be compared in simulation under identical initial conditions, constraints, disturbances, and noise. Third, hardware-in-the-loop testing should establish solver timing, sensor tolerance, and fallback behavior. Fourth, continuous reactor experiments should report treatment performance, net energy, fouling, drift, and maintenance over biologically meaningful periods. Finally, stack-scale demonstrations should evaluate whether the gains remain positive after auxiliary energy and operational costs are included.

9. Conclusion

Predictive control and artificial intelligence can address important limitations of microbial fuel cells, particularly nonlinear dynamics, multivariable interaction, and incomplete state measurement. PID control remains a necessary baseline, while MPC provides a structured method for anticipation and constraint handling. ANNs, support vector regression, and neuro-fuzzy systems can model complex relations and support soft sensing, but their practical value depends on representative data and rigorous external validation.

The strongest pathway is a hybrid, constraint-aware architecture in which mechanistic balances preserve physical feasibility, data-driven components capture residual dynamics, and predictive optimization coordinates operational decisions. Future progress should be judged by disturbance rejection, net energy recovery, treatment stability, uncertainty management, computational feasibility, and long-duration experimental performance. Intelligent control can accelerate MFC development, but simulation-only comparisons and isolated accuracy metrics are not sufficient evidence for scale-up.

10. Declarations

10.1. Ethical considerations

Not applicable. This article is a critical review and did not involve human participants, animals, or the collection of personal data.

10.2. Use of artificial intelligence (AI)

Generative artificial intelligence was used to support English-language editing and structural reorganization during preparation of this adapted version. The authors are responsible for verifying every scientific statement, citation, interpretation, and conclusion before submission, and the tool was not listed as an author.

10.3. Conflict of interest

The authors declare no conflicts of interest.

10.4. Funding

This research did not receive any financial support.

10.5. Data availability

No new dataset was generated for this review. The evidence discussed is available in the cited publications.

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