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Review

A Comprehensive Review of Parameter Estimation and Modeling Approaches for Proton Exchange Membrane Fuel Cells: Challenges, Methods, and Future Directions

Abdullah M. Alharbi [1,*] and Ahmed A. Zaki Diab [2,3,*]

[1] Department of Electrical Engineering, College of Engineering in Wadi Alddawasir, Prince Sattam Bin Abdulaziz University, Wadi Alddawasir 11942, Saudi Arabia
[2] Electrical Engineering Determent, Faculty of Engineering, Minia University, Minia 61519, Egypt
[3] Department of Mechatronics Engineering, Faculty of Engineering, Nahda University in Beni Suef, Beni Suef 62764, Egypt
* Correspondence: am.alharbi@psau.edu.sa (A.M.A.); a.diab@mu.edu.eg (A.A.Z.D.)

Abstract

Proton Exchange Membrane Fuel Cells (PEMFCs) have emerged as promising clean-energy-conversion devices for various applications, including transportation and stationary power generation. The accurate modeling and parameter estimation of PEMFCs are fundamental to optimizing their performance, extending their operational lifespan, and facilitating their widespread commercialization. However, their inherent nonlinear characteristics and complex electrochemical processes present significant challenges in developing accurate mathematical models and reliable parameter-estimation methods. This review systematically examines the state of the art in PEMFC parameter estimation and modeling, with particular emphasis on the critical challenges posed by nonlinearities, the evolution of analytical and computational methods, and the role of sensitivity analysis in model refinement. The paper synthesizes findings from recent studies employing evolutionary algorithms, metaheuristic techniques, reinforcement learning, and hybrid approaches, evaluating their relative merits in terms of accuracy, convergence speed, and robustness. Furthermore, it explores how sensitivity analysis provides valuable insights into parameter influence under varying operational conditions, guiding model optimization efforts. The review identifies persistent gaps in current methodologies, particularly regarding generalizability across different fuel cell types and real-time applicability, while highlighting promising directions for future research, including hybrid algorithms and advanced data-preprocessing techniques.

Keywords: sustainability; green energy; energy; proton exchange membrane fuel cell; parameter estimation; nonlinear modeling; optimization algorithms; sensitivity analysis; metaheuristic techniques

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1. Introduction

1.1. The Importance of PEMFC Modeling and Associated Challenges

Proton Exchange Membrane Fuel Cells (PEMFCs) represent a cornerstone technology in the transition toward sustainable energy systems, offering high efficiency, low operating temperatures, and zero direct emissions [1]. The accurate modeling of PEMFCs is essential for understanding their complex electrochemical behavior, optimizing design parameters, and developing effective control strategies for real-world applications [2]. However, the ex-

traction, estimation, and identification of PEMFC parameters remain critical yet challenging tasks due to the system's inherent complexities.

The significance of precise parameter estimation extends across multiple domains, including performance prediction, fault diagnosis, and system optimization. Accurate models enable engineers to simulate fuel cell behavior under various operating conditions, identify optimal design configurations, and implement model-based control strategies that enhance efficiency and durability [3]. Conversely, imprecise parameter identification can lead to suboptimal performance, accelerated degradation, and reduced system reliability. Moreover, recent studies have also demonstrated that accurate parameter estimation is closely related to other key aspects of PEMFC research, including performance degradation prediction and fault diagnosis. Advanced deep learning architectures and electrochemical diagnostic techniques increasingly rely on accurate models and reliable parameter identification to improve prediction accuracy, health monitoring performance, and system reliability. These developments further emphasize the importance of robust parameter-estimation methods for next-generation PEMFC applications [4,5].

Despite decades of research, PEMFC modeling continues to face substantial challenges. The mathematical representation of PEMFCs involves numerous parameters—typically seven or more in semiempirical models—that exhibit complex interdependencies and nonlinear relationships [6]. These parameters are often difficult to measure directly, and their values may vary with operating conditions such as temperature, pressure, and humidity. Furthermore, the polarization curve, which describes the relationship between voltage and current density, incorporates nonseparable nonlinearities that complicate both online and offline estimation procedures [7].

Although several review articles have discussed PEMFC modeling or optimization techniques independently, most of them focus on specific algorithm families or particular aspects of parameter estimation. A comprehensive review that integrates the challenges of nonlinear PEMFC modeling, parameter estimation strategies, sensitivity analysis, and emerging intelligent optimization methods within a unified framework remains limited [1,2]. As shown in Table 1, previous review articles primarily focused on conventional parameter estimation techniques and metaheuristic optimization algorithms. Although these reviews provided valuable summaries of the available methods, they offered limited coverage of recent developments such as deep learning, reinforcement learning, hybrid AI-based approaches, online parameter estimation, and sensitivity analysis. In contrast, the present review provides a comprehensive and critical assessment of recent advances through 2025, benchmarks different approaches in terms of estimation accuracy, convergence speed, robustness, computational complexity, and practical applicability, and identifies current research gaps and future research directions. This review addresses this gap by critically synthesizing these interconnected topics, comparing their advantages and limitations, identifying unresolved research challenges, and highlighting promising directions for future developments. Novelty and contributions of this review can be summarized as follows:

- This review analyzes recent advances rather than older reviews.
- It compares analytical, optimization, AI, deep learning, reinforcement learning, and hybrid approaches in a unified framework.
- It critically discusses accuracy, convergence speed, robustness, computational complexity, scalability, and practical applicability.
- It identifies current research gaps and future research opportunities.

Table 1. Comparison of the scope and contributions of representative review articles on PEMFC parameter estimation and modeling, including the present review.

Feature	Priya et al. (2018) [1]	Ashraf et al. (2022) [2]	This Review
Publication period covered	Up to 2018	Up to 2022	Up to 2025
Conventional/semiempirical models	✓	✓	✓
Metaheuristic optimization methods	✓	✓	✓
Evolutionary algorithms	✓	✓	✓
Machine learning methods	Limited	Limited	✓
Deep learning methods	✗	✗	✓
Reinforcement learning methods	✗	✗	✓
Hybrid optimization and AI methods	Limited	Limited	✓
Online parameter estimation	✗	✗	✓
Sensitivity analysis	✗	Limited	✓
Comparative performance benchmarking	Partial	Partial	✓
Discussion of convergence, robustness, and computational complexity	Partial	Partial	✓
Critical analysis of current research gaps	Limited	Partial	✓
Future research directions	Limited	Partial	✓
Coverage of recent advances (2023–2025)	✗	✗	✓

1.2. Scope and Organization of This Review

This review aims to provide a comprehensive synthesis of recent advances in PEMFC parameter estimation and modeling, with particular emphasis on the methodologies developed to address the challenges of nonlinearity, multivariable optimization, and data limitations. Unlike previous review articles that mainly summarize optimization algorithms or modeling approaches separately, this review provides an integrated perspective on PEMFC parameter estimation. It combines mathematical modeling, nonlinear parameter estimation, sensitivity analysis, recent intelligent optimization techniques, and hybrid algorithms within a single framework. Furthermore, the review critically evaluates the limitations of current methodologies, identifies unresolved research gaps, and discusses future research opportunities that may support the development of more accurate, robust, and real-time PEMFC models.

The paper is organized as follows: Section 2 examines the fundamental challenge of nonlinearity in PEMFC modeling, exploring both separable and nonseparable nonlinearities and their implications for parameter estimation. Section 3 provides a systematic review of estimation methods, categorizing them into analytical approaches, metaheuristic algorithms, and intelligent techniques, with comparative analysis of their performance characteristics. Section 4 discusses the role of sensitivity analysis in understanding parameter influence and guiding model refinement. Section 5 synthesizes key findings and identifies persistent gaps in current methodologies, while Section 6 offers conclusions and recommendations for future research directions.

2. Polarization Behavior and Mathematical Model of the PEMFC

2.1. Basics of PEMFC Physical Process

The conversion of chemical energy into electrical energy can be performed via fuel cells. The structure of predictable PEMFCs is shown in Figure 1. As shown in the figure, the fuel cell model includes two primary electrodes: an anode and a cathode. Between these electrodes are the catalyst layers and the proton exchange membrane, which facilitate electrochemical reactions and proton transport. Hydrogen and air are supplied through dedicated flow channels to the anode and cathode, respectively.

Understanding the fundamental operating principle of PEMFCs is essential for developing a mathematical model for them. Based on the electrochemical reactions occurring during fuel cell operation, the hydrogen oxidation and oxygen reduction processes can be represented by the following reaction [8,9]:

$$2H_2 + O_2 \rightarrow 2H_2O \quad (1)$$

Unlike conventional combustion processes, the electrochemical reactions in a PEMFC directly convert the chemical energy of hydrogen into electrical energy, with heat generated only as a by-product.

At the anode, hydrogen molecules undergo an oxidation reaction, producing protons H^+ and electrons e^-, as expressed by:

$$2H_2 \rightarrow 4H^+ + 4e^- \quad (2)$$

At the cathode, oxygen supplied from the air undergoes a reduction reaction by combining with the electrons arriving through the external circuit and the protons transported across the proton exchange membrane. This electrochemical reaction produces water as the final product and can be expressed as follows:

$$O_2 + 4H^+ + 4e^- \rightarrow 2H_2O \quad (3)$$

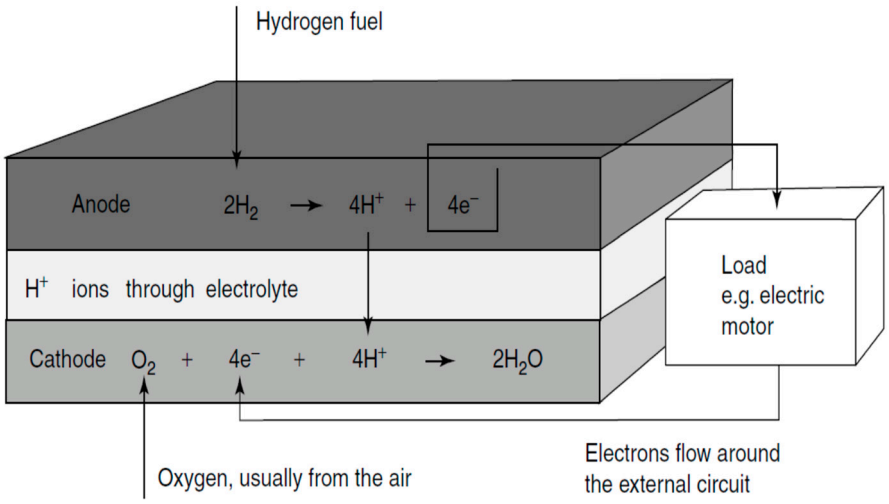


Figure 1. The flow of charges in fuel cells [9].

The nonlinear behavior of PEMFCs not only complicates parameter estimation but also affects degradation prediction and fault diagnosis. Recent studies have shown that combining accurate physical modeling with advanced data-driven techniques can improve prediction performance and provide more reliable system health assessment under dynamic operating conditions [4,5]. Figure 2 presents the polarization curve for a fuel cell operating at 80 °C, which is characterized by three distinct regions corresponding to activation losses, ohmic losses, and concentration losses [10,11]. The initial region, known as the activation zone, exhibits nonlinear behavior and provides detailed insights into the electrochemical reactions occurring within the cell. The subsequent ohmic region is primarily associated with ionic resistance within the membrane electrolyte. The final region represents concentration losses resulting from variations in the concentration gradient across the cell [12].

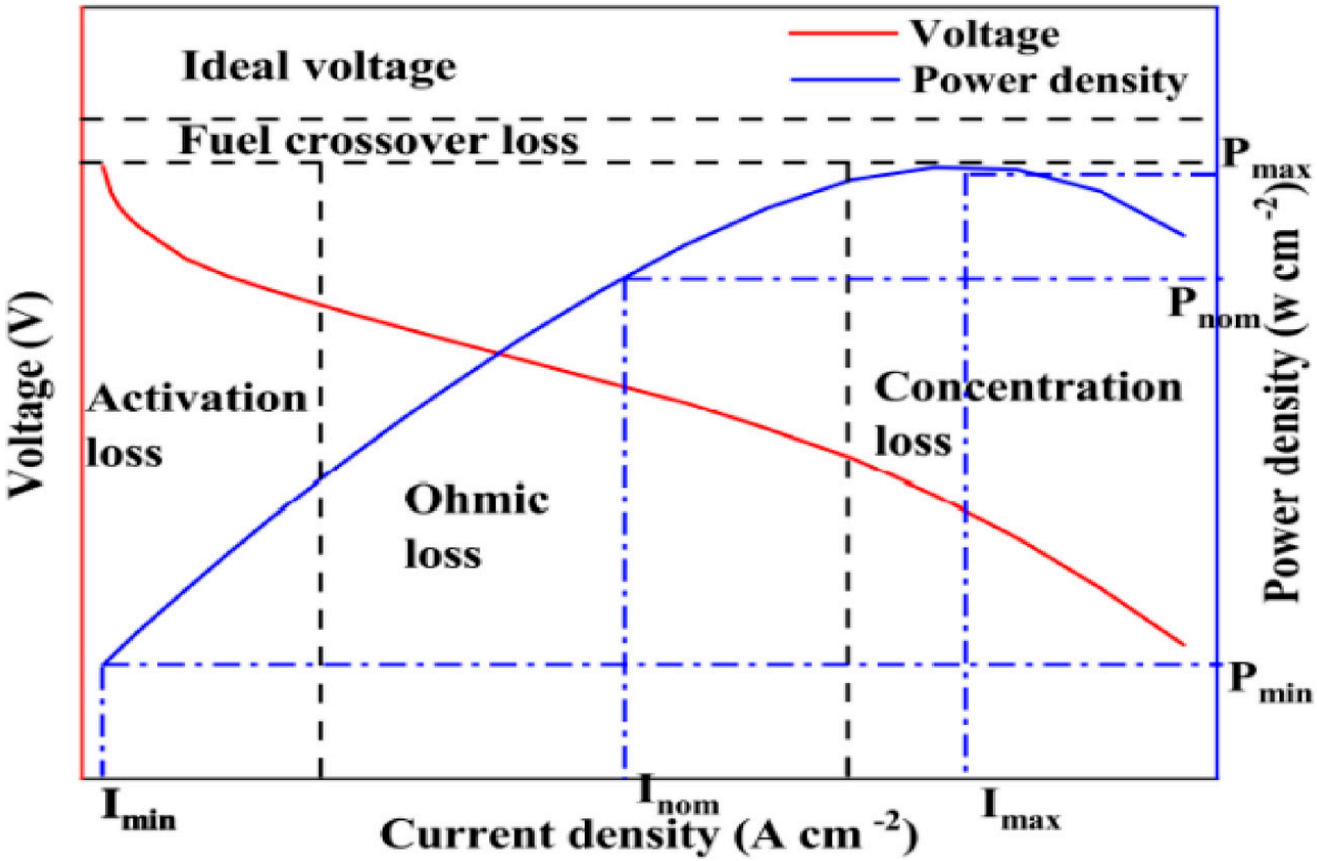


Figure 2. A representation of a generic polarization curve of a fuel cell.

The rapid depletion of fossil fuel resources, together with the continuous increase in global electricity demand, has increased the importance of renewable energy sources for both distributed and large-scale power generation systems. However, although these green technologies are widely deployed, their performance strongly depends on environmental conditions. This variability has encouraged the development of fuel cell systems as complementary and reliable power-generation technologies. Traditionally, fuel cell systems are classified into three main categories: transportable, portable, and stationary applications.

2.2. PEMFC Voltage Characteristics and Modeling

The overall fuel cell voltage, denoted as (V_{Fc}), is expressed as [13]:

$$V_{Fc} = N_{cells} \times (E_{Nernst} - V_{act} - V_{ohmic} - V_{con}) \quad (4)$$

where (E_{Nernst}) denotes the reversible voltage, while (V_{act}), (V_{ohmic}), and (V_{con}) represent the activation voltage drop, ohmic voltage drop, and concentration voltage drop, respectively.

2.2.1. Reversible Voltage Calculation

The reversible voltage represents the open-circuit voltage of the fuel cell when the electrochemical reactions are in equilibrium. It can be calculated as follows:

$$E_{Nernst} = 1.229 - 0.85 \times 10^{-3}(T - 298.15) + 4.3085 \times 10^{-5} \times T\left[\ln(P_{H_2}) - \frac{1}{2}\ln(P_{O_2})\right] \quad (5)$$

where (T) is the operating temperature in Kelvin. P_{H_2} and P_{O_2} represent the partial pressures of hydrogen and oxygen, respectively. These gas pressures can be determined as follows.

2.2.2. Concentration Voltage Drop Calculation

The concentration voltage drop (V_{con}) occurs due to mass transport limitations inside the fuel cell. This phenomenon appears clearly in the polarization curve, where the output voltage decreases sharply at higher current levels.

The partial pressure of nitrogen in the air stream is given by:

$$P_{N_2} = \frac{0.79}{0.21} P_{O_2} \tag{6}$$

The oxygen partial pressure can be calculated as follows:

$$P_{O_2} = P_c - RH_c P^{sat}_{H_2O} - P_{N_2} \times \exp\left(\frac{0.291\left(\frac{I_{fc}}{A}\right)}{T^{0.832}}\right) \tag{7}$$

The saturation pressure of water vapor ($P^{sat}_{H_2O}$) is determined using:

$$\begin{aligned}\log_{10}\left(P^{sat}_{H_2O}\right) =& 2.95 \times 10^{-2}(T - 273.15) - 9.18 \times 10^{-5}(T - 273.15)^2 \\ &+ 1.44 \times 10^{-7}(T - 273.15)^3 - 2.18\end{aligned} \tag{8}$$

In another condition, when the electrochemical reaction between hydrogen and oxygen is considered, the oxygen partial pressure can be expressed as follows:

$$P_{O_2} = RH_c P^{sat}_{H_2O}\left[\left(\exp\left(\frac{4.192\left(\frac{I_{fc}}{A}\right)}{T^{1.334}}\right) \times \frac{RH_c P^{sat}_{H_2O}}{P_a}\right)^{-1} - 1\right] \tag{9}$$

Similarly, the hydrogen partial pressure can be written as follows:

$$P_{H_2} = 0.5RH_a P^{sat}_{H_2O}\left[\left(\exp\left(\frac{1.635\left(\frac{I_{fc}}{A}\right)}{T^{1.334}}\right) \times \frac{RH_a P^{sat}_{H_2O}}{P_a}\right)^{-1} - 1\right] \tag{10}$$

where (RH_a) and (RH_c) represent the relative humidity at the anode and cathode, respectively. (P_a) and (P_c) denote the anode and cathode pressures. (P_{N_2}) is the nitrogen partial pressure in the cathode gas channel, and (A) indicates the active membrane area.

2.2.3. Activation Voltage Drop Calculation

The activation voltage drop, V_{act}, arises due to the electrochemical reaction kinetics at the electrode surfaces. This loss mainly affects the low-current region of the polarization curve, where a noticeable voltage drop occurs.

The activation voltage drop is calculated as follows:

$$V_{act} = -\left[\xi_1 + \xi_2 T + \xi_3 T \ln\left(C_{O_2}\right) + \xi_4 T \ln\left(I_{fc}\right)\right] \tag{11}$$

where ξ_1, ξ_2, ξ_3, and ξ_4 are semiempirical coefficients. (I_{fc}) denotes the fuel cell output current. (C_{O_2}) represents the oxygen concentration at the cathode surface (mol·cm^{-3}), which can be expressed as follows:

$$C_{O_2} = \frac{P_{O_2}}{5.08 \times 10^6 \times e^{-\left(\frac{498}{T}\right)}} \tag{12}$$

2.2.4. Ohmic Voltage Drop Calculation

The ohmic voltage drop (V_{ohmic}) results from the resistance encountered by ions and electrons during their transport through the fuel cell components. It is calculated as follows:

$$V_{ohmic} = I_{fc}(R_M + R_C) \tag{13}$$

where (R_M) is the membrane resistance and (R_C) represents the contact or electronic resistance in the cell.

The membrane resistance is given by:

$$R_M = \frac{\rho_M l}{A} \tag{14}$$

where (l) signifies the effective thickness of the membrane (cm), and (A) represents the active membrane area (cm^2). (ρ_M) is the membrane resistivity ($\Omega \cdot cm$). For a Nafion membrane, it can be calculated as follows:

$$\rho_M = \frac{181.6\left[1 + 0.03\left(\frac{I_{fc}}{A}\right) + 0.062\left(\frac{T}{303}\right)^2\left(\frac{I_{fc}}{A}\right)^{2.5}\right]}{\left[\lambda - 0.634 - 3\left(\frac{I_{fc}}{A}\right)\right] \times \exp\left[4.18\left(\frac{T-303}{T}\right)\right]} \tag{15}$$

where (λ) represents the membrane water content parameter.

The concentration voltage drop can be given by:

$$V_{con} = -\beta \ln\left(1 - \frac{J}{J_{max}}\right) \tag{16}$$

where (β) is the parametric coefficient, while (J) and (J_{max}) denote the actual current density and the maximum current density, respectively.

2.3. Parameter-Estimation Methodology for PEMFC Modeling

Accurate mathematical representation of a PEMFC requires the estimation of seven important parameters: ξ_1, ξ_2, ξ_3, ξ_4, β, R_C, and λ. These parameters significantly affect the precision of the predicted current–voltage polarization curve. Typically, they are determined using experimental data by minimizing the sum of squared errors (SSE) between measured and estimated voltages. This error measure is used as the objective function during the parameter identification process. Parameter optimization methods generally consist of two main elements: the objective function and the constraints imposed on the decision variables. The SSE objective function is expressed as follows:

$$OF = \min SSE(X) = \sum_{i=1}^{N}(V_{meas} - V_{FC})^2 \tag{17}$$

where (V_{meas}) is the measured voltage, (V_{FC}) is the estimated voltage obtained from the model, and (N) represents the total number of experimental data samples. Here, (X) represents the vector of unknown parameters ($\xi_1, \xi_2, \xi_3, \xi_4, \beta, R_C, \lambda$). To determine the optimal parameter values, several optimization techniques can be applied. Figure 3 illustrates the processing of the PEMFC parameter estimation using optimization techniques.

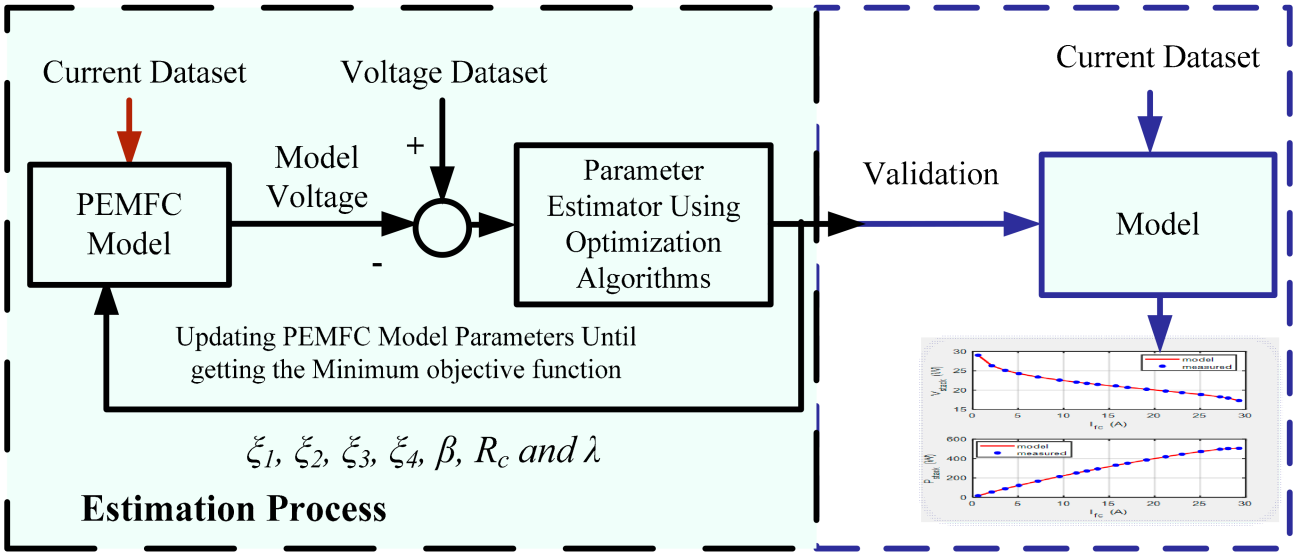


Figure 3. Optimization method based PEMFC parameter identifications.

The parameter estimation process is conducted within predefined search boundaries to ensure physically meaningful and stable solutions during optimization. The lower and upper bounds of the model parameters are not universal and may vary among published studies according to the adopted PEMFC model, stack characteristics, operating conditions, and optimization algorithm. Therefore, the parameter bounds summarized throughout this review are those reported in the corresponding referenced studies in the subsequent sections. Specifically, the parameter (ξ_1) varies between -1.1997 and -0.8532, while (ξ_2) ranges from (10×10^{-4}) to (50×10^{-4}). The coefficient (ξ_3) is bounded between (3.6×10^{-5}) and (9.8×10^{-5}), whereas (ξ_4) varies from (-2.6×10^{-4}) to (-9.54×10^{-4}). The membrane water content parameter (λ) is constrained within the interval of 10 to 23. In addition, the contact resistance (R_c) is limited between 0.1 and 0.8 mΩ. Finally, the concentration loss coefficient (β) is allowed to vary within the range of (1.36×10^{-2}) to 50. These limits guide the optimization algorithms toward feasible parameter values while improving the reliability of the PEMFC model identification. Figure 3 shows the flowchart for applying optimization methods based PEMFC parameter identifications.

There are also other statistical performance indices that are commonly applied in many research areas to evaluate how well a theoretical or estimated model represents the actual system behavior. In this study, the accuracy and effectiveness of the proposed model are examined using several statistical measures. These indices allow a quantitative comparison to be made between the measured data and the simulated results, which helps in verifying the reliability of the estimation methods.

Individual absolute error (IAE) measures the absolute difference between the measured voltage (or current/power) and the corresponding calculated value obtained from the proposed method. It indicates the deviation at each data point and is defined as follows:

$$IAE = |V_{meas,i} - V_{FC,i}| \tag{18}$$

Relative error (RE) is used to evaluate the accuracy of the estimation relative to the measured value. It represents the ratio between the absolute error and the measured voltage. This metric is dimensionless and can be expressed as follows:

$$RE = \frac{|V_{meas,i} - V_{FC,i}|}{V_{meas,i}} \tag{19}$$

Root mean square error (RMSE) evaluates the overall deviation between experimental data and the calculated values over a dataset of (N) samples. It reflects the magnitude of the estimation error and is widely used to quantify the discrepancy between the measured and modeled results. It can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(V_{meas,i} - V_{FC,i})^2} \quad (20)$$

Mean bias error (MBE) represents the average value of the estimation error and provides an indication of the long-term performance of the model. A value close to zero indicates better agreement between measured and calculated values. This metric also shows whether the model tends to overestimate or underestimate the measured data. It is expressed as follows:

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(V_{meas,i} - V_{FC,i}) \quad (21)$$

The autocorrelation function (ACF) evaluates the correlation between values of a signal separated by a specific lag. It describes how the relationship between two points in the error sequence changes with their separation. ACF is a time-domain indicator that reflects the memory characteristics of the stochastic process but does not provide information about the frequency components of the signal. For the error signal (e_t), the ACF can be expressed as follows:

$$ACF = \frac{Conv(e_t, e_{t+k})}{\sqrt{Var(e_t), Var(e_{t+k})}} \quad (22)$$

3. The Challenge of Nonlinearity in PEMFC Modeling

3.1. Fundamental Nonlinear Characteristics of PEMFC Systems

PEMFCs exhibit inherently nonlinear behavior arising from the complex electrochemical, thermodynamic, and transport phenomena that govern their operation. The polarization curve—the fundamental characterization of fuel cell performance—demonstrates distinct nonlinear regions corresponding to activation losses, ohmic losses, and concentration losses [3]. These nonlinearities are not merely superficial characteristics but are deeply embedded in the mathematical structure of PEMFC models.

The nonlinear parameterization of PEMFC models presents particular difficulties for parameter estimation, as parameters are embedded within nonlinear functions that cannot be easily separated or linearized (Qiu et al., 2024) [14]. This characteristic fundamentally distinguishes PEMFC parameter estimation from linear system identification and requires specialized approaches that can navigate complex, multimodal objective functions. Yang et al. [15] emphasize that traditional optimization techniques are often overwhelmed by the nonlinear nature of PEMFC models, leading to potential biases and inaccuracies in parameter estimation. The presence of multiple local optima in the solution space further compounds this difficulty, as gradient-based methods may converge to suboptimal solutions without appropriate initialization or global search capabilities.

3.2. Nonseparable Nonlinearities in Polarization Curves

A particularly challenging aspect of PEMFC modeling is the presence of nonseparable nonlinearities in the polarization curve. Unlike separable nonlinearities, where parameters can be isolated through mathematical transformations, nonseparable nonlinearities involve parameters that interact in ways that prevent simple decomposition [3]. This characteristic significantly complicates both online and offline estimation procedures. Xu et al. [7] highlight that the classical semiempirical model of PEMFC polarization curves suffers from nonseparable parameterization, which complicates its application in real-time scenarios [7]. The concentration loss region, in particular, exhibits nonlinear behavior that cannot be

adequately captured by simplified linear approximations, necessitating more sophisticated modeling approaches.

Recent advances have sought to address this challenge through differential operator-based methods that transform nonseparable models into linear regression equations, enabling the application of conventional estimation techniques [14]. Beltrán et al. [3] demonstrated that such transformations can facilitate online parameter estimation with guaranteed convergence properties, representing a significant advancement in the field.

3.3. Implications for Parameter Estimation

The nonlinear characteristics of PEMFCs have profound implications for parameter-estimation methodologies. First, they necessitate the use of global optimization techniques capable of escaping local optima and exploring the full parameter space [16]. Second, they increase the sensitivity of estimation procedures to initial conditions and measurement noise, requiring robust algorithms that can maintain performance under realistic operating conditions.

The presence of nonlinearities also complicates the assessment of estimation quality. Traditional metrics such as sum of squared errors (SSE) may not fully capture the fidelity of parameter estimates when nonlinear relationships dominate system behavior. Researchers have therefore developed multiple evaluation criteria, including mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2), to provide comprehensive assessments of estimation accuracy [17]. Furthermore, nonlinearities exacerbate the challenges posed by limited and noisy measurement data. He et al. [18] note that insufficient current and voltage data from PEMFC measurements leads to low precision rates in parameter extraction, while excessive noise can significantly distort the estimation process. These challenges have motivated the development of data-preprocessing techniques and hybrid approaches that combine multiple methodologies to enhance robustness.

3.4. Common Themes and Methodological Insights

The reviewed studies consistently evaluate parameter-estimation methods using widely recognized commercial PEMFC stacks. The use of these benchmark systems has become standard practice because it enables objective performance assessment and facilitates direct comparison among different parameter estimation techniques under comparable operating conditions. Such benchmark stacks also provide a common basis for evaluating the accuracy, robustness, and general applicability of the reported methods.

To provide a consistent comparative assessment, this review considers several representative commercial PEMFC stacks with different power ratings, including Ballard, Horizon, NedStack, and BCS fuel cell modules. These systems have been extensively adopted in the literature and represent a broad range of operating characteristics, making them suitable benchmark cases for comparative analysis.

Table 2 summarizes the datasheet specifications of the different reported PEMFC stacks used in the analysis. These specifications include the key operating parameters that characterize each stack and form the basis for the modeling procedure.

Table 3 presents the reported model parameters extracted from the cited literature for the investigated PEMFC stacks. To establish a unified basis for comparison, the published parameter sets were implemented to regenerate the corresponding model responses and reproduce the electrical characteristics reported in the original studies. The parameter search ranges presented in this review are extracted from the corresponding cited publications. Because different studies consider different PEMFC models and optimization strategies, the reported bounds are not identical.

Table 2. Datasheet specifications of different reported stacks.

Fuel Cell	N Cell	A (cm^2)	Jmax Acm^{-2}	L (μm)	PH2 (bar)	Po2 (bar)	T (K)	RHa, RHc
M/S Ballard 1000 W [19]	35	50.6	1.5	178	1	1	343.15	1
Horizon H-12 [20–22]	13	8.1	0.86	25	0.4935	1	302.15	1
NedStack PS6 [22]	65	240	1.4	178	1	1	343	1
250 W [23]	24	27	860	127	1	1	343.15	1
BCS 500 W	32	64	0.469	178	1	0.2095	333	1
3 kW PEMFC	83	40	1.2	100	1.5	1.3	343	1
AVISTA SR12 PEMFC 500 W	48	62.5	0.672	25	1.47628	0.2095	323.15	1

Table 3. Parameter estimation of PEMFC for the different reported stacks models.

	$\varepsilon 1$	$\varepsilon 2$	$\varepsilon 3$	$\varepsilon 4$	λ	RC	β	SSE
Ballard Mark V model [23]	−1.0059	0.0016	3.4698×10^{-5}	-1.6129×10^{-4}	14.6827	0.00031	0.2156	6.6216×10^{-9}
Avista SR-12 model. [23]	−1.0432	0.0014	7.8963×10^{-5}	-1.0965×10^{-4}	14.8896	0.00044	0.2416	5.65×10^{-8}
BCS 500 W [24]	−1.1997	4.04218×10^{-3}	9.799806×10^{-5}	-1.92893×10^{-4}	20.81806	1×10^{-4}	0.0161	0.0115564
NedStack PS6 [25]	−1.008511	3.0434×10^{-3}	4.9796×10^{-5}	-9.54×10^{-5}	13.4457	0.1×10^{-3}	0.0136	2.11125
250 W [26]	−0.979534	3.06503×10^{-3}	5.78132×10^{-5}	-1.736635×10^{-4}	20.52212	3.4052×10^{-4}	1.57026×10^{-2}	0.34237
Temasek 1 KW [27]	−1.1821	4.5823×10^{-3}	9.6303×10^{-5}	-2.2863×10^{-4}	18.3862	1.034×10^{-4}	0.09603	0.792682
Horizon H-12 [28]	−0.85435	20.09613×10^{-4}	6.76763×10^{-5}	-9.54000×10^{-5}	23	0.1×10^{-3}	0.18685	$9.65360596 \times 10^{-2}$

Table 4 compares the reported experimental voltage data with the regenerated model voltages obtained using the published parameter values. This comparison demonstrates the consistency of the reproduced results and provides a common framework for evaluating the performance of different parameter estimation approaches reported in the literature. It should be noted that the performance metrics reported in the literature are not always directly comparable across different PEMFC stacks. In particular, the SSE depends on the number of experimental data points, the voltage range, and the operating conditions considered in each study. Therefore, a lower SSE obtained for one PEMFC stack does not necessarily indicate superior estimation performance compared with a higher SSE reported for another stack. Meaningful performance comparisons should preferably be conducted using identical benchmark datasets and evaluation conditions or by employing normalized error metrics, such as RMSE, normalized RMSE (NRMSE), or relative error measures, whenever these metrics are available. Consequently, the performance indicators summarized in this review should be interpreted within the context of the corresponding experimental setup reported in each reference.

Figure 4 illustrates the current–voltage (I–V) polarization characteristics of the investigated PEMFC stacks. The regenerated model responses, obtained using the published parameter values, are compared with the corresponding experimental data reported in the literature. The close agreement between the two confirms the reproducibility of the reported models and facilitates a consistent comparative evaluation of the parameter-estimation methods discussed in this review. The 250 W stack is presented according to the data available in the original reference. Overall, the figure provides a consistent visual comparison of the reported PEMFC characteristics across the benchmark stacks.

Table 4. Measured and estimated values for the voltage for the different reported stacks.

Ballard Mark V Model.			Avista SR-12 Model.			Temasek 1 KW		
Current Measured (A)	**Voltage Measured (V)**	**Voltage Calculated (V)**	**Current Measured (A)**	**Voltage Measured (V)**	**Voltage Calculated (V)**	**Current Measured (A)**	**Voltage Measured (V)**	**Voltage Calculated (V)**
5.4	0.92	0.9211	1.004	43.17	43.04	10.78	18.5012	17.9776
10.8	0.88	0.8721	3.166	41.14	41.17	14.85	17.1194	17.4359
16.2	0.85	0.8451	5.019	40.09	40.04	19.27	16.6979	16.9739
21.6	0.82	0.8176	7.027	39.04	39.03	23.87	16.4403	16.5757
27.0	0.79	0.7858	8.958	37.99	37.98	28.29	16.089	16.244
32.4	0.77	0.7682	10.97	37.08	37.1	36.95	15.5972	15.686
37.8	0.74	0.7361	13.05	36.03	36.05	41.72	15.4567	15.4137
43.2	0.72	0.7112	15.06	35.19	35.20	46.32	15.1288	15.168
48.6	0.69	0.6887	17.07	34.07	34.09	50.74	15.0117	14.9436
54.0	0.66	0.6562	19.07	33.02	33.04	55.34	14.9415	14.72
59.4	0.62	0.6175	21.08	32.04	32.06	59.05	14.7307	14.5454
64.8	0.60	0.5918	23.01	31.20	31.24	63.65	14.4731	14.3352
70.2	0.55	0.5507	24.94	29.80	29.84	68.42	14.2389	14.1225
			26.87	28.96	28.99	72.67	14.0749	13.9373
			28.96	28.12	28.17	77.44	13.7939	13.7321
			30.81	26.3	26.32	81.33	13.4426	13.567
			32.97	24.06	24.12	86.11	12.9977	13.3659
			34.90	21.40	21.44			
S 500 W			**NedStack PS6**			**250 W**		
Current Measured (A)	**Voltage Measured (V)**	**Voltage Calculated (V)**	**Current Measured (A)**	**Voltage Measured (V)**	**Voltage Calculated (V)**	**Current Measured (A)**	**Voltage Measured (V)**	**Voltage Calculated (V)**
0.6	29	28.9969	2.25	61.64	65.6945	0.29	23.572	23.9369
2.1	26.31	26.3064	6.75	59.57	61.4785	1.9	21.5166	21.2307
3.58	25.09	25.0942	9	58.94	60.3339	2.59	20.5517	20.7328
5.08	24.25	24.2553	15.75	57.54	58.0161	3.82	19.924	20.0661
7.17	23.37	23.376	20.25	56.8	56.9179	5.53	19.5915	19.3706
9.55	22.57	22.585	24.75	56.13	56.0049	6.95	19.0482	18.8939
11.35	22.06	22.0715	31.5	55.23	54.8534	7.89	18.546	18.606
12.54	21.75	21.7586	36	54.66	54.1843	10.94	17.9642	17.7704
13.73	21.45	21.4613	45	53.61	53.0036	13.59	17.3815	17.1
15.73	21.09	20.9876	51.75	52.86	52.2156	16.46	16.2111	16.3775
17.02	20.68	20.6943	67.5	51.91	50.5848	17.48	16.0031	16.1115
19.11	20.22	20.2308	72	51.22	50.1567	18.86	15.5858	15.7304
21.2	19.76	19.7708	90	49.66	48.5531	20.31	15.2107	15.282
23	19.36	19.3661	99	49	47.7981	21.99	14.668	14.6015
25.08	18.86	18.8669	105.8	48.15	47.2417	22.93	13.8297	13.808
27.17	18.27	18.2759	110.3	47.52	46.8787			
28.06	17.95	17.9548	117	47.1	46.3444			
29.26	17.3	17.2921	126	46.48	45.6352			

Table 4. *Cont.*

S 500 W			NedStack PS6			250 W		
Current Measured (A)	**Voltage Measured (V)**	**Voltage Calculated (V)**	**Current Measured (A)**	**Voltage Measured (V)**	**Voltage Calculated (V)**	**Current Measured (A)**	**Voltage Measured (V)**	**Voltage Calculated (V)**
			135	45.66	44.9321			
			141.8	44.85	44.4025			
			150.8	44.24	43.701			
			162	42.45	42.8221			
			171	41.66	42.1067			
			182.3	40.68	41.1904			
			189	40.09	40.6341			
			195.8	39.51	40.0567			
			204.8	38.73	39.2676			
			211.5	38.15	38.6598			
			220.5	37.38	37.799			
	H-12							
Current Measured (A)	**Voltage Measured (V)**	**Voltage Calculated (V)**						
0.104	9.58	9.993						
0.2	9.42	9.5609						
0.309	9.25	9.2698						
0.403	9.2	9.0898						
0.51	9.09	8.9282						
0.614	8.95	8.7991						
0.703	8.85	8.7038						
0.806	8.74	8.6064						
0.908	8.65	8.5203						
1.076	8.45	8.3956						
1.127	8.41	8.3611						
1.288	8.2	8.2601						
1.39	8.12	8.2014						
1.45	8.11	8.1685						
1.578	8.05	8.1018						
1.707	7.99	8.0386						
1.815	7.95	7.9885						
1.9	7.94	7.9506						
2.06	7.9	7.9075						

The analyzed fuel cell stacks include several reported PEMFC systems with different power ratings and manufacturers, namely the Ballard 1000 W PEMFC stack, Horizon H-12 PEMFC stack, NedStack PS6 PEMFC stack, 250 W PEMFC stack, BCS 500 W PEMFC stack, 3 kW PEMFC stack, and AVISTA SR-12 PEMFC 500 W stack. Considering this diverse set of stacks allows evaluation of the proposed parameter estimation technique under various operating capacities and design characteristics. Such diversity provides a broader

validation framework and improves confidence in the accuracy and robustness of the developed model.

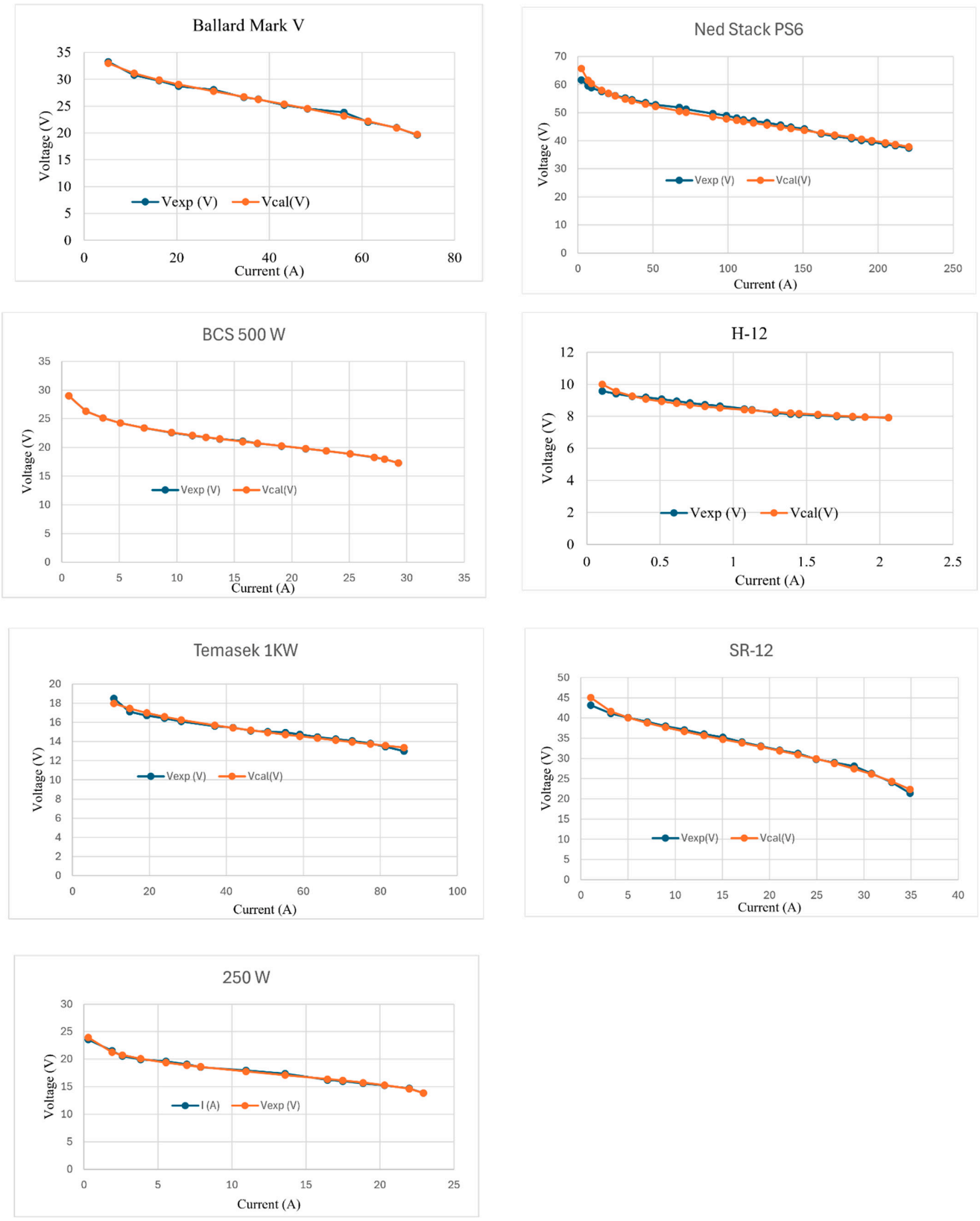


Figure 4. The I/V polarization curves of the different reported stacks.

4. Methods for PEMFC Parameter Estimation

4.1. Analytical and Semiempirical Methods

Analytical and semiempirical methods represent the foundational approaches to PEMFC parameter estimation, rooted in the electrochemical principles governing fuel cell operation. These methods establish mathematical relationships between measurable quantities—such as voltage, current, temperature, and pressure—and the underlying physical parameters that characterize fuel cell behavior. While they have been largely superseded by computational intelligence techniques in recent research, their theoretical rigor and interpretability continue to provide valuable insights for model development and validation.

4.1.1. Fundamental Analytical Models

The analytical modeling of PEMFCs typically begins with the fundamental electrochemical relationship describing cell voltage as a function of current density and operational conditions. The standard semiempirical model, often attributed to Mann and colleagues, expresses the cell voltage as follows:

$$V = E_{Nernst} - V_{act} - V_{ohmic} - V_{conc}$$

where E_{Nernst} represents the thermodynamic reversible potential, while V_{act}, V_{ohmic}, and V_{conc} correspond to voltage losses due to activation polarization, ohmic resistance, and concentration polarization, respectively [1]. Each of these terms incorporates multiple parameters that must be estimated from experimental data.

The Nernst potential itself depends on temperature and partial pressures of reactants, introducing nonlinear dependencies that must be carefully characterized. Activation losses follow Tafel-type kinetics, with parameters reflecting the exchange current density and charge transfer coefficients. Ohmic losses incorporate membrane resistance, which varies with hydration state and temperature. Concentration losses capture mass transport limitations at high current densities, with parameters describing limiting current density and mass transfer coefficients.

The analytical approach to parameter estimation involves fitting these theoretical expressions to experimental polarization curves using regression techniques. However, the nonlinear parameterization and coupling between terms complicate this process, often requiring sophisticated numerical methods even within the analytical framework [29].

4.1.2. Semiempirical Model Formulations

Semiempirical models occupy an intermediate position between purely theoretical analytical models and purely data-driven empirical models. They retain the structural form suggested by physical principles while employing empirical parameters that must be identified from experimental data. This approach balances physical interpretability with practical applicability, making it widely adopted in PEMFC modeling.

The classical semiempirical model of the polarization curve suffers from nonseparable parameterization, which complicates its application in real-time scenarios [7]. The parameters affecting concentration losses, in particular, exhibit nonlinear relationships that cannot be easily decoupled from other loss terms. This characteristic has motivated efforts to transform these models into more tractable forms.

Sultan et al. (2020) [30] developed a precise semiempirical mathematical model for PEMFCs based on multi-nonlinear equations, employing the coyote optimization algorithm to extract seven and ten unknown parameters. Their approach demonstrated

that semiempirical models, when combined with effective optimization techniques, could achieve accurate representation of fuel cell behavior across varying operating conditions.

The choice between seven-parameter and ten-parameter formulations represents an important consideration in semiempirical modeling. Seven-parameter models typically capture the essential electrochemical behavior with reasonable parsimony, while ten-parameter formulations incorporate additional degrees of freedom that may improve fit at the cost of increased identifiability challenges [30]. Riad et al. (2023) [25] utilized Mann's model with seven uncertain parameters to describe the nonlinear voltage–current polarization curve, demonstrating that this formulation, when optimized with the artificial rabbits algorithm, achieved excellent agreement with experimental data from multiple PEMFC stacks.

4.1.3. Classical Optimization Techniques

Traditional optimization techniques applied to analytical and semiempirical PEMFC models have primarily relied on least squares methods and gradient-based algorithms. These approaches offer mathematical rigor and computational efficiency when the optimization problem is well-behaved, but their limitations become apparent in the face of nonlinearity and multimodality.

The least squares method, in both linear and nonlinear formulations, has been extensively applied to PEMFC parameter estimation. The objective function typically minimizes the sum of squared errors between model-predicted and experimentally measured voltages. However, Xu et al. (2025) demonstrated that classical least squares estimators showed inferior performance compared to more advanced techniques in both steady and transient states, highlighting the limitations of conventional approaches [7].

Gradient descent methods, which iteratively adjust parameters in the direction of steepest descent of the objective function, have also been applied to PEMFC models. These methods are sensitive to initial value guesses and can converge to local optima when the objective function is multimodal. The classical GD estimator exhibited less performance compared to dynamic regressor extension and mixing-based least squares (DREM + LS) and composite learning (CL) estimators in comparative studies (Xu et al., 2025) [7].

The Levenberg–Marquardt algorithm, which combines gradient descent and Gauss–Newton approaches, represents a more sophisticated classical method that has shown promise in PEMFC applications. You-sheng (2009) applied the Levenberg–Marquardt algorithm combined with universal global optimization of 1stOpt to optimize parameters in the PEMFC polarization curve model [31,32]. This approach successfully avoided issues and imprecise modeling results arising from inappropriate initial value guesses, demonstrating excellent modeling ability. The study concluded that 1stOpt provides an ideal, practical, and efficient method for PEMFC model optimization, though its reliance on commercial software limits accessibility.

4.1.4. Transformations to Linear Regression Forms

A significant advance in analytical methods has been the development of techniques to transform nonlinear PEMFC models into linear regression equations, enabling the application of conventional linear estimation methods with guaranteed convergence properties. Beltrán et al. (2024) developed a procedure to transform nonseparable nonlinear parameterization (NSNLP) into a separable one, facilitating the implementation of parameter estimators with global convergence properties [3].

Xu et al. (2025) introduced a differential operator-based method to transform the classical semiempirical model of polarization curves into a linear regression equation (LRE) [7]. This transformation enables the application of four online estimators—gradient descent (GD), least squares (LS), dynamic regressor extension and mixing-based least

squares (DREM + LS), and composite learning (CL)—to estimate the derived LRE. Their results demonstrated that the DREM + LS and CL estimators achieved smoother tracking processes and faster response speeds than classical estimators during experiments on two different PEMFCs under varying operating conditions.

This transformation approach represents a promising direction for bridging the gap between theoretically rigorous analytical methods and practically applicable online estimation. By converting nonseparable nonlinear problems into separable forms, these methods retain physical interpretability while gaining the computational advantages and convergence guarantees of linear estimation.

4.1.5. Limitations of Analytical and Semiempirical Methods

Despite their theoretical foundations and interpretability, analytical and semiempirical methods face several inherent limitations that have motivated the development of alternative approaches. Priya et al. (2018) highlighted the challenges posed by nonlinearity, multivariate characteristics, and data shortages in fuel cell modeling, noting that these factors complicate the application of conventional analytical techniques [1].

The presence of a large number of unknown parameters—typically seven or more in comprehensive models—creates identifiability challenges even when the model structure is theoretically sound. Parameters may be correlated in ways that prevent unique identification from available measurements, leading to the duplicity problem where multiple parameter sets yield equivalent model performance [10,11].

The sensitivity of analytical methods to initial value guesses represents another significant limitation. Inappropriate initialization can lead to convergence failures or parameter estimates that represent local rather than global optima [31]. This sensitivity undermines the reliability of analytical approaches, particularly when applied by users without extensive expertise in numerical optimization.

Furthermore, the assumption that model structure perfectly captures physical reality may be violated in practice. Unmodeled dynamics, spatial variations, and degradation effects can introduce discrepancies between analytical predictions and actual fuel cell behavior that cannot be resolved through parameter adjustment alone [3].

These limitations have motivated the development and adoption of metaheuristic optimization algorithms and intelligent techniques, which offer greater flexibility in navigating complex, nonlinear parameter spaces and reduced sensitivity to initial conditions. However, analytical and semiempirical methods continue to provide the theoretical foundation upon which these more advanced techniques are built, and recent advances in transformation methods suggest ongoing opportunities for their refinement and application.

4.2. Metaheuristic Optimization Algorithms

Metaheuristic algorithms have emerged as the dominant approach for PEMFC parameter estimation, offering the ability to explore complex search spaces without requiring gradient information or convexity assumptions. These methods draw inspiration from natural phenomena, social behaviors, and physical processes to balance exploration and exploitation in the search for optimal parameters.

4.2.1. Evolutionary Algorithms

Evolutionary algorithms, including Genetic Algorithms (GAs) and Memetic Algorithms (MAs), have been extensively applied to PEMFC parameter identification. The authors of [33] evaluated multiple evolutionary approaches, including GA, MA, Evolutionary Programming (EP), Flower Pollination Algorithm (FPA), and Coral Reefs Optimization (CRO), for optimizing PEMFC parameters. The Memetic Algorithm demonstrated superior performance, achieving the lowest sum of square error of (2.37) for PEMFC NedStack

PS6 and exhibiting the smallest interquartile range in statistical analysis, indicating both accuracy and consistency.

The effectiveness of evolutionary algorithms derives from their population-based search mechanisms, which maintain diversity and reduce the risk of premature convergence. However, their performance depends critically on parameter tuning and may require substantial computational resources for complex problems [11].

4.2.2. Swarm Intelligence Methods

Swarm intelligence algorithms, which model the collective behavior of decentralized systems, have gained significant traction in PEMFC parameter estimation. These methods leverage simple local interactions to achieve sophisticated global optimization behavior.

The Particle Swarm Optimization (PSO) algorithm, one of the earliest swarm intelligence methods applied to fuel cell parameterization, has been widely studied. The authors of [11] demonstrated that, while PSO is effective for parameter identification, the Differential Evolution (DE) method provides better results and higher robustness. This finding has motivated the development of numerous DE variants and hybrid approaches.

More recent swarm intelligence algorithms have shown promising results. The Whale Optimization Algorithm (WOA) demonstrated significant enhancement in accuracy and convergence speed compared to PSO, achieving a mean absolute error of only 0.0726 V between predicted and real data for Heliocentris-FC50 [34]. The Sea Horse Optimization (SeaHO) algorithm achieved remarkable accuracy with a mean absolute error of 0.001079 and a coefficient of determination (R^2) of 0.999791 for Ballard Mark V PEMFC [17]. The Bald Eagle Search (BES) algorithm exhibited faster convergence compared to other methods, making it particularly suitable for real-time applications [35].

Similarly, the coyote optimization algorithm (COA) developed by Sultan et al. (2023) yielded very competitive outcomes for both seven-parameter and ten-parameter PEMFC models [13].

Table 5 presents a comprehensive compilation of 30 studies published between 2020 and 2025, documenting the rapid evolution of metaheuristic optimization algorithms applied to Proton Exchange Membrane Fuel Cell (PEMFC) parameter estimation. This body of literature reflects the field's recognition that accurate parameter identification is fundamental to PEMFC modeling, performance optimization, and practical deployment. The proliferation of novel algorithms—drawing inspiration from natural phenomena, animal behaviors, physical processes, and mathematical concepts—demonstrates both the importance of the parameter estimation problem and the continuing search for methods that balance accuracy, computational efficiency, and robustness.

4.2.3. Algorithmic Diversity and Innovation

The studies summarized in Table 5 reveal remarkable diversity in optimization approaches. Bio-inspired algorithms dominate the landscape, including those mimicking sea horses [17], bald eagles [35,36], dung beetles [37], gazelles [13], prairie dogs [13], rabbits [25,38], horned lizards [39], spotted hyenas [40], whales [34], and marine predators [24]. This biological inspiration reflects the recognition that nature has evolved efficient search strategies for complex, multimodal optimization problems analogous to PEMFC parameter estimation.

Physics-based and mathematical algorithms complement bio-inspired approaches, including those based on supply–demand dynamics [41], Henry's gas solubility [42], rime-ice formation [43], opposition-based arithmetic [44], and transient search [45]. Evolutionary algorithms, particularly Differential Evolution variants, continue to show strong perfor-

mance, with hierarchical population-based [46], historical population-based [47], and ameliorated [48] versions demonstrating superior results.

4.2.4. Performance Metrics and Comparative Assessment

The studies consistently employ sum of squared errors (SSE) as the primary objective function, quantifying the discrepancy between model-predicted and experimentally measured voltages. Additional metrics include mean absolute error (MAE), root mean square error (RMSE), coefficient of determination (R^2), convergence speed, and computational time. The reported results demonstrate remarkable progress in estimation accuracy for the case of BCS 500 W PEMFC, with [17] achieving MAE of 0.001079 and R^2 of 0.999791, while [49] reported SSE values as low as 0.00002.

Convergence speed emerges as a critical differentiator, with several algorithms demonstrating rapid optimization. Erduman et al. [17] recorded average convergence time of 1.74 s for 5000 iterations with SHO, while Liu et al. [50] achieved convergence in under 30 iterations with momentum PSO. These advances are particularly significant for real-time applications and digital twin development, where computational efficiency is paramount.

4.2.5. Addressing Key Challenges

The reviewed literature explicitly addresses several fundamental challenges in PEMFC parameter estimation. Premature convergence and local optima entrapment—limitations of conventional algorithms—are repeatedly cited as motivations for novel approaches. Zhang et al. (2024) developed IDBO specifically to address local optima issues [37], while Chen et al. (2022) introduced bi-subpopulation strategies to maintain solution diversity and avoid premature convergence [51].

Nonlinearity and parameter coupling represent inherent characteristics of PEMFC models that complicate estimation. Danoune et al. [34] highlighted the challenge of nonlinear coupled parameters, while Priya et al. (2024) addressed the multivariate nature of PEMFC modeling [40]. Algorithms such as HLDTOA [39] and HPDE [46] demonstrate particular effectiveness in navigating these complex search spaces.

Noise and data insufficiency pose practical challenges for real-world applications. Yang et al. (2024) [15] addressed these issues through feedforward neural network preprocessing combined with pelican optimization, achieving 99.44% RMSE reduction. He et al. (2023) employed GRNN for de-noising and data prediction, achieving fitting accuracy exceeding 99% under various operating conditions [18].

Parameter uncertainty and identifiability concerns are addressed through comprehensive validation across multiple PEMFC types. Studies routinely test algorithms on commercial stacks including Ballard Mark V, NedStack PS6, BCS 500 W, and Horizon stacks, demonstrating generalizability. Khishe et al. (2024) validated HPDE on 12 distinct PEMFCs [46], while Priya et al. (2024) compared SHO against 25 established methodologies [40].

4.2.6. Limitations and Research Gaps

The studies in Table 5 exhibit limitations consistent with the broader literature. Most notably, several studies do not explicitly discuss algorithm limitations, potentially presenting an incomplete picture of method capabilities and constraints. When limitations are acknowledged, they typically reference challenges of conventional algorithms rather than the proposed methods themselves.

He et al. (2023) provide the most comprehensive limitation discussion, noting the complexity of nonlinear optimization, the inadequacy of traditional numerical methods, the challenges of insufficient data, and complications from measurement noise [18]. This transparency is valuable for researchers seeking to understand the boundaries of current approaches.

Abbassi et al. (2023) identify specific weaknesses addressed by their DO algorithm—self-adaptation, convergence stagnation, whole population reference—providing insight into the design rationale [6]. However, limitations of the proposed method itself are not elaborated.

4.2.7. Validation and Practical Applicability

The studies demonstrate increasing emphasis on experimental validation and practical applicability. Baz et al. (2024) [38] validated ARO on a SCRIBNER 850e fuel cell test system, bridging the gap between simulation and laboratory implementation. Danoune et al. [34] conducted experiments on a commercial 40 W Heliocentris PEMFC, confirming algorithm effectiveness under real conditions. Sultan et al. employed MATLAB/Simulink (R2018a) for validation across multiple PEMFC models, ensuring reproducibility and practical utility [13,30].

Several studies explicitly target applications such as digital twins in the automotive industry [35], smart transportation [52], and clean energy systems [42], demonstrating awareness that algorithmic advances must ultimately translate to real-world impact.

4.2.8. Limitations and Persistent Challenges of Metaheuristic Optimization Algorithms for PEMFC Parameter Estimation

Despite impressive advances, the reviewed literature reveals persistent limitations. Many studies do not explicitly discuss algorithm limitations, potentially overstating capabilities. When limitations are acknowledged, common themes include the following:

1. Sensitivity to parameter ranges: Abdi et al. (2021) noted that optimal objective function values are significantly influenced by specified parameter bounds, highlighting the importance of appropriate initialization [53].
2. Computational requirements: While many algorithms demonstrate efficiency, the computational demands of population-based methods for high-dimensional problems remain a consideration for real-time applications.
3. Generalizability concerns: Despite validation across multiple PEMFC types, questions remain about algorithm performance on novel configurations or degraded systems not represented in training data.
4. Noise sensitivity: He et al. (2023) and Yang et al. (2024) explicitly address noise challenges, acknowledging that measurement uncertainty continues to complicate parameter identification [15,18].
5. Theoretical foundations: While empirical performance is well-documented, theoretical understanding of convergence properties and optimal parameter selection for many novel algorithms remains limited.

4.2.9. Addressing Practical Challenges

Several studies explicitly address real-world challenges including data noise [18], computational efficiency [17], and parameter uncertainty [41]. This practical orientation reflects maturation of the field beyond purely algorithmic demonstrations toward application-relevant contributions.

4.2.10. Synthesis and Future Directions of Metaheuristic Optimization Algorithms for PEMFC Parameter Estimation

The collective findings from Table 5 support several overarching conclusions about the state of metaheuristic optimization for PEMFC parameter estimation:

1. First, algorithmic diversity has enriched the field but also creates challenges for method selection. The proliferation of algorithms—many demonstrating excellent performance—suggests that no single method universally dominates, and selection

should be guided by problem-specific requirements including accuracy needs, computational constraints, and data quality.

2. Second, convergence speed has emerged as a critical performance dimension alongside accuracy. Algorithms achieving rapid convergence without compromising solution quality are particularly valuable for real-time monitoring, adaptive control, and digital twin applications.
3. Third, validation across multiple PEMFC types has become standard practice, enhancing confidence in algorithm generalizability. Studies testing algorithms on 5–12 distinct stacks [40,46] provide particularly compelling evidence of robustness.
4. Fourth, integration with machine learning for data preprocessing represents a promising direction for addressing practical challenges of noise and data insufficiency. The success of FNN-POA [15] and GRNN-based approaches [18] suggests that hybrid methodologies will increasingly dominate future research.
5. Fifth, the gap between algorithmic development and practical deployment is narrowing, with increasing emphasis on experimental validation and application-specific targeting. This trend should accelerate as PEMFC technology matures toward commercialization.

Moreover, several studies suggest several directions for future investigation:

1. Hybrid methodologies combining neural network preprocessing with metaheuristic optimization, as demonstrated by He et al. (2023), merit further development for addressing data quality challenges [18].
2. Algorithm-specific sensitivity analysis, as conducted by Erduman et al. (2025) [17], provides valuable insights for parameter tuning and should be extended across optimization methods.
3. Application-focused validation targeting specific domains such as digital twins [35] and electric vehicles (Mujeer et al., 2024) should be expanded to accelerate technology transfer [52].
4. Transparent limitation reporting would enhance the field's ability to identify persistent challenges and match algorithms to appropriate applications.
5. Comparative studies like those of Khajuria et al. [54] provide valuable guidance for algorithm selection and should be extended to include emerging methods.

4.2.11. Comparative Algorithm Evaluations

Rezk et al. (2023) evaluated five optimization algorithms for PEMFC parameter identification, identifying Bald Eagle Search (BES) as achieving the lowest SSE (0.035102) and fastest convergence [35]. The study's focus on digital twin applications in the automotive industry reflects growing interest in translating algorithmic advances to practical deployment contexts. Khajuria et al. [54] compared six nature-inspired algorithms across two studies, consistently identifying Swarm Robotics Search and Rescue (SRSR) as the best-performing method for extracting seven parameters and analyzing temperature and pressure effects on polarization curves.

4.2.12. Emphasis on Multiple Evaluation Criteria

Beyond reporting best-case performance, studies increasingly employ comprehensive evaluation metrics including worst SSE, mean SSE, standard deviation, and convergence speed. This multi-criteria assessment provides a more nuanced understanding of algorithm reliability and consistency.

4.2.13. Integration of Domain Knowledge

The selection of parameters for estimation—typically seven to nine critical variables derived from electrochemical models—demonstrates integration of domain knowledge with optimization methodology. This synergy between fuel cell science and computational intelligence is essential for meaningful parameter identification.

The studies in Table 5 reinforce and extend the findings from the broader literature on metaheuristic optimization for PEMFC parameter estimation. They demonstrate continued innovation in algorithm development, increasing sophistication in validation methodologies, and growing attention to practical deployment considerations. The diversity of approaches—from market-inspired SDO to biologically inspired SHO, from neural network enhancement to Differential Evolution variants—reflects the richness of the optimization landscape and the complexity of the parameter estimation challenge. As the field progresses toward real-time applications, digital twins, and commercial deployment, the foundation established by these studies will prove invaluable for developing robust, accurate, and efficient parameter-estimation methodologies.

Table 5. Comprehensive summary of metaheuristic optimization algorithms for PEMFC parameter estimation.

No.	Reference	Optimization Algorithm	Key Results	Main Contributions
[17]	Erduman et al. (2025)	Sea Horse Optimization (SeaHO)	MAE of 0.001079; R^2 of 0.999791; model-to-experiment fit of 99.92%; convergence time of 1.74 s for 5000 iterations	Introduces SeaHO as novel metaheuristic for PEMFC parameter estimation; conducts parametric sensitivity analysis on SeaHO control parameters; demonstrates rapid convergence and low computational cost
[35]	Rezk et al. (2023)	Bald Eagle Search (BES), Equilibrium Optimizer (EO), Coot (COOT), Antlion Optimizer (ALO), Heap-Based Optimizer (HBO)	BES achieved lowest SSE of 0.035102; BES showed faster convergence speed than other algorithms	Utilizes optimization algorithms for PEMFC parameter identification; develops accurate performance prediction model for digital twin applications in automotive industry
[37]	Zhang et al. (2024)	Improved Dung Beetle Optimization (IDBO)	IDBO demonstrated better convergence and higher accuracy than traditional DBO; successfully applied to BCS 500 W, NedStack PS6, and 3 kW custom system	Addresses local optima entrapment in existing intelligent algorithms; validates robustness on commercial and custom PEMFC systems
[46]	Khishe et al. (2024)	Hierarchical Population-Based Differential Evolution (HPDE)	Efficiently identifies parameters for 12 distinct PEMFCs; outperforms various DE algorithms with superior results	Introduces novel HPDE with diversity metrics; demonstrates effectiveness across diverse fuel cell types; validates against simulated and experimental data
[13]	Sultan et al. (2023)	Gazelle Optimization (GOA), Prairie Dog (PDO), Reptile Search (RSA)	GOA achieved best average objective (0.0115 for BCS 500 W); tracking efficiencies: GOA 100%, PDO 99.99%, RSA 100%; I/V curves show good agreement with measured data	Evaluates three novel metaheuristics for PEMFC parameter identification; validates on three PEMFC models (BCS 500 W, SR-12 500 W, 250 W stack); formulates SSE-based objective function

Table 5. *Cont.*

No.	Reference	Optimization Algorithm	Key Results	Main Contributions
[38]	Baz et al. (2024)	Artificial Rabbits Optimization (ARO)	ARO outperformed GWO, PSO, SSA, and SCA; validated on SCRIBNER 850e fuel cell test system; minimizes SSE between measured and output voltages	Introduces ARO mimicking natural rabbit survival strategies; demonstrates practical applicability through laboratory tests; provides comparative analysis with four established algorithms
[39]	Kanouni et al. (2025)	Horned Lizard Defense Tactics Optimization (HLDTOA)	SSE improvements: 37.23% (1.02274 to 0.64193), 18.37% (0.11827 to 0.09653), 3.32% (1.09268 to 1.05637), 27.32% (2.07 to 1.50433)	Introduces HLDTOA for precise parameter identification; demonstrates significant SSE reductions across multiple PEMFCs; confirms robustness through statistical analyses
[44]	Sharma et al. (2021)	Opposition-Based Arithmetic Optimization (OBAOA)	Accurately retrieves PEMFC parameters; cost function based on sum of square deviations; validated on Ballard Mark V	Introduces novel OBAOA for parameter extraction; validates through benchmark functions; demonstrates efficiency compared to other optimizers
[36]	Zaky et al. (2023)	Modified Bald Eagle Search (mBES)	Outperforms other comparison models; achieves best results in system correctness and convergence	Proposes precise unknown parameter extraction method using mBES; demonstrates superiority over other metaheuristic algorithms
[41]	Al-Shamma'a et al. (2021)	Supply–Demand-Based Optimization (SDO)	Minimizes SSE between experimental and simulated I-V curves; evaluates nine parameters (ξ1-ξ4, Rc, β, λ, l, Jmax); outperforms WOA, GWO, HHO, GA	Introduces SDO for parameter extraction; validates on four experimental datasets and two PEMFC stacks (BSC500 W, 500 W Horizon); comprehensive evaluation criteria
[55]	Mossa et al. (2021)	Harris Hawks Optimization (HHO), Atom Search Optimization (ASO)	HHO and ASO effectively estimated parameters; HHO outperformed other algorithms in accuracy and convergence speed	Applies novel metaheuristics for PEMFC parameter estimation; validates on three commercial PEMFC stacks; achieves precise polarization curve identification
[48]	Kanouni and Laib (2024)	Differential Evolution Ameliorated (DEA)	Rapidly and accurately identifies optimal PEMFC parameters; superior performance compared to other optimization algorithms	Introduces hybridized DEA algorithm for parameter extraction; conducts comparative analysis in MATLAB/Simulink; minimizes SSE between experimental and obtained voltage data
[6]	Abbassi et al. (2023)	Dandelion Optimizer (DO)	Outperforms GWO, GBO, HHO, IAEO, VSDE, ABCDESC; effective in steady-state and dynamic situations	Proposes DO for accurate parameter identification; addresses self-adaptation and convergence stagnation; evaluates on 250 W PEMFC and NedStack PS6
[47]	Aljaidi et al. (2024)	Historical Population-Based Differential Evolution (HiP-DE)	Outperforms JADE, SaDE, LSHADE, iLSHADE, PalmDE, PSO-DE, jSO, LPalmDE, HARD-DE; evaluated on six commercial stacks (twelve distinct PEMFCs); I/V and P/V curves closely match datasheet	Introduces dynamic HiP-DE with novel diversity metric; validates across multiple operating conditions; demonstrates superior solution accuracy and convergence speed

Table 5. *Cont.*

No.	Reference	Optimization Algorithm	Key Results	Main Contributions
[53]	Abdi et al. (2021)	PSO with Constriction Coefficient (PSO-χ)	Optimal parameter values significantly influenced by specified ranges; noticeable performance improvement compared to other methods; confirms suitability for PEMFC optimization	Introduces PSO variants with constriction coefficient for enhanced convergence; validates against experimental polarization curves; demonstrates improved stack performance
[40]	Priya et al. (2024)	Spotted Hyena Optimizer (SHO)	Achieved lowest SSE for five fuel cell stacks; best objective function efficiency of 98.6034%; outperforms 25 established methodologies	Presents novel SHO based on hyena hunting behavior; addresses nonlinearity and multivariate challenges; ranks algorithms using TOPSIS, MOORA, and COPRAS
[54]	Khajuria et al. (2022a)	Bald Eagle Search (BES), Coyote Optimization (COA), Brain Storm Optimization (BSO), Harris Hawks (HHO), Gradient-Based Optimizer (GBO), Swarm Robotics Search and Rescue (SRSR)	SRSR identified as best for optimal parameter estimation; evaluated parameters aid in studying pressure and temperature effects	Compares six nature-inspired algorithms; extracts seven parameters; analyzes polarization curves and operating condition effects
[52]	Mujeer et al. (2024)	Dandelion Optimizer (DO)	Excellent accuracy in parameter estimation; simulation results outperform traditional optimization techniques; applied to Ballard Mark V and BCS 500-W stacks	Introduces DO for parameter identification based on I-V characteristics; demonstrates effectiveness for real-world applications; emphasizes importance for smart transportation
[51]	Chen et al. (2022)	Bi-Subgroup Optimization Algorithm (BSOA)	Effectively divides population into two sub-populations; proven global convergence through Markov model analysis; outperforms state-of-the-art algorithms	Introduces BSOA to enhance solution diversity; addresses limitation of single population searches; provides mathematical proof of global convergence
[34]	Danoune et al. (2020)	Whale Optimization Algorithm (WOA)	MAE of 0.0726 V; significant enhancement in accuracy and convergence speed vs. PSO; validated on 40 W Heliocentris PEMFC	Introduces swarm-intelligence WOA for PEMFC; addresses nonlinear coupled parameter challenges; demonstrates experimental validation
[45]	Duan and Fathi (2024)	Modified Transient Search Optimization (MTSO) + Modified SqueezeNet	Achieved lowest SSE compared to GRU/IMRFO and GNNM/PSO; highest accuracy in modeling output voltage	Proposes enhanced SqueezeNet with MTSO; addresses slow convergence, high computational cost, low accuracy; facilitates optimal design and control
[43]	Ismaeel et al. (2024)	Rime-Ice Algorithm (RIME)	Achieved SSE of 1.945417827; superior to MFO, GWO, TSA, SCA, OOA; quicker convergence speed; validated on Ned Stack PS6	Introduces RIME for parameter identification; demonstrates strong agreement with experimental I-V curves; ensures fair comparison with same dataset and computational burden

Table 5. *Cont.*

No.	Reference	Optimization Algorithm	Key Results	Main Contributions
[50]	Liu et al. (2021)	Inertia Weight PSO, Constriction PSO, Momentum PSO	Momentum PSO achieved rapid convergence (<30 iterations); SSE of 2.0656 for PEMFC; RMSE of 8.839×10^{-4} for PV cells	Compares three PSO variants; establishes momentum PSO as most suitable for multivariate, nonlinear systems; provides systematic approach for error minimization
[25]	Riad et al. (2023)	Artificial Rabbits Optimization (ARO)	Best SSE compared to other methods; high accuracy with fast convergence and minimal deviation; validated on NedStack PS6, BCS 500 W, Ballard Mark V	Introduces ARO for seven-parameter Mann's model; evaluates under varying temperature and pressure; demonstrates close alignment with measured curves
[42]	Singh and Sandhu (2022)	Henry Gas Solubility Optimization (HGSO)	Provides high-quality solutions and faster convergence; less errors compared to other algorithms; validated on three alternative PEMFC models	Introduces HGSO mimicking gas behavior; balances exploration and exploitation; avoids local minima; tested on ten benchmark functions
[24]	Diab et al. (2020)	Marine Predators Algorithm (MPA), Political Optimizer (PO)	MPA outperformed other algorithms in solution accuracy and speed; I/V curves matched datasheet curves for all studied cases; validated on three commercial PEMFC stacks	Introduces MPA and PO for PEMFC parameter estimation; demonstrates robustness through statistical analysis; minimizes SSE between estimated and experimental results
[56]	Premkumar et al. (2024)	Orthogonal learning-based GOOSE algorithm	Demonstrated superior performance compared to state-of-the-art algorithms across multiple experimental datasets	Introduces bio-inspired algorithm mimicking geese adaptive behaviors with orthogonal learning mechanism; enhances simulation tool robustness
[33]	Khajuria (2022)	Genetic Algorithm (GA), Memetic Algorithm (MA), Evolutionary Programming (EP), Flower Pollination Algorithm (FPA), Coral Reefs Optimization (CRO)	MA achieved lowest SSE (2.37), mean (3.267), and SD (0.533); smallest interquartile range among all algorithms tested	Provides comprehensive comparison of evolutionary algorithms; identifies MA as most effective for PEMFC parameter optimization
[6]	Abbassi et al. (2023)	Dandelion Optimizer (DO)	Outperformed GWO, GBO, HHO, IAEO, VSDE, and ABCDESC on 250 W and NedStack PS6 modules; effective in both steady-state and dynamic conditions	Addresses self-adaptation limitations and local minima convergence issues in metaheuristics; advances PEMFC modeling for sustainable energy applications
[57]	Salem et al. (2024)	Reinforcement Learning (RL)	Achieved superior accuracy versus traditional metaheuristics; validated on Temasek 1 kW, NedStack PS6, and Horizon H-12 12 W stacks	First RL-based parameter estimation for PEMFC; features adaptive self-improving capability through continuous system feedback

Table 5. *Cont.*

No.	Reference	Optimization Algorithm	Key Results	Main Contributions
[10]	Alotto et al. (n.d.)	Particle Swarm Optimization (PSO), Differential Evolution (DE)	DE demonstrated better results and higher robustness than PSO; computational times within few tens of seconds	Establishes DE as novel application for PEMFC identification; addresses parameter duplicity; handles multimodal and noisy functions effectively
[1]	Priya et al. (2018)	Review of AI and bio-inspired methods	Comprehensive consolidation of optimization techniques for PEMFC modeling	Provides integrated resources for researchers; addresses nonlinearity, multivariate characteristics, and data limitations
[34]	Danoune et al. (2020)	Whale Optimization Algorithm (WOA)	Achieved MAE of 0.0726 V; significant improvements in accuracy and convergence speed versus PSO	Introduces novel swarm-intelligence method for PEMFC; effectively extracts nonlinear coupled parameters
[2]	Ashraf et al. (2022)	Review of meta-heuristic algorithms (BWO, FFO, NNO, MRFO)	Summarizes 27 PEMFC models and 30 MHAs across four categories	Comprehensive survey of 350+ articles; categorizes MHAs into swarm-based, nature-based, physics-based, and evolutionary-based approaches
[58]	Khajuria et al. (2024)	Hybrid INFONM (Weighted Mean of Vectors + Nelder–Mead)	Achieved SSE: 1.242 (NedStack PS6), 0.0111 (BCS 500 W), 0.317 (250 W), 0.619 (Ballard Mark V); maximum voltage deviation 2.69%	Introduces novel hybrid approach with SOBOL sensitivity analysis; demonstrates robustness through comprehensive statistical validation
[59]	Ćalasan et al. (2024)	Iterative techniques + hybrid OOA-COA	Increased iterations substantially enhance accuracy; hybrid algorithm surpasses existing methods in convergence speed and accuracy	Proposes two innovative iterative techniques for nonlinear equation solving; introduces novel hybrid optimization algorithm
[60]	Shaheen et al. (2024)	Enhanced Artificial Hummingbird Algorithm (EAHA)	Achieved improvements: 2.97% over AHA, 6.49% over AVO, 1.49% over EO for 250 W stack; up to 82.86% improvement for BCS 500 W	Enhances territorial foraging with linear regulating mechanism; employs AQD-based cost function for improved estimation
[37]	Zhang et al. (2024)	Improved Dung Beetle Optimization (IDBO)	Demonstrated superior convergence and accuracy versus traditional DBO; successfully applied to BCS 500 W, NedStack PS6, and 3 kW custom system	Addresses local optima entrapment; enhances parameter identification accuracy through algorithmic improvement
[61]	Menesy et al. (2020)	Equilibrium Optimizer (EO)	Demonstrated reliable performance across commercial stacks; validated through statistical assessment and dynamic characteristics analysis	Introduces novel metaheuristic for PEMFC parameter extraction; tested under varying temperature and pressure conditions
[30]	Sultan et al. (2020)	Coyote Optimization Algorithm (COA)	Achieved competitive outcomes for 7 and 10 parameter cases; validated through parametric and nonparametric statistical analyses	Develops precise semiempirical model; introduces novel COA application for PEMFC parameter extraction

Table 5. *Cont.*

No.	Reference	Optimization Algorithm	Key Results	Main Contributions
[7]	Xu et al. (2025)	Online estimators (GD, LS, DREM + LS, CL)	DREM + LS and CL outperformed classical GD and LS; demonstrated smoother tracking and faster response; validated on two PEMFCs	Introduces differential operator-based transformation to LRE; provides comparative analysis of four online estimators; addresses nonseparable parameterization
[10]	Guarnieri and Alotto (2014)	Stochastic methods (artificial bee colony, simulated annealing, PSO, DE)	Identifies stochastic algorithms as promising for parameter duplicity; main limitation is high function evaluations	Addresses multiphysics model parameter identification; proposes specific PEMFC formulation to mitigate computational cost
[62]	Mei et al. (2024)	Multi-Strategy Tuna Swarm Optimization (MS-TSO)	Achieved superior convergence speed and estimation accuracy compared with DE, WOA, SSA, PSO, HHO, and SMA; validated on BCS500 W, NedStack PS6, Horizon500 W, and experimental datasets	Proposed an enhanced multi-strategy TSO for accurate PEMFC voltage model parameter estimation with improved convergence and generalization
[41]	Al-Shamma'a et al. (2021)	Supply–Demand-Based Optimization (SDO)	Outperformed WOA, GWO, HHO, GA; validated on four experimental datasets and two PEMFC stacks	Evaluates nine critical parameters; demonstrates superiority over five established algorithms
[29]	You-sheng (2009)	Levenberg–Marquardt + Universal Global Optimization (1stOpt)	Successfully optimized PEMFC parameters; avoided issues from inappropriate initial guesses	Addresses limitations of traditional least squares; demonstrates excellent modeling capability of 1stOpt
[29]	Wang et al. (2009)	Levenberg–Marquardt + Universal Global Optimization (1stOpt)	Successfully optimized PEMFC parameters; avoided issues from inappropriate initial guesses	Demonstrates 1stOpt as practical and efficient method for PEMFC optimization
[63]	Abdel-Basset et al. (2021)	Modified Gorilla Troops Optimizer (MGTO)	Outperformed eight algorithms across all metrics (best, average, worst, SD, CPU time, MAPE, MAE)	Addresses local optima and low convergence speed of GTO; enhances exploitation operator based on population diversity
[64]	Sedighizadeh et al. (2014)	Hybrid Big Bang-Big Crunch (HBB-BC)	Demonstrated superiority over GA, PSO, and standard BB-BC at 60 °C and 70 °C; effective and reliable identification	Combines BB-BC with PSO to enhance exploration; addresses the lack of manufacturing information
[13]	Sultan et al. (2023)	Gazelle Optimization (GOA), Prairie Dog (PDO), Reptile Search (RSA)	All three algorithms effective; GOA achieved best average objective (0.0115 for BCS 500 W); tracking efficiencies: GOA 100%, PDO 99.99%, RSA 100%	Provides comparative analysis of three novel metaheuristics; validates on three PEMFC models; employs SSE-based objective function

Note: MAE = mean absolute error; SSE = sum of squared errors; RMSE = root mean square error; R^2 = coefficient of determination; HTLP = High Temperature–Low Pressure; MTMP = Medium Temperature–Medium Pressure; LTHP = Low Temperature–High Pressure; GRU = Gated Recurrent Unit; IMRFO = Improved Manta Ray Foraging Optimization; GNNM = Grey Neural Network Model; PSO = Particle Swarm Optimization; DE = Differential Evolution; WOA = Whale Optimization Algorithm; GWO = Grey Wolf Optimizer; HHO = Harris Hawks Optimization; SSA = Salp Swarm Algorithm; SCA = Sine Cosine Algorithm; MFO = Moth–Flame Optimizer; TSA = Tunicate Swarm Algorithm; OOA = Osprey Optimization Algorithm; SeaHO = Sea Horse Optimization; SHO = Spotted Hyena Optimizer.

5. Advanced and Hybrid Approaches and Synergistic Combinations

Algorithms inspired by physical phenomena have also contributed significantly to PEMFC parameter estimation. The Equilibrium Optimizer (EO), inspired by control volume mass balance models, demonstrated reliability across multiple commercial PEMFC stacks [61]. The supply–demand-based optimization (SDO) algorithm, which models market dynamics, outperformed established methods including Whale Optimization, Grey Wolf Optimization, and Genetic Algorithms in minimizing sum squared deviation [41].

Hybrid approaches that combine multiple algorithms have shown particular promise in addressing the limitations of individual methods. Khajuria et al. (2024) introduced a hybrid approach combining Weighted Mean of Vectors and Nelder–Mead methods (INFONM), which produced superior sum of squared error values across multiple PEMFC stacks and demonstrated robustness through statistical analysis [58]. The combination of the Osprey optimization algorithm (OOA) and Coati optimization algorithm (COA) proposed by Ćalasan et al. (2024) outperformed existing algorithms in convergence speed, accuracy, and statistical performance [59].

The modified gorilla troops optimizer (MGTO) developed by Abdel-Basset et al. (2021) addressed the local optima and low convergence speed issues of the original GTO algorithm, outperforming eight well-known optimization algorithms across all performance metrics assessed [63]. Similarly, the Depth Information-Based Differential Evolution (Di-DE) algorithm introduced by Jangir et al. (2024) achieved a minimum objective function value of 0.0255 with an average runtime improvement of 98.8% compared to other advanced evolutionary algorithms for the case of BCS 500 W [49].

A notable trend is the emergence of hybrid algorithms combining complementary optimization strategies. Yang et al. (2024) [15] integrated neural network preprocessing with pelican optimization, leveraging the strengths of both machine learning and metaheuristic search. Kanouni and Laib (2024) developed DEA as a hybridized Differential Evolution variant, demonstrating rapid and accurate parameter identification [48]. Duan and Fathi [45] combined modified SqueezeNet with transient search optimization, addressing multiple limitations of existing methods simultaneously.

These hybrid approaches reflect recognition that no single optimization paradigm suffices for all aspects of PEMFC parameter estimation. By combining global exploration capabilities, local exploitation efficiency, noise handling, and domain-specific knowledge, hybrid algorithms achieve performance surpassing their constituent methods.

Table 6 presents ten studies that represent the frontier of PEMFC parameter-estimation methodology, encompassing hybrid approaches combining neural networks with optimization algorithms, online estimation techniques with guaranteed convergence properties, and advanced variants of established metaheuristic methods. These studies, published between 2020 and 2024, reflect the field's maturation toward addressing practical challenges—noise, data insufficiency, nonlinear parameterization, and real-time applicability—that limit the utility of conventional approaches.

5.1. Hybrid Neural Network-Optimization Approaches

5.1.1. Feedforward Neural Network with Pelican Optimization

Yang et al. (2024) demonstrate the power of hybrid methodology through their FNN-POA strategy, which combines feedforward neural network preprocessing with pelican optimization algorithm for parameter identification [15]. The dramatic 99.44% reduction in root-mean-square error under medium temperature and pressure conditions illustrates the transformative potential of addressing data quality before optimization. By introducing Gaussian and Rayleigh noise at multiple signal-to-noise ratios to simulate real-world disturbances, the study provides rigorous validation of the approach's robustness. The

explicit acknowledgment of nonlinear characteristics, noise, and data insufficiency as fundamental challenges positions this work as addressing core limitations in the field.

Table 6. Summary of advanced and hybrid approaches for PEMFC parameter estimation.

No.	Reference	Method/Approach	Key Results	Main Contributions	Primary Objectives
[15]	Yang et al. (2024)	Feedforward Neural Network + Pelican Optimization Algorithm (FNN-POA)	RMSE reduced by 99.44% under medium temperature/pressure; outperformed seven advanced competitive algorithms; FNN effectively preprocesses noisy data	Proposes hybrid FNN-POA strategy addressing noise and data insufficiency; simulates disturbances with Gaussian and Rayleigh noise; demonstrates superior robustness and optimization quality	Nonlinear characteristics of PEMFC model; noise data and insufficient measurement data pose challenges
[16]	Li et al. (2022)	Critical review of meta-heuristic and neural network methods	Identifies challenges and risks in practical application of PEMFC parameter extraction; discusses different parameter identification methods	Clarifies problems in PEMFC parameter extraction methods; discusses potential risks of various identification approaches	Parameter extraction strategy not fully considered in peer-reviewed literature; potential risks worth considering
[14]	Qiu et al. (2024)	Adaptive nonlinear parameter estimation with linear parameterization	Transforms nonlinear function into linearly parameterized form with exponentially decaying remainder; prescribed-time robust differentiator ensures fast convergence; high accuracy without observer/predictor	Proposes adaptive algorithm specifically for nonlinear parameterization; introduces linear parameterization method based on direct differential and filter design; enhances calculation efficiency	Nonlinear parameterization complicates precise parameter value extraction; direct differential operation introduces derivation signal challenges
[49]	Jangir et al. (2024)	Depth Information-Based Differential Evolution (Di-DE)	Achieved SSE as low as 0.00002; voltage–current characteristics within 1% error of experimental data; 98.8% runtime improvement	Introduces Di-DE algorithm for precise parameter estimation; demonstrates exceptional accuracy and computational efficiency; tested on 12 different PEMFC models	Not specified
[18]	He et al. (2023)	GRNN + Meta-Heuristic Algorithms (six typical MhAs)	GRNN reduces data noise impact; fitting accuracy: 99.39% (HTLP), 99.07% (MTMP), 98.70% (LTHP)	Proposes GRNN for de-noising and data prediction; enhances parameter identification accuracy; evaluates under three operating conditions	Nonlinear optimization complexity; insufficient data; measurement noise; limited GRNN generalizability
[65]	Ali et al. (2025)	Heterogeneous Comprehensive Learning Bald Eagle Search (HCLBES)	Achieved superior convergence speed, estimation accuracy, and robustness compared with recent optimization algorithms; validated on 250 W, 500 W, BCS 500 W, Horizon 500, and NedStack PS6 PEMFCs	Proposed HCLBES by integrating comprehensive learning and heterogeneous exploration–exploitation strategies for accurate PEMFC parameter estimation under dynamic conditions	Improve PEMFC parameter identification accuracy and robustness through an enhanced Bald Eagle Search optimization algorithm
[23]	Menesy et al. (2020)	Modified Artificial Ecosystem Optimization (MAEO)	High accuracy and reliability on BCS-500 W, AVISTA SR-12 500 W, 250 W, and Temasek 1 kW stacks; outperforms conventional AEO and other algorithms	Introduces MAEO with faster convergence and reduced local optima likelihood; formulates SSE objective function; demonstrates robustness through statistical measures	Not explicitly mentioned

Note: RMSE = root mean square error; FNN = Feedforward Neural Network; POA = Pelican Optimization Algorithm; GRNN = Generalized Regression Neural Network; MhAs = Meta-Heuristic Algorithms; SSE = sum of squared errors; NSNLP = Nonseparable Nonlinear Parameterization; SNLP = Separable Nonlinear Parameterization; LSD = Least-Squares plus Dynamic regression equation and mixing; HTLP = High Temperature–Low Pressure; MTMP = Medium Temperature–Medium Pressure; LTHP = Low Temperature–High Pressure; BES = Bald Eagle Search; COA = Coyote Optimization Algorithm; BSO = Brain Storm Optimization; HHO = Harris Hawks Optimization; GBO = Gradient-Based Optimizer; SRSR = Swarm Robotics Search and Rescue; AEO = Artificial Ecosystem Optimization; MAEO = Modified Artificial Ecosystem Optimization.

5.1.2. Generalized Regression Neural Network with Meta-Heuristic Algorithms

He et al. (2023) independently validate the neural network preprocessing concept using generalized regression neural networks (GRNNs) combined with meta-heuristic algorithms [18]. Achieving fitting accuracy exceeding 99% across three distinct operating conditions (HTLP: 99.39%, MTMP: 99.07%, LTHP: 98.70%), this approach demonstrates that data de-noising and prediction can dramatically enhance parameter identification reliability. The study's candid discussion of limitations—including nonlinear optimization complexity, insufficient data, measurement noise, and questions about GRNN generalizability—provides valuable perspective on the boundaries of current methods.

5.1.3. Modified Artificial Ecosystem Optimization

Menesy et al. (2020) contribute an enhanced metaheuristic approach through the Modified Artificial Ecosystem Optimization (MAEO) algorithm [23]. Validated on four commercial PEMFC stacks (BCS-500 W, AVISTA SR-12 500 W, 250 W, and Temasek 1 kW), MAEO demonstrates superior performance compared to conventional AEO and other algorithms. The focus on faster convergence and reduced likelihood of local optima addresses persistent challenges in metaheuristic optimization, while the formulation of sum of squared errors (SSEs) as an objective function provides a clear optimization target.

5.2. Online Estimation with Guaranteed Convergence

5.2.1. Transformation of Nonseparable Nonlinear Parameterization

The complementary studies by Beltrán et al. represent a significant theoretical advance in online parameter estimation [3]. By developing procedures to transform nonseparable nonlinear parameterization (NSNLP) into separable forms, these works enable the application of estimation techniques with guaranteed convergence properties—a capability previously unavailable for realistic PEMFC polarization curve models. The least-squares plus dynamic regression equation and mixing (LSD) estimator demonstrates robust performance, with model M4 accurately representing the entire operational range of a 1.26 kW PEMFC stack.

The significance of this work extends beyond algorithmic novelty: guaranteed convergence properties are essential for real-time monitoring, fault detection, and adaptive control applications where estimator reliability cannot be compromised. The ability to track slow parameter variations during operation addresses a fundamental limitation of offline fitting methods.

5.2.2. Adaptive Nonlinear Parameter Estimation

Qiu et al. (2024) address the specific challenge of nonlinear parameterization through an adaptive algorithm that transforms nonlinear functions into linearly parameterized forms with exponentially decaying remainders [14]. The incorporation of a prescribed-time robust differentiator ensures fast convergence of derivation signals, while the elimination of observer/predictor requirements enhances computational efficiency. This work directly tackles the mathematical complexity that makes PEMFC parameter estimation fundamentally challenging.

5.3. Advanced Differential Evolution and Comparative Studies

5.3.1. Depth Information-Based Differential Evolution

Jangir et al. (2024) introduce the Depth Information-Based Differential Evolution (Di-DE) algorithm, achieving remarkable results including SSE values as low as 0.00002 and voltage–current characteristics within 1% error of experimental data for the case of BCS 500 W PEMFC, [49]. The 98.8% runtime improvement compared to other advanced evolutionary

algorithms demonstrates that accuracy need not come at the expense of computational efficiency. Validation on twelve different PEMFC models provides compelling evidence of generalizability.

5.3.2. Comparative Algorithm Evaluation

Khajuria et al. [54] contribute systematic comparisons of six nature-inspired algorithms across two studies, consistently identifying Swarm Robotics Search and Rescue (SRSR) as the best-performing method for extracting seven parameters. The inclusion of temperature and pressure effects on polarization curves adds practical relevance, while the focus on identifying optimal algorithms for specific applications provides guidance for practitioners.

5.3.3. Critical Perspectives and Methodological Reflection

Li et al. (2022) offer a critical perspective on parameter extraction methods, highlighting challenges and potential risks in practical applications [16]. The observation that parameter extraction strategies are not fully considered in peer-reviewed literature serves as an important reminder that methodological sophistication must be balanced with practical applicability. The discussion of potential risks—while not elaborated in the provided context—points to the need for careful consideration of how parameter-estimation methods perform under real-world conditions.

5.4. Synthesis and Emerging Themes

5.4.1. Convergence of Machine Learning and Optimization

The studies by Yang et al. (2024) and He et al. (2023) exemplify a powerful trend: the integration of neural-network-based data preprocessing with metaheuristic optimization [15,18]. This hybrid approach acknowledges that parameter estimation accuracy depends not only on optimization algorithm capability but also on data quality. By addressing noise and data insufficiency at the preprocessing stage, these methods achieve performance improvements that would be unattainable through optimization alone.

5.4.2. Theoretical Foundations for Online Estimation

The work of [3,14] address the theoretical underpinnings of parameter estimation, developing methods with guaranteed convergence properties and rigorous handling of nonlinear parameterization. These contributions are essential for applications requiring reliability and real-time capability, where empirical performance demonstrations without theoretical guarantees may be insufficient.

5.4.3. Emphasis on Computational Efficiency

Multiple studies [49,61] explicitly address computational efficiency alongside accuracy, recognizing that practical deployment requires methods that deliver results within acceptable timeframes. The 98.8% runtime improvement demonstrated by Di-DE illustrates the potential for substantial efficiency gains without sacrificing solution quality.

5.4.4. Comprehensive Validation Across Multiple Platforms

The trend toward validation on multiple PEMFC types—four stacks in [61], twelve in [49], multiple operating conditions in [18]—reflects increasing rigor in demonstrating generalizability. This practice is essential for establishing confidence that methods will perform reliably across the diversity of PEMFC configurations encountered in practice.

5.5. Limitations and Persistent Challenges of Advanced and Hybrid Approaches for PEMFC Parameter Estimation

Despite significant advances, the studies in Table 6 reveal persistent challenges. Nonlinear parameterization continues to complicate precise parameter extraction [14]. Noise and data insufficiency remain fundamental obstacles [15,18]. The generalizability of neural-network-based approaches across diverse operating scenarios requires further investigation [18]. Several studies do not explicitly discuss limitations, potentially presenting an incomplete picture of method capabilities.

Li et al. (2022) raise the important point that parameter extraction strategies may not be fully considered in the literature, suggesting that methodological choices deserve more critical examination [16]. The identification of "potential risks worth considering" highlights the need for continued reflection on how estimation methods perform under real-world conditions.

5.6. Implications for Future Research of Advanced and Hybrid Approaches for PEMFC Parameter Estimation

The studies in Table 6 point toward several promising directions for future investigation:

1. Further development of hybrid approaches combining machine learning preprocessing with optimization, exploring alternative neural network architectures and preprocessing strategies.
2. Extension of theoretically grounded online estimation methods to incorporate additional physical effects and operating conditions, building on the foundation established by [3].
3. Systematic comparison of computational efficiency across algorithms, identifying trade-offs between accuracy and speed that inform method selection for specific applications.
4. Investigation of generalizability boundaries for neural-network-based methods, determining the conditions under which preprocessing models remain valid.
5. Integration of uncertainty quantification into parameter estimation, providing confidence intervals alongside point estimates.

Table 6 captures the vanguard of PEMFC parameter-estimation methodology, where hybrid approaches, theoretically grounded online estimation, and advanced algorithm variants are pushing the boundaries of what is achievable. The convergence of machine learning and optimization, the development of methods with guaranteed convergence properties, and the emphasis on computational efficiency and comprehensive validation collectively represent the field's response to the fundamental challenges of nonlinearity, noise, and practical applicability. As these methodologies mature and integrate, they promise to deliver increasingly reliable, accurate, and efficient parameter estimation capabilities essential for advancing PEMFC technology from laboratory demonstrations to widespread commercial deployment.

6. Online Estimation, Polynomial Modeling, and Neural Network Approaches for PEMFC Characterization

Table 7 presents ten studies that collectively illuminate three complementary approaches to PEMFC characterization: online estimation methods with guaranteed convergence properties, simplified polynomial modeling for computational efficiency, and neural-network-based nonlinear system identification. Spanning nearly two decades from 2005 to 2025, these studies trace the evolution of PEMFC modeling from foundational neural network demonstrations to sophisticated online estimation algorithms with rigorous theoretical guarantees. Together, they demonstrate that accurate PEMFC characterization

requires not only powerful optimization algorithms but also careful attention to model structure, parameterization, and real-time applicability.

6.1. Online Estimation with Guaranteed Convergence Properties

6.1.1. Transformation of Nonseparable Nonlinear Parameterization

The complementary studies by Beltrán et al. [3] represent a significant theoretical breakthrough in online parameter estimation. By developing procedures to transform nonseparable nonlinear parameterization (NSNLP) into separable forms, these works enable the application of estimation techniques with guaranteed convergence properties—a capability previously unavailable for realistic PEMFC polarization curve models. The least-squares plus dynamic regression equation and mixing (LSD) estimator demonstrates robust performance, with model M4 accurately representing the entire operational range of a 1.26 kW PEMFC stack.

The significance of guaranteed convergence cannot be overstated for applications requiring real-time monitoring, fault detection, and adaptive control. Traditional offline fitting methods, while valuable for initial model development, cannot adapt to changing operating conditions or track parameter variations during operation. The Beltrán et al. estimators address this gap by ensuring that parameter estimates converge to true values under suitable excitation conditions, with robustness against additive noise and structural uncertainty [3].

The identification of appropriate model complexity is particularly noteworthy: model M2 accurately represents the [10A, 20A] current range, model M3 suits the [1A, 30A] range, while model M4 exhibits robust performance across the entire operational envelope. This nuanced understanding of model applicability domains provides practical guidance for estimator selection based on expected operating conditions.

6.1.2. Comparative Evaluation of Online Estimators

Xu et al. (2025) extend the online estimation literature through a differential operator-based transformation of the classical semiempirical model into a linear regression equation (LRE), followed by comparative evaluation of four online estimators [7]. The superior performance of dynamic regressor extension and mixing-based least squares (DREM + LS) and composite learning (CL) estimators compared to classical gradient descent (GD) and least squares (LS) methods demonstrates the value of advanced estimation techniques. The validation on two different PEMFCs under varying operating conditions supports claims of estimator universality, while the smoother tracking and faster response of advanced estimators address practical requirements for real-time applications.

6.1.3. Classical Optimization Approaches: The 1stopt Method

The studies in [29,32] document the application of Levenberg–Marquardt combined with Universal Global Optimization of 1stOpt for PEMFC parameter optimization. While predating many metaheuristic approaches, these works remain relevant for their emphasis on avoiding issues related to inappropriate initial value guesses—a persistent challenge in nonlinear optimization. The demonstration of excellent modeling ability through simulation and experimental results establishes 1stOpt as a practical and efficient method, particularly valuable in contexts where metaheuristic algorithm implementation may not be feasible.

The explicit acknowledgment that strong nonlinearity and numerous parameters complicate optimization with traditional methods (e.g., least squares) provides context for the subsequent proliferation of more sophisticated approaches. These studies serve as important benchmarks against which newer methods can be compared.

6.2. Simplified Polynomial Modeling for Computational Efficiency

6.2.1. Low-Order Polynomial Approximation

Kuznyetsov and Bilyakovskyy (2024) [66] offer a refreshingly pragmatic perspective on PEMFC modeling, demonstrating that low-order polynomials can achieve accuracy comparable to higher-order representations while significantly reducing computational load. The finding that a 3rd-order polynomial achieves RMSE of 3.5–3.9—comparable to the 5th-order polynomial's RMSE of 3.9—has important implications for applications where computational efficiency is paramount, such as embedded control systems or real-time optimization.

The focus on maximum power point operation, utilizing truncated polarization curve input data to ignore the activation loss region, reflects practical engineering judgment about which aspects of fuel cell behavior merit detailed modeling. The achievement of maximum PowerPoint values with 1.3% relative error using a 2nd-order polynomial demonstrates that parsimonious models can suffice for specific applications.

6.2.2. Numerical Comparison of Polarization Curve Methods

Azzone et al. (2024) contribute a comprehensive numerical comparison of state-of-the-art methods for calculating polarization curves, addressing the gap in systematic evaluation of competing approaches [67]. The sensitivity analysis of polarization curves to various parameters enhances understanding of which factors most influence model predictions, while verification in dynamic scenarios ensures that conclusions hold under realistic operating conditions. This work provides valuable guidance for method selection based on quantitative performance comparisons rather than anecdotal evidence.

6.3. Neural Network Approaches for Nonlinear System Identification

The integration of neural networks with optimization algorithms represents a significant advancement in addressing the challenges of noise and limited data in PEMFC parameter estimation. Yang et al. (2024) proposed a hybrid strategy combining a feedforward neural network (FNN) with the pelican optimization algorithm (POA) [15], demonstrating that the FNN effectively preprocesses measured data to reduce noise and enrich measurement information. The proposed FNN-POA strategy reduced root-mean-square error by 99.44% under medium temperature and medium pressure conditions through noise reduction.

He et al. (2023) employed a generalized regression neural network (GRNN) combined with meta-heuristic algorithms [18], showing that GRNN significantly decreased the influence of data noise on parameter identification. Following data prediction using GRNN, the precision rate and reliability of parameter identification were greatly enhanced, achieving fitting accuracy of 99.39% under high-temperature and low-pressure conditions.

These neural-network-based approaches address a critical gap in PEMFC parameter estimation: the sensitivity of optimization algorithms to noisy and insufficient measurement data. By incorporating data preprocessing as an integral component of the estimation framework, these methods enhance robustness and enable more reliable parameter identification under realistic operating conditions.

6.3.1. Foundational Neural Network Modeling

The studies in [31,68] represent early applications of neural networks to PEMFC modeling, establishing the feasibility of data-driven approaches for capturing nonlinear system behavior. Using the Levenberg–Marquardt Back-Propagation (LMBP) algorithm, these works demonstrate that neural networks can successfully perform dynamic identification and generate accurate voltage–current output curves.

The observation that increasing working temperature at constant current density increases output voltage—while perhaps intuitive to experienced practitioners—illustrates how neural network models can capture and quantify physical relationships. The explicit acknowledgment of modeling difficulty due to system complexity (integrating thermodynamics, electrochemistry, hydrodynamics, and mass transfer) justifies the adoption of data-driven approaches when first-principles modeling proves intractable.

6.3.2. Reinforcement Learning Approaches

Reinforcement learning (RL) has recently emerged as a novel paradigm for PEMFC parameter estimation, offering adaptive and self-improving capabilities that distinguish it from conventional optimization methods. Salem et al. (2024) introduced an RL-based technique that continuously learns from system feedback to minimize the sum of squared errors between measured and simulated voltages [57]. This approach demonstrated superior accuracy and performance compared to traditional metaheuristic techniques when validated on commercial PEMFCs including the Temasek 1 kW, Nedstack PS6 6 kW, and Horizon H-12 12 W.

The adaptive nature of reinforcement learning is particularly well-suited to PEMFC applications, where system characteristics may change over time due to degradation or varying operating conditions. Unlike static optimization algorithms that produce fixed parameter estimates, RL-based methods can continuously refine their estimates as new data becomes available, potentially enabling real-time adaptation to changing system behavior.

6.3.3. Advanced Neural Network Implementations

Xiuping et al. (2009) extend the neural network methodology by focusing on dynamic identification, using trained networks to compare discrete temperature values with actual sampled data [31]. The recommendation of measures to prevent membrane dehydration and increased vapor partial pressure demonstrates how modeling insights can translate into practical operational guidance.

6.4. Physics-Based Nonlinear State Space Modeling

6.4.1. Incorporation of Liquid Water Effects

Hernandez et al. (2006) address a critical gap in PEMFC modeling through incorporation of liquid water formation within fuel cell channels [69]. The probabilistic approach to evaporation-condensation phenomena represents an innovative solution to a challenging multiphysics problem, improving model stability while preserving dynamic characteristics. Validation against experimental results from a 500 W fuel cell demonstrates practical applicability.

The improved stability of models including liquid water compared to those neglecting it underscores the importance of capturing relevant physical phenomena, even when doing so increases model complexity. The successful reproduction of dynamic behavior at low temperatures and high humidity—conditions where liquid water effects are most pronounced—validates the modeling approach.

6.4.2. Limitations and Challenges

Hernandez et al. (2006) provide notably candid discussion of model limitations: inability to reproduce some dynamic behaviors complicates fault source identification; nitrogen diffusion is not accounted for, potentially leading to abnormal voltage drops; the two-phase model may become unstable after prolonged operation; direct experimental validation of liquid water models remains difficult [69]. This transparency is valuable for researchers seeking to understand the boundaries of current modeling capabilities and identify priorities for future development.

6.5. Synthesis and Cross-Cutting Themes

6.5.1. Evolution from Offline to Online Estimation

The progression from early neural network demonstrations (2005–2009) to recent online estimation with guaranteed convergence (2023–2025) reflects the field's maturation toward real-time applicability. While early work established that nonlinear PEMFC behavior could be captured through data-driven methods, recent contributions address the harder problem of doing so adaptively during operation.

6.5.2. Trade-Offs Between Accuracy and Complexity

The studies in Table 7 illustrate diverse approaches to managing the accuracy–complexity trade-off. Kuznyetsov and Bilyakovskyy (2024) pursue simplification through low-order polynomials, accepting modest accuracy losses for substantial computational gains [66]. Beltrán et al. [3] pursue theoretical rigor, developing methods with guaranteed convergence at the cost of mathematical sophistication. Hernandez et al. (2006) pursue physical fidelity, incorporating complex multiphysics phenomena despite challenges in validation and stability [69].

6.5.3. Importance of Model Structure Selection

Multiple studies emphasize that model structure—whether polynomial order, separable versus nonseparable parameterization, or inclusion of liquid water effects—critically influences estimation performance. The finding that different models suit different operating ranges [3] suggests that adaptive model selection based on current conditions may be a fruitful direction for future research.

6.5.4. Validation Under Realistic Conditions

The increasing emphasis on validation under varying operating conditions, across multiple PEMFC types, and in dynamic scenarios reflects growing rigor in the field. Studies that verify conclusions through both simulation and experiment [3] provide stronger evidence of practical utility than those relying solely on theoretical demonstrations.

6.6. Limitations and Persistent Challenges

Despite significant advances, the studies in Table 7 reveal persistent challenges:

1. Nonlinear parameterization continues to complicate precise parameter extraction [3,7].
2. Model instability under certain conditions remains a concern, particularly for two-phase models [69].
3. Fault diagnosis is complicated when models cannot reproduce all dynamic behaviors [69].
4. Experimental validation of complex physical phenomena (e.g., liquid water dynamics) remains difficult [69].
5. Computational requirements of sophisticated methods may limit applicability in resource-constrained environments [66].
6. Initial value sensitivity persists as a challenge for some optimization approaches [29,32].

6.7. Implications for Future Research for Online Estimation, Polynomial Modeling, and Neural Network Approaches for PEMFC Characterization

The studies in Table 7 point toward several promising directions:

1. Integration of guaranteed-convergence online estimation with simplified model structures suitable for real-time implementation.
2. Adaptive model selection frameworks that choose appropriate model complexity based on current operating conditions.

3. Hybrid approaches combining physics-based modeling with neural networks to leverage the strengths of both paradigms.
4. Enhanced validation methodologies for complex multiphysics phenomena, potentially incorporating advanced experimental techniques.
5. Extension of online estimation methods to additional PEMFC subsystems and degradation phenomena.

Table 7 also highlights several important research trends. While early studies established the feasibility of neural-network-based PEMFC modeling, more recent work has increasingly emphasized online parameter estimation, computational efficiency, and theoretical guarantees for convergence and stability. This progression reflects the growing demand for models that can support real-time monitoring, adaptive control, fault diagnosis, and digital twin applications. Future research is expected to combine physics-based knowledge with data-driven techniques to achieve improved accuracy, robustness, and computational efficiency under a wide range of operating conditions.

Table 7. Summary of online estimation, polynomial modeling, and neural network approaches for PEMFC characterization.

No.	Reference	Method/Approach	Key Results	Main Contributions	Primary Objectives
[3]	Beltrán et al. (2024b)	LSD estimator; transformation of NSNLP to SNLP	Model M4 best represents full operational range; LSD estimator demonstrates parameter convergence; simulations on 1.26 kW PEMFC stack validate approach	Develops procedure to transform nonseparable nonlinear parameterization into separable form; introduces LSD estimator for SNLP; first guaranteed convergence online estimator for realistic polarization curve models	Complexity of nonlinearities acknowledged; robustness to noise highlighted but extreme conditions not addressed; rapid parameter variation effects not discussed
[70]	Zhang et al. (2024)	Deep learning (LSTM, GRU, TCN, Transformer)	Shorter sampling intervals and larger training datasets improved SOH estimation accuracy; crack-free PEMFCs achieved better prediction performance than cracked cells	Comprehensive comparison of four deep learning models for SOH estimation under dynamic operating conditions; analyzed effects of sampling interval, training data size, and crack-induced degradation	Develop accurate SOH estimation for PEMFCs under dynamic operating conditions to improve reliability and lifetime
[7]	Xu et al. (2025)	Online estimators (GD, LS, DREM + LS, CL) with differential operator-based transformation	DREM + LS and CL outperform classical GD and LS in steady and transient states; smoother tracking and faster response; validated on two PEMFCs under different operating conditions	Introduces differential operator-based method to transform semiempirical model into LRE; provides comparative analysis of four online estimators; addresses nonseparable parameterization for real-time applications	Not specified
[32]	You-sheng (2009)	Levenberg–Marquardt + Universal Global Optimization (1stOpt)	Successfully optimizes PEMFC parameters; avoids issues from inappropriate initial guesses; demonstrates excellent modeling ability	Addresses limitations of traditional least squares; demonstrates practical application for PEMFC model optimization; provides efficient method for improving modeling accuracy	Strong nonlinearity complicates modeling; many parameters are difficult to optimize with traditional methods
[29]	Wang et al. (2009)	Levenberg–Marquardt + Universal Global Optimization (1stOpt)	Successfully optimizes PEMFC parameters; avoids issues from inappropriate initial guesses; demonstrates excellent modeling ability	Presents novel optimization method for PEMFC polarization curve; addresses challenges of traditional techniques with nonlinearities and initial value sensitivity	Strong nonlinearity; numerous parameters difficult to optimize with traditional methods

Table 7. *Cont.*

No.	Reference	Method/Approach	Key Results	Main Contributions	Primary Objectives
[66]	Kuznyetsov and Bilyakovskyy (2024)	Low-order polynomial approximation (2nd, 3rd, 5th order)	3rd-order polynomial achieves RMSE of 3.5–3.9 (comparable to 5th-order RMSE 3.9); 2nd-order polynomial yields 1.3% relative error for maximum PowerPoint; 5th-order achieves 1.2% relative error	Proposes simplified modeling using low-order polynomials; reduces computational load for control and energy algorithms; focuses on maximum power point operation with truncated polarization curve	Not specified
[67]	Azzone et al. (2024)	Numerical comparison of polarization curve methods	Reviews and compares state-of-the-art methods for calculating polarization curve; conducts sensitivity analysis; verifies best-performing method in dynamic scenarios	Provides comprehensive performance comparison of modeling methods for different loss contributions; enhances understanding of factors influencing fuel cell performance through sensitivity analysis	Not specified
[31]	Xiuping et al. (2009)	Neural networks with Levenberg–Marquardt BP (LMBP) algorithm	Successfully performs dynamic identification of PEMFC system; increasing working temperature at same current density increases output voltage; learning error documented	Presents neural network approach for nonlinear PEMFC modeling; demonstrates feasibility for dynamic identification; provides insights into temperature effects on performance	Difficulty in establishing mathematical model due to complexity; operating temperature greatly affects output voltage–current performance
[69]	Hernandez et al. (2006)	Nonlinear state space model with liquid water effects	Model including liquid water shows improved stability; probabilistic approach to evaporation-condensation increases stability; reproduces dynamic behavior at low temperatures and high humidity	Introduces reduced input nonlinear state space model incorporating liquid water; addresses nitrogen migration often overlooked; validates on 500 W fuel cell	Model cannot reproduce some dynamic behavior, complicating fault diagnosis; does not account for nitrogen diffusion; two-phase model may become unstable after prolonged operation
[71]	Zhang et al. (2024)	TabNet + Segmented Random Sampling Correction (SRSC)	Improved PEMFC remaining useful life (RUL) prediction accuracy; enhanced model interpretability and generalization under varying operating conditions	Introduced an interpretable TabNet-based PHM framework with SRSC noise reduction and Gaussian augmentation for robust RUL prediction	Improve predictive health management by providing accurate and interpretable RUL estimation for PEMFCs
[68]	Sun et al. (2005)	Neural networks with Levenberg–Marquardt BP (LMBP) algorithm	Establishes nonlinear PEMFC model using artificial neural networks; voltage–current output curves provide guidance for performance improvement	Highlights PEMFC as green power solution; addresses complexity of mathematical modeling; adapts LMBP for electric characteristic model	Not explicitly mentioned

Note: NSNLP = Nonseparable Nonlinear Parameterization; SNLP = Separable Nonlinear Parameterization; LSD = Least-Squares plus Dynamic regression equation and mixing; LRE = Linear Regression Equation; GD = Gradient Descent; LS = Least Squares; DREM + LS = Dynamic Regressor Extension and Mixing-based Least Squares; CL = Composite Learning; RMSE = root mean square error; LMBP = Levenberg–Marquardt Back-Propagation; PEMFC = Proton Exchange Membrane Fuel Cell.

7. Sensitivity Analysis in PEMFC Modeling: Insights for Parameter Identification and Model Optimization

7.1. Fundamentals and Significance of Sensitivity Analysis

Sensitivity analysis constitutes an essential methodological framework for understanding how variations in model inputs influence predictions in Proton Exchange Membrane Fuel Cell (PEMFC) systems. As mathematical models grow increasingly sophisticated—incorporating electrochemical kinetics, transport phenomena, and thermal dynamics—the need to identify which parameters warrant precise characterization be-

comes paramount. Sensitivity analysis addresses this need by systematically quantifying parameter influence, thereby guiding experimental efforts, model reduction, and optimization strategies.

The studies summarized in Table 8 span nearly two decades of research, from early investigations of parameter importance [72] to contemporary applications of Monte Carlo methods and machine learning [73]. This evolution reflects growing recognition that sensitivity analysis is not merely an adjunct to modeling but a fundamental tool for ensuring model credibility and practical utility.

7.2. Methodological Approaches to Sensitivity Analysis

The reviewed literature reveals diverse methodological approaches to sensitivity analysis, each offering distinct advantages and limitations. Kannan et al. employed Monte Carlo-based sensitivity analysis with an accelerated 1D mechanistic model, simultaneously varying over 30 normally distributed parameters [74]. Their use of multiple linear regression and sigma-normalized derivative methods to rank parameter contributions demonstrates how statistical techniques can extract meaningful insights from stochastic simulations. The application of the Kolmogorov–Smirnov test to ensure sample size reliability further illustrates attention to statistical rigor.

Testa et al. similarly adopted Monte Carlo Simulation approaches, introducing Sample Random Sampling (SRS) to generate uniformly distributed parameter values [75]. Their emphasis on evaluating input variable orthogonality through correlation matrices addresses a critical consideration: when input factors exhibit high correlation, distinguishing their individual effects becomes problematic. The demonstration of direct proportionality between current density and anode relative humidity, visualized through Pareto plots, exemplifies how sensitivity analysis can guide design variable reduction. Pant et al. (2021) advanced the field through uncertainty propagation-based sensitivity analysis using a robust 2D membrane electrode assembly model [76]. Their examination of nearly 50 input parameters across multiple operating conditions represents one of the most comprehensive sensitivity studies in the PEMFC literature. The distinction between local sensitivity analysis—examining parameter effects around nominal values—and the more computationally demanding global approaches reflects fundamental trade-offs between analytical depth and practical feasibility.

Li et al. (2023) introduced the elementary effect method for global sensitivity analysis with a 1D transient multiphase model [77]. This approach offers computational efficiency while capturing parameter interactions, making it particularly suitable for screening large parameter sets to identify influential factors before conducting more detailed analyses.

7.3. Critical Parameters Across Modeling Contexts

A synthesis of findings across the reviewed studies reveals both consistent themes and context-dependent variations in parameter importance. At the electrochemical level, cathode kinetics and exchange current density emerge as pervasively influential, particularly under low humidity conditions [76]. Membrane-related parameters—thickness, ionomer volume fraction, and ohmic loss characteristics—consistently rank among the most sensitive factors affecting cell performance [76,77].

Transport parameters exhibit humidity-dependent significance. Under dry conditions, membrane hydration and ohmic losses dominate, while at elevated humidity, gas diffusion layer properties and mass transport characteristics become increasingly critical [76]. This contextual sensitivity has profound implications: optimization efforts must target different parameter sets depending on intended operating conditions.

Structural parameters display varying degrees of influence. Li et al. (2023) identified membrane thickness and anode ionomer volume fraction as highly sensitive [77], particularly at high current densities, while micro-porous layer thickness and gas diffusion layer porosity were classified as insensitive. Such findings enable model reduction by fixing insensitive parameters, focusing computational and experimental resources on factors that materially affect predictions.

Operating conditions—temperature, stoichiometry, backpressure—exert substantial influence on fuel cell power output. Liao et al. (2024) demonstrated through combined sensitivity analysis and Bayesian optimization that temperature exerts the greatest impact, followed by stoichiometry and backpressure [73]. Their identification of optimal operating parameters (80 °C, stoichiometry 4, backpressure 1.7 bar) illustrates how sensitivity analysis can directly inform operational strategies.

7.4. Dynamic Response and Control Implications

Sensitivity analysis extends beyond steady-state characterization to illuminate dynamic behavior critical for control system design. Mantelli et al. (2024) investigated a turbocharged PEMFC system, revealing strong sensitivity to fuel valve opening that necessitates feedback control for operational stability [78]. Their analysis of power load ramps demonstrated that while load increases are readily accommodated, load reductions face compressor surge constraints—a finding with direct implications for control logic development.

Lorandi et al. (2004) examined output impedance sensitivity in PEMFCs, identifying anode and cathode volumes as significant factors affecting dynamic response [79]. This work underscores that parameters influencing transient behavior may differ from those dominating steady-state performance, necessitating distinct sensitivity analyses for control-oriented applications.

Cao et al. (2005) demonstrated an innovative application of sensitivity analysis within neural network modeling, using parameter sensitivity to guide network structure optimization [68]. By pruning or inserting hidden nodes based on sensitivity results, their approach achieved more compact architectures, higher accuracy, and faster convergence—illustrating how sensitivity concepts can enhance machine learning applications.

7.5. Model Dimensionality and Computational Considerations

The reviewed studies consistently highlight trade-offs between model fidelity and computational tractability in sensitivity analysis. Kannan et al. (n.d.) acknowledge that mechanistic model sensitivity analysis entails significant computational cost, while their 1D approach may limit accuracy compared to higher-dimensional alternatives. Pant et al. (2021) explicitly note that truly global sensitivity analysis with 3D models remains infeasible due to impractical computation times, necessitating compromise through 2D representations and local sensitivity methods [76].

Testa et al. address computational challenges through methodological innovation, developing approaches suited for fast-running analyses while acknowledging that comprehensive parameter space exploration would require unacceptable simulation times [75]. Their separation of tuning parameters (control factors) from uncontrollable inputs (noise factors) offers a pragmatic framework for managing complexity.

These considerations underscore an important principle: sensitivity analysis methodology must be tailored to the specific modeling context, available computational resources, and intended application. No single approach universally suffices; rather, researchers must navigate trade-offs between comprehensiveness, accuracy, and practical feasibility.

7.6. Uncertainty and Parameter Identifiability

Several studies illuminate the relationship between parameter sensitivity and uncertainty. Pant et al. (2021) observed that many sensitive parameters—particularly the cathode transfer coefficient—exhibit medium to high uncertainty in available literature values [76]. This finding highlights a critical challenge: parameters that most influence model predictions are often those most poorly characterized, creating a paradox where models are most sensitive to their least certain inputs.

The duplicity problem, wherein multiple parameter combinations yield equivalent model performance, compounds this challenge. Kannan et al. address this through ranking and quantification of parameter contributions, providing guidance for experimental efforts to reduce uncertainty in the most influential factors [74].

7.7. Implications for Model Development and Optimization

The collective insights from sensitivity analysis studies carry profound implications for PEMFC model development and application. First, sensitivity analysis enables targeted experimental design by identifying which parameters require precise measurement. Resources can be directed toward characterizing sensitive parameters while accepting literature values for insensitive ones.

Second, sensitivity analysis supports model reduction by identifying parameters with negligible influence on predictions of interest. Li et al. (2023) demonstrated this by classifying micro-porous layer thickness and gas diffusion layer porosity as insensitive, enabling their fixation in subsequent optimization studies [77].

Third, sensitivity analysis reveals how parameter importance varies with operating conditions, informing adaptive modeling strategies. Pant et al. (2021) showed that cathode kinetics dominate at low humidity while gas transport becomes critical at high humidity, suggesting that model complexity might be selectively activated based on operating regime [76].

Fourth, sensitivity analysis guides control system design by identifying variables to which system outputs are most responsive. Mantelli et al. (2024) leveraged such insights to design feedback controllers maintaining operational parameters within acceptable ranges despite disturbances [78].

7.8. Synthesis and Future Directions of Sensitivity Analysis Studies for PEMFC Modeling and Optimization

The body of sensitivity analysis research summarized in Table 8 collectively demonstrates that understanding parameter influence is as important as developing sophisticated models themselves. Key findings include the following:

1. Parameter importance is context-dependent: Factors dominating predictions vary with humidity, current density, and operating conditions, necessitating sensitivity analysis tailored to specific applications.
2. Structural and operational parameters exhibit distinct influence patterns: Membrane properties and kinetic parameters consistently rank among sensitive factors, while some transport-layer properties may be fixed without compromising accuracy.
3. Dynamic behavior reveals sensitivities that are not apparent in steady-state analysis: Control-oriented applications require dedicated sensitivity analysis of transient response characteristics.
4. Computational constraints necessitate methodological compromises: The trade-off between model dimensionality and sensitivity analysis comprehensiveness requires careful consideration of objectives and resources.

5. Uncertainty in sensitive parameters presents both a challenge and an opportunity: Improving the characterization of influential but uncertain parameters offers substantial potential for enhancing model predictive capability.

Future research directions emerging from this synthesis include the following: development of efficient global sensitivity methods compatible with high-fidelity 3D models; integration of sensitivity analysis with uncertainty quantification to address parameter identifiability; extension of sensitivity concepts to degradation phenomena and lifetime prediction; and application of machine learning to accelerate sensitivity computations while maintaining accuracy. Sensitivity analysis has matured from an optional complement to PEMFC modeling into an essential methodology for ensuring model credibility, guiding experimental efforts, and enabling practical optimization. The studies reviewed in Table 8 demonstrate that systematic investigation of parameter influence reveals insights unattainable through model development alone—insights that directly translate to improved fuel cell design, more effective control strategies, and enhanced operational efficiency. As PEMFC technology continues advancing toward commercialization, sensitivity analysis will remain indispensable for translating modeling investments into practical performance improvements.

Table 8. Summary of sensitivity analysis studies for PEMFC modeling and optimization.

No.	Reference	Model/Method	Key Findings	Main Contributions	Identified Limitations
[74]	Kannan et al. (n.d.)	Monte Carlo-based sensitivity analysis with 1D mechanistic model	Varied over 30 normally distributed parameters (10% SD); ranked parameter contributions using multiple linear regression and sigma-normalized derivative methods; sample size of 10,000 enabled identification of optimal operating and physical parameters	Presents Monte Carlo sensitivity analysis using accelerated time-marched 1D model; employs Kolmogorov–Smirnov test for sample size reliability; enables improved accuracy, faster diagnosis, and easier PEMFC optimization	Mechanistic model computational cost; 1D limitations vs. higher-dimensional models; 10% SD may not capture all real-world variations; sample size may not account for all stochastic influences
[78]	Mantelli et al. (2024)	Dynamic model of turbocharged PEMFC system in Matlab-Simulink	Strong sensitivity to fuel valve opening; proper operation maintained during load increases; load reductions constrained by compressor surge risk (max ramp rate 35 A/s); feedback controller necessary for operational stability	Develops detailed dynamic TC-PEMFC model; investigates fluid dynamic and thermal transients; implements and assesses control logics for different power load ramps; addresses compressor surge limitations	Load reductions limited by compressor surge risk; strong sensitivity to fuel valve opening necessitates feedback control, indicating limited self-regulation capability
[72]	Correa et al. (2005)	Multiparametric sensitivity analysis of electrochemical models	Choice of modeling parameters significantly affects simulation outcomes; specific parameter values are essential for adequate PEMFC model; analysis encompasses entire parameter space	Defines relative importance of various modeling parameters; utilizes multiparametric sensitivity analysis for comprehensive parameter space evaluation; contributes to alternative energy source development	Not specified
[68]	Cao et al. (2005)	Dynamic neural networks with sensitivity analysis-based structure optimization	Proposed model achieved more compact structure, higher accuracy, and faster convergence than traditional models; validated on commercial dual-system fuel cell test platform	Introduces sensitivity analysis to evaluate network structure rationality; optimizes structure by pruning or inserting hidden nodes based on SA results; enhances approximating and self-adaptive abilities of PEMFC models	Not specified

Table 8. *Cont.*

No.	Reference	Model/Method	Key Findings	Main Contributions	Identified Limitations
[76]	S Stewart, et al. (2021)	2D membrane electrode assembly (MEA) model with uncertainty propagation-based sensitivity analysis	At low humidities: cathode kinetics and membrane-ohmic-loss parameters crucial; at humidified conditions: gas transport and porous-media saturation significant; several sensitive parameters have medium–high literature uncertainty; permeability, MPL saturation, evaporation rate show negligible impact	Comprehensive sensitivity analysis of nearly 50 input parameters across operating conditions; identifies critical parameters differing from previous literature; provides manageable parameter set for heavy-duty vehicle applications	Local sensitivity study only; 2D vs. 3D model limitations; truly global 3D sensitivity analysis infeasible due to computation time; some sensitive parameters not easily changeable
[77]	Li et al. (2023)	1D transient multiphase PEMFC model with global sensitivity analysis (elementary effect method)	MEM thickness and anode ionomer volume fraction identified as highly sensitive; MPL thickness and GDL porosity classified as insensitive; thicker MEM and CL increase ohmic loss and transfer resistance; sensitivity of parameters increases at high current densities	Establishes 1D transient multiphase model and global sensitivity analysis framework; quantifies influence of structural parameters on output performance; provides insights for critical parameter identification in PEMFC design	Not explicitly mentioned
[79]	Lorandi et al. (2004)	Sensitivity analysis on output impedance from linear small-signal model	Characterized quantitative effects of parameters on output impedance; anode and cathode volumes significantly impact dynamic response; sensitivity functions derived using Matlab	Focuses on internal design modifications to enhance dynamic response; identifies key parameters affecting transient response; distinguishes output impedance for dynamic response evaluation	External factors (fuel supply regulators, humidifiers) acknowledged but not explored; applicability to different configurations not discussed
[73]	Liao et al. (2024)	Sensitivity analysis + Bayesian-optimized Gaussian process regression	Temperature identified as most significant factor affecting power, followed by stoichiometry and backpressure; RMSE reduced from 0.1 to 0.0556; optimal parameters: 80 °C, stoichiometry 4, backpressure 1.7 bar	Employs sensitivity analysis to investigate operating condition impacts; utilizes Bayesian-optimized GPR for parameter optimization; provides theoretical support for performance enhancement	Not specified
[75]	Testa et al. (2015a)	Monte Carlo Simulation with Sample Random Sampling (SRS) technique	Noise and control factors exhibited high orthogonality; direct proportionality between current density and anode relative humidity; Pareto plot enabled targeted design variable reduction	Introduces the method to reduce problem complexity by identifying minimal-impact parameters; enhances input design matrix orthogonality; facilitates multi-disciplinary design optimization	Geometrical parameters excluded; significant simulations required for even distribution; method suited for fast-running analyses only; simultaneous parameter analysis would require unacceptable simulation time

Note: SD = standard deviation; MEM = membrane; CL = catalytic layer; MPL = micro-porous layer; GDL = gas diffusion layer; TC-PEMFC = Turbocharged Proton Exchange Membrane Fuel Cell; MEA = membrane electrode assembly; SA = sensitivity analysis; GPR = Gaussian process regression; RMSE = root mean square error; MDO = multidisciplinary design optimization; SRS = Sample Random Sampling.

8. Synthesis and Identification of Research Gaps

To distinguish this review from previous surveys, this section synthesizes the major limitations of the existing literature, identifies unresolved research gaps, and discusses the research opportunities that should receive greater attention in future PEMFC studies.

8.1. Current State of Knowledge

The preceding sections have documented substantial progress in PEMFC parameter estimation and modeling over recent decades. The field has evolved from reliance on analytical methods with limited applicability to a rich ecosystem of metaheuristic algorithms, intelligent techniques, and hybrid approaches capable of addressing the nonlinear, multimodal optimization problems characteristic of PEMFC systems.

Key advances include the following:

1. Algorithmic diversity: The development of numerous metaheuristic algorithms inspired by natural, physical, and social phenomena has provided researchers with a versatile toolkit for parameter estimation, enabling method selection based on problem-specific requirements.
2. Hybrid methodologies: The integration of complementary algorithms has yielded approaches that surpass the performance of individual methods, addressing limitations such as premature convergence and computational inefficiency.
3. Data-preprocessing techniques: The incorporation of neural networks and other preprocessing methods has enhanced robustness to noise and data limitations, addressing fundamental challenges in practical PEMFC applications.
4. Online estimation capabilities: Recent developments in online parameter estimation with guaranteed convergence properties have opened possibilities for real-time monitoring and adaptive control [3,7].
5. Sensitivity-guided modeling: The integration of sensitivity analysis with optimization has improved understanding of parameter importance and guided model refinement efforts.

Comparative Assessment of Existing Parameter Estimation Approaches

Although numerous parameter estimation techniques have been proposed for PEMFC modeling, their reported performance should not be evaluated solely based on statistical indicators such as SSE or RMSE. These metrics are influenced by the benchmark PEMFC stack, operating conditions, dataset size, and experimental protocols, making direct comparison across different studies challenging. A comprehensive assessment therefore requires consideration of the underlying assumptions, convergence behavior, computational complexity, robustness, and practical applicability of each method.

Analytical and deterministic approaches generally provide fast convergence and low computational cost because they rely on established electrochemical relationships. However, their performance is often limited by simplifying assumptions and reduced flexibility when modeling highly nonlinear operating conditions. Metaheuristic optimization algorithms have become the dominant approach for PEMFC parameter estimation due to their strong global search capability and ability to solve complex nonlinear optimization problems without requiring gradient information. Nevertheless, their stochastic nature may result in different convergence behavior across independent runs, and many algorithms require careful tuning of control parameters. Furthermore, improved estimation accuracy is frequently achieved at the expense of increased computational cost.

Machine learning and deep learning methods offer excellent predictive capability when sufficient training data are available and are particularly effective for nonlinear system identification. However, their performance strongly depends on data quality, data diversity, and training strategies. Many deep learning models also operate as black-box systems, limiting their interpretability and practical acceptance in safety-critical applications.

Hybrid approaches combine the complementary strengths of optimization algorithms and artificial intelligence techniques, often improving convergence speed, estimation accuracy, and robustness compared with individual methods. These advantages, however, are

generally accompanied by increased algorithmic complexity, additional hyperparameter tuning, and greater computational requirements.

Online parameter-estimation methods provide an important step toward real-time monitoring and adaptive control by continuously updating model parameters during operation. Despite their potential, their application remains relatively limited compared with offline optimization methods, and further validation under practical operating conditions is still required.

Moreover, no single parameter estimation technique consistently outperforms all others under every operating condition. The selection of an appropriate method depends on the specific application requirements, including estimation accuracy, convergence speed, computational resources, robustness against measurement noise, implementation complexity, and real-time capability. Consequently, future research should emphasize balanced evaluation frameworks that consider these practical trade-offs rather than relying exclusively on individual error metrics.

Table 9 summarizes the principal characteristics of the major categories of PEMFC parameter estimation approaches reviewed in this work. Rather than comparing methods solely on reported SSE or RMSE values, the table highlights their underlying assumptions, convergence behavior, computational complexity, robustness, practical applicability, and inherent limitations. Analytical methods generally provide fast and computationally efficient solutions but rely on simplified electrochemical assumptions. Metaheuristic algorithms have become the dominant approach because of their strong global optimization capability, although they typically require higher computational effort. Machine learning and deep learning techniques offer excellent predictive performance for nonlinear systems but depend heavily on the availability of representative training data and often suffer from limited interpretability. Reinforcement learning has recently emerged as a promising solution for adaptive and online parameter estimation, although its practical application remains limited. Hybrid methods combine complementary optimization and artificial intelligence techniques to improve estimation accuracy and robustness, but these improvements are often achieved at the expense of increased implementation complexity. These observations indicate that no single approach consistently outperforms all others, and the selection of an appropriate method should be guided by the specific application requirements and operational constraints.

8.2. Persistent Challenges and Limitations

Despite these advances, significant challenges remain in PEMFC parameter estimation and modeling. The limitations identified across the reviewed literature can be categorized into several themes.

8.2.1. Generalizability Across Fuel Cell Types

A persistent concern is the limited generalizability of parameter-estimation methods across different PEMFC types, configurations, and operating conditions. Studies typically validate proposed algorithms on a small number of commercial stacks—commonly BCS 500 W, NedStack PS6, and Ballard Mark V—raising questions about performance on novel or custom-designed fuel cells. The effectiveness of optimization algorithms can vary significantly based on specific operational conditions and model configurations [6], suggesting that method validation across diverse platforms remains insufficient.

8.2.2. Computational Efficiency for Real-Time Applications

While many algorithms demonstrate excellent accuracy in offline parameter estimation, their computational requirements may preclude real-time applications. The high number of objective function evaluations needed for convergence in stochastic methods

remains a significant limitation [10,11]. Although recent algorithms have shown improved convergence speed, the gap between research demonstrations and practical real-time implementation persists.

Table 9. Comparative assessment of major PEMFC parameter estimation approaches based on the reviewed literature.

Method Category	Underlying Assumptions	Convergence Characteristics	Computational Complexity	Robustness	Practical Applicability	Primary Limitations
Analytical and deterministic methods	Accurate electrochemical model and mathematical formulation	Fast and deterministic	Low	Moderate	Suitable for offline modeling and theoretical analysis	Limited capability for highly nonlinear systems and parameter uncertainty
Metaheuristic optimization methods	No gradient information required; optimization based on objective function	Good global search capability; stochastic convergence	Medium–High	High	Widely adopted for offline parameter estimation	Sensitive to algorithm settings and computationally intensive
Machine learning methods	Availability of representative training data	Fast after training	Medium	Moderate–High	Suitable for nonlinear modeling and prediction	Performance depends on data quality and generalization ability
Deep learning methods	Large and diverse datasets are required	High prediction accuracy after training	High	High	Effective for complex nonlinear behavior and health monitoring	Limited interpretability and high computational requirements
Reinforcement learning methods	Continuous interaction with the operating environment	Adaptive and self-learning	High	High	Promising for real-time estimation and control	Limited practical validation and high training complexity
Hybrid approaches	Integration of complementary optimization and AI techniques	Improved convergence and estimation accuracy	High	Very High	Well suited for complex PEMFC parameter estimation problems	Increased implementation complexity and hyperparameter tuning

8.2.3. Handling of Nonseparable Nonlinearities

Despite advances in transforming nonseparable models into more tractable forms, the fundamental challenge of nonseparable nonlinearities continues to complicate parameter estimation. Traditional methods often fail to effectively handle these nonlinearities, resulting in poor convergence and estimation accuracy. While differential operator-based methods show promise, their applicability across the full range of PEMFC operating conditions requires further investigation.

8.2.4. Data Quality and Availability

The quality and quantity of available measurement data remain fundamental constraints on parameter estimation accuracy. Insufficient measurement data can lead to incomplete or unreliable parameter identification [16], while noise in measurement data can significantly distort the extraction process [15]. Although neural network preprocessing offers partial mitigation, the fundamental limitation of data availability in many practical contexts persists.

8.2.5. Parameter Duplicity and Identifiability

The duplicity problem—where multiple parameter sets yield equivalent or similar model performance—complicates parameter identification and undermines confidence in estimation results [10,11]. This issue arises from correlations between parameters and limitations in the information content of available measurements, and it fundamentally limits the identifiability of certain parameters regardless of algorithmic sophistication.

8.2.6. Critical Analysis and Research Gaps

Despite the remarkable progress achieved in PEMFC parameter estimation, several fundamental challenges remain unresolved. Most existing optimization algorithms are developed and validated under offline conditions using predefined polarization curves or

laboratory datasets. Although these approaches achieve high estimation accuracy, their applicability to real-time monitoring and adaptive control remains limited.

Another important limitation is the lack of online parameter estimation. Many studies estimate parameters after data collection rather than continuously updating model parameters as operating conditions change. This limitation reduces their suitability for practical PEMFC applications operating under dynamic loads, aging effects, and environmental variations. Experimental validation also remains insufficient. Although many studies compare optimization algorithms using commercial PEMFC stacks, relatively few validate their methods under long-term real-time operating conditions or practical industrial applications. Consequently, the robustness of many algorithms under realistic operating environments has not yet been fully demonstrated.

The reviewed studies also reveal that many machine learning and deep learning approaches are trained using relatively small datasets collected under limited operating conditions. Such datasets may not adequately represent the wide range of temperatures, pressures, humidity levels, and degradation states encountered in practice, limiting the generalization capability of the developed models. Another common limitation is the limited consideration of uncertainty. Most parameter-estimation methods provide deterministic parameter values without quantifying the uncertainty associated with measurement noise, model assumptions, or operating condition variations. Incorporating uncertainty quantification would improve the reliability and confidence of parameter estimation results.

Furthermore, the absence of standardized benchmark datasets makes objective comparison among different parameter estimation algorithms difficult. Most studies employ different PEMFC stacks, operating conditions, objective functions, and evaluation metrics, preventing fair performance comparisons across the literature.

Computational complexity also remains an important concern. While recent hybrid and metaheuristic algorithms generally improve estimation accuracy, these improvements are often achieved at the expense of increased computational cost, making their deployment in embedded controllers and real-time applications challenging.

Although artificial intelligence techniques continue to demonstrate excellent predictive capability, many deep learning models operate as black-box systems with limited interpretability. The lack of explainable artificial intelligence reduces user confidence and limits their adoption in safety-critical applications such as fault diagnosis and health management. Another important challenge is the limited transferability of parameter estimation algorithms across different PEMFC stacks. Algorithms optimized for one stack configuration often require parameter retuning or complete retraining before they can be applied to other commercial stacks or operating environments. Developing generalized and transferable estimation frameworks therefore remains an important research direction.

9. Future Research Directions

Future research should prioritize the development of online and real-time parameter-estimation methods that can continuously update model parameters under changing operating conditions. Such capabilities are essential for enabling digital twins, predictive maintenance, and advanced control strategies in practical PEMFC applications.

Enhancing the interpretability of artificial intelligence models is another important research direction. Explainable AI techniques can improve understanding of the prediction process by identifying the most influential parameters and providing greater transparency, thereby increasing confidence in AI-assisted PEMFC monitoring and decision making.

Integrating digital twin technology with physics-based and data-driven models offers promising opportunities for continuous performance monitoring, early fault detection, and

accurate lifetime prediction. This integration can support more reliable and intelligent PEMFC operation throughout its service life.

Physics-informed artificial intelligence has also emerged as a promising approach for PEMFC modeling. By incorporating electrochemical knowledge into machine learning frameworks, these methods can improve prediction accuracy while reducing the dependence on large volumes of experimental data.

Future optimization methods should move beyond single-objective formulations and consider multiple performance criteria simultaneously, including estimation accuracy, convergence speed, computational efficiency, robustness, and implementation cost. Such multi-objective frameworks can provide more balanced and practical solutions for real-world applications.

Reinforcement learning represents another promising direction for adaptive parameter estimation and control under dynamic operating conditions. Its ability to learn optimal decision-making strategies through continuous interaction with the operating environment makes it well suited for autonomous PEMFC management.

Greater attention should also be given to transfer learning techniques to improve the adaptability of trained models across different PEMFC stacks and operating conditions while minimizing the need for extensive retraining.

Further research is needed on online adaptive estimation methods that continuously update model parameters as the fuel cell degrades over time. Such approaches can improve model accuracy and support more effective health monitoring throughout the PEMFC lifetime.

Another important direction is the development of uncertainty-aware parameter estimation frameworks that integrate probabilistic modeling with optimization techniques. These frameworks can provide more reliable parameter estimates by explicitly accounting for measurement noise and uncertainties in operating conditions.

Establishing standardized benchmark datasets, unified evaluation protocols, and consistent performance metrics is equally important. These efforts would enable objective comparisons among emerging parameter-estimation methods, improve the reproducibility of published studies, and facilitate the transition of advanced algorithms from research to practical industrial applications. Moreover, based on the synthesis of the current literature and the identified gaps, several directions for future research emerge as particularly promising.

9.1. Standardized Benchmarking Frameworks

The development of standardized benchmarking frameworks for PEMFC parameter estimation would facilitate meaningful comparisons between algorithms and accelerate progress. Such frameworks should include diverse PEMFC types, operating conditions, and data quality scenarios, enabling comprehensive evaluation of algorithm performance, robustness, and generalizability. Standardized metrics encompassing accuracy, computational efficiency, and statistical reliability would support evidence-based method selection.

9.2. Advanced Hybrid and Ensemble Methods

The demonstrated success of hybrid approaches suggests that further exploration of ensemble methods—combining multiple algorithms with weighted contributions or adaptive selection mechanisms—could yield additional improvements. Research might investigate optimal combinations of exploration- and exploitation-oriented algorithms, dynamic adjustment of hybrid composition based on optimization progress, and integration of domain knowledge to guide hybrid search.

9.3. Physics-Informed Machine Learning

The integration of physical principles with machine learning approaches offers opportunities to combine the interpretability and theoretical foundation of physics-based models with the flexibility and pattern recognition capabilities of data-driven methods. Physics-informed neural networks, which incorporate governing equations into training objectives, could potentially address the data limitations and generalizability concerns that constrain purely empirical approaches.

9.4. Uncertainty Quantification and Robust Estimation

Future research should place greater emphasis on uncertainty quantification in parameter estimation, moving beyond point estimates to characterize confidence intervals and parameter distributions. Bayesian approaches, ensemble methods, and probabilistic programming offer frameworks for quantifying estimation uncertainty and propagating it through subsequent analyses. Robust estimation methods that maintain performance under model misspecification and data anomalies also warrant further investigation.

9.5. Online and Adaptive Estimation

The development of online estimation methods with guaranteed convergence properties represents a significant advance, but substantial work remains to realize their full potential. Research is needed on adaptive algorithms that can track parameter variations during operation, methods for detecting and responding to changes in system behavior, and integration of online estimation with model predictive control for real-time optimization.

9.6. Multi-Objective Optimization

Most current approaches frame parameter estimation as a single-objective optimization problem—typically minimizing error between predicted and measured voltages. However, practical applications may require balancing multiple objectives, including accuracy across different operating conditions, computational efficiency, and robustness to measurement noise. Multi-objective optimization frameworks could enable systematic trade-off analysis and support method selection based on application-specific priorities.

10. Conclusions

This review has examined the current state of parameter estimation and modeling for Proton Exchange Membrane Fuel Cells, synthesizing findings from a diverse body of literature spanning analytical methods, metaheuristic algorithms, intelligent techniques, and sensitivity analysis. The field has witnessed remarkable progress, with the development of numerous optimization algorithms capable of addressing the nonlinear, multimodal challenges inherent in PEMFC parameter identification.

Metaheuristic algorithms, particularly those inspired by natural and physical phenomena, have demonstrated substantial success in extracting accurate parameter estimates across various PEMFC types. Evolutionary algorithms, swarm intelligence methods, and physics-inspired approaches each offer unique advantages, with hybrid combinations often surpassing the performance of individual algorithms. The integration of neural networks for data preprocessing has enhanced robustness to noise and data limitations, while reinforcement learning approaches offer adaptive capabilities well-suited to evolving system behavior.

Sensitivity analysis has emerged as a valuable complement to optimization, providing insights into parameter importance, guiding model refinement, and supporting the development of parsimonious representations. The integration of sensitivity methods with

optimization frameworks enables more informed interpretation of estimation results and identification of critical parameters requiring precise characterization.

Despite these advances, persistent challenges remain, including limited generalizability across fuel cell types, computational constraints on real-time applications, difficulties in handling nonseparable nonlinearities, and fundamental limitations imposed by data quality and parameter identifiability. Addressing these challenges will require continued innovation in algorithmic development, standardized benchmarking frameworks, and deeper integration of physical principles with data-driven methods.

As PEMFC technology continues to mature toward widespread commercialization, the importance of accurate parameter estimation and modeling will only increase. Precise models enable optimal design, efficient operation, and effective control all essential for realizing the full potential of fuel cells in sustainable energy systems. The foundations established by current research provide a solid basis for future advances, and the continued evolution of estimation methodologies promises to support the next generation of PEMFC applications.

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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Definition
AEO	Artificial Ecosystem Optimization
AI	artificial intelligence
ALO	Antlion Optimizer
ANN	artificial neural network
ARO	Artificial Rabbits Optimization
ASO	Atom Search Optimization
BES	Bald Eagle Search
BSO	Brain Storm Optimization
BSOA	Bi-Subgroup Optimization Algorithm
CL	composite learning
COA	Coyote Optimization Algorithm
COOT	Coot Optimization Algorithm
CRO	Coral Reefs Optimization
DE	Differential Evolution
DEA	Differential Evolution Ameliorated
Di-DE	Depth Information-Based Differential Evolution
DNN	Deep Neural Network
DO	Dandelion Optimizer
DREM	Dynamic Regressor Extension and Mixing
EAHA	Enhanced Artificial Hummingbird Algorithm
EO	Equilibrium Optimizer
EP	Evolutionary Programming
FC	fuel cell
FNN	feedforward neural network
FNN-POA	feedforward neural network–Pelican Optimization Algorithm

FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GBO	Gradient-Based Optimizer
GD	Gradient Descent
GOA	Gazelle Optimization Algorithm
GRNN	Generalized Regression Neural Network
GRU	Gated Recurrent Unit
GTO	Gorilla Troops Optimizer
GWO	Grey Wolf Optimizer
HBO	Heap-Based Optimizer
HCLBES	Heterogeneous Comprehensive Learning Bald Eagle Search
HGSO	Henry Gas Solubility Optimization
HHO	Harris Hawks Optimization
HiP-DE	Historical Population-Based Differential Evolution
HLDTOA	Horned Lizard Defense Tactics Optimization Algorithm
HPDE	Hierarchical Population-Based Differential Evolution
HTLP	High Temperature–Low Pressure
IAEO	Improved Artificial Ecosystem Optimization
IDBO	Improved Dung Beetle Optimization
IMRFO	Improved Manta Ray Foraging Optimization
LMBP	Levenberg–Marquardt Back-Propagation
LRE	Linear Regression Equation
LS	Least Squares
LSD	Least-Squares Dynamic Estimator
LSTM	Long Short-Term Memory
MA	Memetic Algorithm
MAE	mean absolute error
MAEO	Modified Artificial Ecosystem Optimization
MAPE	mean absolute percentage error
MFO	Moth–Flame Optimization
MGTO	Modified Gorilla Troops Optimizer
MhAs	Metaheuristic Algorithms
MPA	Marine Predators Algorithm
MS-TSO	Multi-Strategy Tuna Swarm Optimization
MTSO	Modified Transient Search Optimization
NSNLP	Nonseparable Nonlinear Parameterization
OBAOA	Opposition-Based Arithmetic Optimization Algorithm
OOA	Osprey Optimization Algorithm
PEMFC	Proton Exchange Membrane Fuel Cell
PHM	Predictive Health Management
PO	Political Optimizer
POA	Pelican Optimization Algorithm
PDO	Prairie Dog Optimization
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
RMSE	root mean square error
RSA	Reptile Search Algorithm
RUL	Remaining Useful Life
SCA	Sine Cosine Algorithm
SDO	Supply–Demand-Based Optimization
SHO	Spotted Hyena Optimizer
SeaHO	Sea Horse Optimization

SMA	Slime Mould Algorithm
SNLP	Separable Nonlinear Parameterization
SOH	State of Health
SRSC	Segmented Random Sampling Correction
SRSR	Swarm Robotics Search and Rescue
SSA	Salp Swarm Algorithm
SSE	sum of squared errors
TabNet	Attentive Interpretable Tabular Learning Network
TCN	Temporal Convolutional Network
TSA	Tunicate Swarm Algorithm
TSO	Tuna Swarm Optimization
VSDE	Variable Strategy Differential Evolution
WOA	Whale Optimization Algorithm
1stOpt	Universal Global Optimization Software

References

1. Priya, K.; Sathishkumar, K.; Rajasekar, N. A comprehensive review on parameter estimation techniques for Proton Exchange Membrane fuel cell modelling. *Renew. Sustain. Energy Rev.* **2018**, *93*, 121–144. [CrossRef]
2. Ashraf, H.; Abdellatif, S.O.; Elkholy, M.M.; El-Fergany, A.A. Computational Techniques Based on Artificial Intelligence for Extracting Optimal Parameters of PEMFCs: Survey and Insights. *Arch. Comput. Methods Eng.* **2022**, *29*, 3943–3972. [CrossRef]
3. Beltrán, C.A.; Bobtsov, A.; Ortega, R.; Langarica-Córdoba, D.; Cisneros, R.; Díaz-Saldierna, L.H. Online Parameter Estimation of the Polarization Curve of a Fuel Cell with Guaranteed Convergence Properties: Theoretical and Experimental Results. *IEEE Trans. Ind. Electron.* **2024**, *71*, 14776–14783. [CrossRef]
4. Ma, Y.; Li, S.; Zhou, S.; Wang, X.; Yuan, H.; Chang, G.; Zhu, J.; Dai, H.; Wei, X. Performance degradation prediction of proton exchange membrane fuel cells based on CNN-LSTM network with squeeze-and-excitation attention mechanism. *Energy* **2025**, *335*, 138127. [CrossRef]
5. Ma, Y.; Wang, X.; Yuan, H.; Chang, G.; Zhu, J.; Dai, H.; Wei, X. Review of electrochemical impedance spectroscopy in fault diagnosis for proton exchange membrane fuel cells. *Renew. Sustain. Energy Rev.* **2025**, *211*, 115226. [CrossRef]
6. Abbassi, R.; Saidi, S.; Abbassi, A.; Jerbi, H.; Kchaou, M.; Alhasnawi, B.N. Accurate Key Parameters Estimation of PEMFCs' Models Based on Dandelion Optimization Algorithm. *Mathematics* **2023**, *11*, 1298. [CrossRef]
7. Xu, H.; Wang, L.; Liu, Z.; Su, H.; Ortega, R. Online Identification of PEMFC Polarization Curves with Nonlinear Concentration Loss. *IEEE Trans. Ind. Electron.* **2025**, *72*, 7544–7552. [CrossRef]
8. Mo, Z.-J.; Zhu, X.-J.; Wei, L.-Y.; Cao, G.-Y. Parameter optimization for a PEMFC model with a hybrid genetic algorithm. *Int. J. Energy Res.* **2006**, *30*, 585–597. [CrossRef]
9. Diab, A.A.Z.; Abdelhamid, A.M. Optimal identification of model parameters for PEMFCs using neoteric metaheuristic methods. *IET Renew. Power Gener.* **2022**, *17*, 659–680. [CrossRef]
10. Alotto, P.; Guarnieri, M. Stochastic Methods for Parameter Estimation of Multiphysics Models of Fuel Cells. *IEEE Trans. Magn.* **2014**, *50*, 701–704. [CrossRef]
11. Alotto, P.; Negro, E.; Di Noto, V.; Guarnieri, M. Stochastic Methods for PEMFC Parameter Identification. *ECS Meet. Abstr.* **2014**, *MA2014-01*, 12. [CrossRef]
12. Ashraf, H.; Abdellatif, S.O.; Elkholy, M.M.; El-Fergany, A.A. Honey badger optimizer for extracting the ungiven parameters of PEMFC model: Steady-state assessment. *Energy Convers. Manag.* **2022**, *258*, 115521. [CrossRef]
13. Sultan, H.M.; Menesy, A.S.; Alqahtani, M.; Khalid, M.; Zaki Diab, A.A. Accurate parameter identification of proton exchange membrane fuel cell models using different metaheuristic optimization algorithms. *Energy Rep.* **2023**, *10*, 4824–4848. [CrossRef]
14. Qiu, Z.; Xing, Y.; Na, J.; Gao, G. Adaptive Parameter Estimation for a Polymer Electrolyte Membrane Fuel Cell with Nonlinear Parameterization. In *Proceedings of the 2024 43rd Chinese Control Conference (CCC)*; IEEE: New York, NY, USA, 2024; pp. 1414–1419.
15. Yang, B.; Liang, B.; Qian, Y.; Zheng, R.; Su, S.; Guo, Z.; Jiang, L. Parameter identification of PEMFC via feedforward neural network-pelican optimization algorithm. *Appl. Energy* **2024**, *361*, 122857. [CrossRef]
16. Li, D.; Yang, B.; Han, Y. A Critical Note of Major Parameter Extraction Methods for Proton Exchange Membrane Fuel Cell (PEMFC). *Front. Energy Res.* **2022**, *9*, 835397. [CrossRef]
17. Erduman, A.; Hazar, G.; Aydın, E.B. A Sea Horse Optimization-Based Approach for PEM Fuel Cell Model Parameter Estimation. *Appl. Sci.* **2025**, *15*, 8316. [CrossRef]
18. Alhendi, A.; Al-Sumaiti, A.S.; Marzband, M.; Kumar, R.; Diab, A.A.Z. Short-term load and price forecasting using artificial neural network with enhanced Markov chain for ISO New England. *Energy Rep.* **2023**, *9*, 4799–4815. [CrossRef]

19. Askarzadeh, A.; Rezazadeh, A. A grouping-based global harmony search algorithm for modeling of proton exchange membrane fuel cell. *Int. J. Hydrogen Energy* **2011**, *36*, 5047–5053. [CrossRef]
20. El-Fergany, A.A.; Hasanien, H.M.; Agwa, A.M. Semi-empirical PEM fuel cells model using whale optimization algorithm. *Energy Convers. Manag.* **2019**, *201*, 112197. [CrossRef]
21. Stacks, H.-S.F.C. H-12 PEM Fuel Cell 12W-Horizon Educational. Available online: https://www.horizoneducational.com/advancedproducts/h-12-pem-fuel-cell-12w/ (accessed on 8 March 2026).
22. Louzazni, M.; Al-Dahidi, S.; Mussetta, M. Fuel cell characteristic curve approximation using the Bézier curve technique. *Sustainability* **2020**, *12*, 8127. [CrossRef]
23. Menesy, A.S.; Sultan, H.M.; Korashy, A.; Banakhr, F.A.; G. Ashmawy, M.; Kamel, S. Effective Parameter Extraction of Different Polymer Electrolyte Membrane Fuel Cell Stack Models Using a Modified Artificial Ecosystem Optimization Algorithm. *IEEE Access* **2020**, *8*, 31892–31909. [CrossRef]
24. Diab, A.A.Z.; Tolba, M.A.; El-Magd, A.G.A.; Zaky, M.M.; El-Rifaie, A.M. Fuel Cell Parameters Estimation via Marine Predators and Political Optimizers. *IEEE Access* **2020**, *8*, 166998–167018. [CrossRef]
25. Riad, A.J.; Hasanien, H.M.; Turky, R.A.; Yakout, A.H. Identifying the PEM Fuel Cell Parameters Using Artificial Rabbits Optimization Algorithm. *Sustainability* **2023**, *15*, 4625. [CrossRef]
26. Saidi, S.; Horchani, E.; Khriji, W. Highly accurate extraction of PEM fuel cell parameters using an innovative hybrid salp swarm algorithm with a chaotic system and adaptive differential evolution. *Energy Convers. Manag.* **2026**, *348*, 120472. [CrossRef]
27. Sultan, H.M.; Menesy, A.S.; Kamel, S.; Selim, A.; Jurado, F. Parameter identification of proton exchange membrane fuel cells using an improved salp swarm algorithm. *Energy Convers. Manag.* **2020**, *224*, 113341. [CrossRef]
28. Hachana, O.; El-Fergany, A.A. Efficient PEM fuel cells parameters identification using hybrid artificial bee colony differential evolution optimizer. *Energy* **2022**, *250*, 123830. [CrossRef]
29. Wang, K.; Ye, M.; Xu, Y. Proton exchange membrane fuel cell model optimization based on 1stOpt. *Chin. J. Power Sources* **2009**, *33*, 698–700.
30. Sultan, H.M.; Menesy, A.S.; Kamel, S.; Jurado, F. Developing the coyote optimization algorithm for extracting parameters of proton-exchange membrane fuel cell models. *Electr. Eng.* **2020**, *103*, 563–577. [CrossRef]
31. Yuan, X.; Fang, Z.; Sun, T.; Yan, S. Research on Neural Networks Identification of a Nonlinear Modeling for PEMFC. In *Proceedings of the 2009 Fifth International Conference on Natural Computation*; IEEE: New York, NY, USA, 2009; pp. 399–402.
32. Zhang, N.Y.; Tent, S.-Y.; Song, H.-S.; Liu, G.-Y.; Cheng, C.-F. Extraction of Parameters of Random Self-Affine Fractal Surfaces from Light Scattered Intensity by Levenberg–Marquardt Algorithm. *Chin. Phys. Lett.* **2009**, *26*, 034209. [CrossRef]
33. Khajuria, R.; Lamba, R.; Kumar, R. Parameters extraction of PEMFC model using evolutionary based optimization algorithms. *Proc. ICAER* **2022**, *2022*, 443–451.
34. Danoune, M.B.; Djafour, A.; Gougui, A. Accurate PEM Fuel Cell Parameters Identification Using Whale Optimization Algorithm. In *Springer Proceedings in Energy*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 203–210. [CrossRef]
35. Rezk, H.; Wilberforce, T.; Olabi, A.G.; Ghoniem, R.M.; Sayed, E.T.; Ali Abdelkareem, M. Optimal Parameter Identification of a PEM Fuel Cell Using Recent Optimization Algorithms. *Energies* **2023**, *16*, 5246. [CrossRef]
36. Zaky, A.A.; Ghoniem, R.M.; Selim, F. Precise Modeling of Proton Exchange Membrane Fuel Cell Using the Modified Bald Eagle Optimization Algorithm. *Sustainability* **2023**, *15*, 10590. [CrossRef]
37. Zhang, J.; Sun, Y.; Dong, H.; He, X. Parameter Identification of PEMFC Model Using Improved Dung Beetle Optimization Algorithm. *Electronics* **2024**, *14*, 35. [CrossRef]
38. Baz, F.B.; El Sehiemy, R.A.; Bayoumi, A.S.A.; Abaza, A. Parameter extraction of proton exchange membrane fuel cell based on artificial rabbits' optimization algorithm and conducting laboratory tests. *Sci. Rep.* **2024**, *14*, 21145. [CrossRef] [PubMed]
39. Kanouni, B.; Laib, A.; Krama, A.; Necaibia, S.; Guerrero, J.M. Horned Lizard Defense Tactics Optimization Algorithm for Precise Identification of PEMFC Parameters. *Fuel Cells* **2025**, *25*, e70011. [CrossRef]
40. Priya, K.; Selvaraj, V.; Ramachandra, N.; Rajasekar, N. Modelling of PEM fuel cell for parameter estimation utilizing clan co-operative based spotted hyena optimizer. *Energy Convers. Manag.* **2024**, *309*, 118371. [CrossRef]
41. Al-Shamma'a, A.A.; Ali, F.A.A.; Alhoshan, M.S.; Alturki, F.A.; Farh, H.M.H.; Alam, J.; AlSharabi, K. Proton Exchange Membrane Fuel Cell Parameter Extraction Using a Supply–Demand-Based Optimization Algorithm. *Processes* **2021**, *9*, 1416. [CrossRef]
42. Singh, P.; Sandhu, A. Optimal parameter extraction of proton exchange membrane fuel cell using Henry gas solubility optimization. *Int. J. Energy Res.* **2022**, *46*, 18212–18224. [CrossRef]
43. Ismaeel, A.A.K.; Houssein, E.H.; Khafaga, D.S.; Aldakheel, E.A.; Said, M. Performance of rime-ice algorithm for estimating the PEM fuel cell parameters. *Energy Rep.* **2024**, *11*, 3641–3652. [CrossRef]
44. Sharma, A.; Khan, R.A.; Sharma, A.; Kashyap, D.; Rajput, S. A Novel Opposition-Based Arithmetic Optimization Algorithm for Parameter Extraction of PEM Fuel Cell. *Electronics* **2021**, *10*, 2834. [CrossRef]
45. Duan, R.; Lin, D.; Fathi, G. PEMFC model identification using a squeezenet developed by modified transient search optimization algorithm. *Heliyon* **2024**, *10*, e27555. [CrossRef] [PubMed]

46. Khishe, M.; Jangir, P.; Arpita; Agrawal, S.P.; Pandya, S.B.; Parmar, A.; Abualigah, L. Innovative Diversity Metrics in Hierarchical Population-Based Differential Evolution for PEM Fuel Cell Parameter Optimization. *Eng. Rep.* **2024**, *7*, e13065. [CrossRef]
47. Aljaidi, M.; Jangir, P.; Agrawal, S.P.; Pandya, S.B.; Parmar, A.; Anbarkhan, S.H.; Abualigah, L. Historical Population-Based Mutation Strategy with Adaptive Parameter Mechanism in Differential Evolution for PEM Fuel Cell Parameter Estimation. *Res. Sq.* **2024**. [CrossRef] [PubMed]
48. Kanouni, B.; Laib, A. Extracting Accurate Parameters from a Proton Exchange Membrane Fuel Cell Model Using the Differential Evolution Ameliorated Meta-Heuristics Algorithm. *Energies* **2024**, *17*, 2333. [CrossRef]
49. Jangir, P.; Ezugwu, A.E.; Arpita; Agrawal, S.P.; Pandya, S.B.; Parmar, A.; Gulothungan, G.; Abualigah, L. Precision parameter estimation in Proton Exchange Membrane Fuel Cells using depth information enhanced Differential Evolution. *Sci. Rep.* **2024**, *14*, 29591. [CrossRef] [PubMed]
50. Liu, E.-J.; Hung, Y.-H.; Hong, C.-W. Improved Metaheuristic Optimization Algorithm Applied to Hydrogen Fuel Cell and Photovoltaic Cell Parameter Extraction. *Energies* **2021**, *14*, 619. [CrossRef]
51. Chen, Y.; Pi, D.; Wang, B.; Chen, J.; Xu, Y. Bi-subgroup optimization algorithm for parameter estimation of a PEMFC model. *Expert Syst. Appl.* **2022**, *196*, 116646. [CrossRef]
52. Mujeer, S.A.; Chandrasekhar, Y.; Kumari, M.S.; Salkuti, S.R. An accurate method for parameter estimation of proton exchange membrane fuel cell using Dandelion optimizer. *Int. J. Emerg. Electr. Power Syst.* **2024**, *25*, 333–344. [CrossRef]
53. Abdi, H.; Ait Messaoudene, N.; Kolsi, L.; Naceur, M.W. Modeling and optimization of a proton exchange membrane fuel cell using particle swarm algorithm with constriction coefficient. *J. Therm. Anal. Calorim.* **2020**, *144*, 1749–1759. [CrossRef]
54. Khajuria, R.; Lamba, R.; Kumar, R. Optimal Parameter Extraction and Performance Analysis of Proton Exchange Membrane Fuel Cell. In *Proceedings of the 2022 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*; IEEE: New York, NY, USA, 2022; pp. 1–6.
55. Mossa, M.A.; Kamel, O.M.; Sultan, H.M.; Diab, A.A.Z. Parameter estimation of PEMFC model based on Harris Hawks' optimization and atom search optimization algorithms. *Neural Comput. Appl.* **2020**, *33*, 5555–5570. [CrossRef]
56. Manoharan, P.; Ravichandran, S.; Kavitha, S.; Tengku Hashim, T.J.; Alsoud, A.R.; Sin, T.C. Parameter characterization of PEM fuel cell mathematical models using an orthogonal learning-based GOOSE algorithm. *Sci. Rep.* **2024**, *14*, 20979. [CrossRef] [PubMed]
57. Salem, N.M.; Shaheen, M.A.M.; Hasanien, H.M. Novel reinforcement learning technique based parameter estimation for proton exchange membrane fuel cell model. *Sci. Rep.* **2024**, *14*, 27475. [CrossRef] [PubMed]
58. Khajuria, R.; Bukya, M.; Lamba, R.; Kumar, R. Optimal Parameter Extraction of PEM Fuel Cell Using a Hybrid Weighted Mean of Vectors and Nelder-Mead Simplex Method. *IEEE Access* **2024**, *12*, 121346–121367. [CrossRef]
59. Ćalasan, M.; Micev, M.; Hasanien, H.M.; Abdel Aleem, S.H.E. PEM fuel cells: Two novel approaches for mathematical modeling and parameter estimation. *Energy* **2024**, *290*, 130130. [CrossRef]
60. Shaheen, A.M.; Alassaf, A.; Alsaleh, I.; El-Fergany, A.A.; Shi, J. Advancements in Model Parameter Estimation for Proton Exchange Membrane Fuel Cells via Enhanced Artificial Hummingbird Algorithm. *Int. J. Energy Res.* **2024**, *2024*. [CrossRef]
61. Menesy, A.S.; Sultan, H.M.; Kamel, S. Extracting Model Parameters of Proton Exchange Membrane Fuel Cell Using Equilibrium Optimizer Algorithm. In *Proceedings of the 2020 International Youth Conference on Radio Electronics, Electrical and Power Engineering (REEPE)*; IEEE: New York, NY, USA, 2020; pp. 1–7.
62. Mei, J.; Meng, X.; Tang, X.; Li, H.; Hasanien, H.; Alharbi, M.; Dong, Z.; Shen, J.; Sun, C.; Fan, F.; et al. An Accurate Parameter Estimation Method of the Voltage Model for Proton Exchange Membrane Fuel Cells. *Energies* **2024**, *17*, 2917. [CrossRef]
63. Abdel-Basset, M.; Mohamed, R.; Chang, V. An Efficient Parameter Estimation Algorithm for Proton Exchange Membrane Fuel Cells. *Energies* **2021**, *14*, 7115. [CrossRef]
64. Sedighizadeh, M.; Mahmoodi, M.M.; Soltanian, M. Parameter identification of proton exchange membrane fuel cell using a Hybrid Big Bang-Big Crunch optimization. In *Proceedings of the 2014 5th Conference on Thermal Power Plants (CTPP)*; IEEE: New York, NY, USA, 2014; pp. 35–39.
65. Ali, A.K.; Hussain, A.N.; Al-Obaidi, M.A.; Al-Anssari, S. Upgrading Sustainability in Clean Energy: Optimization for Proton Exchange Membrane Fuel Cells Using Heterogeneous Comprehensive Learning Bald Eagle Search Algorithm. *Sustainability* **2025**, *17*, 9729. [CrossRef]
66. Kuznyetsov, O.; Bilyakovskyy, I. Modeling of a Pem Fuel Cell Polarization Curve by Low-Order Polynomials for the Output Power Calculation Algorithms. *Rev. Roum. Des. Sci. Tech.—SÉrie Électrotechnique Et. ÉnergÉtique* **2024**, *69*, 249–254. [CrossRef]
67. Azzone, G.; Alizadehtir, M.; Tebaldi, D.; Zanasi, R. Numerical Comparison of the Polarization Curve Contributions and Simulation of Proton Exchange Membrane Fuel Cells. In *Proceedings of the 2024 IEEE 20th International Conference on Automation Science and Engineering (CASE)*; IEEE: New York, NY, USA, 2024; pp. 3427–3432.
68. Sun, T.; Cao, G.; Zhu, X. Nonlinear modeling of PEMFC based on neural networks identification. *J. Zhejiang Univ.-Sci. A* **2005**, *6*, 365–370. [CrossRef]
69. Hernandez, A.; Hissel, D.; Outbib, R. Non Linear State Space Modelling of a PEMFC. *Fuel Cells* **2006**, *6*, 38–46. [CrossRef]

70. Zhang, Y.; Tang, X.; Xu, S.; Sun, C. Deep Learning-Based State-of-Health Estimation of Proton-Exchange Membrane Fuel Cells under Dynamic Operation Conditions. *Sensors* **2024**, *24*, 4451. [CrossRef] [PubMed]
71. Zhang, B.; Jin, X.; Liang, W.; Chen, X.; Li, Z.; Panoutsos, G.; Liu, Z.; Tang, Z. TabNet: Locally Interpretable Estimation and Prediction for Advanced Proton Exchange Membrane Fuel Cell Health Management. *Electronics* **2024**, *13*, 1358. [CrossRef]
72. Correa, J.M.; Farret, F.A.; Popov, V.A.; Simoes, M.G. Sensitivity Analysis of the Modeling Parameters Used in Simulation of Proton Exchange Membrane Fuel Cells. *IEEE Trans. Energy Convers.* **2005**, *20*, 211–218. [CrossRef]
73. Liao, X.; Photong, C.; Su, J. Sensitivity Analysis and Optimization of Operating Conditions of Proton Exchange Membrane Fuel Cell. *J. Appl. Electrochem.* **2024**, *54*, 2505–2518. [CrossRef] [PubMed]
74. Kannan, V.; Fisher, A.C.; Birgersson, E.K. Sensitivity Analysis Based on Monte Carlo Simulations of a 1D Accelerated Mechanistic Model of a Proton Exchange Membrane Fuel Cell. *ECS Meet. Abstr.* **2019**, *MA2019-01*, 1151. [CrossRef]
75. Vigna Suria, O.; Testa, E.; Peraudo, P.; Maggiore, P. A PEM Fuel Cell Distributed Parameters Model Aiming at Studying the Production of Liquid Water Within the Cell During its Normal Operation: Model Description, Implementation and Validation. In *Proceedings of the SAE Technical Paper Series*; SAE International: Warrendale, PA, USA, 2011.
76. Pant, L.M.; Stewart, S.; Craig, N.; Weber, A.Z. Critical Parameter Identification of Fuel-Cell Models Using Sensitivity Analysis. *J. Electrochem. Soc.* **2021**, *168*, 074501. [CrossRef]
77. Li, Y.; Yang, Z.; Ji, X.; Liu, F.; Hao, D. Sensitivity analysis of structural parameters for PEMFCs based on 1D transient model and elementary effect method. *Int. J. Green Energy* **2023**, *21*, 87–101. [CrossRef]
78. Mantelli, L.; Iester, F.; Crosa, S.; Bozzolo, M.; Magistri, L.; Massardo, A. Dynamic Performance Analysis of a Turbocharged PEMFC System. *J. Eng. Gas. Turbines Power* **2025**, *147*, 051010. [CrossRef]
79. Lorandi, L.; Hernandez, E.; Diong, B. Parametric Sensitivity Analysis of Fuel Cell Dynamic Response. In *Proceedings of the SAE Technical Paper Series*; SAE International: Warrendale, PA, USA, 2004.

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