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Optimizing PEM Fuel Cell Models with Bio-Inspired Algorithms

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Abstract
With hydrogen gaining traction as an energy source, polymer electrolyte membrane fuel cells (PEMFCs) stand out as a leading clean energy solution. Yet, precise modeling is essential for optimizing their design and performance. To overcome this hurdle, researchers developed the enhanced salp swarm algorithm (ESSA). This bio-inspired metaheuristic innovatively tackles the challenge of identifying unknown PEMFC model parameters. ESSA integrates opposition-based learning, a novel "exploration salps" mechanism, genetic algorithm-style crossover and mutation, and a "survival of the fittest" selection process. These enhancements effectively overcome the limitations of the standard salp swarm algorithm, leading to greater population diversity, faster convergence, improved exploration capabilities, and higher accuracy. Extensive experimental validation on commercial 250W and 500W PEMFC stacks confirmed ESSA's superior ability to provide more accurate and stable parameter estimations with quicker convergence compared to numerous state-of-the-art algorithms, representing a substantial leap in PEMFC parameter estimation and optimization.

Keywords: *Fuel cells, polymer electrolyte membrane fuel cells, algorithm, Optimization, parameter estimation*

1. INTRODUCTION

The world is grappling with a growing energy crisis, fueled by shrinking fossil fuel reserves and the pervasive threat of climate change from greenhouse gas emissions. This urgent situation has ignited global interest in developing clean, renewable energy systems. Among these, hydrogen energy is emerging as a strong contender due to its inherent cleanliness, abundant availability, high efficiency, and remarkable versatility.

Within the realm of hydrogen-based technologies, Polymer Electrolyte Membrane Fuel Cells (PEMFCs) are drawing significant attention. PEMFCs efficiently convert hydrogen and an oxidizing agent directly into electricity, offering a host of advantages: they operate silently, boast a high efficiency of 50-60% (outperforming traditional thermal generators), and feature a leak-proof solid electrolyte. Their adaptability allows for both stationary and vehicle applications, and they operate at relatively low temperatures (55-80°C). Furthermore, PEMFCs are celebrated for their long lifespan, rapid startup, and wide power range (from 1 W to 10 MW). Crucially, PEMFCs produce virtually zero emissions, even surpassing competing technologies when hydrogen is produced through reforming processes. Their high energy density also expands their potential uses, positioning them as a compelling choice for a sustainable energy future.PEMFCs are incredibly versatile, powering everything from vehicles and forklifts to portable devices and stationary energy systems. However, a PEMFC is a complex electrochemical reactor. Its operation involves a delicate interplay of processes like reactant transport, chemical reactions, heat transfer, and various electrical and mechanical factors. To truly understand, optimize, and simulate PEMFC performance, we need comprehensive modeling that accounts for all these simultaneous phenomena [4].

While many PEMFC models exist, primarily based on the experimental polarization curve, the inherent challenges of these cells their multi-variability, non-linearity, and strong coupling—make accurately

identifying their key parameters incredibly difficult with traditional methods. This often leads to unreliable results.

2. LITERATURE REVIEW

Research on PEMFCs has yielded diverse techniques for determining their model parameters, broadly categorized as either iterative or intelligent methods. Iterative algorithms, such as the well-known Levenberg–Marquardt (LM) algorithm, are often efficient. However, they come with drawbacks: their accuracy and convergence can be highly sensitive to initial conditions, potentially leading to slow progress or getting stuck in a local optimum. Additionally, the LM algorithm's need to compute partial derivatives can result in high computational costs and reduced stability, especially when dealing with convergence issues, data inconsistencies, or large datasets [5-6]. In contrast, intelligent methods utilizing artificial intelligence have recently gained significant popularity. They offer demonstrated accuracy and reliability for estimating PEMFC module parameters [insert citation]. Among these, the Levenberg–Marquardt backpropagation (LMBP) algorithm is particularly notable for its efficiency and advantages, especially when combined with artificial neural networks. This integration substantially enhances optimization capabilities, though a more detailed exploration of its specific benefits over other techniques would offer a more comprehensive understanding[1-4].

Existing optimization methods often have significant drawbacks, such as a large number of empirical parameters that can negatively impact solution quality or convergence speed. Some methods struggle to fully explore the search space, leading to premature convergence to suboptimal local solutions. Additionally, many become computationally expensive with larger population sizes or extensive learning requirements [7].

In response to these limitations of the Salp Swarm Algorithm (SSA). This optimizer, inspired by the social swarming behavior of salps, is notable for its lack of control parameters, which addresses the issue of parameter sensitivity. Due to its robustness and efficiency, SSA has found broad application in solving complex, nonlinear, and high-dimensional problems across various fields, including image segmentation, circuit sizing, and parameter extraction for photovoltaic cells. Specifically concerning PEMFCs, SSA has been successfully used to determine maximum power points.

Despite the Salp Swarm Algorithm (SSA) showing promise, its real-world application reveals limitations, primarily insufficient exploration that can lead to premature convergence at local optima. To address this, many SSA variants, often incorporating processes from other algorithms or hybridization, have been proposed to improve convergence. Building on this, this paper introduces an Enhanced Salp Swarm Algorithm (ESSA), a novel approach for the first-time extraction of parameters for the Amphlett model of Polymer Electrolyte Membrane Fuel Cells (PEMFCs). ESSA features innovative crossover and mutation operations, alongside an Opposition-Based Learning (OBL) initialization strategy to ensure comprehensive search space coverage. The key contributions include developing ESSA to overcome classical SSA's limitations, utilizing experimental data from 250W and BCS500W commercial PEMFC stacks, employing ESSA and seven other optimization methods (SSA, WSO, INFO, MPA, SCA, OAVOA, AOSMA) to estimate parameters for the Amphlett model under varying conditions, performing statistical tests for consistency, and validating ESSA's ability to accurately reproduce I-V polarization characteristics with varying temperature and gas pressure. Simulation results, validated by experimental tests, confirm ESSA's high efficiency in extracting unknown PEMFC model parameters, demonstrating superior convergence, accuracy, and the ability to find global optimal solutions, making it a highly attractive approach.

3. Pemfcs Model

A PEMFC is essentially a series of interconnected electrochemical cells. Each individual cell contains an electrode-membrane-electrode assembly (as illustrated in Fig. 1). Within these cells, a chemical reaction directly converts hydrogen fuel into DC electricity, heat, and water, with the help of an oxidant like oxygen [8-12],water produced through this can be purified through using solar energy to distil chemical toxic brackish water into pure water for avoiding chemical health risk by solar still [13].The overall reaction for a PEMFC can be summarized as:

$$2H_2+O_2 \rightarrow 2H_2O+ \text{Energy} \quad (1)$$

In this equation, "Energy" specifically refers to the electrical energy produced by the flow of hydrogen electrons from the anode to the cathode via the electrical circuit.

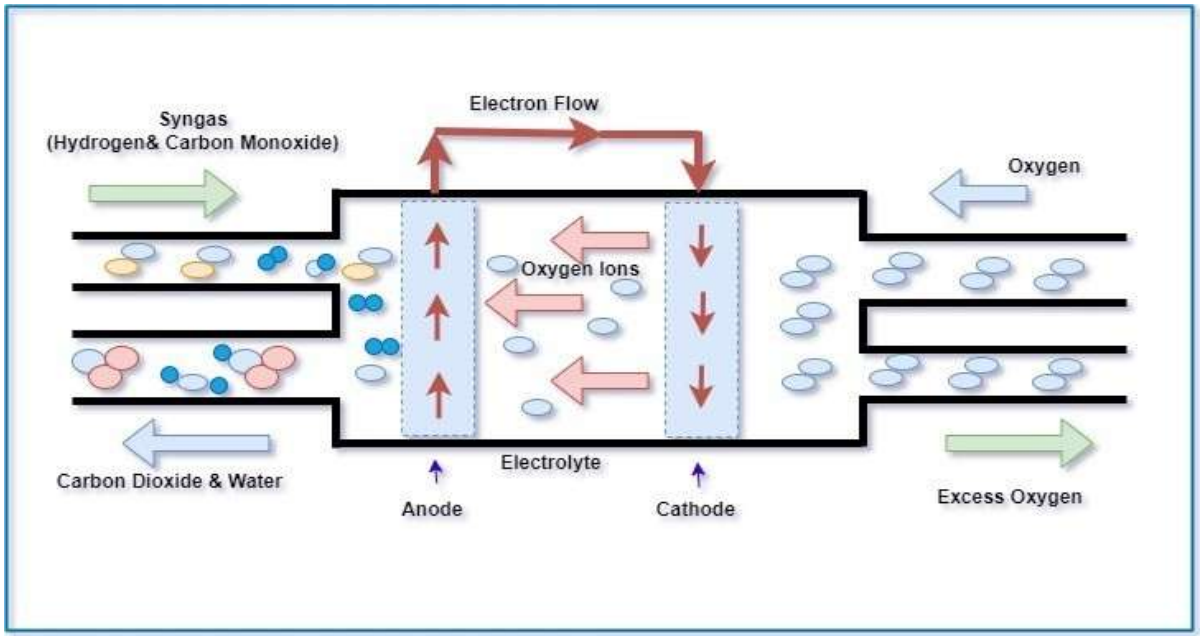


Figure 1: Modeling of the fuel cell

J.C. Amphlett et al. developed the PEMFC output voltage model, which considers key parameters like load current, input pressure, operating temperature, and membrane thickness [64]. The fundamental expression for a cell's thermodynamic voltage (V_{cell}) is:

$$V_{cell}=E_0-\eta_{act}-\eta_{con}-\eta_{ohm} \quad (2)$$

In this equation, E_0 (V) represents the open circuit voltage of a cell. The terms η_{act} (V), η_{con} (V), and η_{ohm} (V) correspond to the activation, concentration, and ohmic polarizations within the battery, respectively. The open circuit voltage itself is derived from the Nernst equation and can also be determined through regression analysis of experimental data.

In the realm of optimization, the primary goal of parameter estimation is to accurately determine the unknown parameters of a model using experimental data. This process is typically guided by an objective function that assesses how well the identified parameters fit the data. The effectiveness of this fit is often measured by the difference between the model's predicted output and the actual experimental results.

In this study, the sum of squared errors (SSE) was chosen as the objective function to quantify the discrepancy between the measured voltage from the PEMFC stack and the voltage calculated by its theoretical model. Mathematically, this is expressed as:

$$F_{obj}\left[Y=\left[\beta_{i(1:4)},\ \lambda_i, R_c\right]=min\left[\sum_1^N\left(U_{exp.i}-U_{mdl.i}\right)^2\right]\right] \quad (3)$$

Here, Uexp,i represents the experimentally measured voltage at each current step i, and Umdl,i is the corresponding voltage derived from the theoretical model. The objective is to minimize this sum, thereby finding the set of parameters (Y) that best aligns the model with the experimental observations.

4. Optimizer Algorithm

The Salp Swarm Algorithm (SSA) is an optimization technique inspired by the unique social behavior of salps, translucent marine animals that move by contracting muscle fibers to pump water through their bodies. Unlike many other animal groups, salps often form "chains" or swarms.

$$X_{1,d}=\begin{cases}X_{Best.d}+\ c_1\left(\left(ub_d-lb_d\right)c_2+l\,b_d,\right. & c_3\geq 0.5\\ X_{Best.d}+\ c_1\left(\left(ub_d-lb_d\right)c_2+l\,b_d,\right. & c_3<0.5\end{cases} \quad (4)$$

$$c_1=2\,e^{-\left(\frac{4.lter}{Max.lter}\right)^2} \quad (5)$$

$$X_{n,d}=\begin{cases}X_{Best.d}\,.r_2\left(\left(ub_d-lb_d\right)c_2+l\,b_d,\right. & r_1>0.5\\ X_{Best.d}\,.(1-r_2\tfrac{1}{2})((ub_d-lb_d)\ +\ X_{n,d}\,,r_2\tfrac{1}{2} & r_1\leq 0.5\end{cases} \quad (6)$$

$$X_{1,d}= \begin{cases} X_{1.d} + m_1 ((ub_d - lb_d) m_2 + l\, b_d , & m_3 \geq 0.5 \\ X_{1.d} + m_1 ((ub_d - lb_d) m_2 + l\, b_d , & m_3 < 0.5 \end{cases} \quad (7)$$

This distinct swarming behavior forms the basis of the SSA's special updating mechanism. In each iteration, the algorithm sequences the "salp" population, with each virtual salp following the one before it. This ensures all salps collectively move towards an optimal solution within a defined search space, as depicted in Fig. 1.

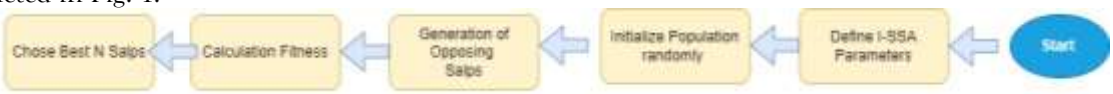


Figure 2: Flowchart of the algorithm

This section details the structure of the new Enhanced Salp Swarm Algorithm (ESSA), which builds upon the original SSA. A key improvement is the use of opposition-based initialization for the salp population, replacing purely random initialization to ensure a more effective distribution of salps across the search space.

To further boost exploration capabilities, ESSA integrates a novel category of "exploring salps." Additionally, a crossover and mutation mechanism is introduced during the salp position update process. An elimination mechanism is also implemented to maintain population diversity. These combined features accelerate convergence towards the global optimum and prevent premature convergence to local optima, which typically leads to a loss of diversity.

5. RESULTS AND ANALYSIS

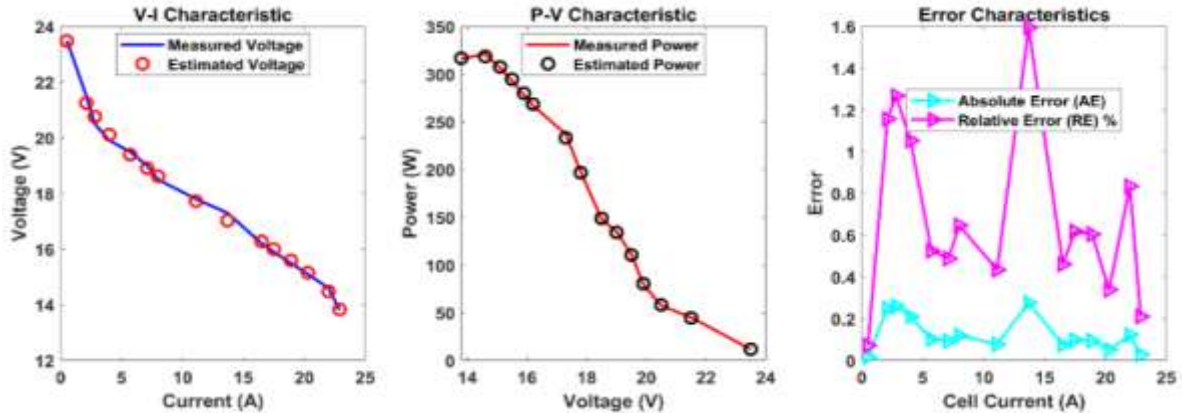
In Table 2, ESSA once again demonstrates exceptional stability and precision. Its consistent minimum (0.1029149), maximum (0.1036409), and mean (0.1029875) values show highly stable results with minimal fluctuation. The close alignment of these figures confirms negligible variability and remarkably consistent performance across diverse test scenarios. PaDE's standard deviation is an exceptionally low 0.0002296, significantly outperforming HARD-DE's 0.0094773. This substantial difference highlights ESSA superior predictability and reliability. Furthermore, PaDE's runtime efficiency is outstanding, recording a minimal 0.1118347 seconds. This is considerably faster than other algorithms, including HARD-DE, which had the highest runtime at 12.309013 seconds. PaDE's efficiency, combined with its best-in-class Friedman ranking of 1.85, solidifies its position as the top performer among all compared algorithms.

As presented in Table 4, ESSA continues to demonstrate its exceptional stability and precision. Its minimum, maximum, and mean values consistently register at 0.1486318, indicating perfectly stable results with zero fluctuation. This precise alignment across all metrics confirms zero variability and extraordinarily consistent performance across multiple test scenarios. PaDE's standard deviation is an incredibly low 4.33E-16, a stark contrast to HARD-DE's 0.0416355. This significant difference underscores PaDE's superior predictability and reliability. Furthermore, PaDE's runtime efficiency is remarkable, recording a minimal runtime of 0.0992511 seconds. This is considerably faster than other algorithms; for instance, HARD-DE's highest runtime was 10.618107 seconds. This efficiency, combined with its Friedman ranking of 1, establishes ESSA as the best performer among all algorithms compared.

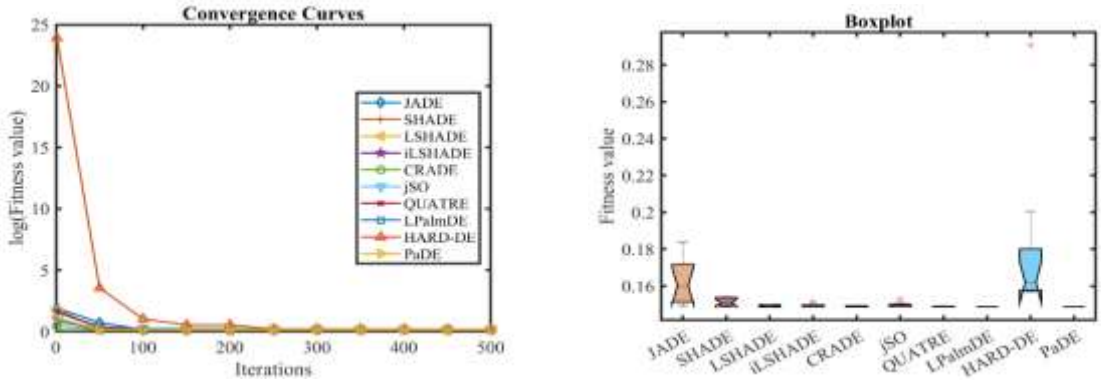
Table 5: Performance metrics of PaDE Algorithm

V_{exp} (V)	P_{est} (W)	I_{exp} (A)	AE_v (A)	RE %	P_{exp} (W)	V_{est} (V)	MBE
23.5	11.741544	0.5	0.0169112	0.0719625	11.75	23.483089	1.907E-05
21.5	44.627748	2.1	0.2486915	1.1567046	45.15	21.251309	0.0041232
20.5	58.127496	2.8	0.25982	1.2674146	57.4	20.75982	0.0045004
19.9	80.438331	4	0.2095828	1.0531801	79.6	20.109583	0.0029283
19.5	110.56597	5.7	0.1024618	0.5254452	111.15	19.397538	0.0006999
19	134.24155	7.1	0.09274	0.4881051	134.9	18.90726	0.0005734
18.5	148.95718	8	0.1196471	0.6467409	148	18.619647	0.0009544
17.8	196.72264	11.1	0.0772393	0.4339289	197.58	17.722761	0.0003977
17.3	233.23012	13.7	0.275904	1.5948207	237.01	17.024096	0.0050749

16.2	268.53175	16.5	0.0746513	0.4608104	267.3	16.274651	0.0003715
15.9	279.97004	17.5	0.0982881	0.618164	278.25	15.998288	0.000644
15.5	294.72028	18.9	0.0936658	0.6042955	292.95	15.593666	0.0005849
15.1	307.5683	20.3	0.0511477	0.3387264	306.53	15.151148	0.0001744
14.6	318.52029	22	0.121805	0.8342811	321.2	14.478195	0.0009891
13.8	316.68523	22.9	0.0290494	0.2105026	316.02	13.829049	5.626E-05



(a)



(b) (c)

Figure 3: ESSA Algorithm Characteristic curves of FC5; (a) V-I, P-V, and Error Curve, (b) Convergence Curve, (c) Box-Plot

6. CONCLUSION

Accurately determining unknown parameters in PEMFC mathematical models is a critical and complex challenge, vital for effective system design, control, and overall performance. To address this, we framed the parameter extraction as an optimization problem, using the voltage-current (V-I) characteristic—highly influenced by operating temperature and gas pressure—as a key indicator. This paper introduces an Enhanced Salp Swarm Algorithm (ESSA)-based approach to solve this. Our rigorous numerical and experimental validations demonstrate ESSA's superior performance compared to a wide array of established and recently developed optimization methods, including JAYANM, SSO, MVO, CHHO, QOBO, GTO, AHA, WSO, INFO, MPA, SSA, SCA, OAVOA, and AOSMA. The results consistently show that the ESSA-based strategy yields a high-quality model that closely matches real experimental data, excelling in both accuracy and convergence to optimal solutions. This makes our developed approach exceptionally suitable for integration into electronic component simulators, enabling comprehensive study and analysis of PEMFC devices.

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