A Bio-Inspired Approach for Accurate Parameter Identification of PEM Fuel Cells Based on Water Uptake and Transport in Plants

Houda Allagui[1], Ahmed Jeridi[2] and Abderrahmen Zaafouri[3]

***Abstract*— Reliable modeling of proton exchange membrane fuel cells (PEMFCs) strongly depends on the accurate estimation of electrochemical parameters that are not explicitly provided in manufacturers' specifications. This paper addresses the parameter optimization problem of PEMFCs by adopting the Amphlett semi-empirical model to describe the voltage-current characteristics of the fuel cell. The overall cell voltage is expressed as a combination of reversible voltage and activation, ohmic, and concentration overpotentials. The unknown model parameters are determined by minimizing the sum of squared errors (SSE) between measured and simulated polarization curves. To efficiently solve the resulting nonlinear optimization problem, the Water Uptake and Transport in Plants (WUTP) metaheuristic algorithm is employed. The effectiveness of the proposed approach is examined using experimental data from two different PEMFC stacks, namely the NedStack PS6 and the BCS500W. The optimization results are further analyzed through statistical boxplot representations obtained from multiple independent runs. The obtained findings demonstrate that the WUTP algorithm ensures accurate and stable parameter estimation for both fuel cell systems, highlighting its potential for PEMFC modeling and control-oriented energy management applications.**

***Index Terms*— Proton exchange membrane fuel cell, parameter optimization, WUTP algorithm, Amphlett model, metaheuristic optimization.**

I. Introduction

Accurate modeling of PEMFC systems plays a crucial role in performance analysis, control design, and energy management. However, PEMFC models are inherently nonlinear and depend on several electrochemical, thermodynamic, and empirical parameters [3]. These parameters are often difficult to determine precisely, as they vary with operating conditions and degradation effects [4], [5]. Consequently, parameter identification and optimization remain challenging tasks that significantly influence the accuracy of PEMFC voltage-current characteristics. In addition, the parameter estimation process is characterized by a nonlinear and multimodal search space resulting from the strong interactions among activation, ohmic, and concentration losses. These characteristics increase the difficulty of obtaining reliable parameter estimates and motivate the use of advanced optimization techniques.

Conventional optimization techniques, including gradient-based and deterministic methods, often suffer from premature convergence and sensitivity to initial conditions when applied to highly nonlinear problems. Moreover, their performance may deteriorate in the presence of multiple local optima. To overcome these limitations, metaheuristic optimization algorithms have been widely adopted for PEMFC parameter estimation. Algorithms such as Harris Hawks Optimization (HHO) [6], Gravitational Search Algorithm (GSA) [7], Salp Swarm Algorithm (SSA) [8], and Grey Wolf Optimizer (GWO) [9] have demonstrated promising results in minimizing modeling errors and improving parameter estimation accuracy.

II. Mathematical Modeling

A Proton Exchange Membrane Fuel Cell (PEMFC) is an electrochemical energy conversion system that transforms hydrogen and oxygen into electrical energy through an electrochemical reaction. The system consists of an anode, a cathode, and a polymer electrolyte membrane that allows proton transfer while blocking electrons [11], [12] In this work, the stack voltage is modeled using a semi-empirical Amphlett-based formulation, which captures the main voltage loss mechanisms including activation, ohmic, and concentration losses. The model takes the stack current I as input, while the output is the corresponding stack voltage V_{stack}. The relationship between stack and single-cell voltage is given by:

$$V_{stack} = N_{cell} \cdot V_{cell} \tag{1}$$

where N_{cell} is the number of cells in the stack. The model input is the stack current I, while the output is the stack voltage V_{stack}. The objective of parameter identification is to adjust the unknown parameters in order to minimize the error between simulated and experimental voltage values.

A. Operating Principles

The electrochemical reactions occurring in a PEM fuel cell are given by:

$$\text{Anode:} \quad 2\mathrm{H_2} \rightarrow 4\mathrm{H^+} + 4e^- \tag{2}$$

$$\text{Cathode:} \quad 4\mathrm{H^+} + 4e^- + \mathrm{O_2} \rightarrow 2\mathrm{H_2O} \tag{3}$$

$$\text{Overall:} \quad 2\mathrm{H_2} + \mathrm{O_2} \rightarrow 2\mathrm{H_2O} \tag{4}$$

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TABLE I
NOMENCLATURE OF PEMFC SYMBOLS

Symbol	Description	Unit
PEMFC	Proton exchange membrane fuel cell (acronym)	–
N_{cell}	Number of cells in the stack	–
A	Active area	cm^2
I	Stack current	A
J	Current density ($J = I/A$)	A cm^{-2}
$J_{\max}$	Maximum current density	A cm^{-2}
V_{cell}	Single-cell voltage	V
V_{stack}	Stack voltage ($N_{\text{cell}} V_{\text{cell}}$)	V
E_{Nernst}	Open-circuit/Nernst potential	V
η_{act}	Activation overpotential	V
η_{ohm}	Ohmic overpotential	V
η_{conc}	Concentration/mass-transport overpotential	V
R_c	Contact resistance (interfaces, bipolar plates, etc.)	$\Omega\,\text{cm}^2$
ρ_m	Membrane resistivity	$\Omega\,\text{cm}$
ℓ_m	Membrane thickness	cm
λ	Membrane water content	–
p_{H_2}	Partial pressure of hydrogen	bar (or atm)
p_{O_2}	Partial pressure of oxygen	bar (or atm)
$p^{\text{sat}}_{\text{H}_2\text{O}}$	Saturation vapour pressure of water	bar (or atm)
RH_C, RH_A	Relative humidity (anode, cathode)	%
T	Absolute temperature	K
B	Concentration-loss coefficient (Amphlett model)	V
$\xi_{1..4}$	Semi-empirical coefficients (Amphlett model)	–
R	Universal gas constant	$\text{J mol}^{-1}\,\text{K}^{-1}$
F	Faraday constant	C mol^{-1}

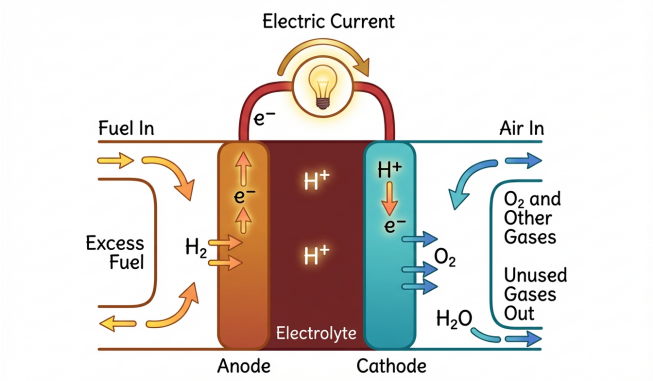

Fig. 1. Schematic representation of a Proton Exchange Membrane Fuel Cell (PEMFC)

B. Cell-Voltage Model (Amphlett Form)

Let $J = I/A$ denote the current density, where I is the cell current and A is the effective active area of the fuel cell. The cell voltage is expressed as:

$$V_{\text{cell}} = E_{\text{Nernst}} - V_{\text{act}} - V_{\text{ohm}} - V_{\text{conc}}. \tag{5}$$

C. Reversible Potential

The temperature- and pressure-dependent Nernst potential is given by:

$$E_{\text{Nernst}} = 1.229 - 8.5 \times 10^{-4}(T - 298.15) + 4.3085 \times 10^{-5} T \left[\ln(P_{H_2}) + \frac{1}{2}\ln(P_{O_2})\right], \tag{6}$$

D. Voltage Losses

1) Activation Losses: The activation overvoltage is modeled as:

$$V_{\text{act}} = \xi_1 + \xi_2 T + \xi_3 T \ln(C_{O_2}) + \xi_4 T \ln(J), \tag{7}$$

where ξ_1–ξ_4 are empirical coefficients. The oxygen concentration at the cathode is given by:

$$C_{O_2} = \frac{P_{O_2}}{5.08 \times 10^6 \exp(498/T)}. \tag{8}$$

2) Ohmic Losses: The ohmic voltage drop combines membrane and contact resistances:

$$V_{\text{ohm}} = J(r_m + r_c), \qquad r_m = \rho_m \ell, \tag{9}$$

where r_c is the area-specific contact resistance. The membrane resistivity is modeled as:

$$\rho_m = \frac{181.6(\lambda - 0.634 - 3J)}{[1 + 0.03J + 0.062(T/303)^2]J^{2.5}} \times \exp\left(\frac{4.18(T - 303)}{T}\right), \tag{10}$$

3) Concentration Losses: Mass-transport limitations at high current densities are expressed as:

$$V_{\text{conc}} = -B \ln\left(1 - \frac{J}{J_{\max}}\right), \tag{11}$$

E. Parameter Identification Problem

The unknown parameters of the PEMFC model are identified by minimizing the sum of squared errors between simulated and experimental voltages:

$$F_{\text{obj}} = \sum_{i=1}^{N} (V_{\text{sim},i} - V_{\text{exp},i})^2, \tag{12}$$

where N is the number of experimental polarization points. The optimization variables are:

$$\{\xi_1, \xi_2, \xi_3, \xi_4, \lambda, r_c, B\}.$$

III. WUTP ALGORITHM AND ITS APPLICATION TO PARAMETER EXPANSION

A. Algorithmic Inspiration

The Water Uptake and Transport Plants (WUTP) algorithm is a novel bio-inspired optimization method derived from the natural processes governing water uptake and transport in plant root networks. Candidate solutions are treated as virtual roots whose movements are guided by hydraulic flow, diffusion phenomena, and adaptive transport strategies. These biologically inspired mechanisms enhance the search capability of the algorithm by promoting both extensive

exploration of the solution space and intensive exploitation of promising regions, thereby improving optimization performance.[10]

B. Pseudo-code WUTP

Algorithm 1 WUTP Metaheuristic Algorithm

Initialize population $X = \{x_1, \ldots, x_N\}$
Evaluate fitness of each solution x_i
while stopping criteria not met **do**
  for each solution x_i **do**
    Compute gradient-inspired update Δx_i
    Generate random perturbation R
    Update solution:

$$x_i \leftarrow x_i + \alpha \Delta x_i + \beta R$$

    Evaluate fitness of updated x_i
  end for
  Adapt coefficients α and β
  Update global best solution
end while
return Best solution found

The Flowchart of the proposed WUTP in the optimization process is illustrated in fig 2.

C. Mathematical Model

Let $\mathbf{y}_i^t \in \mathbb{R}^{dim}$ denote the position of the i-th particle at iteration t. The initial population is randomly generated within the search bounds as follows:

$$\mathbf{y}_i^0 = \mathbf{lb} + rand \cdot (\mathbf{ub} - \mathbf{lb}) \tag{13}$$

To model the water transport dynamics, a hydraulic flux vector $\mathbf{J}_i^t$ is associated with each particle and initialized as:

$$\mathbf{J}_i^0 = 0.1\, \mathbf{y}_i^0 \tag{14}$$

At each iteration, the hydraulic flux is updated according to:

$$\mathbf{J}_i^{t+1} = \gamma \mathbf{J}_i^t + c_1 L_p \left(\mathbf{y}_i^t - \sigma \mathbf{pbest}_k\right) + c_2 \rho g \left(\mathbf{y}_i^t - \mathbf{y}_i^{t-1}\right) \tag{15}$$

where γ is a damping coefficient, L_p denotes the hydraulic permeability, ρ is the fluid density, g is the gravitational acceleration, and $\mathbf{pbest}_k$ represents a randomly selected personal best position. The position update mechanism is governed by two main phases, corresponding to water uptake and water transport processes. In the water uptake phase, the particle position is updated as:

$$y_{i,j}^{t+1} = y_{i,j}^t - \frac{J_{i,j}^t}{K} \tag{16}$$

where K is the hydraulic conductivity coefficient. Alternatively, a diffusion-based transport mechanism is employed:

$$y_{i,j}^{t+1} = y_{i,j}^t - \frac{J_{i,j}^t}{2\pi D a^2} \tag{17}$$

where D is the diffusion coefficient and a represents the effective root radius. To enhance exploration and avoid premature convergence, an adaptive perturbation term is introduced:

$$\nu(t) = \frac{10^{-7}}{1 + \exp\left(\frac{t - T/2}{100}\right)} \tag{18}$$

The WUTP algorithm is applied to identify the optimal parameters of a PEMFC model through minimization of the SSE and STD between experimental and simulated polarization characteristics.

$$x_i^{t+1} = x_i^t + \alpha \Delta x_i + \beta R \tag{19}$$

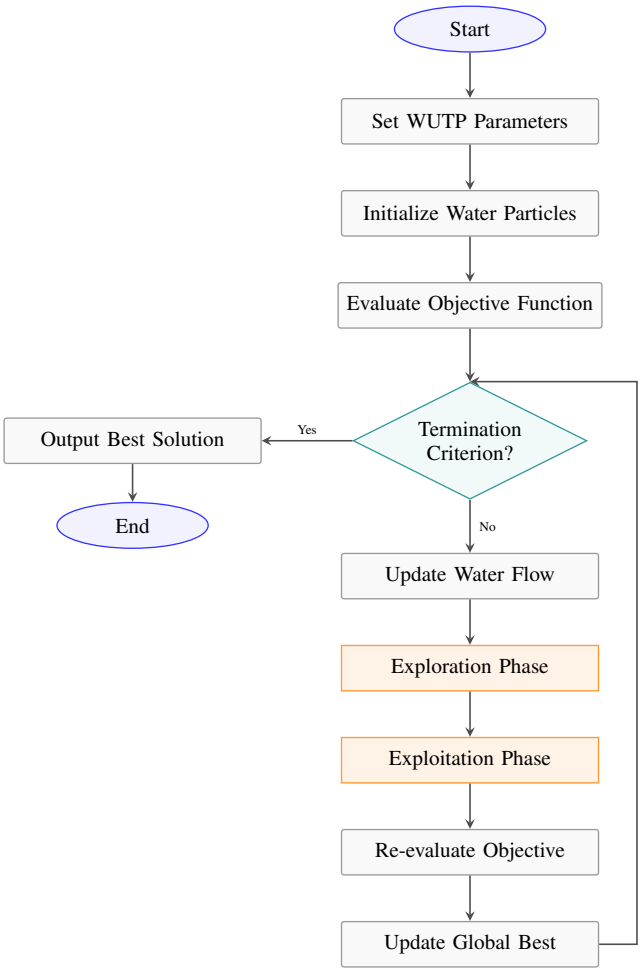

Fig. 2. Flowchart of the WUTP algorithm .

D. Application to parameter extraction of Fuel cell model

Evaluating fuel cell performance accurately depends on determining the optimal parameters of the model. This is done by defining an objective function that reduces the difference between measured experimental data and the corresponding model predictions. Through an iterative optimization process, the model parameters are tuned to achieve strong agreement between simulations and experiments, improving both the reliability and predictive capability of the fuel cell model. The extraction procedure begins by setting the fixed characteristics of the PEMFC, such as the membrane thickness l, active area A, operating temperature

TABLE II

SEARCH BOUNDS FOR THE SEVEN AMPHLETT-BASED PEMFC MODEL PARAMETERS

Parameter	Unit	Min	Max
ξ_1	–	-1.1997	-0.08532
ξ_2	–	8.0×10^{-4}	6.0×10^{-3}
ξ_3	–	3.6×10^{-5}	9.8×10^{-5}
ξ_4	–	-2.6×10^{-4}	-9.54×10^{-5}
γ	–	10.00	24.00
B	V	0.0136	0.50
R_c	$\Omega \cdot \mathrm{cm}^2$	1.0×10^{-4}	8.0×10^{-4}

T, hydrogen and oxygen partial pressures P_{H_2} and P_{O_2}, and the maximum current density $J_{\max}$, as listed in Table II. The optimization targets the parameters ξ_1, ξ_2, ξ_3, ξ_4, λ, the contact resistance R_c, and the empirical coefficient B, with their respective search ranges also summarized in Table 2. Using the equations described in Section 2, the stack voltage is computed for each operating condition. The objective function then measures the deviation between simulated and experimental voltages, usually expressed as the sum of squared errors. Within the proposed Water Uptake and Transport of Plants (WUTP) algorithm, candidate solutions are evaluated and iteratively updated through cooperative and stochastic mechanisms until convergence, as depicted in Fig. 2.

IV. RESULTS AND DISCUSSION

To assess the effectiveness of the proposed WUTP algorithm, simulations were conducted using two widely recognized commercial PEMFCs: the BCS500W and the NedStackPS6. These datasets were chosen because they encompass a broad spectrum of operating conditions and performance profiles, enabling a comprehensive evaluation of the fuel cell models' accuracy and reliability across different scenarios. Seven critical parameters—ξ_1, ξ_2, ξ_3, ξ_4, λ, R_c, and B—were identified as having a significant impact on the algorithm's search performance.The parameter extraction process was performed in MATLAB R2023a using a population size of 50, 30 independent runs, and a maximum of 1000 iterations. Finally, the convergence performance of the WUTP algorithm was benchmarked against several established population-based metaheuristic methods, including GSA, GWO, HHO, and SSA.

A. BCS500W

The effectiveness of the WUTP-based parameter identification is demonstrated through the polarization curves, where the estimated voltage exhibits a very small deviation from the experimental measurements, confirming the accuracy of the extracted parameters, as shown in Fig. 3. The power–current characteristics illustrated in Fig. 4 further support the validity of the proposed model, with the predicted maximum power reaching approximately 500 W, which is in close agreement with the rated output of the BCS-500 W stack. The convergence behavior presented in Fig. 5 clearly indicates the superior performance of the WUTP algorithm, which rapidly attains the optimal solution while achieving the lowest mean squared error (MSE) and total squared error (SSE). Moreover, the statistical error analysis depicted in Fig. 6 highlights the robustness of the proposed approach. The boxplot reveals a noticeably smaller variance for WUTP when compared with SSA ,GSA, GWO and HHO, which exhibit larger error dispersions and reduced stability. Overall,

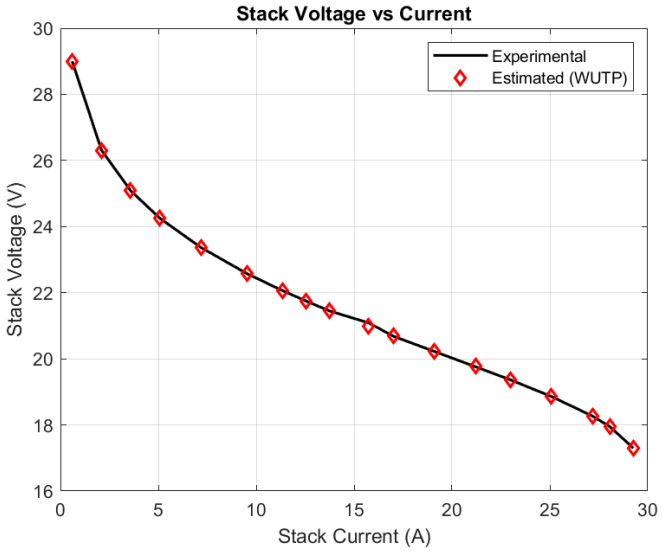

Fig. 3. Polarization curve-WUTP-BCS500W

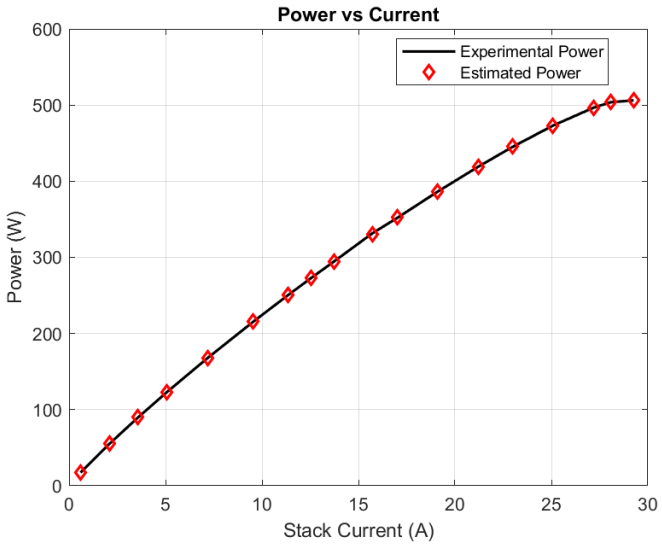

Fig. 4. Power curve-WUTP-BCS500W

the obtained results demonstrate that the WUTP algorithm ensures fast convergence, low estimation error, and high robustness, making it a reliable and effective optimization technique for PEMFC parameter identification.

B. NedStackPS6

The obtained results demonstrate the effectiveness of the WUTP algorithm in accurately identifying the parameters of the NedStack PS6 PEMFC stack. As illustrated by the

TABLE III

SPECIFICATIONS OF THE BCS-500 W AND NEDSTACK PS6 PEMFC STACKS

Parameter	BCS-500 W	Nedstack PS6
N_{cell}	32	65
A (cm^2)	64	240
P (μm)	178	178
$J_{\max}$ (mA/cm^2)	1500	2000
T (K)	333	343
P_{H_2} (atm)	1.5	2.5
P_{O_2} (atm)	1.0	1.0

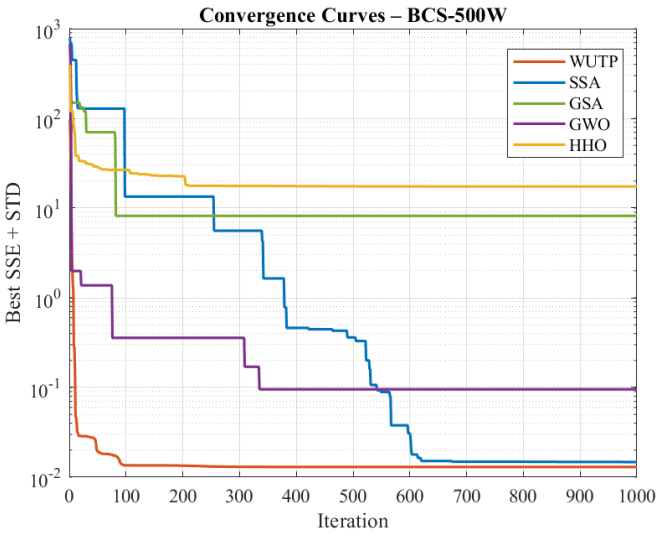

Fig. 5. Convergence curves for BCS-500 W

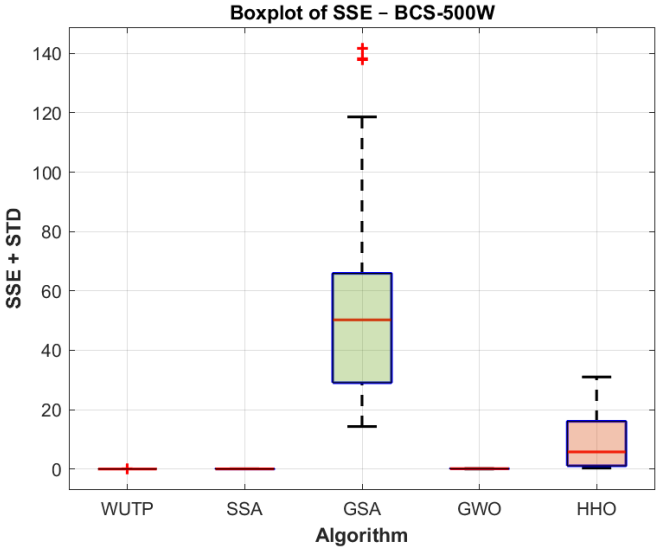

Fig. 6. BoxPlot BCS500W

polarization characteristics presented in Fig. 8, the estimated voltage values closely follow the experimental measurements over the entire operating range. This strong agreement confirms the capability of WUTP to accurately represent the complex nonlinear behavior of the fuel cell system. Such accuracy is essential for advanced modeling, monitoring, and control applications, where precise parameter estimation plays a key role in improving system efficiency and operational reliability. The convergence behavior shown in Fig. 9 further validates the optimization capability of the proposed method. WUTP rapidly approaches the optimum solution within approximately the first 100 iterations, demonstrating a fast convergence rate and efficient search mechanism. This characteristic reduces computational effort while ensuring accurate parameter identification. In comparison, the SSA, GSA, HHO, and GWO algorithms require more iterations to reach convergence and generally exhibit larger objective-function values. These observations indicate that the search strategy employed by WUTP is particularly effective for solving the nonlinear and high-dimensional optimization problems associated with PEMFC parameter estimation. The robustness of the proposed algorithm is also confirmed through the statistical results presented in Fig. 10. The narrow distribution observed in the boxplot reflects the high consistency of WUTP over multiple independent runs, indicating low sensitivity to random initialization. Consequently, the algorithm produces reliable parameter estimates with limited variability, which is highly desirable for practical applications. Conversely, larger dispersions can be observed for GWO and HHO, suggesting less stable performance. Overall, the obtained results demonstrate that WUTP provides an effective combination of accuracy, convergence speed, and robustness, making it a promising optimization framework for PEMFC modeling, parameter identification, and intelligent energy management applications. The comparative results demonstrate the strong performance of the WUTP algorithm in identifying the optimal parameters of both BCS-500W and NedStack PS6 PEMFC stacks. As reported in Tables IV and V, WUTP consistently achieves the smallest SSE values together with the lowest standard deviation, indicating a high level of accuracy and robustness compared with the other investigated optimization techniques. For the BCS-500W stack, algorithms such as GWO and GSA exhibit larger estimation errors and greater variability between runs, whereas WUTP maintains superior consistency and precision. For the NedStack PS6 stack, although HHO attains a level of accuracy close to that of WUTP, the proposed algorithm demonstrates a faster convergence behavior and improved stability throughout the optimization process. This combination of rapid convergence, reduced estimation error, and low performance variability confirms the effectiveness of

TABLE IV
PARAMETER ESTIMATES (AMPHLETT MODEL) AND SSE FOR THE TWO PEMFC STACKS.

Algorithme	ε_1	ε_2 $(\times 10^{-3})$	ε_3 $(\times 10^{-5})$	ε_4 $(\times 10^{-4})$	Λ	b	RC $(\times 10^{-3})$	**SSE**
BCS-500W								
WUTP	-9.8509	3.3989	8.9033	-1.9302	2.0877	1.6126	1.0000	**0.013009**
SSA	-1.1550	3.0715	3.5089	-1.9105	2.0058	1.5304	1.6936	1.4767
GSA	-1.1653	3.7700	8.8437	-9.1290	1.8424	2.8946	1.0000	8.1852
GWO	-8.7054	2.4767	5.1149	-1.9937	1.9690	1.2903	1.1739	9.5517
HHO	-8.0022	1.4110	1.0002	-1.0790	6.4478	1.0002	1.0730	1.7372
NedStack PS6								
WUTP	-8.9754	3.1834	8.2855	-9.5400	1.2574	1.3600	1.0000	**2.065557**
SSA	-1.0373	3.3739	6.6355	-9.5400	2.0027	3.7072	1.9910	4.0916
GSA	-1.0621	3.8714	9.8000	-9.5400	1.7043	1.8978	2.2564	4.6596
GWO	-9.7768	3.0525	5.6663	-9.5400	1.6022	2.8803	1.0000	3.3506
HHO	-8.5320	2.7642	6.1031	-9.5400	1.6102	1.9580	2.1490	3.4475

TABLE V
SSE STATISTICS (MIN, STD, MAX) FOR THE TWO PEMFC STACKS

Algorithme	**Min (SSE)**	**Std (SSE)**	**Max (SSE)**
BCS-500W			
WUTP	**1.3009e-02**	**1.8780e-13**	**1.3009e-02**
SSA	1.3209e-02	2.8293e-02	9.9346e-02
GSA	1.4337e+01	3.8358e+01	1.4175e+02
GWO	2.3353e-02	4.0318e-02	1.8127e-01
HHO	3.5233e-01	7.8266e+00	3.1002e+01
NedStack PS6			
WUTP	**2.0656**	**2.6234e-15**	**2.0656**
SSA	2.1652	5.7019e-01	4.07395
GSA	2.9663	6.9093e-01	6.15494
GWO	2.1184	6.7721e-01	4.60744
HHO	2.1561	1.1226	6.53608

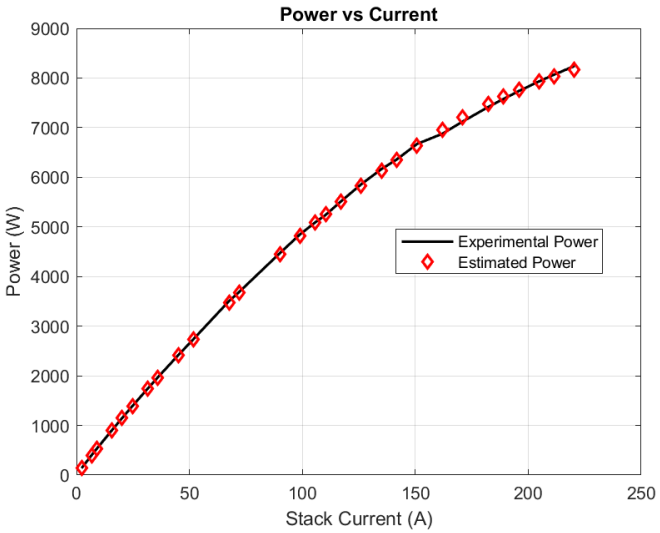

Fig. 7. Power curve-WUTP NedStackPs6

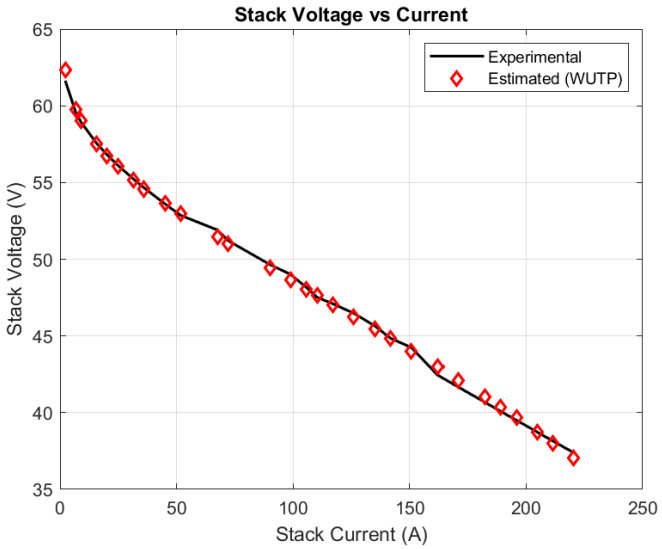

Fig. 8. Convergence curves for NedStackPs6

WUTP in handling the nonlinear parameter estimation problem of PEMFC systems. Overall, these findings highlight the capability of WUTP to provide reliable and accurate parameter identification, thereby improving model fidelity and supporting more efficient simulation, analysis, and control of fuel cell-based energy systems.

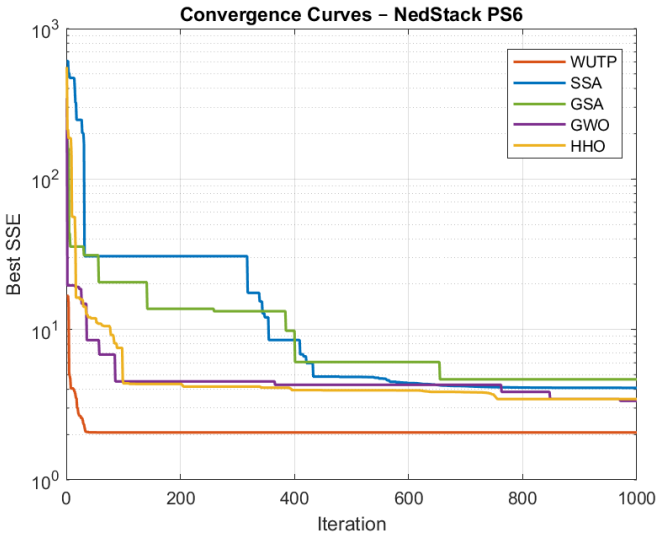

Fig. 9. Convergence curves for NedStackPs6

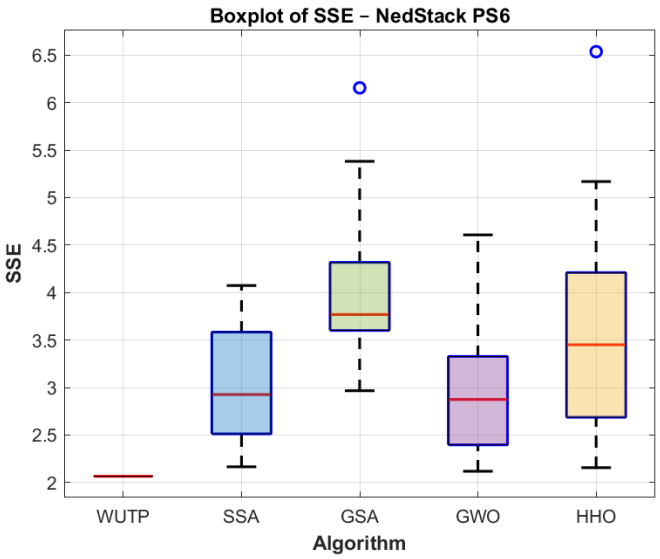

Fig. 10. BoxPlot NedStackPs6

V. CONCLUSION

This work demonstrates that the proposed WUTP algorithm can significantly improve PEMFC parameter identification accuracy, leading to more reliable fuel cell performance prediction and control. Such improvements can support advanced applications including fault diagnosis, predictive maintenance, and energy management in hydrogen-based energy systems. Future work will focus on integrating the optimized PEMFC models into real-time energy management frameworks and exploring hybrid optimization strategies to further enhance convergence speed and solution quality. Although the present study is based on the Amphlett semi-empirical model, future investigations will evaluate the performance of WUTP on more complex electrochemical and CFD-based fuel cell models.

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