

Review

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Review

A Comparative Review of Modeling and Metaheuristic Parameter Identification Strategies for Zero-Dimensional PEMFC Polarization Models

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Abstract

Proton exchange membrane fuel cells (PEMFCs) are promising energy conversion devices owing to high efficiency and zero local emissions. Accurate PEMFC performance assessment and control require well-posed models, whose predictive accuracy is largely determined by the correct calibration of key parameters. Metaheuristic algorithms (MHAs) have therefore been widely applied to PEMFC stack parameter estimation, but their rapid proliferation calls for a more systematic and fine-grained synthesis. This review refines the taxonomy of PEMFC mathematical modeling approaches and summarizes Zero-Dimensional PEMFC modeling methods, key parameters, and representative improvement directions aimed at reducing identification difficulty while retaining physical meaning. Newly developed MHAs and enhanced variants of existing methods are then surveyed, and over 40 distinctive optimization approaches are selected for systematic comparison. Key fuel-cell parameters, evaluation criteria, and representative commercial PEMFC types are summarized. In addition, 26 representative algorithms and their variants are compiled and benchmarked across the five most widely used commercial PEMFC models to enable cross-model comparison.

Keywords: proton exchange membrane fuel cell; steady-state polarization modeling; parameter identification; optimization algorithms

1. Introduction

In recent years, the urgent need for clean energy sources has grown significantly due to the severe environmental impact of fossil fuels. As a result, renewable energy sources (RES) such as fuel cells (FC), solar, and wind energy are becoming important alternatives due to their advantages of zero emissions, high efficiency, and wide applicability across various scales[1].

Among these types, hydrogen energy, in particular, stands out for its efficiency and sustainability[2]. Among them, proton exchange membrane fuel cells (PEMFC) are notable for their ability to maximize hydrogen energy use, offering low operational pressure, high energy density, and zero emissions[3]. They also have rapid startup, consistent efficiency, long lifespan, and fast charging, making them suitable for diverse applications, from portable systems to transportation[4]. The integration of hydrogen and fuel cells, especially PEMFCs, is critical for achieving sustainable energy solutions, addressing growing energy demands, and reducing environmental impacts[5].

To clarify the position of PEMFCs within the broader fuel cell technology landscape, the main FC types are briefly summarized in Table 1. Fuel cell (FC) systems encompass a range of technologies, including alkaline fuel cells (AFC), molten carbonate fuel cells (MCFC), phosphoric acid fuel cells (PAFC), proton exchange membrane fuel cells (PEMFC), direct methanol fuel cells (DMFC) and solid oxide fuel cells (SOFC), each with distinct characteristics that are systematically compared in Table 1. Among these, PEMFCs have received particular attention due to their high efficiency, low

operating temperature, and quick startup behavior. The PEMFC system is inherently a highly nonlinear, multi-variable, and strongly coupled system, with its behavior significantly influenced by changing operating conditions[6,7]. To effectively evaluate and utilize PEMFC systems, researchers have proposed various modeling strategies, including mechanistic (white-box)[6], empirical (gray-box)[7], and data-driven (black-box)[8] approaches. Conventional modeling methods, though widely used, often fall short in addressing this complexity due to their limited adaptability.

Some traditional approaches typically struggle with accurately capturing the system's dynamic response, leading to increased computational costs and reduced modeling efficiency^{9,10}. As a result, there is a growing demand for more flexible and robust modeling techniques that can effectively handle such challenges. Springer[11] and Bernardi[10] proposed a one-dimensional model in the early 1990s: the former designed a model based on the membrane water content and electrode water vapor balance conditions, while the latter derived a mathematical model of the polymer electrolyte attached to the gas diffusion electrode and pointed out that water transport during fuel cell operation is driven by both pressure and electromotive force. Subsequently, two-dimensional models were developed to consider mass transfer along the length of the fuel cell. Dannenberg[12] et al. established a two-dimensional mass and heat transfer model to analyze different operating conditions and optimize parameters such as humidification and heat transfer. Hosseini[13] et al. used a two-dimensional agglomerate model to study the effect of bubbles and found that increasing relative humidity enhances the migration of water from the cathode to the anode. In addition, 3D models are now widely used. Ferng and Su developed a three-dimensional, full-cell CFD model to examine how flow-field design influences PEMFC performance[14]. Zhang[15] et al. adopted a 3D comprehensive multiphase anisotropic model to study the influence of GDL anisotropy, liquid saturation jump, and baffles inserted to the cathode channel on the performance of PEMFC. Table 2 outlined the dimensional classification of PEMFC models and their characteristics. In the PEMFC model classification system mentioned above, the 0-D model is widely used because of its low computational cost, and ease of rapid fitting with experimental data such as polarization curves. Among various 0-D modeling methods, the semi-empirical model developed by Amphlett is widely adopted due to its effectiveness in capturing the voltage–current (V–I) characteristics of PEMFCs under different operating conditions. This gray-box model combines physical mechanisms with data-driven features and can be used to simulate thermal conduction, mass transport, and electrochemical behaviors within the fuel cell stack[7]. While it does not offer a complete physical interpretation, it provides accurate output prediction with relatively low computational complexity. In addition, the complexity of PEMFC behavior has led to increasing interest in black-box models based on artificial intelligence and neural networks, which are capable of learning system dynamics directly from data without explicit knowledge of internal processes[16,17].

In recent years, the development of computer-based methods and artificial intelligence has facilitated the emergence of metaheuristic algorithms (MHAs) as powerful tools for solving complex optimization problems[16]. Parameter identification in PEMFCs, essentially an optimization task involving multiple unknowns, benefits greatly from the adaptive search mechanisms of MHAs. These algorithms are capable of finding optimal solutions with high precision while maintaining low computational burden.

As a result, various metaheuristic algorithms have been utilized to estimate the unknown parameters in PEMFC models[17]. Commonly adopted methods include genetic algorithm[18], differential evolution[19], particle swarm optimization[20], salp swarm optimization[21], grey wolf optimization[22], and others. Accordingly, a detailed and systematic survey is necessary to comprehensively analyze and synthesize these metaheuristic-based approaches. An earlier study in[23] reviewed and categorized twenty-eight metaheuristic algorithms for PEMFC parameter estimation and further discussed fifteen representative techniques. In addition, a more recent survey was presented in[24], where presented a more recent survey that summarized twenty-seven up-to-date PEMFC models and discussed thirty up-to-date metaheuristic algorithms.

Therefore, this work presents a comprehensive review of unknown-parameter identification for PEMFC models, incorporating 0-D model formulation and refinement and emphasizing metaheuristic-optimization-based parameter identification, aiming to serve as a consolidated reference for future in-depth investigations. The main contributions are summarized as follows:

- i. Refined taxonomy of PEMFC mathematical modeling approaches, with an in-depth summary of 0D model formulation, parameterization, and improvement strategies.
- ii. Based on the established PEMFC model taxonomy, the applied metaheuristic algorithms are further categorized, and their suitability for different model structures and identification objectives is systematically discussed.
- iii. Five summary tables compile optimization results for the five most commonly used commercial PEMFC models, while a comparative analysis of 26 algorithms and their variants (over 40 metaheuristic approaches in total) is provided, including a formula-level comparison of their iterative update mechanisms.

Section 2 presents the 0-D modeling of PEMFC, including the electrochemical processes and the mathematical framework. Section 3 outlines the identification criteria and commercial models used for parameter estimation. Section 4 thoroughly reviews latest meta-heuristic algorithms for PEMFC parameter identification, with a particular emphasis on summarizing the iterative formulas of different optimization algorithms. Section 5 provides a discussion of the reviewed methods. Finally, Section 6 concludes the paper and highlights future research directions.

Table 1. Fundamental properties of five representative fuel cells.

FC Type	Anode	Electrolyte	Fuel	Operating Temp.	Efficiency	Power Output	Startup Time	Pros	Cons
Proton Exchange (PEM & HT-PEM)[25,26]	Platinum	Polymer Membrane	Hydrogen	80–100 °C (176–212 °F), 200 °C (224 °F)	30–40%	0.12–30 kW	< 1 minute	•Quick startup, •Small, •Lightweight	•Sensitive to humidity, •salinity, •cold temperatures
Alkaline (AFC) [27,28]	Platinum or Carbon	Potassium Hydroxide (KOH)	•Hydrogen, •Ammonia	60–70 °C (140–158 °F)	60–70% (80% CHP)	0.5–200 kW	< 1 minute	•Quick startup, •Temp resistant, •Low-cost ammonia fuel	•Liquid catalyst adds weight, •relatively bulky
Phosphoric Acid (PAFC)[29,30]	Platinum	Phosphoric Acid (H ₃ PO ₄)	•Hydrogen, •Methanol •Natural gas, •Methanol, •Ethanol, •Biogas, •Coal gas	150–200 °C (336–448 °F)	40–50% (80% CHP)	100–400 kW	10–30 minutes	•Stable, •Mature technology	•Acid vapor, •less power-dense
Molten Carbonate (MCFC)[31,32]	Steel/Nickel	Molten Carbonate	•Methanol, •Ethanol, •Biogas, •Coal gas	650 °C (1202 °F)	50% (80% CHP)	10 kW–2 MW	10 minutes	•Fuel variety, •High efficiency	•Slow response, •highly corrosive
Direct Methanol (DMFC)[33,34]	Platinum-Ruthenium on Carbon	Polymer Membrane	•Methanol •Natural gas,	50–120 °C (122–248 °F)	20–30%	0.01–100 kW	< 5 minutes	•Simple fuel storage, •Compact system, •No reformer required	•Low efficiency, •Methanol crossover, •Expensive catalysts
Solid Oxide (SOFC)[19,35,36]	Ceramic	Yttria-Stabilized Zirconia (YSZ)	•Methanol, •Ethanol, •Biogas,	500–1000 °C (932–1832 °F)	60%	0.01–2000 kW	60 minutes	•Fuel variety	•Long startup time, •intense heat

Table 2. Comparison of PEMFC Models.

Dimension	Spatial description	Main phenomena	Typical type	Main outputs	Strengths	Limitations
0-D[10,11]	No spatial resolution	Empirical polarization (V–I)	No spatial direction	•Overall cell/stack voltage–current relationship; •Lumped outputs	•Extremely fast; - parameter fitting;	•Minimal mechanistic insight; - easy•Cannot capture spatial non-uniformity; •Limited for design optimization across varying conditions

1-D[12,13]	One direction	spatial	Reaction and transport in MEA/porous media; Charge transfer	Through-plane; Along-channel	·1-D profiles of species, water, potentials, etc.; ·Trend of current density along the flow channel and location	·Suitable for system-level studies and control-oriented models	·Misses in-plane effects (rib/channel); ·Accuracy depends on effective parameters and simplifying assumptions
						·Low cost; ·Retains key physics along a dominant direction; ·Efficient for parametric sweeps and sensitivity studies	
						·Captures major non-uniformities (rib/channel and along-channel); ·Balances fidelity and cost for engineering analysis	
2-D[14,15]	Two directions (plane)		·Rib/channel effects; ·Reactant depletion; ·Water buildup	Cross-channel; Along-channel	Distributions of water, temperature, and reactants within the PEMFC (2-D fields)	·Cannot capture inherently 3-D local effects; ·Relies on effective averaging in the third direction.	
						·Highest spatial fidelity; ·Best for local phenomena, detailed diagnostics, and geometry/design evaluation	
3-D[9]	Full geometry	3-D	Full spatial coupling (multi-physics)	Full 3-D	Full 3-D fields	·Highest computational cost; ·Demanding meshing and parameterization; ·Often impractical for large parametric studies	

2. PEMFC Zero-Dimensional Model

2.1. Electrochemical Process Mechanism

Figure 1 presents the schematic diagram of a typical fuel cell. At the anode, hydrogen molecules are split into protons and electrons with the assistance of a platinum catalyst. The protons then pass through the proton exchange membrane (PEM) to the cathode, while the electrons flow through an external circuit, generating an electric current and voltage across the load[37,38]. At the cathode, the protons and electrons reunite and react with oxygen, forming water and releasing heat as byproducts of the electrochemical process[39]. The complete reaction occurring within the fuel cell is expressed in equation (1), which can be separated into two half-cell reactions shown in equations (2) and (3), corresponding to the anode and cathode reactions, respectively[40].

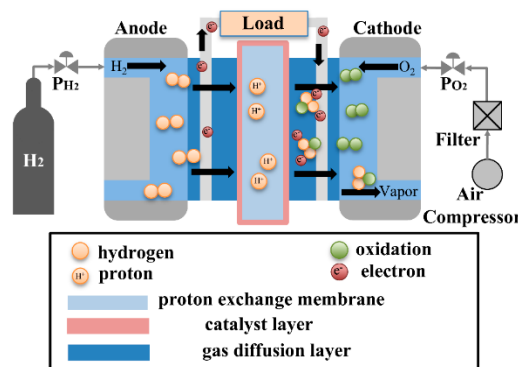
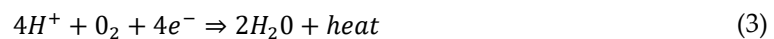
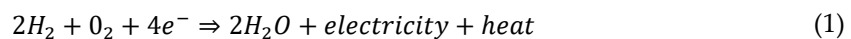


Figure 1. Basic description of fuel cell operation.

2.2. Mathematical Modelling

Figure 2(a) illustrates the different model dimensionalities along with the key components of the cell[41]. Higher-dimensional models provide a more accurate representation of reality but come with increased computational cost. Lower-dimensional models, while sacrificing some spatial detail, often enable the inclusion of more complex physical phenomena. As shown in Figure 2(b), the I-V polarization curve of a single PEMFC consists of three distinct regions: activation losses, ohmic losses, and concentration losses. At low current densities, a steep decline in cell voltage is observed, primarily caused by activation losses resulting from sluggish electrochemical reaction rates. As the current increases, the voltage drop becomes more linear, which is attributed to ohmic losses stemming from the internal resistance faced by protons and electrons. At higher current densities, the voltage declines more sharply again due to reactant depletion, often caused by water accumulation that hinders gas diffusion at the electrodes. This final region is known as the concentration loss region[39].

Fuel cells are multi-physics systems, and PEMFC modeling approaches vary depending on the physical phenomena being addressed[42]. Accurate modeling is crucial for analyzing PEMFC performance under different conditions and reproducing polarization curves. In a zero-dimensional (0-D) framework, spatial variations are neglected and the cell behavior is described using lumped operating variables such as voltage, current, temperature and pressure, together with simple semi-empirical or empirical relations. Although 0-D models cannot resolve spatial non-uniformities, they are computationally efficient and are commonly used to represent polarization behavior and support

parameter identification at the system level. Accordingly, the output voltage in Figure 2(b) can be expressed as [7]:

$$V_{FC} = E_{Nernst} - V_{act} - V_{ohm} - V_{con} \quad (4)$$

where V_{act} is the activation overpotential(V), V_{ohm} is the ohmic voltage loss(V), V_{con} is the concentration overpotential(V), and E_{Nernst} denotes the thermodynamic potential(V), which is given by equations (5):

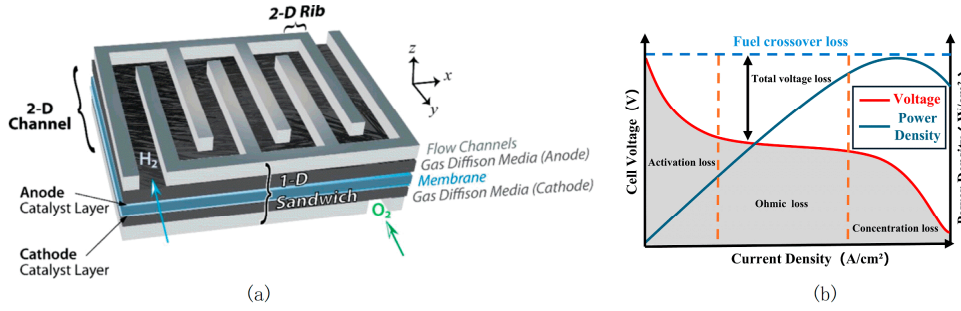


Figure 2. (a)Diagram of spatial domains and their corresponding modeling[39]; (b)Typical polarization curve.

$$E_{Nernst} = 1.229 - 0.85 \times 10^{-3} \cdot (T - 298.15) + 4.3085 \times 10^{-5} \cdot T \cdot \ln(P_{H_2}^* \sqrt{P_{O_2}^*}) \quad (5)$$

where T is the temperature of cell in Kelvin.

2.2.1. Seven Parameters Model

Among various 0-D strategies, the semi-empirical model proposed by Amphlett and Mann[7] is widely used for its balance between physical insight and empirical accuracy. It effectively captures polarization effects—including thermodynamic potential, activation, ohmic, and concentration losses—despite the system's complexity, multivariable nature, and strong internal coupling. To implement this formulation, each term must be expressed as an explicit function of operating conditions. $P_{H_2}^*$ and $P_{O_2}^*$ are the partial pressures of hydrogen and oxygen, they can be calculated as (6) and (7) follows[7]:

$$P_{H_2}^* = 0.5 \cdot RH_a \cdot P_{H_2O}^{sat} \cdot \left(\frac{1}{\frac{RH_a \cdot P_{H_2O}^{sat}}{P_a} \exp\left(\frac{1.635 \left(\frac{i}{A}\right)}{T^{1.334}}\right)} - 1 \right) \quad (6)$$

$$P_{O_2}^* = RH_c \cdot P_{H_2O}^{sat} \cdot \left(\frac{1}{\frac{RH_c \cdot P_{H_2O}^{sat}}{P_c} \exp\left(\frac{4.192 \left(\frac{i}{A}\right)}{T^{1.334}}\right)} - 1 \right) \quad (7)$$

where RH_a and RH_c are the relative humidities of the anode and cathode, respectively; P_a and P_c denote the inlet pressures at the anode and cathode in atmospheres (atm); A represents the electrode area in square centimeters (cm²); i is the cell current in amperes (A); and $P_{H_2O}^{sat}$ is the saturation pressure of water vapor in atmospheres, which is given by equation (8)[43]:

$$\log_{10}(P_{H_2O}^{sat}) = 2.95 \times 10^{-2} \cdot (T - 273.15) - 9.19 \times 10^{-5} \cdot (T - 273.15)^2 + 1.44 \times 10^{-7} (T - 273.15)^3 - 2.18 \quad (8)$$

The activation voltage drop can be expressed as (9) follows:

$$V_{act} = -[\xi_1 + \xi_2 \cdot T + \xi_3 \cdot T \cdot \ln(C_{O_2}^*) + \xi_4 \cdot T \cdot \ln(i)] \quad (9)$$

where ξ_1 , ξ_2 , ξ_3 , and ξ_4 are the parametric coefficients of the cell model, and $C_{O_2}^*$ denotes the oxygen concentration at the catalytic interface (mol/cm³). The oxygen concentration can be calculated as (10) follows[7]:

$$C_{O_2}^* = \frac{P_{O_2}^*}{5.08 \times 10^6 \cdot \exp\left(\frac{-498}{T}\right)} \quad (10)$$

The ohmic voltage drop arises from the internal resistance of the fuel cell and can be expressed as (11) follows:

$$V_{ohm} = i \cdot (R_M + R_C) \quad (11)$$

where R_C denotes the equivalent resistance associated with electron conduction through contact interfaces, and R_M represents the equivalent resistance of the membrane related to proton conduction, which can be expressed as (12) and (13)[7]:

$$R_M = \frac{\rho_M \cdot l}{A} \quad (12)$$

$$\rho_M = \frac{181.6 \cdot \left[1 + 0.03 \cdot \left(\frac{i}{A}\right) + 0.062 \cdot \left(\frac{T}{303}\right) \cdot \left(\frac{i}{A}\right)^{2.5}\right]}{\left[\lambda - 0.634 - 3 \cdot \left(\frac{i}{A}\right)\right] \cdot \exp\left[4.18 \cdot \left(\frac{T - 303}{T}\right)\right]} \quad (13)$$

where R_M is the specific resistivity of the membrane (Ω·cm); l denotes the membrane thickness in centimeters (cm) and λ is an adjustable parameter^{7,44}. The concentration overpotential arises due to variations in reactant concentrations at the electrode surface and can be defined as (14) follows[7]:

$$V_{con} = -\beta \cdot \ln\left(1 - \frac{J}{J_{max}}\right) \quad (14)$$

where β is a parametric coefficient (V), J is the actual current density of the cell (A/cm²), and J_{max} represents the maximum allowable current density. When the current density exceeds J_{max} , the fuel cell output voltage experiences a sharp drop[39].

It is worth noting that the concentration polarization term may become overly sensitive when applied to high-power PEMFC stack datasets with coarse current steps. In such cases, V_{con} tends to be overestimated, leading to anomalous behavior in the predicted voltage output. To address this issue, an improved formulation was proposed in [45] to reduce the current sensitivity of V_{con} , making it more consistent with the gradual variation of reactant concentrations under practical steady-state conditions. Accordingly, the original expression in equation (14) was updated to the improved form in equation (16), which significantly enhances the stability and accuracy of the model output:

$$V_{con} = -\beta \ln\left(\frac{J_{max} - \frac{i}{1000 \times A}}{J_{max}}\right) \quad (15)$$

The fuel cell stack is constructed by connecting N_{cell} individual cells in series; thus, the total stack voltage can be expressed as (16):

$$V_{stack} = N_{cell} \times V_{FC} = N_{cell} \times (E_{Nernst} - V_{act} - V_{ohm} - V_{con}) \quad (16)$$

As can be inferred from the aforementioned formulas, at least seven parameters (ξ_1 , ξ_2 , ξ_3 , ξ_4 , R_C , λ and β) must be assigned to fully define an electrochemical-based model.

2.2.2. Two Parameters Model

Building on the classical seven-parameter framework, the proposed two-parameter 0-D PEMFC model explicitly couples reactant partial pressures with operating pressure and gas utilization[46]. Instead of treating hydrogen and oxygen pressures as fixed inputs, the model calculates effective partial pressures of hydrogen and oxygen in the cell based on inlet conditions (pressure, humidity) and the fraction of reactant consumed in equation (16):

$$\begin{aligned} P_{H_2}^* &= (1 - U_a) \cdot (P_a - P_{H_2O}^{sat} \cdot RH_a) \\ P_{O_2}^* &= (1 - U_c) \cdot (P_c - P_{H_2O}^{sat} \cdot RH_c) \cdot 0.21 \end{aligned} \quad (17)$$

This approach enhances physical realism by accounting for the progressive reduction in fuel and oxidant availability along the flow channels at higher utilization. The gas utilization rate U_a and U_c can be defined as:

$$\begin{aligned} U_a &= 60000 \times \frac{NiART}{2FQ_a(P_a - P_{H_2O}^{sat} \cdot RH_a)} \\ U_c &= 60000 \times \frac{NiART}{4FQ_c(P_c - P_{H_2O}^{sat} \cdot RH_c) \cdot 0.21} \end{aligned} \quad (18)$$

where Q_a and Q_c denote the volumetric flow rates of hydrogen and air, respectively. The constant 60,000 converts the flow rate from standard liters per minute to the international system of units. F and R are Faraday constant and gas constant. Based on this, the description of activation overpotential can be simplified[46]:

$$V_{act} = \frac{RT}{2\alpha F} \ln\left(\frac{i}{i_0}\right) \quad (19)$$

where i_0 is reference exchange current density, and α denotes charge transfer coefficient with the value range of 0 ~ 1. Compared to the seven-parameter model, this activation overpotential expression better reflects the mechanism of activation loss and requires fewer parameters to be optimized.

3. Identification Criteria and Commercial Models

3.1. Identification Criteria

To fully define an electrochemical model, at least seven parameters must be assigned. The parameters of a fuel cell model change significantly under different operating conditions, and these parameters are strongly interdependent. Additionally, these parameters are typically not listed in the manufacturer's specification sheets and need to be determined through experiments or other methods. As a result, the polarization curve and the nonlinear nature of the model can vary greatly, which increases the difficulty of model identification[47]. Therefore, to efficiently and accurately determine the unknown parameters with minimal effort, this process is treated as an optimization problem and solved using various optimization techniques[43,48]. In summary, the procedures for modeling the PEMFC stacks, based on the information extracted from the datasheet and experimental data, are illustrated in Figure 3.

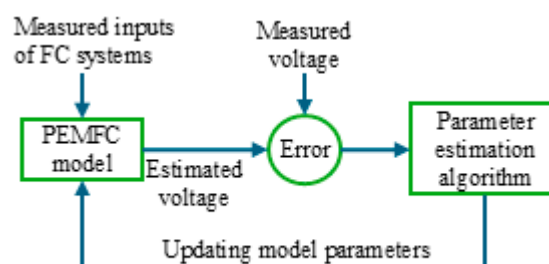


Figure 3. The sequence of PEMFC modelling.

In parameter identification for PEMFC models, selecting an appropriate fitness function is crucial for accurately determining the unknown parameters[46]. These functions help minimize the error between the model’s predictions and experimental data. Choosing the appropriate fitness function (FF) simplifies the parameter identification process and allows for a clear distinction between different modeling methods, both quantitatively and qualitatively, based on the acceptable range of results. A summary of the most commonly used fitness functions (FFs) for parameter estimation in PEMFCs is presented in Table 3.

It is clear that the features and variables used in different fitness functions vary. For example, some functions use squared formulas to more accurately compute the outcomes, while others apply absolute values to avoid negative results.

3.2. Commercial Models

To accurately evaluate and optimize the performance of PEMFCs, it is crucial to understand both their fundamental features and the parameter limits that govern their behavior[49]. Table 4 presents the fundamental features of different PEMFC types, providing an overview of key characteristics such as membrane area, current density, and operating temperature for various commercial models. This information helps in comparing the specifications and understanding the potential applications of each type of PEMFC. Additionally, the typical lower and upper limits of the PEMFC unknown parameters, commonly used in recent research, are summarized in Table 5[41,50].

Table 3. Overview of Commonly Used Objective Functions.

Fitness function	Fundamental equations	Optimization Objective
Sum of Squared Errors (SSE)[51]	$SSE = \sum_{j=1}^K (V_{meas,j} - V_{calc,j})^2$	Minimizing the sum of squared errors between predicted and observed values.
Mean square error (MSE)[52]	$MSE = \frac{1}{N} \sum_{i=1}^N (V_{exp} - V_{calc})^2$	Minimize the average squared difference between predicted and observed values.
Root mean square error (RMSE)[46]	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (V_{actual} - V_{calc})^2}$	Minimize the square root of the mean squared error, reducing large prediction errors.
Normalized root mean square error (NRMSE)[53]	$NRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (V_{exp} - V_{cal})^2}}{\hat{V}_{exp}}$	Measures error relative to the range or mean of observed values.
Absolute error (AE) [54]	$AE = V_{mes} - V_{cal} $	Measures the absolute difference between predicted and observed values.
Mean absolute error (MAE)[48]	$MAE = \frac{1}{N} \sum_{i=1}^N V_{exp} - V_{est} $	Evaluates the average of absolute differences between predicted and observed values.

Table 4. Fundamental features of different PEMFC types.

PEMFCs’ type	Power (W)	N	A(cm2)	l (um)	J _{max} (mA/cm2)	T(K)	P _{H2} [*] (bar)	P _{O2} [*] (bar)
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Ballard Mark V [53]	5000	35	50.6	178	1500	343	1	1
SR-12 Modular[55]	500	48	62.5	25	672	323	1.47628	0.2095
NedStack PS 6KW[51]	6000	65	240	178	937	343	0.5–5	0.5–5
BCS 500W[47]	500	32	64	178	469	333	1	0.2095
250W Stack[56]	250	24	27	178	680	343	1	1
Temasek 1 kW[57]	1000	20	150	51	1500	323	0.5	0.5
Horizon H-12[58]	12	13	8.1	25	246.9	302.15	0.4935	1
30kw stack[59]	30000	30	250	32	2.424	338.15	1.577	1.678

Table 5. Typical limits of the unknown parameters.

Parameter	Low	High
ξ_1	-1.1997	-0.8532
$\xi_2 \times 10^{-3}$	1.00	5.00
$\xi_3 \times 10^{-5}$	3.60	9.80
$\xi_4 \times 10^{-5}$	-26.00	-9.54
$R_c \times 10^{-5}$	13.00	23.00
λ	0.10	0.80
β	0.0136	0.5000

4. Meta-Heuristic Algorithms for PEMFC Parameter Identification

Among various AI-based optimization techniques, metaheuristic algorithms (MHAs) have demonstrated superior accuracy and computational efficiency compared to traditional optimization methods[24,53,58]. Besides, “No Free Lunch Theorem” states that no single metaheuristic algorithm can independently and efficiently solve all engineering problems [60].

So far, numerous metaheuristic algorithms, along with some modifications or variants, have been employed in PEMFC parameter identification. This section highlights the latest research that introduces new metaheuristic algorithms (MHAs) for identifying the unknown parameters of PEMFCs, based on the semi-empirical model presented in [11].

4.1. Evolution-Based Metaheuristic Algorithms

4.1.1. Differential Evolution (DE)

Differential Evolution (DE) is a simple yet powerful population-based evolutionary algorithm[61,62]. After initialization, DE iteratively refines solutions through three stages: mutation, crossover, and selection, which correspond to generating a new vector by differential variation, recombining it with the current solution, and choosing the better one based on fitness, respectively.

Despite its effectiveness, DE suffers from issues such as slow convergence and parameter sensitivity. To address these issues, various enhanced variants have been developed. One example is Adaptive DE (ADE), which significantly improves search efficiency and helps avoid local optima by introducing two adaptive strategies that enable dynamic adjustment of control parameters[19]. Later, the Adaptive Guided Differential Evolution (AGDE) was proposed as a further enhancement over ADE[63]. It introduced a guiding mutation strategy that utilizes the global best individual to steer the population toward promising regions in the solution space. Furthermore, one recent advancement is the Improved Adaptive Guided Differential Evolution (IAGDE)[64], which not only inherits the adaptive parameter control but also introduces a guided mutation strategy based on the global best solution. This dual improvement enables IAGDE to enhance convergence accuracy while avoiding premature stagnation, making it particularly effective for PEMFC parameter estimation tasks. To evaluate the robustness and stability of different AGDE-based variants across multiple PEMFC models, Figure 1 presents radar plots of the standard deviation (STD) in parameter estimation results, providing a visual comparison of their stability performance[63]. Due to IAGDE's

simplicity and robustness, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Tables 6-9.

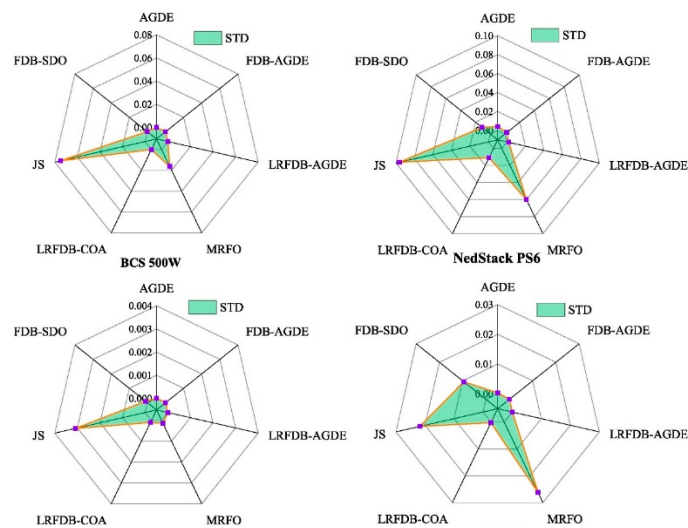


Figure 1. Std values for various AGDE-based algorithms of the PEMFCs.

Table 6. PEMFC parameter estimation using Ballard-Mark-V dataset.

Years	Methods	Parameters							SSE
		ξ_1	$\xi_2 \times 10^{-3}$	$\xi_3 \times 10^{-5}$	ξ_1	λ	$R_c \times 10^{-4}$	ξ_1	
2025	IAGDE[64]	-0.8946	2.5300	3.6100	-0.0009	3.56382	15200	0.0920	0.00104
2025	PO[65]	-1.1997	3.5758	3.6000	-1.6729	24.0000	1.0000	0.0159	0.81280
2025	PO[66]	-0.9382	3.1690	8.3200	-1.7000	14.4391	1.0000	0.0138	0.14860
2024	FNN-POA[67]	-0.8851	2.7882	6.3684	-1.7105	15.6807	5.1874	0.0168	-
2024	RBMO[68]	-1.0006	3.8364	9.7953	-1.6283	22.9999	1.0000	0.0136	0.85360
2024	DACO[69]	-1.0950	3.4120	7.9310	-0.9540	14.0800	0.8000	0.0182	0.00001
2024	SHO[70]	-1.1993	3.6200	3.6704	-1.7840	19.6862	3.0390	0.0665	0.00001
2023	CBO[57]	-1.1788	2.8743	3.6400	-1.1950	12.0800	8.0000	0.0136	0.00060
2023	IAHA[71]	-1.0130	4.0000	8.9800	-1.6300	23.0000	1.0000	0.0136	0.85360
2023	ICSO[72]	-0.9600	-	4.2500	-1.7000	23.0000	1.0000	0.0140	0.85300
2023	ARO[73]	-1.1589	3.5208	4.0526	-1.6725	23.9900	1.0000	0.0159	0.81391
2021	ASSA[74]	-1.1100	3.1900	7.1700	-1.5970	22.0000	1.0000	0.0110	0.82000
2019	SSO[21]	-1.1827	3.7080	9.3600	-1.1925	11.7603	7.8773	0.0136	0.00210
2019	CS-EO[52]	-0.9728	3.4480	8.3832	-1.1328	21.6995	8.0000	0.0136	0.00240
2019	FPA[75]	-1.0257	3.4000	6.7952	-1.2850	15.6446	5.2906	0.0614	0.00060
2019	WOA[76]	-1.1978	4.4183	9.7214	-1.6273	23.0000	1.0020	0.0136	0.02390

4.1.2. Fish Migration Optimization (FMO)

The design of the Fish Migration Optimization Algorithm (FMOA) is inspired by the migratory life cycle of grayling fish, where individuals gradually evolve from local food searching in early life to long-distance migration in adulthood. In FMOA, the population is divided into five age stages (from 0+ to 4+), and the survival and reproduction of individuals are determined by their fitness and migration energy[77]. Through simulated natural selection and aging mechanisms, fish evolve across generations to explore the search space. However, the original FMOA suffers from weak exploitation and insufficient convergence accuracy. To address these limitations, To address these limitations, researchers proposed an Improved Fish Migration Optimizer (IFMO)[78]. Two key strategies were introduced: a linearly decreasing weight factor ω to balance global exploration and local exploitation dynamically, and a modified position update formula that guides the search using both the current

best individual and the differential information between randomly selected peers. The improved update rule is given by equation (20):

$$X_i^{t+1} = \omega \cdot X_i^t + r_1 \cdot (X_{\text{best}} - |X_i^t|) + r_2 \cdot (X_j^t - X_k^t) \quad (20)$$

Third, the algorithm uses Opposition-Based Learning (OBL) during initialization—40% of the individuals are generated by reflecting positions across the search space center—to enhance diversity. In addition, a Sine-Cosine mechanism is applied in the migration phase to enrich search trajectories. These enhancements significantly improve the convergence speed, precision, and robustness of IFMO in PEMFC parameter estimation. The overall process of the Improved Fish Migration Optimizer (IFMO) is illustrated in . Due to IFMO's enhanced convergence precision and balanced search dynamics, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 9.

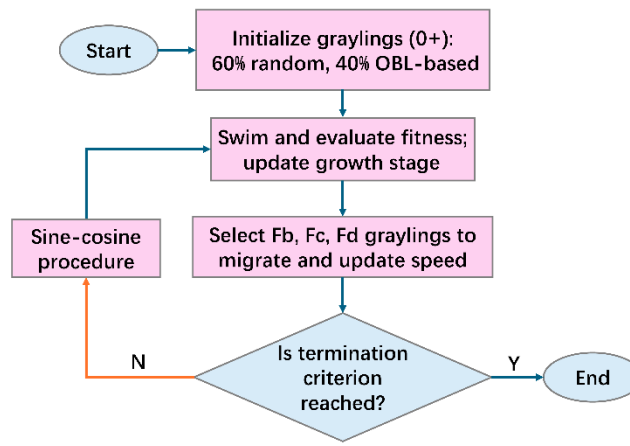


Figure 5. The general flowchart of IFMO.

4.2. Swarm Intelligence Metaheuristic Algorithms

4.2.1. Black Kite Algorithm (BKA)

The Black Kite Algorithm (BKA) is inspired by the hunting and migratory behavior of black kites. It operates in two main phases: the predation phase, where the kites adjust their positions using a sinusoidal strategy to explore the search space, and the migration phase, where they converge toward the best solution found so far[79]. The update mechanism is given by equation (21):

$$X_{i,j}(t+1) = \begin{cases} X_{i,j}(t) + n(1 + \sin(r)) \times X_{i,j}(t), & p < r \\ X_{i,j}(t) + n(2r - 1) \times X_{i,j}(t), & \text{else} \end{cases} \quad (21)$$

In this context, $X_{i,j}(t+1)$ represents the position of the i -th black-winged kite in the j -th dimension after the $t+1$ -th iteration following its predation of prey, while $X_{i,j}(t)$ denotes the position of the same kite in the j th dimension after the t -th iteration. Although BKA performs well, it suffers from premature convergence and lack of diversity early on. To address this, the Improved Black Kite Algorithm (IBKA) was introduced, building upon BKA's structure. IBKA integrates chaotic opposition-based learning (COBL) for better initial population diversity, Lévy flight for more effective exploration, and a nonlinear decreasing inertia weight to balance exploration and exploitation [59]. These improvements lead to faster convergence and greater accuracy in parameter identification. Due to IBKA's strong global exploration and convergence capabilities, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 9.

4.2.2. Red-Billed Blue Magpie Optimizer (RBMO)

The Red-Billed Blue Magpie Optimizer (RBMO) is inspired by the cooperative foraging behavior of red-billed blue magpies. These birds hunt in groups, using a combination of exploration and exploitation to locate, pursue, and store food. In the algorithm, the exploration phase involves searching for new solutions, while the exploitation phase focuses on refining the best solutions found[68]. The update rule for RBMO is given by equation (22):

$$X_i(t + 1) = X_i(t) + r_2 \left(\frac{1}{p} \sum_{m=1}^p X_m(t) - X_{rs}(t) \right) \tag{22}$$

where $X_i(t)$ is the position of the i -th agent, r_2 is a random factor, and $X_{rs}(t)$ is the position of a randomly selected agent[68]. This algorithm excels in balancing the global search for new solutions with the local refinement of the best-found solutions. Due to RBMO’s efficient balance between exploration and exploitation, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 6.

4.2.3. Manta Ray Foraging Optimization (MRFO)

The Manta Ray Foraging Optimization (MRFO) algorithm is inspired by the foraging strategies of manta rays, which include chain foraging, cyclone foraging, and somersault foraging. In chain foraging, individuals follow leaders to form a guided search path; cyclone foraging simulates spiral movements around food sources, promoting exploration; and somersault foraging allows individuals to jump toward or away from the best positions found so far. These strategies are translated into three mathematical operators that govern MRFO’s position updates during optimization[80].

While MRFO balances exploration and exploitation effectively, it suffers from low population diversity and a tendency toward premature convergence, especially in high-dimensional, nonlinear problems like PEMFC parameter identification. To improve its performance, the Modified MRFO (MMRFO) incorporates a sine–cosine mechanism into the chain and cyclone foraging stages [80]. This enhancement modifies the original update formulas to increase the algorithm’s global exploration during the early phase and local exploitation during the later phase. By generating candidate solutions that fluctuate both toward and away from the current best solution, the sine–cosine component helps avoid premature convergence[80]. An overview of the MMRFO workflow is provided in Figure 2. Furthermore, MMRFO enables adaptive switching between chain and cyclone foraging based on the improved equations, providing better search dynamics across the optimization process. Due to MMRFO’s adaptive switching and enhanced search dynamics, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 7-9.

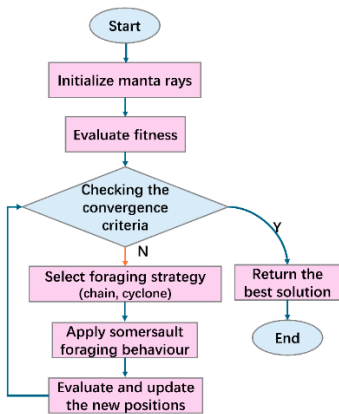


Figure 2. Flowchart of the MMRFO.

4.2.4. Spotted Hyena Optimizer (SHO)

The Spotted Hyena Optimizer (SHO) is inspired by the hunting behavior of spotted hyenas, which involves group coordination, circling, and attacking prey[70]. In this algorithm, each solution is treated as a hyena, and the optimization mimics the group's ability to cooperatively encircle and converge toward prey. The core update mechanism is defined by equation (23):

$$X(t+1) = X^* - A \cdot |C \cdot X^* - X(t)| \quad (23)$$

where $X(t)$ is the position of a hyena (solution), X^* is the position of the prey (best solution found so far), and A , C are coefficient vectors that regulate the balance between exploration and exploitation[70]. Additionally, Figure 3 depicts the overall procedure of the SHO algorithm. This formulation enables SHO to adjust its search dynamically depending on how close or far the agents are from the global optimum. Due to SHO's cooperative hunting-inspired convergence mechanism, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 6,8,9.

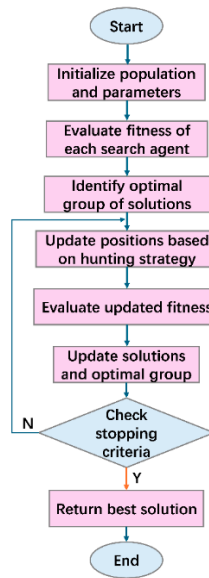


Figure 3. Flowchart of the proposed SHO.

4.2.5. Artificial Bee Colony (ABC)

The Artificial Bee Colony (ABC) algorithm simulates the foraging behavior of honey bees through three types of agents: employed bees, onlooker bees, and scout bees[81]. Each agent searches the solution space and evaluates nectar quality (fitness), updating positions based on the difference with a randomly selected peer. The original position update rule is equation (24)[82]:

$$x_{\text{new}}(i, j) = x(i, j) + \phi_{ij}[x(i, j) - x(r1, j)] \quad (24)$$

where $\phi_{ij} \in [-1, 1]$ is a random coefficient and $x(r1, j)$ is the position of a randomly chosen solution. Despite its simplicity and global search capacity, ABC suffers from slow convergence and weak local exploitation near the optimum[81].

To overcome these limitations, an Improved Artificial Bee Colony (IABC) algorithm introduces crossover and mutation strategies inspired by GA and DE[83]. In the employed bee phase, a dual-strategy update is applied based on the fitness probability P_i , as defined in equation (205).

$$x_{\text{new}}(i, j) = \begin{cases} x_{\text{best}}(j) + \phi_{ij}[x_{\text{best}}(j) - x(r1, j)], & P_i \geq cr \\ x(i, j) + \phi_{ij}[x(i, j) - x(r2, j)], & \text{otherwise} \end{cases} \quad (25)$$

In the onlooker bee phase, a DE-like mutation mechanism is used, just as equation (21) follows:

$$x_{G+1}^{OB}(i, j) = x_G(r1, j) + \beta[x_G(r3, j) - x_G(r2, j)], \text{ if } \text{rand} \leq cr \text{ or } j = k \quad (21)$$

These enhancements greatly improve convergence speed, solution quality, and robustness. When applied to PEMFC parameter identification, IABC achieves lower error and faster convergence than traditional ABC, PSO, and Bayesian optimization. Due to IABC’s dual-strategy update and fast convergence, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 9.

Table 7. PEMFC parameter estimation using SR-12 500W PEMFC dataset.

Years	Methods	Parameters							SSE
		ξ_1	$\xi_2 \times 10^{-3}$	$\xi_3 \times 10^{-5}$	$\xi_4 \times 10^{-4}$	λ	$R_c \times 10^{-4}$	b	
2025	IAGDE[64]	-1.1489	3.9900	9.2500	-0.0010	13.0000	0.0149	0.1633	6.1350
2025	PO[65]	-1.1052	3.0679	3.6176	-0.9540	24.0000	4.7655	0.1794	1.0072
2025	PO[66]	-0.8959	2.4210	3.6000	-0.9500	23.0000	6.7300	0.1753	0.2424
2024	OL-GOOSE[84]	-0.2294	1.0770	8.2300	-0.9540	23.5065	8.0000	0.1739	1.3310
2024	HMO[85]	-0.9364	2.9547	6.5378	-1.0632	22.6025	2.8713	0.1501	0.0001
2024	MMRFO[86]	-1.1914	3.8170	6.3251	-0.9541	21.1078	6.7613	0.1752	1.0566
2023	QOBO[87]	-1.0178	3.5590	9.7710	-0.9540	22.9990	6.7230	0.1753	1.0460
2023	CBO[88]	-0.8863	2.7936	8.9200	-0.9540	10.0000	6.7766	0.1631	1.1171
2023	CBO[89]	-1.1619	3.5759	5.3503	-0.9540	23.0000	1.0000	0.1523	-
2023	IAHA[71]	-0.8554	2.4000	3.6000	-1.0600	21.5388	2.7300	0.1500	0.00015
2022	BES[90]	-0.8845	2.5870	5.1800	-1.0200	24.0000	5.8200	0.1471	0.03510
2021	MAEFA[91]	-1.1155	3.3490	4.4000	-0.9500	15.5857	8.0000	0.0818	0.5607
2021	HHO[92]	-0.8543	2.4162	4.2195	-0.9554	13.2011	3.5029	0.1766	1.0678
2020	ISSA[93]	-1.1589	4.1455	5.6443	-2.2908	13.7793	1.0000	0.0742	0.7916
2020	VSDE[94]	-0.8576	3.0100	7.7800	-0.9540	23.0000	1.3390	0.1516	1.2660
2019	SSO[21]	-0.9664	2.2833	3.4000	-0.9540	15.7969	6.6853	0.1804	1.5170
2019	FPA[75]	-1.0509	3.4000	6.5880	-1.0622	12.7962	1.9101	0.2256	0.0019
2019	WOA[76]	-0.8902	3.3088	9.7546	-1.0330	22.8311	5.6770	0.1464	0.0018
2019	CS-EO[52]	-1.0353	3.354	7.2428	-0.9540	10.0000	7.1233	0.1471	7.5753

4.2.6. Grey Wolf Optimizer (GWO)

The Grey Wolf Optimizer (GWO) is a swarm intelligence algorithm inspired by the hunting behavior and social hierarchy of grey wolves. The population is classified into alpha (best), beta (second-best), delta (third-best), and omega wolves[95,96]. Position updates are guided by the top three wolves and computed using equation (22)[96]:

$$X(t + 1) = \frac{1}{3}(X_{\alpha} + X_{\beta} + X_{\delta})$$

(22)

While GWO is effective in global optimization, it may suffer from premature convergence and inaccurate exploration, especially in complex search landscapes. Several studies have aimed to enhance the standard Grey Wolf Optimizer (GWO) for more effective parameter identification of PEMFC models. Then a repairable GWO (RGWO) was proposed, introducing an elite archive-based repair mechanism to reinitialize stagnating wolves and a nonlinear adaptive control parameter to balance exploration and exploitation[95]. And the WNT-GWO further improved local search accuracy by incorporating a weighted neighborhood trust model, allowing wolves to update positions based on the fitness-weighted influence of neighbors and dynamically adjust leadership roles[97]. These improvements consistently demonstrated superior performance over the conventional GWO in terms of convergence speed, accuracy, and robustness across different PEMFC parameter estimation tasks. Due to their advantages such as simple tuning process and lower computational time and burden, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 6,7,10.

4.2.7. Coot Bird Optimizer (CBO)

The Coot Bird Optimizer (CBO) is a metaheuristic algorithm inspired by the social movement patterns of coot birds in flocks[98]. It mimics four behavioral stages: random wandering, adjusted direction toward the group, movement toward the best solution, and collision avoidance[57,99]. The algorithm balances global exploration and local exploitation through these mechanisms[57]. For each subordinate i , the position is updated using the following equation (23):

$$x_i(t+1) = 2 \cdot \text{rand} \cdot \cos(2\pi r) \cdot (x_k(t) - x_i(t)) + x_k(t) \quad (23)$$

where $x_i(t)$ denotes the position of the i -th coot at iteration t ; $x_k(t)$ is the corresponding leader's position; rand is a uniform random number in $(0,1)$; r is a stochastic variable in $(1,3)$, and the cosine term ensures oscillatory convergence behavior. Additionally, elite coots (leaders) are adaptively attracted toward the global best solution x_{best} , enhancing convergence accuracy and speed[98]. This update rule improves the optimizer's ability to escape local optima and maintain diversity in complex multimodal search spaces. Due to CBO's oscillatory convergence and leader-driven dynamics, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 6-9.

4.2.8. Artificial Hummingbird Algorithm (AHA)

The Artificial Hummingbird Algorithm (AHA) is a bio-inspired optimizer that simulates three key foraging strategies of hummingbirds: guided foraging, territorial foraging, and migration[100]. These stages together enable a balance between global exploration and local exploitation. However, the original AHA suffers from slow convergence and a tendency to get trapped in local optima in complex problems such as PEMFC parameter identification. To overcome these issues, the Improved Artificial Hummingbird Algorithm (IAHA) introduces two major enhancements. The first is a Convergence Improvement Strategy (CIS), which enhances the global search and accelerates convergence using the equation (249) and (25) update rules[71]:

$$X_i(t+1) = X^*(t) + L \cdot (r \cdot X^*(t) - L \cdot X_i(t)) \quad (249)$$

$$X_i(t+1) = X^*(t) + r_1 \cdot (X^*(t) - X_i(t)) \quad (25)$$

where $X_i(t)$ is the current solution, $X^*(t)$ is the global best, r and r_1 are uniformly distributed random numbers in $[0,1]$, and L is a Levy-distributed vector.

The second enhancement is an Improved Territorial Foraging (ITF) strategy that strengthens exploitation around the best-so-far solution, and its mathematical formulation is expressed in equation (31):

$$X_i = \begin{cases} X^*(t) + (X_c - X_d) \cdot \frac{e^{\frac{t}{T}}}{r} \cdot |r_3|, & \text{if } r_4 < r_5 \\ X^*(t) + (X_c - X_d) \cdot L, & \text{otherwise} \end{cases} \quad (31)$$

normalized iteration count, r_3, r_4, r_5 are random values (uniform or normal), and L is a Levy-based scalar[71]. In parallel, the Enhanced Artificial Hummingbird Algorithm (EAHA) was proposed as a variant of AHA. It integrates a dynamically weighted sine-cosine mechanism into the migration phase to further strengthen the global search capability[71]. This design enables the population to escape local optima through periodic and nonlinear perturbations, and improves convergence performance in PEMFC parameter estimation tasks. This mechanism enables the population to escape local optima more effectively by introducing periodic and non-linear perturbations, and its mathematical formulation is expressed in equation (32):

$$X_i^{t+1} = X_i^t + r_1 \cdot \sin(r_2) \cdot |r_3 \cdot X_{best} - X_i^t| \quad (32)$$

where $r_1, r_2, r_3 \in [0,1]$ are random control parameters. Both IAHA and EAHA independently enhance the performance of AHA by addressing its limitations from different perspectives, and each has demonstrated superior convergence speed and accuracy in PEMFC parameter estimation tasks. Due to IAHA's ability to overcome local optima and accelerate convergence, they have been

employed in the parameter estimation of the PEMFC model, while the results are gathered in Tables 6-10.

4.2.9. Chicken Swarm Optimization (CSO)

The Chicken Swarm Optimization (CSO) algorithm is a population-based metaheuristic inspired by the social hierarchy and interaction behaviors of chickens. Individuals are categorized into three roles: roosters, hens, and chicks[101,102]. Roosters exhibit independent behavior with stronger exploration, hens follow roosters or better individuals, and chicks follow their mother hens. Although CSO exhibits a good balance between global exploration and local exploitation, it often falls into premature convergence and lacks robustness in complex scenarios like PEMFC parameter estimation. To address these limitations, researchers proposed an Improved Chicken Swarm Optimization (ICSO) algorithm that introduces two enhancement strategies: reverse learning and Levy flight-based disturbance[58]. Due to ICSO's enhanced diversity and disturbance-based exploitation, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 6,8Table and Table 9.

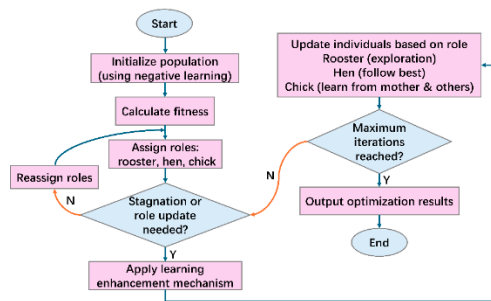


Figure 4. Flowchart of the proposed ICSO.

4.2.10. Bonobo Optimizer (BO)

BO was originally structured around three behavioral phases—positive (PS), negative (NS), and diffusion—mimicking bonobos' decision-making in favorable or hostile environments. However, the original BO lacked adaptivity in parameter tuning and suffered from performance degradation in dynamic search spaces[58]. To overcome these limitations, SABO incorporates a self-adaptive mechanism that dynamically adjusts the control parameter γ , which governs the influence between social learning and stochastic behavior during the solution update phase. Moreover, The Chaotically based Bonobo Optimizer (CBO) is a refined version of the original Bonobo Optimizer (BO), specifically developed to enhance global exploration capabilities and avoid premature convergence[103]. CBO introduces chaotic dynamics into BO by replacing fixed parameters with values generated from chaos maps such as the logistic or Henon map. The normalized chaotic value is used to dynamically control the individual update behavior. The position update rule is given by equation (33):

$$X_i^{t+1} = \gamma \cdot X_{\text{best}}^t + (1 - \gamma) \cdot r \cdot (X_{r1}^t - X_{r2}^t) \tag{33}$$

where γ is a chaotic value generated by a map. This adaptive mechanism introduces more diversity into the search process and improves convergence speed and robustness. Due to CBO's chaotic dynamics and robust convergence, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 7-10.

4.2.11. Whale Optimization Approach (WOA)

The Whale Optimization Algorithm (WOA) is a swarm intelligence algorithm inspired by the bubble-net hunting strategy of humpback whales[104]. It simulates three main behaviors: encircling the prey, spiral updating toward the prey, and searching for prey globally[104,105],. Despite its

success in various engineering fields, classical WOA often suffers from slow convergence and insufficient adaptability in high-dimensional problems. To address these limitations, researchers proposed the Enhanced Dimension Learning Whale Optimization Algorithm (EDWOA) by modifying the original WOA position update formula and incorporating two new mechanisms: event-triggered control and dimension learning[104]. In classical WOA, the position update depends on the global best and a fixed update pattern. In EDWOA, this is replaced by a more dynamic form triggered by stagnation events and focused on dimension-wise updates. Its enhanced position update formula is as (34) follows:

$$X_i^{t+1}(d) = \begin{cases} X_i^t(d) + r_1 \cdot (X_{kest}^t(d) - X_i^t(d)) + r_2 \cdot (X_j^t(d) - X_k^t(d)), & \text{if triggered} \\ X_i^t(d), & \text{otherwise} \end{cases} \tag{34}$$

where $X_i^{t+1}(d)$ is the position of individual i at dimension d and iteration t ; $X_j^t(d)$, $X_k^t(d)$ are two randomly selected individuals. The dimension learning mechanism ensures that updates are applied selectively to informative dimensions, thus reducing redundancy and accelerating convergence. Due to EDWOA’s dimension-wise control and event-triggered updating, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table .

Table 9. PEMFC parameter estimation using EDWOA using 250W PEMFC dataset.

EDWOA	ξ_1	$\xi_2 \times 10^{-3}$	$\xi_3 \times 10^{-5}$	$\xi_4 \times 10^{-4}$	λ	$R_c \times 10^{-4}$	b
Range Set	(-0.952,-0.944)	(0.001, 0.005)	(7.4e-5, 7.8e-5)	(-1.98e-4, -1.88e-4)	(14,23)	(1.0e-4,8.0e-4)	(0.016,0.05)
Extracted							
Parameter	-0.9440	3.0770	7.8000	-1.880	23.000	1.0000	0.0327
s							
SSE	15.6669						

4.2.12. GOOSE Optimization Algorithm (GOA)

The GOOSE optimization algorithm is a metaheuristic method inspired by the collective behaviors of geese during foraging and resting periods[106]. In its basic version, the algorithm initializes a population matrix X , where each row represents an agent’s position. Out-of-bound solutions are immediately corrected. In each iteration, the algorithm evaluates the fitness of each individual and identifies the best one as *BestFitness* and *BestX*. Despite this balance strategy, the standard GOOSE may still face premature convergence in high-dimensional spaces. To address this, researchers proposed an enhanced variant, called the Orthogonal Learning GOOSE Optimization Algorithm (OL-GOOSE). This variant incorporates an orthogonal learning strategy that systematically generates informative search directions by constructing orthogonal arrays[84]. These arrays allow the algorithm to explore combinations of decision variable values with reduced redundancy and increased efficiency. Instead of purely random updates, the algorithm leverages orthogonally learned solutions to refine its position update process. This enhancement is formulated as equation (35):

$$X_i^{t+1} = X_i^t + \gamma \cdot (X_{OL}^t - X_i^t) \tag{35}$$

where X_{OL}^t is the direction learned via orthogonal array experiments, and $\gamma \in [0,1]$ is a learning rate. By introducing this structure-aware direction into the update mechanism, OL-GOOSE achieves improved convergence speed and robustness in complex optimization tasks such as PEMFC parameter identification. By incorporating structure-aware guidance, OL-GOOSE improves convergence speed and robustness in complex tasks like PEMFC parameter identification. Due to OL-GOOSE’s structure-aware learning and convergence efficiency, it has been employed in the parameter estimation of the PEMFC model, while the results are gathered in **Table 7,8,9**.

Table 10. PEMFC parameter estimation using NedStack PS 6KW PEMFC dataset.

Years	Methods	Parameters							SSE
		ξ_1	$\xi_2 \times 10^{-3}$	$\xi_3 \times 10^{-5}$	$\xi_4 \times 10^{-4}$	λ	$R_c \times 10^{-4}$	b	
2025	IAGDE[64]	-1.1846	3.6500	5.9700	-0.0007	15.7311	3.9402	0.0136	1.2173
2025	IBKA[59]	-0.8225	2.3000	3.9500	-0.8000	13.1539	2.1500	0.0100	0.0715
2025	PO[65]	-0.8532	2.3988	3.6022	-0.9540	13.0947	1.0000	0.0136	2.0862
2025	PO[66]	-0.8549	2.4380	3.8500	-0.9500	14.0000	1.2000	0.0168	0.2752
2024	OL-GOOSE[84]	-1.0363	2.9300	3.6000	-0.9540	13.0223	1.0000	0.0136	2.1042
2024	ADSOOA[107]	-1.1710	4.4040	9.6120	-0.9540	13.3460	1.0000	0.0136	-
2024	HMO[85]	-1.1997	3.7318	5.9205	-0.9540	13.4650	1.0000	0.0136	2.1457
2024	SHO[70]	-0.8532	2.4170	3.6000	-0.9540	15.7764	7.5400	0.0323	0.1308
2024	RIME[108]	-0.8819	2.4385	3.4000	-0.9540	13.0000	-	0.0019	1.9459
2024	INFO[108]	-1.1976	4.0142	7.9847	-0.9540	10.0000	3.1111	0.1611	2.2881
2023	DO[109]	-1.1082	3.4849	5.2333	-0.9530	23.0714	1.2753	0.0836	2.0776
2023	IABC[83]	-0.9892	3.5544	8.3970	-0.9540	11.8775	1.0000	0.0136	2.9848
2023	CBO[88]	-1.0945	2.8818	5.6600	-1.1620	16.2870	1.0125	0.1148	1.5734
2023	CBO[89]	-1.1706	4.4040	9.6121	-0.9540	13.3460	1.0000	0.0136	-
2023	IAHA[71]	-0.8831	2.6000	3.6000	-0.9500	13.4650	1.0000	0.0136	2.1457
2023	ICSO[72]	-0.8500	-	9.7800	-0.9560	13.3300	1.0000	0.0130	2.1390
2023	ARO[73]	-1.0085	3.0434	4.9796	-0.9540	13.4457	1.0000	0.0136	2.1113
2022	ICSO[72]	-0.8760	2.6500	4.1900	-0.1028	13.0000	1.0000	0.0530	1.8600
2021	MAEFA[91]	-1.1490	3.3490	3.6000	-0.9500	13.0975	1.0000	0.0136	2.0794
2021	ASSA[74]	-0.7800	3.4400	8.2400	-0.9590	13.1300	0.1100	0.0600	2.0300
2020	VSDE[94]	-1.1212	3.3487	4.6787	-0.9540	13.0000	1.0000	0.0494	2.0885
2019	FPA[75]	-1.1605	4.0000	8.4565	-1.0123	15.1264	1.2863	0.0153	0.0983
2019	SFLA[55]	-1.0231	3.4760	7.7883	-9.5400	15.0323	1.6200	0.0136	2.1671

4.3. Bio-Inspired Metaheuristic Algorithm

4.3.1. Puma Optimization Algorithm (PO)

The Puma Optimization Algorithm (PO) is a novel bio-inspired metaheuristic algorithm that mimics the predatory behavior of pumas in the wild. PUMAs are solitary hunters that exhibit strategic stalking and pouncing behavior to capture prey[110]. This ecological behavior is abstracted into an optimization framework where each solution is modeled as a puma, and the optimization process emulates hunting through two primary mechanisms: tracking and attacking. In the tracking phase, pumas move in the solution space toward prey positions, using information from better solutions to guide their movement. In the attacking phase, once a target is identified, the puma performs a rapid exploitation maneuver to refine its current position[66]. The position update rule during the attacking phase is given by equation (26):

$$X_i^{t+1} = X_{\text{prey}} - r_1 \cdot |r_2 \cdot X_{\text{prey}} - X_i^t|$$

(26)

where X_i^t is the position of puma iii at iteration t , X_{prey} is the target (best solution), and r_1, r_2 are random numbers in $[0,1]$ to maintain exploration diversity. This formula allows a balance between convergence and exploration by dynamically adjusting the puma’s approach toward promising regions in the search space. The algorithm was applied to the parameter identification of PEM fuel cells, and the corresponding results are summarized in Table 6-10.

4.3.2. Dandelion Optimization Algorithm (DOA)

The Dandelion Optimization Algorithm (DOA) is inspired by the natural dispersal behavior of dandelion seeds. It simulates the life cycle of seeds drifting in air currents through three consecutive stages[111] : fluctuation, rotational drift, and directional motion. In the fluctuation phase, seeds spread randomly under the influence of environmental wind, which encourages global exploration by introducing high randomness, individuals move outward from their current position following a

logarithmic spiral flight influenced by wind velocity and humidity. The second phase, rotational drift, guides seeds to rotate around promising regions and transitions the algorithm from exploration to exploitation. This behavior is modeled by a cosine-based update strategy defined as equation (27):

$$x_i^{t+1} = x_i^t + \alpha \cdot \cos(\theta) \cdot (x_{\text{best}} - x_i^t) \quad (27)$$

where α is a step size coefficient, and θ is a randomly selected angle. This equation guides individuals to rotate toward the optimal region, intensifying the exploitation phase. Finally, in the landing phase, individuals perform a Lévy flight around the elite solution to locally refine the search space. To dynamically control the step size during updates, a factor is introduced [109], which applied DOA to the parameter estimation of PEMFCs, where its balance between search phases helped achieve lower sum-of-squares error compared to other metaheuristics, the results are gathered in Table 8 and Table 9. Experimental results demonstrated that this enhancement improves convergence speed and parameter estimation accuracy of the PEMFC model.

4.3.3. Bald Eagle Search (BES)

The Bald Eagle Search (BES) algorithm is a nature-inspired metaheuristic that mimics the hunting behavior of bald eagles through three sequential phases: selecting space, searching within that space, and swooping. In the first phase, the eagle chooses a promising region based on statistical information about the population. The second phase focuses on exploration around the center of the selected space to ensure diversity. The third phase, swooping, guides the individual toward the best-known solution to intensify exploitation. As presented by [90], during the swooping phase, the position update of an individual is governed by the following equation (28):

$$X_{\text{new}} = X_{\text{best}} + F \cdot (X_r - X) \quad (28)$$

where X_{best} is the global best solution found so far, X_r is a randomly selected individual from the population, X is the current position of the individual, and F is a scaling factor. The overall procedure of BES is illustrated in the Figure 5. BES has been employed in the parameter estimation of the PEMFC model, while the results are gathered in Table 7.

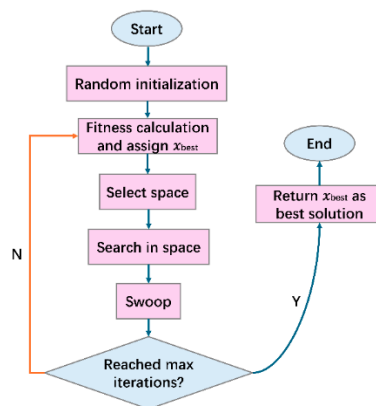


Figure 5. Flowchart of the proposed BES.

4.3.4. Parrot Optimizer (PO)

The Parrot Optimizer (PO) is a recently proposed swarm intelligence algorithm that mimics the intelligent behavior and vocal learning dynamics of parrots[65]. Individuals in PO interact via a social communication model where each parrot can imitate successful calls or behaviors from other members of the population. The algorithm operates in a loop of exploration and exploitation phases, where parrots adjust their position based on personal experience, global knowledge, and a vocal learning mechanism. The main position update formula is given as equation (29)[65]:

$$x_i^{t+1} = x_i^t + r \cdot (\beta \cdot (x_{\text{best}} - x_i^t) + (1 - \beta) \cdot (x_{\text{rand}} - x_i^t)) \quad (29)$$

where x_{rand} is a randomly selected parrot's position, $r \in [0,1]$ is a uniformly distributed random number used to introduce stochastic variability, and $\beta \in [0,1]$ is a weighting parameter that controls the influence between social learning and random imitation. This formulation allows PO to dynamically balance exploration and exploitation. PO achieved superior robustness and scalability when applied to PEMFC parameter estimation, outperforming traditional methods in convergence speed and prediction accuracy, the results are gathered in Table 6-9.

4.3.5. Pelican Optimization Algorithm (POA)

The Pelican Optimization Algorithm (POA) is a nature-inspired metaheuristic algorithm that mimics the cooperative hunting behavior of pelicans. It consists of two main phases: "moving toward the prey," where individuals explore the search space by approaching promising regions, and "gliding over the water surface," where fine adjustments are made to exploit the local neighborhood around the best solutions[112]. Moreover, in the literature[67], the feedforward neural network (FNN) is trained to approximate the ideal polarization curve of the PEMFC system using limited and noise-corrupted voltage-current (V-I) data. The key innovation lies in using the FNN as a data preprocessor, which filters out Gaussian and Rayleigh noise from the experimental V-I measurements, providing a denoised target curve. This refined data is then used as the input to POA, which searches for the optimal set of PEMFC parameters by minimizing the RMSE between the FNN-reconstructed curve and the modeled output. Through this two-stage hybrid strategy, the FNN enhances data quality, while POA ensures efficient global parameter optimization. The overall procedure of FNN-POA is illustrated in the Figure 6. Due to FNN-POA's hybrid strategy with FNN and strong noise immunity, it stands out among various optimization methods for PEMFC parameter identification, with its results presented in Table 6.

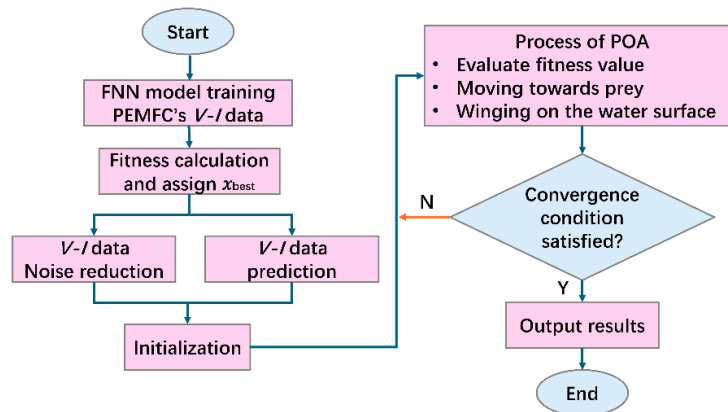


Figure 6. The flow chart of the FNN-POA.

4.4. Physics-based Metaheuristic Algorithms

4.4.1. Archimedes Optimization Algorithm (AOA)

The Archimedes Optimization Algorithm (AOA) is a recently introduced metaheuristic based on the physical principles of buoyant force and fluid dynamics, where candidate solutions are modeled as objects submerged in a fluid medium[113,114]. The algorithm iteratively updates the volume, density, and acceleration of these objects to simulate their motion toward optimal regions in the search space[113,114]. In the study, an improved AOA is applied to estimate the unknown parameters of a PEMFC system. To enhance its convergence and robustness, an improved strategy is embedded during the acceleration update phase, described by the equation (40)[114]:

$$Acc_i = D \cdot \left(\frac{V_i}{D_i}\right) \cdot (X_{best} - X_i) \tag{40}$$

where Acc_i is the updated acceleration of the i -th object, V_i is its volume, D_i is its density, X_{best} is the global best solution, X_i is the current position of the object, and D is a control parameter. This equation directs individuals toward the best-known solution by leveraging adaptive control over physical properties. As demonstrated in the paper, the improved AOA outperformed other algorithms in terms of precision and convergence when applied to the PEMFC parameter identification task. With its fluid dynamics-inspired convergence behavior, AOA has distinguished itself among multiple approaches in PEMFC modeling tasks, and the relevant performance is reported in Table 8.

4.4.2. Artificial Electric Field Algorithm (AEFA)

The Artificial Electric Field Algorithm (AEFA) is a physics-based metaheuristic that simulates the interaction of charged particles within an electric field, where candidate solutions are treated as charged bodies influencing each other’s motion. AEFA updates the positions and velocities of these particles by computing the resultant electric force and acceleration based on Coulomb's law[115]. To enhance convergence accuracy and speed, researchers proposed a modified version called MAEFA, which integrates an improved velocity update strategy incorporating global and personal best guidance. The modified velocity equation is given as equation (41)[91]:

$$V_i(t + 1) = w \cdot V_i(t) + r_1 \cdot a_i(t) + r_2 \cdot (X_{best} - X_i(t)) + r_3 \cdot (X_{pbest} - X_i(t)) \tag{41}$$

where $V_i(t)$ is the velocity of the i -th particle at iteration t , $a_i(t)$ is its acceleration, X_{best} denotes the global best solution, X_{pbest} represents the individual’s personal best, r_1, r_2, r_3 are uniformly distributed random numbers in $[0,1]$, and w is the inertia weight. This updated strategy enhances the exploitation of the best-found regions while maintaining diversity in the search space. The authors validated the effectiveness of MAEFA through its superior performance in parameter estimation of PEMFC models. Its force-based velocity update mechanism enables it to outperform many conventional algorithms in PEMFC parameter estimation, as evidenced by the results shown in Table 7,8.

Table 8. PEMFC parameter estimation using BCS 500W PEMFC dataset.

Years	Methods	Parameters							SSE
		ξ_1	$\xi_2 \times 10^{-3}$	$\xi_3 \times 10^{-5}$	$\xi_4 \times 10^{-4}$	λ	$R_c \times 10^{-4}$	b	
2025	IAGDE[64]	-0.6306	1.5400	3.8100	-1.9300	17.8000	16.100	0.1991	0.0116
2025	IBKA[59]	-1.0222	3.0000	5.8800	-1.9300	20.8637	1.0600	0.0163	0.0119
2025	PO[65]	-0.8532	2.1800	3.6000	-1.9000	20.8772	1.0000	0.0161	0.0255
2025	PO[66]	-0.8532	2.1793	3.6000	-1.9289	20.8145	1.0000	0.0161	0.0126
2024	OL-GOOSE[84]	- 1.099	3.1900	6.0000	-1.9000	23.9986	4.0000	0.0163	0.0117
2024	MSMA[116]	-1.1996	3.1413	3.6003	-1.9265	22.0849	2.1398	0.0163	0.0117
2024	HMO[85]	-1.0573	3.3155	6.9733	-1.9302	20.8769	1.0001	0.0161	0.0117
2024	AGPSO[117]	-1.0283	3.4000	8.2000	-1.9300	20.7300	1.1000	0.0162	0.0107
2024	ESSA[118]	-0.8532	2.2577	3.6000	-1.9275	20.7722	1.0007	0.0162	0.0117
2024	MMRFO[86]	-1.1421	3.1442	4.8535	-1.9298	21.0712	1.1625	0.0162	0.0116
2024	AOA[114]	-0.9712	2.7704	4.3020	-1.9520	19.9760	1.7720	0.0154	0.0123
2024	SHO[70]	-1.1995	3.2690	3.6100	-2.1000	10.1424	1.7300	0.0309	0.0021
2024	INFO[119]	-1.1548	3.3586	5.3564	-1.9176	10.0000	1.9130	0.0168	0.0128
2024	SL-PSO[120]	-0.8963	4.8000	8.6424	-1.4400	17.6400	36.300	0.1018	0.0380
2023	IABC[83]	-0.9467	3.3973	7.5589	-1.9275	20.8709	1.1000	0.0163	0.0117
2023	CBO[88]	-1.0922	2.8264	6.9700	-1.2120	23.1540	1.4445	0.0141	0.0116
2023	CBO[89]	-1.1997	3.2414	3.6000	-1.9302	20.8772	1.0000	0.0161	-
2023	IAHA[71]	-0.8774	3.5000	9.5600	-1.9300	20.8772	1.0001	0.0161	0.0117

2023	ARO[73]	-1.1762	3.7344	7.3729	-1.9302	20.8772	1.0000	0.0161	0.0117
2022	ICSO[72]	-0.8420	5.1500	9.5400	-2.7000	23.0000	3120.0	0.0190	0.0100
2021	HHO[92]	-1.0931	3.2804	5.6740	-1.8967	20.0436	2.2579	0.0151	0.0149
2020	ISSA[93]	-1.0979	3.3352	5.9034	-1.9275	21.2495	1.4823	0.0161	0.0116
2020	VSDE[94]	-1.1970	4.2330	9.7990	-0.1920	20.1940	1.1080	0.0157	0.0121
2019	SSO[21]	-1.0180	2.3151	5.2400	-1.2815	18.8547	7.5036	0.0136	7.1889
2019	CS-EO[52]	-1.1365	2.9254	3.7688	-1.3949	18.5446	8.0000	0.0136	5.5604
2019	FPA[75]	-0.9851	2.8000	4.4600	-2.3200	17.4598	1.6600	0.0697	0.0164
2019	SFLA[55]	-0.9657	3.0800	7.2236	-1.9300	20.8862	1.0000	0.0161	0.0117

4.4.3. Rime-Ice Algorithm (RIME)

The RIME (Rime-Ice) algorithm is a physics-based metaheuristic inspired by the natural phenomenon of rime ice formation in cold environments. It simulates the physical behaviors of nucleation, accumulation, and surface growth of ice particles[108]. In this algorithm, candidate solutions are treated as rime ice particles, and their positions evolve iteratively to simulate the growth and diffusion toward optimal regions. To balance global exploration and local exploitation, RIME introduces an adaptive inertia weight and an exponential fitness-based factor, enabling the algorithm to guide the search adaptively. Researchers applied RIME to the parameter identification of PEM fuel cells, achieving superior convergence precision[108]. The solution update mechanism is expressed as equation (42) follows:

$$X_i^{t+1} = X_i^t + w \cdot \exp\left(-\frac{f_i}{f_{avg}}\right) \cdot (X_{best} - X_i^t) \tag{42}$$

where w is a time-decreasing inertia weight, f_i is the fitness of the current solution, f_{avg} is the average fitness of the population. This update mechanism allows high-quality solutions to exert stronger attraction while maintaining population diversity. Thanks to its unique simulation of exponential frost growth and adaptive exploration strategy, RIME has emerged as a competitive algorithm for PEMFC modeling, with outcomes summarized in Table .

4.4.4. Weighted Mean of Vectors Optimizer (INFO)

The Weighted Mean of Vectors Optimizer (INFO) simulates the dynamic generation and combination of weighted vectors to perform global and local search. The algorithm operates in three main phases: updating rules, vector combination, and local search. In the first phase, INFO generates intermediate candidate solutions using a weighted mean of randomly selected vectors combined with a convergence adjustment term (CA)[119], which enhances global exploration. In the second phase, multiple vector-based search strategies are fused to maintain population diversity and improve convergence. The third phase introduces an intensified local search mechanism to fine-tune solutions around promising regions. One of the core update equations applied in PEMFC parameter identification is as equation (43) follows:

$$y_l^g = x_l^g + \gamma \cdot \text{MeanRule} + \text{randn} \cdot \frac{x_{bs} - x_{a1}^g}{f(x_{bs}) - f(x_{a1}^g) + 1} \tag{43}$$

where x_l^g is the position of the l -th solution at generation g , x_{bs} is the global best solution, x_{a1}^g is a randomly selected individual, γ is a scaling factor, and randn is a normally distributed random value. The MeanRule term represents the collaborative behavior encoded through the weighted mean of selected vectors. This formulation enhances convergence speed while preserving solution diversity. INFO was successfully applied to identify parameters for three different PEMFC systems and achieved lower standard deviations and sum of squared errors, demonstrating its robustness and accuracy in engineering-level parameter estimation tasks, and its performance in PEMFC parameter estimation is detailed in Table ,9.

4.5. Social-Based Metaheuristic Algorithms

4.5.1. Human Memory Optimizer (HMO)

The Human Memory Optimizer (HMO) is a novel metaheuristic algorithm inspired by human memory processes. It simulates human memory behavior, where individuals remember successful and unsuccessful experiences and adjust their actions accordingly[122]. The algorithm continuously updates its search direction by recalling both successes and failures, with the goal of achieving optimal solutions for optimization problems. The update mechanism of HMO is represented as equation (30) follows[85]:

$$X_i(t + 1) = \tilde{X} + k \cdot \sin\left(\frac{1}{k}\right) \cdot b \cdot (UB - LB) \cdot \text{rand}(1, D) \tag{30}$$

where $\tilde{X}$ denotes the mean position, k is a random value between 0.1 and 1.3, and UB and LB represent the upper and lower bounds of the search space. The algorithm excels at balancing the exploration and exploitation phases, allowing it to avoid local minima and converge faster. Consequently, the study in employed HMO to estimate the unknown parameters of PEMFCs[85], and the corresponding results are summarized in Table 7,9 and Table 9.

4.5.2. Artificial Rabbits Optimization (ARO)

Artificial Rabbits Optimization (ARO) is a social behavior-inspired metaheuristic algorithm, mimicking the dual behavior of rabbits in nature, namely “hiding” and “running,” which correspond to local exploitation and global exploration[123]. The transition between these behaviors is regulated by a dynamic energy factor $E \in [0,1]$. When the energy level is high ($E > 0.5$), the individual performs a local search near its current position, simulating hiding in burrows. When the energy decreases, the individual switches to a running mode, performing broad exploration. Researchers applied ARO to the parameter identification of PEM fuel cells, leveraging its adaptive behavior to improve convergence and accuracy[73]. The core improvement of the ARO algorithm lies in the hiding phase, and its overall procedure is illustrated in . By incorporating dual behavioral modes of hiding and escaping, ARO exhibits superior adaptability compared to many existing algorithms, as reflected in its performance results in Table 6,8,9.

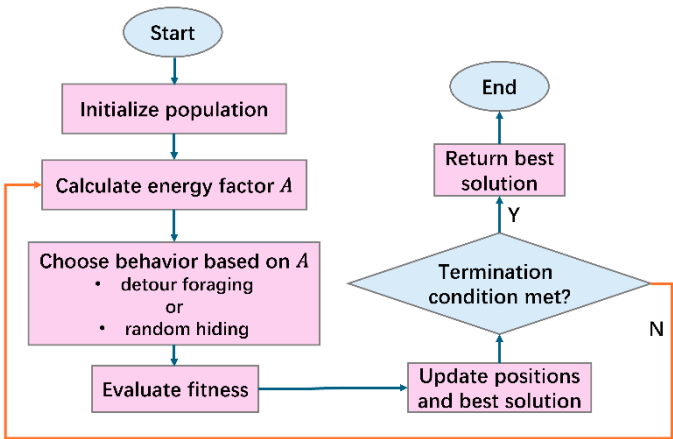


Figure 11. The flow chart of the ARO.

4.5.3. Social Learning-based Particle Swarm Optimization (SL-PSO)

Social Learning-based Particle Swarm Optimization (SL-PSO) is a socially inspired metaheuristic algorithm that builds upon the classical Particle Swarm Optimization (PSO) by introducing a novel learning mechanism based on social interactions. In the standard PSO, each particle adjusts its trajectory by considering its personal best position and the global best solution found by the entire

population. However, this rigid learning framework often limits the diversity of the search process and may lead to premature convergence, especially in high-dimensional or multimodal problems such as PEMFC parameter identification[20].

To address these limitations, SL-PSO incorporates the principles of social learning theory, where particles learn not only from their own experience but also from the observed behaviors of others[120]. Specifically, each particle selects a subset of peers from the population and evaluates their fitness. Among them, the particle with the best performance is chosen as the "social exemplar," denoted as x_{social} . The velocity and position update rules are then modified to include this exemplar, allowing particles to explore the solution space more intelligently based on socially guided behavior. The modified update rules are as equation (31) and (32) follows:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (p_i - x_i^t) + c_2 \cdot r_2 \cdot (x_{\text{social}} - x_i^t) \tag{31}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{32}$$

Here, x_i^t and v_i^{t+1} represent the position and velocity of particle i at iteration t , p_i is its personal best solution, x_{social} is the position of the selected social peer, r_1 and r_2 are random values uniformly distributed in $[0,1]$, and w , c_1 , c_2 are inertia and acceleration coefficients. This socially guided learning strategy enhances both the exploration and exploitation abilities of the swarm by maintaining solution diversity and adapting the search direction based on group-level knowledge. Researchers successfully applied SL-PSO to identify key parameters of proton exchange membrane fuel cells (PEMFCs), and experimental results demonstrated that SL-PSO outperformed conventional PSO in terms of convergence speed, solution accuracy, and robustness[120]. Its results are included in Table 8.

Table 9. PEMFC parameter estimation using 250W PEMFC dataset.

Years	Methods	Parameters							SSE
		ξ_1	$\xi_2 \times 10^{-3}$	$\xi_3 \times 10^{-5}$	$\xi_4 \times 10^{-4}$	λ	$R_c \times 10^{-4}$	b	
2025	MM-MFO[124]	-0.8000	2.3000	5.6837	-1.3587	13.9909	8.3000	0.0100	1.0996
2025	PO[65]	-0.8603	2.2782	3.6001	-1.7382	14.4208	1.0000	0.0138	0.3314
2024	ESSA[118]	-1.1763	3.1115	3.6000	-1.3495	11.6174	1.0000	0.0139	0.6013
2024	HMO[85]	-1.1041	2.9895	3.6021	-1.7389	14.4394	1.0000	0.0138	0.3314
2024	WNT-GWO[97]	-0.8532	2.8105	8.0883	-1.2887	14.3197	1.6833	0.0339	7.9547
2024	ADSOOA[107]	-0.8490	2.4230	5.2830	1.8800	23.0000	1.0070	0.0292	-
2024	MSMA[116]	-1.0986	2.7246	3.6000	-1.5603	23.0000	1.0000	0.0545	0.6420
2023	IFMO[78]	-0.8010	2.9620	6.0890	-1.5830	14.0000	2.6700	0.0270	-
2023	GTO[125]	-0.9468	3.2000	7.5200	-1.7000	15.4931	1.0000	0.0160	0.3378
2023	DO[109]	-0.9616	2.5344	3.6000	-1.3825	13.3372	4.2320	0.0150	0.1584
2023	CBO[89]	-0.8490	2.4220	5.2826	-1.8800	23.0000	1.0068	0.0291	-
2023	QOBO[87]	-0.9493	2.2890	3.6000	-1.5580	23.0000	1.0000	0.0545	0.6355
2023	IAHA[71]	-1.0866	3.3000	5.1000	-1.7000	19.9358	1.0000	0.0145	0.3359
2023	ICSO[72]	-1.0700	-	7.9100	-1.5000	23.0000	1.0000	0.0550	0.6070
2022	BSOA[126]	-0.8560	2.6400	7.9800	-1.2100	13.2000	1.0000	0.0333	0.7200
2022	GBO[127]	-0.9909	3.0800	7.0000	-2.1000	10.7636	-4.3900	0.0185	0.0557
2021	CEPSO[128]	-0.8556	2.4024	5.7420	-1.5838	25.0000	1.0000	0.0555	0.6112
2021	IAEO[129]	-0.9991	2.8250	4.4700	-1.7000	19.9358	1.0000	0.0145	0.3360
2021	HHO[92]	-1.1097	3.4586	8.3168	-1.5168	22.9454	3.8308	0.0543	0.6458
2020	ISSA[93]	-0.8616	3.1548	9.7857	-1.5423	22.8812	1.0016	0.0547	0.6434
2020	VSDE[94]	-1.1921	3.1990	3.7990	-1.8700	22.8170	1.2020	0.0290	1.0526
2020	TGA[130]	-1.1914	4.1120	6.0570	-1.7090	18.6800	4.8520	0.0544	0.7496
2019	JAYA-NM[49]	-1.1996	3.5500	6.0000	-1.2000	13.2287	1.0000	0.0333	5.2513
2019	CS-EO[52]	-0.8532	2.8121	8.1180	-1.2623	14.4722	1.0000	0.0353	8.0665
2019	FPA[75]	-0.8775	2.5000	6.4439	-1.2531	12.0160	0.6369	0.0198	0.2872

2019	WOA[76]	-0.9565	3.2221	8.2328	-1.7541	20.4470	1.0820	0.0152	0.0493
2019	SSO[21]	-1.0554	3.7953	9.8000	-1.1755	24.0000	1.0884	0.0136	1.1508

5. Summary and discussion

To facilitate the reader's review of the previously discussed metaheuristic algorithms (MHAs), a comprehensive summary is provided in Table 6-10. These tables also include several additional algorithms and their variants that have been extensively reviewed in the existing literature; therefore, detailed descriptions of these methods are omitted in this paper.

In recent years, a number of newly metaheuristic algorithms are proposed. Taking the Puma Optimization Algorithm (PO) and the Bald Eagle Search (BES) algorithm mentioned in this paper as examples, they have demonstrated remarkable effectiveness in PEMFC parameter identification. These algorithms offer improved global search capability and faster convergence due to their novel search strategies and hybridized exploration–exploitation mechanisms. For instance, PUMA mimics the cooperative hunting behavior of pumas, dynamically adjusting the movement of candidate solutions based on prey escape patterns, while BES combines migration, attacking, and swooping phases to efficiently cover the solution space. Their ability to adaptively escape local optima and maintain solution diversity throughout the optimization process makes them well-suited to the highly nonlinear and strongly coupled nature of PEMFC models.

In addition to newly developed algorithms, many classical metaheuristics have been enhanced through a variety of well-established improvement techniques tailored to the PEMFC parameter identification problem. These modifications aim to address challenges such as premature convergence, local optima trapping, and limited solution diversity. Commonly employed strategies include chaotic initialization to increase initial solution diversity, opposition-based learning (OBL) to accelerate convergence by evaluating both current and opposite solutions, and Lévy flight mechanisms to enable long-distance jumps in the search space. Other techniques such as adaptive weight adjustment, elitism retention, and Gaussian perturbation improve stability and convergence precision. Furthermore, hybrid strategies, which combine the strengths of multiple algorithms, and mechanisms like escape energy modeling, which is often used in predator-prey-inspired algorithms—further enhance global exploration. These enhancements collectively improve the robustness and search efficiency of classical algorithms, making them better suited for the high-dimensional, nonlinear, and strongly coupled nature of PEMFC models.

The parameter identification task in PEMFC modeling presents several intrinsic challenges, including highly nonlinear behavior, strong coupling between variables, and a complex, multi-modal solution space. These characteristics make it easy for conventional algorithms to fall into local optima or suffer from premature convergence. Moreover, PEMFC performance is highly sensitive to small parameter deviations, which demands robust and precise optimization strategies. Compared to earlier methods, both newly developed algorithms and improved variants offer stronger capabilities in global search, adaptability, and convergence stability. Specifically, effective algorithms for this domain must rapidly cover the search space, maintain solution diversity, and dynamically balance exploration and exploitation to escape local minima and identify globally optimal parameter sets.

6. Conclusions

This paper aims to summarize, classify and compare the metaheuristic methods for PEMFC parameter estimation in detail from the aspects of application year, application method, usage data, advantages and disadvantages and PEMFC cell type. And the following suggestions are made for the direction of in-depth research in related fields in the future:

In summary, the problem of PEMFC parameter identification fundamentally involves four key elements: the PEMFC model, the optimization algorithm, the dataset, and the objective function.

Among these, optimization algorithms have seen rapid advancements in recent years, with a growing number of novel and hybrid metaheuristic techniques being applied. Also, other approaches

such as Artificial Neural Network (ANN)-based strategies have also demonstrated promising results in PEMFC parameter estimation, yet remain relatively underexplored. Greater attention to these alternative methods, especially when integrated with metaheuristic frameworks, may lead to more accurate and efficient parameter identification in the future.

However, PEMFC models themselves still have substantial room for improvement, particularly in terms of dynamic representation and real-time adaptability. For example, a novel methodology of polarization curve fitting for PEMFC, uses only two parameters to accurately fit the polarization curve by adopting a genetic algorithm. This approach simplifies the identification process while maintaining high fidelity, providing a promising path for efficient PEMFC modeling under practical conditions.

On the other hand, due to the high cost and complexity associated with PEMFC systems, the acquisition of new commercial datasets remains a significant challenge for future research. In this regard, methods such as data preprocessing and enhancement, as seen in the FNN-POA framework[67], offer a promising workaround. By applying techniques like noise filtering, normalization, and quality screening to existing datasets, it is possible to improve the reliability and representativeness of the training data. This not only alleviates the dependence on expensive physical experiments, but also enhances the generalizability and accuracy of parameter identification under limited data availability.

At last, the design of new objective functions that better reflect algorithm performance under varying operating conditions can further enhance accuracy and robustness.

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