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Control Strategies for Microbial Fuel Cells: A Review of Modelling, Classical, Nonlinear and Adaptive Approaches

Bhavesh R. Patel[1], Dr. R. K. Aparanathi[2], Dr. Vipul kumar Dabhi[3]

[1]Research Scholar, Faculty of Engineering, Gokul Global University, Siddhpur, Gujarat, India.

[2]Professor, Faculty of Engineering, Gokul Global University, Siddhpur, Gujarat, India.

[3] Professor, Faculty of Engineering, Gokul Global University, Siddhpur, Gujarat, India.

Emails: *br_eoe@rediffmail.com[1], rajendraaparnathi@gmail.com[2], vipuldabhi@yahoo.co.in[3]*

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Abstract

Microbial fuel cells (MFCs) convert the chemical energy of organic waste into electricity through the metabolism of electrogenic bacteria, but their behaviour is nonlinear, slow and sensitive to substrate load, dilution rate, temperature and drift in biological parameters. This review surveys the control literature for MFCs, starting from engineering-based and control-oriented models and moving through classical PI/PID, gain-scheduled, sampled-time, fuzzy and predictive schemes to robust LMI, exact input–output linearisation, backstepping, integral backstepping, model reference adaptive and adaptive backstepping controllers. The studies are compared by MFC configuration, manipulated input, controlled variable, stability argument and the type of evidence offered. The simulation results reported indicate that nonlinear and adaptive designs track substrate-concentration and voltage references more accurately and with fewer oscillations than tuned linear controllers, particularly under parametric uncertainty and reference disturbances. However, among the works surveyed the evidence is almost entirely simulation-based, performance metrics differ from study to study, and closed-loop experimental validation is scarce. Open problems include hardware implementation, multi-species and stack-level models, systematic gain tuning and common benchmarks.

1. Introduction

Rapid industrial growth and rising population density have increased both the demand for electricity and the burden of polluted water. Microbial fuel cells (MFCs) address the two problems together: electrogenic microorganisms oxidise organic substrates present in wastewater and release electrons and protons, so that electricity is generated while the waste stream is treated (Rahimnejad et al., 2015; Choudhury et al., 2017; Kumar et al., 2015). Compared with conventional wastewater treatment, MFCs are attractive for their conversion rate, their ability to generate electric power and their operation at ambient temperature (Patel & Deb, 2019). The technology is nevertheless still largely at the laboratory stage and has not been commercialised at scale (Patel & Aparanathi, 2024). Present MFCs suffer from moderate reliability, low power density and the cost of the chemical processes needed to obtain acceptable output, so continuing improvement of materials and components is required (Patel, 2018). A complementary route is better operation. An MFC

is a complex, nonlinear device in which biological, electrochemical and thermal phenomena interact, and parameters such as temperature, pH and substrate concentration must be held within limits to meet the load and to avoid damaging the cell (Patel, 2018). Closed-loop operation is therefore not optional, and the quality of the controller largely determines how much of the cell's potential output is delivered reliably. The control literature for MFCs has grown from simple linear regulators to nonlinear and adaptive designs, but it is scattered across journals, conference papers and a small number of monographs, and the studies use different MFC configurations, manipulated inputs and performance measures. This review organises that literature from a control engineer's point of view. Its contributions are: (i) a summary of MFC models according to their usefulness for controller design; (ii) a classification of the controllers reported for MFCs, with the design idea, stability argument and validation evidence of each; (iii) a critical comparison that separates what has been demonstrated from what has been assumed; and (iv) a list of open problems. Section 2 states the scope and method of the review. Section 3 reviews models, Section 4 reviews controllers, Section 5 compares and discusses them, and Section 6 closes with conclusions.

1.1. Construction and Components of an MFC

An MFC consists of an anode, a cathode, a substrate, an optional membrane and, in some designs, a mediator. The properties that matter for control are summarised below (Patel, 2018; Patel et al., 2020).

Anode:- The anode must be conductive, non-corrosive, non-toxic, biocompatible and chemically stable. Carbon in the form of rods, graphite plates, felt, foam or cloth is the most common material, and graphite plates or rods are cheap with a well-defined surface area. The anode surface carries the biofilm through which electrons are transferred.

Cathode:- The working potential of the cathode material should be close to the open-circuit potential. Ferricyanide performs well as an electron acceptor but its diffusion limits long-term operation; platinum catalysts improve oxygen reduction at a high cost, which motivates bio-cathodes in which bacteria act as the catalyst.

Substrate:- The substrate is the most important biological factor. Acetate, lactate, ethanol, glucose and complex wastewaters are used; simple substrates are easy to degrade whereas composite substrates are harder to degrade but help build an electrochemically active community.

Membrane:- A proton- or cation-exchange membrane (Nafion is the best known) separates the compartments in two-chamber cells, passing positive ions while limiting the crossover of substrate and oxygen. Single-chamber cells omit the membrane.

Mediator:- Electrons reach the anode directly (through nanowires, intracellular mediators or the biofilm) in mediator-less cells, or through an added external mediator such as methylene blue or neutral red.

1.2. MFC Configurations and the Need for Feedback

MFCs are classified by the number of chambers modelled, the number of microbial cultures, the mode of substrate supply and the way ions and electrons are transferred (Patel, 2018). Controller design depends strongly on these choices: a single-chamber, single-population cell has two or three dynamic states, whereas a two-chamber cell has separate anode and cathode dynamics, and a single-chamber cell with anodophilic and methanogenic populations adds a competing biological state (Pinto et al., 2010; Patel & Deb, 2019). Linear controllers developed around an operating point can lose performance in the presence of unmodelled dynamics, modelling error, disturbances and parameter uncertainty, and these are exactly the conditions under which MFCs operate (Patel, 2018). That observation motivates the nonlinear and adaptive methods reviewed here.

2. Review Scope and Method

This is a narrative review, not a systematic review: no PRISMA protocol was followed and no exhaustive database search was run. The evidence base was assembled from (a) the authors' own MFC control publications and their master's-thesis and monograph treatments (Patel & Deb, 2019; Patel & Deb, 2018; Patel & Deb, 2017; Patel & Aparanathi, 2024; Patel, 2018; Patel et al., 2020); (b) a manuscript in preparation by the authors (Patel & Aparanathi, n.d.); and (c) the modelling and control studies cited in those works. A study was included if it reported a mathematical model used explicitly for control design, or a feedback controller for an

MFC regulating voltage, substrate concentration, oxygen concentration or a related variable.

For each included study the following items were extracted: MFC configuration, manipulated input, controlled variable, design method, stability argument and the type of validation (simulation, identification from experimental data, or closed-loop experiment). Numerical values are quoted exactly as reported in the sources. Because the pool is bounded by what was accessible to the authors and is weighted towards one research group's work, coverage should not be read as complete, and the conclusions in Section 5 are limited accordingly.

3. Modelling of MFCS for Control

3.1. Engineering-Based Models

Engineering-based models use ordinary differential equations (ODEs) to describe the mass balances of substrate, biomass, by-products, mediator and charge, and partial differential equations (PDEs) to describe ion transport through the membrane, biofilm growth and substrate diffusion within the biofilm (Patel, 2018; Luo et al., 2016). Bacterial growth and substrate oxidation are normally represented by Monod kinetics, electrode behaviour by the Tafel or Butler–Volmer equations, and cell potential and current by the Nernst equation and Ohm's law (Patel, 2018; Ortiz-Martínez et al., 2015). Esfandyari et al. (2017) compared Monod, Blackman and Tessier kinetics for a two-chamber batch cell with a pure Shewanella culture and found that Monod kinetics fitted best. Broader reviews of MFC modelling and control are given in (Ortiz-Martínez et al., 2015; Luo et al., 2016; Recio-Garrido et al., 2016a). Table 1 summarises representative models.

Table 1 Representative MFC Models Relevant to Control Design

Study	Configuration	Modelling basis and focus
Zhang and Halme (1995)	1-D two-chamber; one anode, three parallel cathodes	Monod kinetics for substrate and mediator redox; Faraday's law and Nernst equation; output current validated under different loads
Picioreanu et al. (2009)	Batch two-chamber; acetate; *G. sulfurreducens*	ODE mass balances (substrate, biomass), PDE biofilm; Butler–Volmer; effect of internal and external resistance
Zeng et al. (2010)	Continuous two-chamber; one species; acetate or glucose–glutamic acid	Monod with Butler–Volmer; anode and cathode reactions only, biofilm growth not studied
Pinto et al. (2010)	Continuous single-chamber; anodophilic and methanogenic populations; acetate	Monod mass balances; Ohm's law and Nernst equation; four set-ups, two for parameter estimation and two for validation
Shankar et al. (2013)	Continuous double-chamber; glucose–glutamic acid	Cell voltage, power density and temperature variation; heat transfer through the membrane
Oliveira et al. (2013)	1-D two-chamber; steady state	Mass and heat transport (Fick); Monod–Tafel at the anode, Tafel at the cathode
Recio-Garrido et al. (2015)	Single-chamber; two populations	Combined bioelectrochemical–electrical model; off-line simulation versus on-line parameter estimation
Abul et al. (2016)	Single-chamber; one species; acetate; *G. sulfurreducens*	Control-oriented state representation of the anode mass balance (Monod)
Esfandyari et al. (2017)	Batch double-chamber; *Shewanella*	Monod, Blackman and Tessier kinetics compared; Monod best

3.2. Control-Oriented Parametrised Models

Detailed models are rarely suitable for controller design because of their size and the number of unknown parameters. Control-oriented models retain a small set of states, make the manipulated input explicit and isolate the uncertain parameters so that they appear linearly where possible (Patel & Deb, 2018; Patel & Deb, 2017; Patel et al., 2020). For a single-chamber, single-population cell the states are substrate and biomass concentration and the input is either the dilution rate or the influent substrate concentration (Patel & Deb, 2018; Abul et al., 2016). Patel and Deb (2019) extended this to a single-chamber cell with two populations, anodophilic (x_1) and methanogenic (x_2), consuming a common substrate x_3 (acetate). The model is

$$\dot{x}_1 = \theta_1 \, x_3/(k_\alpha + x_3)\cdot x_1 - k_a x_1 - \alpha_a \, d \, x_1 \quad (1)$$

$$\dot{x}_2 = \theta_2 \, x_3/(k_\beta + x_3)\cdot x_2 - k_d x_2 - \alpha_m \, d \, x_2 \quad (2)$$

$$\dot{x}_3 = -k_1\theta_1 \, x_3/(k_\alpha + x_3)\cdot x_1 - k_2\theta_2 \, x_3/(k_\beta + x_3)\cdot x_2 + d[u - x_3] \quad (3)$$

where d is the dilution rate, u the influent substrate concentration, k_1 and k_2 the reciprocals of the bacterial yields, and θ_1 and θ_2 the uncertain maximum growth-rate parameters. The model assumes a uniform bacterial distribution in the anode compartment, constant temperature and pH, and negligible gas transport through the cathode and substrate gradient in the biofilm. Including the methanogenic population matters because methanogens compete for substrate and can reduce both power generation and coulombic efficiency (Capodaglio et al., 2017; Patel & Deb, 2019). Typical values reported for the model include half-rate constants of 20 and 80 for the two populations and yields of 0.232 and 0.012 for the anodophilic and methanogenic species respectively (Patel & Deb, 2019).

3.3. Linearisation and System Identification

Linearisation about an equilibrium by Taylor expansion gives a state-space model that supports classical analysis (root locus, Bode and Nyquist plots), but it is valid only in a small neighbourhood of the operating point (Patel, 2018). For the linearised single-chamber, single-population cell at the nominal dilution rate of 0.09, the system matrix reported is diag(−0.09, −0.174), so the equilibrium is locally stable (Patel, 2018). When physical parameters are uncertain, a transfer-function model can instead be identified from data. Patel (2018) built an up-flow two-chamber MFC using cow manure from a local dairy farm as the waste (Vijay et al., 2016), with a stainless-steel mesh anode and an activated-carbon-cloth cathode separated by a membrane filter. Five set-ups were run in each of three experimental rounds, and ten-day average voltages were used for identification (Patel, 2018). Table 2 and Fig. 2 show how estimation accuracy varied with the assumed numbers of poles and zeros. Models with four anode poles and three cathode poles and no zeros fitted best (90.4 %), and adding zeros reduced the fit. The selected anode model is

$$T_a(s) = 4.16\times10^4 / (s^4 + 11.44s^3 + 60.71s^2 + 180.9s + 312.1) \quad (4)$$

together with a third-order cathode model (Patel, 2018; Patel et al., 2020). Identification of this kind is a well-established route when first-principles parameters are unavailable (Wang & Zhao, 2013), although an accuracy near 90 % means a non-trivial part of the measured behaviour is unexplained by the model that the controller is then designed on.

Table 2. Transfer-function structures tested on the experimental MFC data (source: Patel (2018))

Label	Poles [anode, cathode]	Zeros [anode, cathode]	Accuracy (%)
tf1	[4, 3]	[1, 1]	63.17
tf2	[3, 2]	[1, 1]	40.43
tf3	[3, 2]	[0, 0]	38.53
tf4	**[4, 3]**	**[0, 0]**	**90.4**
tf5	[4, 3]	[2, 2]	53.39
tf6	[4, 3]	[3, 2]	56.72

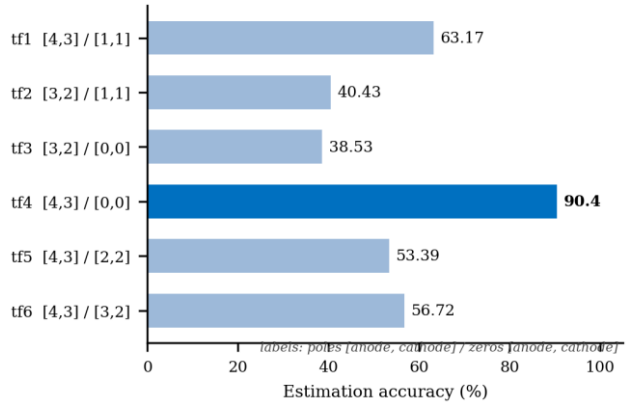


Figure 2 Estimation Accuracy of Candidate Transfer-Function Structures (Data from Table 2)

4. Control Strategies for MFCS

The controllers reported for MFCs fall into five groups, shown in Fig. 1: classical and gain-scheduled, intelligent and predictive, robust linear, nonlinear model-based, and adaptive. The manipulated variable differs between studies: external resistance or load, dilution rate, or influent substrate concentration. The controlled variable is usually output voltage or the substrate (or oxygen) concentration that determines it.

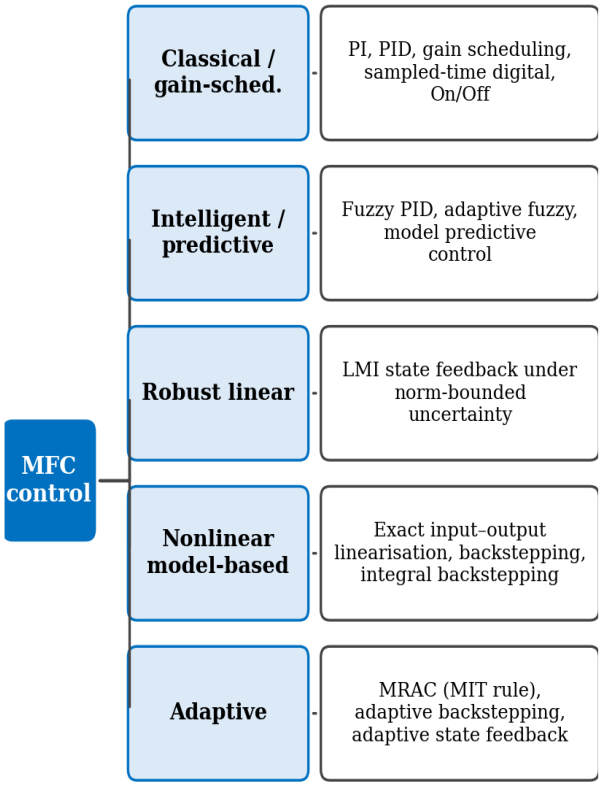


Figure 1 Classification of Control Strategies Reported for MFCs

4.1. Classical and Gain-Scheduled Control

PI and PID control are widely used because they are easy to design and implement, inexpensive and simple to realise, but they cannot be expected to deliver good performance for higher-order, nonlinear plants or for systems with uncertainties and disturbances (Patel & Deb, 2019). In the MFC literature, Boghani et al. (2017) developed a sampled-time digital controller, implemented with microcontrollers, for an MFC stack that holds the output voltage constant despite variations in electrical load, ambient temperature and substrate depletion. Boghani et al. (2016) developed a PI-based gain-scheduling scheme for a non-parametric MFC model obtained with a system-identification toolbox. Recio-Garrido et al. (2016b) described a PID and On/Off scheme for effluent control in staged MFCs with periodic connection of the external resistance. These works show that linear control is practical for MFC hardware, particularly where implementation simplicity matters, and they set the baseline against which later nonlinear designs are judged.

4.2. Fuzzy, Predictive and Intelligent Control

Yan and Fan (2013) applied fuzzy PID control to a two-chamber MFC to obtain a constant output voltage. Fan et al. (2015b) and Fan et al. (2015a) reported performance improvement of a two-chamber MFC using model predictive control and adaptive fuzzy control respectively, under temperature disturbance (Patel & Deb, 2019). These schemes relax the need for an exact analytical model, or use the model to optimise future behaviour, but the cited descriptions do not include the Lyapunov-type stability guarantees that accompany the adaptive designs in Section 4.6.

4.3. Robust Linear Control using LMIs

The dilution rate is fixed by the feed flow rate because the anode volume is fixed, and the bacterial reaction is slow. Fast fluctuation in the dilution rate therefore has little effect, but slow, persistent fluctuation degrades MFC performance (Patel, 2018). For the linearised single-chamber, single-population model, Patel (2018) represented the uncertainty as time-varying and norm-bounded, $\Delta A(t) = D_a F_a(t) E_a$ with $F_a^T F_a \leq I$, using a sinusoidal term $\delta \cdot \sin(\omega t)$ with $\delta = 0.08$, and computed a state-feedback gain $u = Kx$ through a linear-matrix-inequality (LMI) formulation (Boyd et al., 1994). Simulation at 0.05 Hz and 0.1 Hz showed that the uncontrolled system became sluggish at low

frequency while the robust controller maintained good performance at both frequencies. The approach is attractive because it yields guaranteed robustness for a stated uncertainty bound, but it applies to the linearised model and is therefore local.

4.4. Exact Input–Output Linearisation

Exact input–output linearisation cancels the nonlinear dynamics through a feedback transformation so that a linear controller can be applied to the transformed system, and has been compared across structures for continuous bioreactors (Wang et al., 1993). Patel (2018) applied it to a two-chamber MFC with the dilution rates D_1 and D_2 of the two chambers as inputs: the anode controller tracks substrate concentration and the cathode controller tracks oxygen concentration, with gains K_1 to K_4 of 1, 1, 2 and 1. Both set points were tracked well in simulation. The thesis notes that classical linear control of biological systems generally performs poorly even over a small operating range, which is the motivation for this method. Its limitation is that the cancellation relies on an accurate model.

4.5. Backstepping and Integral Backstepping

Backstepping treats each state except the last as a virtual control and builds the actual control and a Lyapunov function recursively, which guarantees tracking and stabilisation for strict-feedback nonlinear systems (Zhou & Wen, 2008). Its drawbacks are the need for accurate parameter knowledge and the growing complexity of the derivatives of the virtual controls (Patel & Aparanathi, n.d.). Integral action adds robustness to unmodelled effects: with tracking errors $e_1 = x_{1d} - x_1$ and $e_2 = x_{2d} - x_2$ and an integral state $\chi = \int e_1 d\tau$, the virtual control is $x_{2d} = c_1 e_1 + \dot{x}_{1d} + \lambda\chi$.

Patel and Aparanathi (2024) designed an integral backstepping controller for a two-compartment MFC using reduced second-order models of the anode and cathode chambers, obtained by order reduction of the identified transfer functions (the anode model becomes $0.224\times10^4/(s^2 + 2.78s + 13.42)$). The controller gains for the anode were $c_1 = 0.001$, $c_2 = 0.09$ and $\lambda = 100$, and the Lyapunov derivative was shown to be $-c_1 e_1^2 - c_2 e_2^2$. In MATLAB/Simulink the controller was compared with a PID controller tuned using the Simulink PID tuner: the integral backstepping controller was reported to give better tracking and shorter settling time for the anode chamber, and a smooth response for the cathode chamber where the PID response oscillated. The controller was validated on the reduced-order models, not on the original fourth- and third-order ones.

4.6. Adaptive Control

Adaptive controllers are designed for plants with unknown or uncertain parameters: the controller parameters change with time as estimates are updated on line, and the structure of the plant must be known (Patel et al., 2020). Fig. 3 shows the model-reference form used in the studies reviewed, in which a reference model defines the desired behaviour and adaptation laws drive the error between plant and reference to zero.

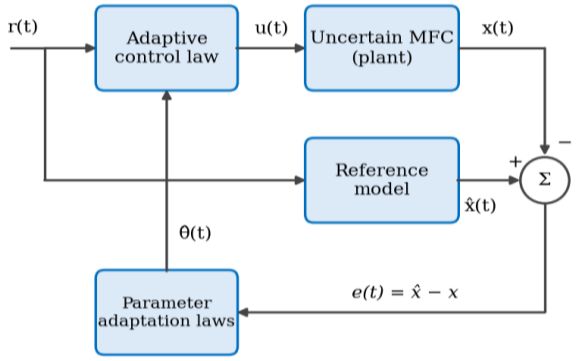


Figure 3 Model-Reference Adaptive Control Structure for an MFC with Uncertain Parameters

Model reference adaptive control (MRAC):- Patel et al. (2020) designed MRAC for the two-chamber MFC using the gradient (MIT) rule, which minimises a cost $J(\theta) = \frac{1}{2}e^2$ of the adjustable parameter, and a Lyapunov-based design. The adaptive gains for the anode and cathode chambers were 0.0005 and 0.000015. Without adaptation the actual outputs showed a finite error with respect to the reference systems; with MRAC the outputs of both chambers were reported to follow the reference systems.

Adaptive backstepping, single-chamber single-population:- Patel and Deb (2018) combined backstepping with parameter estimation, taking the dilution rate as the manipulated input and aiming for constant output voltage under variable load by regulating substrate concentration. With $C_1 = 0.13$, $C_2 = 0.4$, $\gamma_1 = 0.03$ and $\gamma_2 = 50$ (Patel, 2018), the non-adaptive case let the substrate concentration switch between 18 and 23 mg/L around a 20 mg/L

set point, while the adaptive controller held it at the desired value. Biomass concentration, which is not controlled, stayed between 0.5 and 3 mg/L.

Adaptive state feedback, two-population MFC:- Patel and Deb (2019) designed a nonlinear adaptive controller for the model in Eqs. (1)–(3) with influent substrate concentration as the input. A reference model, error signals $e_i = \hat{x}_i - x_i$, adaptive laws for θ_1 and θ_2 and a control signal were derived from a quadratic Lyapunov function containing the tracking and parameter errors. The proof concludes that all closed-loop signals are bounded and the tracking errors tend to zero; convergence of the parameter estimates is not required. In a 35-day simulation with a stepped influent profile between 500 and 2500 mg/L, the state errors converged within about a day and the estimates stayed inside the stated bounds (θ_1: 0.1 to 2.5; θ_2: 0.05 to 0.5). When θ_1 was changed from 1.4 to 1.9 at day 25 the estimator recovered after a short transient.

Adaptive backstepping versus backstepping versus PID:- Patel and Aparanathi (n.d.) compared the three controllers on a single-chamber, single-population MFC for step-up and step-down reference voltages and for voltage sags and swells. The adaptive backstepping controller was reported to give lower overshoot, faster settling, smaller steady-state error and smoother control action, and the PID controller was reported to become unstable when the reference level was changed in the sag and swell tests. These results are from an unpublished manuscript and are included as indicative only.

5. Comparative Analysis and Discussion

5.1. Comparative Summary

Table 3 collects the reviewed controllers by configuration, input and the outcome reported by the authors. Outcomes are as stated in the sources and are not directly comparable, since the models, horizons and metrics differ.

Table 3 Summary of Reviewed MFC Controllers

Method (source)	Configuration and input	Reported outcome
Sampled-time digital (Boghani et al., 2017)	MFC stack; microcontroller implementation	Constant output voltage despite load, temperature and substrate-depletion variation
PI gain scheduling (Boghani et al., 2016)	Non-parametric model from system identification	Voltage control via gain-scheduled PI
PID with On/Off (Recio-Garrido et al., 2016b)	Staged MFCs; periodic external resistance	Effluent control
Fuzzy PID (Yan & Fan, 2013)	Two-chamber MFC	Constant output voltage
Adaptive fuzzy (Fan et al., 2015a); MPC (Fan et al., 2015b)	Two-chamber MFC	Improved performance under temperature disturbance
LMI robust state feedback (Patel, 2018)	Linearised single-population cell; uncertain dilution rate	Robust at 0.05 and 0.1 Hz; open loop degraded
Exact I/O linearisation (Patel, 2018)	Two-chamber; dilution rates D_1, D_2	Anode substrate and cathode oxygen set points tracked
Adaptive backstepping (Patel & Deb, 2018)	Single-chamber, single population; dilution rate	Substrate held at 20 mg/L; non-adaptive case varied 18–23 mg/L
Adaptive state feedback (Patel & Deb, 2019)	Single-chamber, two populations; influent concentration	Errors to zero; estimates within bounds; recovery after θ_1 step
MRAC, MIT rule (Patel et al., 2020)	Two-chamber; identified transfer functions	Outputs follow reference model; finite error without MRAC
Integral backstepping (Patel & Aparanathi, 2024)	Two-chamber; reduced-order models	Better tracking and settling than PID; PID oscillatory (cathode)
Adaptive backstepping vs backstepping vs PID (Patel & Aparanathi, n.d.)	Single-chamber, single population; step, sag, swell references	Lower overshoot, faster settling; PID unstable at changed levels

5.2. 5.2 Trade-offs between Methods

Model dependence versus robustness. Linear PI/PID and gain-scheduled schemes need little or no mechanistic model and are the easiest to deploy, which explains their use on MFC stacks (Boghani et al., 2017; Boghani et al., 2016). Exact linearisation and backstepping exploit the nonlinear structure and give clean design equations but rely on accurate parameters (Patel, 2018; Patel & Aparanathi, n.d.). Adaptive versions relax that requirement by estimating the uncertain parameters on line, at the price of a more complicated controller (Patel & Deb, 2019).

Guarantees. The adaptive designs reviewed come with a Lyapunov argument. In Patel and Deb (2019) the argument establishes boundedness and convergence of the tracking errors, not of the parameter estimates, and the authors state explicitly that parameter convergence is not an intrinsic requirement. Because the Lyapunov derivative in such designs is typically negative semi-definite, convergence of the errors follows from boundedness arguments (Barbalat-type reasoning) rather than from strict decrease. The fuzzy and predictive schemes in Section 4.2 are described without comparable guarantees (Patel & Deb, 2019).

Tuning burden. Every method needs gains to be chosen: PID gains in the Simulink tuner, backstepping constants c_i, and adaptation gains γ_i. The adaptive designs add a trade-off between adaptation speed and transient behaviour, and Patel and Deb (2019) note that tuning becomes harder as model complexity increases and may require optimisation techniques.

5.3. Quality of the Evidence

Three limitations apply to the body of work surveyed here. First, the nonlinear and adaptive controllers were validated in simulation, usually on the same model used for design; the experimental work in the thesis was used to identify transfer-function models and not to close a loop (Patel, 2018). Second, the baselines and metrics are not uniform: the PID baselines were tuned with an automatic tuner (Patel & Aparanathi, 2024), horizons range from days (Patel & Deb, 2019) to unspecified time units (Patel & Aparanathi, 2024), and outcomes are often given qualitatively (better tracking, faster settling) rather than as overshoot, settling time or integral error. Third, reduced-order models and ~90 % identification accuracy mean that robustness to model error, rather than only to parameter drift, is not yet demonstrated for the hardware case. These points do not diminish the design contribution of the studies, but they limit how strongly the superiority of one method over another can be claimed.

5.4. Research Gaps and Future Directions

Experimental closed-loop validation:- Implement the nonlinear and adaptive controllers on a laboratory MFC, using identified models such as those in Table 2, and report measured rather than simulated regulation.

Multi-species and higher-order models:- Extend the adaptive designs to more than two bacterial populations and to more complex MFC models, with systematic, optimisation-based tuning of adaptation gains (Patel & Deb, 2019).

Stacks and scale-up:- Sampled-time control has been shown for stacks (Boghani et al., 2017); nonlinear and adaptive methods have not yet been extended to stack-level models with load and temperature disturbances.

Common benchmarks:- Adopt shared reference profiles and metrics (overshoot, settling time, integral absolute error, control effort) so that classical, intelligent, robust and adaptive schemes can be compared fairly.

Hybrid schemes:- Combine adaptive or robust designs with fuzzy or predictive layers, in line with the adaptive-and-intelligent theme of the monograph literature (Patel et al., 2020).

Conclusion

This review has organised the control literature for microbial fuel cells by model type, controller class and validation evidence. Classical PI/PID, gain-scheduled and sampled-time controllers are simple and have been realised on MFC stacks, while robust LMI, exact linearisation, backstepping, integral backstepping and adaptive designs address nonlinearity and parametric uncertainty and, in the simulations reported, track substrate and voltage references with less oscillation than tuned linear controllers. The adaptive schemes add on-line parameter estimation with Lyapunov guarantees of bounded signals and vanishing tracking error. The main weaknesses of the evidence are its reliance on simulation, non-uniform baselines and metrics, and the lack of closed-loop experiments. Experimental validation, multi-species and stack-level extensions,

gain-tuning methods and standard benchmarks are the priorities for future work.

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