



# Article Adaptive Estimation of Quasi-Empirical Proton Exchange Membrane Fuel Cell Models Based on Coot Bird Optimizer and Data Accumulation

Mohamed Ahmed Ali<sup>1,\*</sup>, Mohey Eldin Mandour<sup>2</sup> and Mohammed Elsayed Lotfy<sup>2,3</sup>

- <sup>1</sup> Egyptian National Railways (ENR), Cairo 11794, Egypt
- <sup>2</sup> Electrical Power and Machines Department, Faculty of Engineering, Zagazig University,
- Zagazig 44519, Egypt; mohey\_mandour@yahoo.com (M.E.M.); mohamedabozed@zu.edu.eg (M.E.L.)
- <sup>3</sup> Electrical and Electronics Engineering Department, University of the Ryukyus, Nishihara 903-0213, Japan
- \* Correspondence: ma.ali21@eng.zu.edu.eg

**Abstract:** The ambitious spread of fuel cell usage is facing the aging problem, which has a significant impact on the cells' output power. Therefore, it is necessary to develop reliable techniques that are capable of accurately characterizing the cell throughout its life. This paper proposes an adaptive parameter estimation technique to develop a robust proton exchange membrane fuel cell (PEMFC) model over its lifespan. This is useful for accurate monitoring, analysis, design, and control of the PEMFC and increasing its life. For this purpose, fair comparisons of nine recent optimization algorithms were made by implementing them for a typical quasi-empirical PEMFC model estimation problem. Investigating the best competitors relied on two conceptual factors, the solution accuracy and computational burden (as a novel assessment factor in this study). The computational burden plays a great role in accelerating the model parameters' update process. The proposed techniques were applied to five commercial PEMFCs. Moreover, a necessary statistical analysis of the results was performed to make a solid comparison with the competitors. Among them, the proposed cootbird-algorithm (CBO)-based technique achieved a superior and balanced performance. It surpassed the closest competitors by a difference of 16.01% and 62.53% in the accuracy and computational speed, respectively.

**Keywords:** adaptive fuel cell model; model parameters' optimization; coot bird algorithm; computational burden; numerical statistical assessment

# 1. Introduction

Currently, the turbulent prices of fossil fuel due to current conflicts have had greatly adverse effects on the supply of energy and on dependent economies. That is why decisionmakers and researchers are paying great attention to the rapid shift to renewable and sustainable energy sources. Among those transitional strategies, hydrogen fuel cells represent promising energy conversion devices, which could provide an innovative solution for sustainable energy systems. Specifically, polymer electrolyte membrane fuel cell (PEMFC) technology is considered as a potential contender in this pathway as it excels with various advantages, such as fast starting up due to the low operating temperature (70–85  $^{\circ}$ C), high efficiency (50–70%), high current intensity, zero emissions (just water vapor), reliability, longer lifetime (due to using a solid polymer electrolyte), high energy density (39.7 kWh/kg), and compact modular design [1-3]. These merits have led the PEMFC to be a widely spreading integral part of modern energy applications such as stationary renewable power systems, transportation, spacecraft, and military applications [4,5]. Like any unmature technological system, it has some drawbacks. The main one is the lifetime with respect to the PEMFC's initial cost due to the fuel cell degradation process, which slows the widespread adoption of this technology [6,7]. The PEMFC degradation process



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**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). includes the cell membrane aging, catalyst dissolution, and wear of the electrodes occurring along the operating lifetime of the cell, scaling down its performance and changing its characteristics. Fuel cell aging is accelerated by means of aggressive operating conditions, which should be avoided, such as power peaks, start/stop operation, and cold start up [8]. There is a bright side though, as the research race heats up to develop long-life-cycle materials to enhance the potential of emerging fuel cell technologies. Recent improvements in the PEMFC's lifetime and energy density could lead to a major breakthrough for this technology in the power system suite [9–11]. Mathematical modeling of the PEMFC is of interest to determine the best performance conditions depending on the mass of the reactants and heat transfer [12–15].

The challenge here is to develop an efficient adaptive PEMFC model that is capable of precisely predicting its characteristics. This can help the cell controller make convenient decisions and effectively adjust the PEMFC operating point. Whatever the operating conditions, the adaptive estimated model can help achieve the desired performance. Indeed, the modeling criteria of the PEMFC have seen extensive efforts from researchers to express the dynamic characteristics of the cell. Three models have been nominated, categorized as: (i) the physical model depending on the cell material characteristics (1D, 2D, and 3D), targeted at studying the distribution of the gas pressure and temperature in the membrane, so it is useful for the design and testing stages; (ii) the empirical model derived from collected data from extensive experiments based on artificial intelligence regardless of the physical background of the cell, for which collecting the experimental data is difficult and requiring difficult computational processes; (iii) the quasi-empirical model, which is developed based on experimental data based on the physical mechanistic background; consequently, it accumulates the advantages of the two aforementioned models [16]. The quasi-empirical model voltage–current (V–I) polarization curves depend on many operating variables such as the hydrogen gas pressure, air flow rate, and cell temperature. This is why it has been utilized in many studies such as the simulation, modeling, performance analysis, and design of fuel cell systems, so it was taken into consideration in this study [17–20].

As is well known, the PEMFC model is a time-varying nonlinear multi-variable system. This represents a sophisticated problem for estimating the optimal values of its unknown parameters. However, the deterministic techniques struggle in dealing with this type of problem, and the nature-inspired meta-heuristic algorithms have shown a significant performance in solving this type of problem. This is due to the multiple advantages of meta-heuristic algorithms such as the flexibility of implementation, unconditional problem formulation, and being derivative free. Thus, many studies have concerned the PEMFCs' parameter estimation and efficient model development based on nature-inspired metaheuristic algorithms and artificial intelligence [21,22]. In this context, the PEMFC model parameters' estimation was attempted in [23] using a hybrid genetic algorithm (HGA). After that, many modifications of the genetic algorithm have been applied to the fuel cell modeling problem such as the real coded GA (Real GA) and adaptive RNA genetic algorithm (ARNA-GA), as addressed, respectively, in [24,25]. However, genetic algorithms suffer from inherently premature convergence. Consequently, particle swarm optimization (PSO) was adopted in [26]. These techniques achieve recognized results that have paved the way for attempting other efficient algorithms such as differential evolution (DE) and its modifications, which have been adapted to the PEMFC problem in the pursuit of improving the model parameter estimation accuracy [27]. Furthermore, the vortex search algorithm (VSA) and differential evolution hybridization (VSDE) have been implemented to improve the accuracy of the PEMFC model. The results of the proposed hybrid approach outperformed the original VSA optimizer and grass hooper optimizer (GOA) [28]. Furthermore, the implementation for the same problem using a novel P-system-based method (BIPOA) [29], the harmony search algorithm (HSA) [30], and teaching-learning-based optimization was described in [31]. In the same context, a hybrid stochastic strategy based on the selectivity feature was applied for the PEMFC's parameter identification in [32]. The experimental data of different commercial types of PEMFCs were adapted to the grey wolf

optimizer (GWO) in order to develop more accurate models, as investigated in [21]. In [17], an attempt was made to enhance the PEMFC models for commercial devices using the flower pollination optimizer (FPO). The author of [33] utilized the salp swarm optimization (SSO) technique to deal with the PEMFCs' modeling problem, achieving good matching between the developed model curve and the measured data. Another methodology called the shark smell optimizer has been adopted to accurately extract the PEMFC's model parameters [34]. The accuracy of the PEMFC's parameter estimation was demonstrated by using the Levenberg–Marquardt backpropagation algorithm, where an artificial neural network (ANN) was used to tackle the insufficient experimental data problem [35]. Metaheuristic algorithms have been adopted for the PEMFC parameter identification problem with noisy experimental data. A Bayesian regularization neural network was utilized as a noisy data filter to enhance the optimization process [36]. In [37], the authors attempted a machine learning method based on an artificial neural network to develop a PEMFC model for different operating conditions that could reduce the need for more experimental data. It is worth noting that there are some difficulties in the implementation of the ANN due to its complexity and increased computational burden. Recently, an improved fluid search algorithm (IFSO) was adopted to estimate the parameters of five PEMFC models based on the summation of squared errors (SSE) objective [38], in addition to utilizing the marine predator optimizer technique for the same problem, and good results were reported [39]. The authors of [40] utilized the improved evaporation rate water cycle algorithm to optimize the static models of two commercial fuel cells, namely the BCS 500 W and Ballard Mark-V 5 kW. Five different algorithms were employed to identify seven unknown parameters of the mathematical model of the SR-12 PEM 500 PEMFC [41].

From this survey, it is clear that most of the reported studies in the domain of PEMFC modeling mainly concern the accuracy of the models' estimated parameters. Fewer studies concern developing adaptive PEMFC models, which depend on extensive computation. No attention is paid to the computational time elapsed in this process. Since computational speed represents a crucial factor in adaptive modeling applications, it is strongly recommended to take it into consideration. It is important for real-time applications to develop an adaptive model that can enhance the PEMFC's performance with less computational effort. According to the concept of the no free lunch theory [42], there is no solution technique suited to all optimization problems under different circumstances. These reasons were the motivation to conduct this study to propose a novel adaptive PEMFC modeling solution. This can reflect the cell's dynamic changes in the polarization curve and performance aberrations caused by aging throughout its lifespan. The proposed technique comprises the accuracy, speed of computation, and simplicity of implementation, which makes it more suitable for on-line applications. In this regard, this technique was validated by implementing it using the experimental data of six PEMFC stacks. The developed models' characteristics are presented with the corresponding statistical analysis and comparisons to other approaches for the evaluation.

The main contributions of this work can be summarized as follows:

- A novel adaptive CBO-based technique was developed for PEMFC modeling.
- The results of the CBO-based technique were compared to those of other state-of-theart competitors, and the required statistical analysis was performed.
- The proposed technique was applied to model a variety of PEMFC devices under different operating conditions, namely the Ballard-Mark-V 5 kW, Nedstack-PS6 6 kW, 250 W PEMFC, Temasek 1 kW, SR-12-PEM 500 W, and BCS 500 W.
- The PEMFCs' model parameters were accurately optimized for six PEMFC devices with minimum computational burden.
- The proposed adaptive modeling technique is capable of reflecting uncertainties in PEMFC performance due to degradation and changes in operating conditions.

# 2. Description of PEMFC Model

# 2.1. PEMFC Notion

The PEMFC is a static electro-chemical device that is capable of developing electrical energy efficiently through internal membrane reactions. The main parts of the cell are two catalyst-coated electrodes (one is called the anode, and the other is the cathode) separated by a solid polymer electrolyte. The construction of the cell membrane is depicted in Figure 1. The hydrogen fuel is supplied through the anode channels, reaching the catalytic layer to initiate the reaction. Then, the hydrogen protons migrate across the membrane to meet the oxygen atoms fed through the cathode channels.



#### Figure 1. PEMFC layout.

The entire chemical reaction takes place in the PEMFC membrane, which can be expressed by:

$$H_2 + \frac{1}{2}O_2 \to H_2O + Energy \tag{1}$$

From Equation (1), the term energy refers to the output electricity produced by the cell by electrons extracted from the hydrogen atoms at the anode side crossing the external electric circuit (supplying a load) to finally reach the cathode side to equalize the chemical reaction, as in Figure 1 [2,4].

## 2.2. PEMFC Quasi-Empirical Model

The most-commonly recognized formulation in PEMFC modeling studies was developed by Amphlett et al. [3]. This model formulation was utilized in this study by taking into account the enhancements, which followed [1,18,28], in which the output voltage at the terminals of the PEMFC ( $V_{FC}$ ) is expressed by the following equation:

$$V_{FC} = N_{Cells} \times E_{Nernst} - V_{Act} - V_{Ohmic} - V_{Conc}$$
(2)

where  $N_{Cells}$  is the number of PEMFC stack cells,  $E_{Nernst}$  represents the PEMFC's theoretical voltage, also called the reversible voltage, given by Equation (3), while the terms  $V_{Act}$  (the cell activation loss due to reaction initiation at the anode and cathode electrodes),  $V_{Ohmic}$  (the cell ohmic loss due to the resistance of the polymer electrolyte membrane met by the migrating protons), and  $V_{Conc}$  (the mass transfer loss, also called the concentration loss, which takes place due to the overcrowding of hydrogen and oxygen migrating in the membrane), respectively, express the entire potential losses internally occurring through the cell membrane [21,27].

The complete model equations and details of the above terms are illustrated in Supplementary Materials.

The mathematical equations of the quasi-empirical PEMFC model contain seven unknown parameters, which are ( $\xi_1$ ,  $\xi_2$ ,  $\xi_3$ ,  $\xi_4$ ,  $\Psi$ ,  $R_c$ , and B). They need to be optimally

estimated to complete the modeling process and to obtain the accurate characteristic curve of a certain PEMFC device.

## 3. CBO Algorithm

The recently proposed CBO is a meta-heuristic optimization algorithm. It is inspired by the natural swarming behavior of an amazing kind of water bird called the coot [43,44]. The coot birds arrange themselves repetitively while surfing the water in an astonishing configuration to overcome strong waves, and this is performed by forwarding the stronger leaders to the flock head. This process is repeated by replacing weak leaders with stronger candidates. This swarming behavior saves the energy of the flock members and accelerates the flock to reach its goal. A brief description of the nature-inspired CBO algorithm is demonstrated below.

#### 3.1. CBO Inspiration

The arrangement of the coot flock while swarming is very inspiring, in which they change between two strategies for the purpose of foraging. The first strategy of movement is irregular with no uniform distribution and a low-density coot flock. The second one is regularized, taking a more uniform distribution with a high-density coot flock. They can move in two directions on the water surface in addition to flying as a third direction to accelerate their surfing on the water in search of food [45]. These strategies have been translated as exploration and exploitation mechanisms, forming the core of the CBO algorithm [46].

# 3.2. CBO Code

According to the original algorithm in [43], the coot flock consists of leader and subordinate coots, each being a percentage of the total flock population ( $N_{Pop}$ ), and this can be expressed mathematically by  $N_{Pop} = N_{leader} + N_{coot}$ . The movement of coots and the promotion of qualified subordinate coots to replace less well-performing leaders are expressed by the symbols  $Pos_{coot}$  and  $Pos_{leader}$ , respectively. The positions of coots are initially randomized to start the algorithm by the following equations:

$$Pos_{\text{coot}} = rand_{\text{coot}} \cdot (U_{\text{b}} - L_{\text{b}}) + L_{\text{b}}$$
(3)

$$Pos_{leader} = rand_{leader} \cdot (U_b - L_b) + L_b \tag{4}$$

where the symbols  $U_b$  and  $L_b$  refer to the problem's upper and lower boundaries, respectively. Accordingly, the fitness of each subordinate coot can be extracted from Equation (5), and the optimal score and optimal position can be computed as follows:

$$Fit_{\text{coot}}(1 \cdot i) = F_{\text{obi}}(Pos_{\text{coot}}(i))$$
(5)

Since  $F_{obj}$  represents the fitness objective function and *i* takes values from 1 to N<sub>coot</sub>:

If 
$$Optim_{score} > Fit_{coot}(1, i)$$
  
 $Optim_{score} = Fit_{coot}(1, i)$   
 $Optim_{pos} = Pos_{coot}(i)$ 
(6)

Similarly, the fitness of each leader can be extracted from Equation (7), and the optimal score and optimal position can be computed as follows:

$$Fit_{\text{leader}}(1 \cdot i) = F_{\text{obj}}(Pos_{\text{leader}}(i)), \ i \text{ belongs to } N_{leader}$$
 (7)

If 
$$Optim_{score} > Fit_{leader}(1, i)$$
  
 $Optim_{score} = Fit_{leader}(1, i)$   
 $Optim_{pos} = Pos_{leader}(i)$ 
(8)

Since  $N_{\text{leader}}$  is the number of coot flock leaders, which represent a part of the total flock  $N_{\text{Pop}}$ , the rest of  $N_{\text{Pop}}$  is given by the number of subordinate coots  $N_{\text{Coot}}$ .

The algorithm identifies a subordinate coot for each leader coot randomly, then their positions are upgraded at each iteration till reaching the maximum limit of iterations ( $It_{max}$ ) using Equations (9) and (10). From Equation (10), the new subordinate coot position is ensured to be within the limits.

$$Pos_{\text{coot}}(i) = 2 \cdot rand_{\text{coot}} \cdot \cos(2 \cdot \pi \cdot r)$$
  
since,  $r = 1 + 2 \cdot rand_{\text{coot}}$  (9)

$$[Pos_{leader}(k) - Pos_{coot}(i)] + Pos_{leader}(k), i \in N_{Coot} \text{ and } k \in N_{leader}$$
(10)

If 
$$Pos_{coot}(i) > U_{b}$$
, make  $Pos_{coot}(i) = U_{b}$   
If  $Pos_{coot}(i) < L_{b}$ , make  $Pos_{coot}(i) = L_{b}$  (11)

where  $rand_{coot}$  and  $rand_{leader}$  are random operators to give the positions of the subordinate and leader coots, respectively. The fitness of each type is computed through Equation (12) in a way that enables comparing and replacing a more weakly performing coot by a stronger subordinate coot and vice versa.

If 
$$\operatorname{Fit}_{\operatorname{coot}}(1 \cdot i) < \operatorname{Fit}_{\operatorname{leader}}(1, k)$$
,  
make  $\operatorname{Fit}_{\operatorname{leader}}(1 \cdot k) = \operatorname{Fit}_{\operatorname{coot}}(1, i)$ , (12)  
and  $\operatorname{Pos}_{\operatorname{leader}}(k) = \operatorname{Pos}_{\operatorname{coot}}(i)$ 

The positions of the leader coot are randomly enhanced using Equations (13) and (14). Subsequently, the optimal score ( $Optim_{score}$ ) and the corresponding positions ( $Optim_{pos}$ ) are computed through Equation (15).

$$b = 2 - (It(L)/It_{max})$$

$$r = 1 + 2 \cdot rand_{leader}$$
(13)

where (It(L)) refers to the current iteration index and  $(It_{max})$  refers to the max number of iterations at which the optimization process terminates.

$$Pos_{leader} = b \cdot rand_{leader} \cdot \cos(2 \cdot \pi \cdot r) \left[Optim_{pos} - Pos_{leader}(k)\right] + Optim_{pos}$$
(14)

If 
$$Optim_{score} > Fit_{leader}(1 \cdot i)$$
,  
make  $Fit_{leader}(1 \cdot k) = Optim_{score}$  (15)  
make  $Pos_{leader}(i) = Optim_{pos}$ 

In Figure 2, the flowchart simply depicts the CBO's mechanism of operation, where the algorithm is initiated by two adjustable parameters (the number of coots in the population and the max iterations required). Then, random positions for leader and subordinate coots are generated. An evaluation process is started depending on the fitness of each coot to enable upgrading the coots' positions based on their performance. This evaluation and repositioning process is repeated till reaching the max number of iterations, obtaining the optimal solution. It is worth mentioning that the CBO algorithm has only two parameters to be tuned: the population size, also called the search agents ( $N_{Pop}$ ), and the max number

of iterations ( $It_{max}$ ). This shows the merits of the CBO algorithm, whereby there is no need for huge efforts in algorithm tuning.



Figure 2. The CBO algorithm flowchart.

## 3.3. Objective Function Formulation

This section represents the main goal of developing a more accurate adaptive model of the PEMFC in order to mimic its real performance in practical applications. In this context, the CBO was implemented to minimize an objective function (*Obj*) formulated as a summation of the squared errors equation, where these errors represent the difference between the actual measured PEMFC data and those extracted from the corresponding developed model. The main output of this process is the optimal values of the aforementioned unknown parameters ( $\xi_1$ ,  $\xi_2$ ,  $\xi_3$ ,  $\xi_4$ ,  $\Psi$ ,  $R_c$ , and B) described in Supplementary Materials.

The objective function (*Obj*) is expressed as follows:

$$Minimize\left(Obj = \sum_{j=1}^{J} \left(V_{actual \cdot j} - V_{mdl \cdot j}\right)^{2}\right)$$
(16)

where  $V_{actual}$  is the actual measured terminal voltage of a real PEMFC,  $V_{mdl}$  is the modelestimated voltage, and *j* represents the number of collected data. The summation of squared errors evaluates the quality of the developed model by comparing the V–I characteristics of the real PEMFC and those for the mathematically estimated model. This evaluation process depends on the estimated parameters of the developed model, so they are constrained by inequality boundaries to prohibit the algorithm from searching in false regions as described in Equation (17). The most-common ranges for these parameters were extracted from [21,35] to be utilized here, as shown in Table 1.

$$\begin{aligned} \xi_{1} \min &\leq \xi_{1} \leq \xi_{1} \max \\ \xi_{2} \min &\leq \xi_{2} \leq \xi_{2} \max \\ \xi_{3} \min &\leq \xi_{3} \leq \xi_{3} \max \\ \xi_{4} \min &\leq \xi_{4} \leq \xi_{4} \max \\ \Psi_{min} \leq \Psi \leq \Psi_{max} \\ R_{c} \min &\leq R_{c} \leq R_{c} \max \\ B_{min} \leq B \leq B_{max} \end{aligned}$$
(17)

Table 1. Unknown parameters' boundaries.

Model Parameter	ξ1	ξ2	ξ3	ξ4	Ψ	$R_c$	В
Lower boundary Upper boundary	-1.1997 -0.8532	0.001 0.005	$3.6 imes 10^{-5}\ 9.8 imes 10^{-5}$	$\begin{array}{c} -2.6\times 10^{-4} \\ -9.54\times 10^{-5} \end{array}$	10 24	0.0001 0.0008	0.0136 0.5

Upgrading the PEMFC model, precisely along the lifetime of operation, is considered as an additional challenge. The upgraded model can predict the effect of the aged membrane on the cell polarization curve with the corresponding changes in the cell terminal voltage (V) and drawn current (I). This is necessary for fuel cell management and control systems to guarantee a more efficient performance [8]. What is new in this paper is that we propose a strategy that can effectively upgrade the PEMFC model, which depends on monitoring the cell output (V–I) over of a full cycle of operation, then the accumulated dataset was compared to previously recorded data to detect any changes in the cell characteristics. Based on this comparison, the strategy makes a decision to renew itself or keep the old model. This strategy excels with the simplicity of implementation depending on the meta-heuristic CBO algorithm in optimizing the model described in Section 2.2. There is no need for complex calculations, and therefore, it can minimize the computational burden and decrease the cost of the PEMFC management and control system. A flowchart describing the entire strategy is depicted in Figure 3.



Figure 3. The PEMFC adaptive model flowchart.

# 4. Cases Studies

An accurate adaptive model of the PEMFC stack can guarantee the appropriate simulation and analysis of the fuel cell stack's performance. Therefore, it is greatly needed for real-time applications. In this regard, this work included the implementation of nine reputable meta-heuristic algorithms for the PEMFC mathematical modeling problem. Firstly, for the purposes of bench marking, the algorithms were adopted to optimize a well-known model in the research community of a 250 W PEMFC with the specifications in Table 2 [23]. The selected algorithms for evaluation in this study have demonstrated good performance in dealing with similar engineering problems. They are named as multi-trial vector-based differential evolution (MTDE) [47], the ant–lion optimizer (ALO) [48], the dragonfly algorithm (DA) [49], atom search optimization (ASO) [50], the grasshopper optimization algorithm (GOA) [51], the improved grey wolf optimizer [52], the marine predator algorithm [53], and the coot bird optimization algorithm (CBO) [43].

Stack Parameters		Operation Ranges	
Number of cells in series $N_{Cells}$	24	Inlet anode pressure $p_a$ (bar)	1–3
Cell's active area $A$ (cm <sup>2</sup> )	27	Inlet cathode pressure $p_c$ (bar)	1–5
Nafion 115:5 mil <i>l</i> (μm)	127	Stack temperature T (K)	353.15-343.15
Maximum current density $i_L$ (mA/cm <sup>2</sup> )	860	Relative humidity in anode $RH_a$	1
Rated power (W)	250	Relative humidity in cathode $RH_c$	1

Table 2. The first case bench mark, the 250 W PEMFC's specifications [27,28].

The algorithms' bench marking process utilizes the described mathematical semiempirical model in Section 2.2 with the boundaries for the seven unknown parameters in Table 1. The adopted PEMFC model has four measured dataset (V–I) characteristics at different operating conditions (inlet pressures and cell temperature) as follows: 3/5 bar, 353.15 K, 1/1 bar, 343.15 K, 2.5/3 bar, 343.15 K, and 1.5/1.5 bar, 343.15 K. This process is considered the first stage of study, which qualifies the algorithm with the best results to go to the second stage of verification.

In the second stage of the study, the qualified approach from the first stage undergoes further verification to deal with five commercial PEMFC models. The five PEMFCs utilized in this stage were the Ballard-Mark-V 5 kW [21,35], Nedstack-PS6 6 kW [18], Temasek 1 kW [39], SR-12-PEM 500 W, and BCS 500 W [28]. Their corresponding specifications, data, and experimental characteristics were extracted from the literature as described in Table 3 and a later section, respectively.

Table 3. Commercial PEMFCs' specifications (Stage 2: verifications).

Stack Type	Ballard-Mark-V 5 kW [21,35]	Nedstack-PS6 6 kW [18,33]	Temasek 1 kW [21,39]	SR-12 PEM 500 W [20,28]	BCS 500 W [28,33]
Number of cells N <sub>Cells</sub>	35	65	20	48	32
Cell's active area $A$ (cm <sup>2</sup> )	232	240	150	62.5	64
Nafion 115:5 mil <i>l</i> (μm)	178	178	51	25	178
Max current density $i_L$ (mA/cm <sup>2</sup> )	1500	1200	1500	672	469
Stack temperature $T(K)$	343	343	323	323	333
Hydrogen pressure $p_{H_2}$ (atm)	1	0.5–5	0.5	1.47628	1
Oxygen pressure $p_{O_2}$ (atm)	1	0.5–5	0.5	0.2095	0.2095

## 5. Methodology and Result Discussions

The bench marking process of the aforementioned algorithms was implemented with the MATLAB software Version R2020a (9.8.0.1323502) 64-bit [54], running on an Intel<sup>®</sup> core<sup>TM</sup> i5-5200U CPU, 2.7 GHz, 6 GB RAM laptop. In the first stage, the eight aforementioned algorithms were subjected to a qualifier bench marking for developing an optimal PEMFC model for the 250 W fuel cell. To ensure a fair comparison with those in the literature, the qualifier bench marking stage was designated as 100 separate runs for each algorithm with the same population size (particles, agents, or individuals) equal to 20 and 500 iterations as a maximum limit in a single run.

The bench marking results of the adopted algorithms are given in Table 4, compared to the same problem solution reported in the literature under the same conditions. The compared literature results included those of the VSDE [28], teaching–learning-based optimization-differential evolution (TLBO-DE) [19], quantum-behaved particle swarm optimizer (QPSO) [21], simulated annealing-differential evolution (Sa-DE) [31], innovative harmony search (IHS) [31], simplified TLBO (STLBO) [31], and modified particle swarm optimizer (MPSO) [21]. From a close look at this table, it is clear that the best obtained results were for the CBO, IGWO, and GOA, respectively, based on the fitness scale, where the best fitness was configured as the minimal value of the summation of squared errors between the estimated polarization curve and the actual experimental data. This is a key factor to ensure the high accuracy of the developed model and suggested the CBO, IGWO, and GOA as the strongest candidates in this case. Despite this, the best fitness values of the

implemented algorithms were close, and there was diversity from the point of view of the time consumed in the optimization process.

Algorithm	Fitness	AV_Time <sup>b</sup>	$\xi_1$	$\xi_2$	ξ3	$\xi_4$	Ψ	R <sub>c</sub>	В
CBO [43]	0.84042	0.38	-0.8593	0.0032844	$9.80  imes 10^{-5}$	$-9.54 imes10^{-5}$	24	0.0001	0.0136
IGWO [52]	1.0006	0.95	-0.85321	0.0032678	$9.799  imes 10^{-5}$	$-9.541 \times 10^{-5}$	24	0.0001	0.013602
GOA [51]	1.0897	5.32	-1.14622	0.00379843	$8.06  imes 10^{-5}$	$-9.54 imes10^{-5}$	24	0.0001	0.0136
MPA [53]	1.1415	0.8	-0.93466	0.0034948	$9.80  imes 10^{-5}$	$-9.54 imes10^{-5}$	24	0.0001	0.0136
MTDE [47]	1.1531	3.8	-1.061	0.0038525	$9.80 imes10^{-5}$	$-9.54 imes10^{-5}$	24	0.0001	0.0136
DA [49]	1.1655	33.24	-0.8532	0.00326576	$9.80 imes10^{-5}$	$-9.54 imes10^{-5}$	24	0.0001	0.0136
ALO [48]	1.1659	2.75	-0.87109	0.00303416	$8.16 imes10^{-5}$	$-9.54 imes10^{-5}$	24	0.0001	0.0136
ASO [50]	1.3483	0.72	-1.00738	0.00318212	$6.75 imes10^{-5}$	$-9.54 imes10^{-5}$	23.72	0.0005574	0.014613
VSDE [28]	1.0526	NR <sup>a</sup>	-1.1921	$3.199 \times 10^{-3}$	$3.79  imes 10^{-5}$	$1.870 imes10^{-4}$	22.81	$1.202  imes 10^{-4}$	0.02903
TLBO-DE [19]	7.2776	NR <sup>a</sup>	-0.8532	$2.6505 \times 10^{-3}$	$8.0016 \times 10^{-5}$	$-1.360  imes 10^{-4}$	15.65	$1.0000 imes10^{-4}$	0.0364
QPSO [21]	7.2776	NR <sup>a</sup>	-0.8569	$2.5665  imes 10^{-3}$	$7.2708  imes 10^{-5}$	$-1.303  imes 10^{-4}$	13.54	$3.9173  imes 10^{-4}$	0.0299
ITHS [31]	7.5798	NR <sup>a</sup>	-0.9228	$2.7348 \times 10^{-3}$	$7.0967 \times 10^{-5}$	$-1.426 imes10^{-4}$	16.52	$1.0091 imes10^{-4}$	0.0362
Sa-DE [31]	7.6276	NR <sup>a</sup>	-0.8534	$2.5846 \times 10^{-3}$	$7.5880 \times 10^{-5}$	$-1.154 imes10^{-4}$	12.6	$1.0000 imes10^{-4}$	0.0329
STLBO [31]	7.6426	NR <sup>a</sup>	-0.8532	2.5843	$7.6892  imes 10^{-5}$	$-1.154 imes10^{-4}$	12.6	$1.0000 imes10^{-4}$	0.0329
BIPOA [29]	7.9416	NR <sup>a</sup>	-0.8016	$2.6673 \times 10^{-3}$	$8.1288  imes 10^{-5}$	$-1.271  imes 10^{-4}$	13.51	0.80	0.0324
ARNA-GA [25]	8.1039	NR <sup>a</sup>	-0.8806	$2.9450 \times 10^{-3}$	$8.4438 \times 10^{-5}$	$-1.288 imes10^{-4}$	13.48	$1.0068 imes10^{-4}$	0.0316
RGA [24]	8.4854	NR <sup>a</sup>	-1.1568	$3.4243  imes 10^{-3}$	$6.4161  imes 10^{-5}$	$-1.154 imes10^{-4}$	12.89	$1.4504  imes 10^{-4}$	0.0343
MPSO [21]	9.7539	NR <sup>a</sup>	-0.9479	$3.0835 \times 10^{-3}$	$7.7990 \times 10^{-5}$	$-1.880  imes 10^{-4}$	20.76	$2.8666  imes 10^{-4}$	0.0296

 Table 4. CBO algorithm results of 250 W PEMFC in comparison with other competitors.

<sup>a</sup> NR means not reported in original reference. <sup>b</sup> Av\_time means average computational time in seconds.

In Table 5, a statistical analysis of the results was performed in the IBM SPSS environment (Version 22) [55]. It was seen that the GOA approach had some problems in its performance with respect to the standard deviation and variance with significant values of 133.37 and 17968.8, respectively. This performance made the GOA an unreliable approach to deal with this problem, and thus, it was removed from the competition. On the other hand, the CBO and IGWO gave a more optimistic impression with very close results for the standard deviation and variance. Therefore, the investigation results depicted the strengths of the best candidates (CBO and IGWO). Over 100 separate runs with frequent results, the CBO surpassed the IGWO in statistical terms (i.e., best fitness, average value, and median). In Figure 4, a boxplot graph describes the resulting fitness distribution of the nine competing algorithms from 100 independent runs. It is noticeable that the GOA's results had the worst distribution with a maximum value of 871.0382, which gave a bad impression of its performance and qualified the previous analysis. The distributions of the DA, ASO, and PSO also had some outliers that affected their reliability in tackling this problem. On the other hand, the superiority of the CBO was clear with very concentrated results at the median. Another key factor of the evaluation was the computational time. In this regard, the CBO-based approach achieved only 0.38 s compared to the 0.98 s for the IGWO approach and far away from that of the GOA approach with a value of 5.32 s.

Tab	le 5.	The	e resul	ts of	different	algorit	hms app	liec	l to t	he	bencl	h marl	k mod	lel a	and	statistica	l anal	lysis
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Algorithm	Best Fitness (min. Obj)	Stand. Deviation	Average	Median	Worst Fitness (Max. Obj)	Variance	Average Elapsed Time
ASO [50]	1.3483	2.9229	4.8585	4.1624	18.323	8.6297	0.7278
ALO [48]	1.1659	0.008722	1.176198	1.17455	1.1937	$7.684 imes10^{-5}$	2.75704
DA [49]	1.1655	1.206342	1.390042	1.1773	11.7925	2.253582	33.24938
MTDE [47]	1.1531	$1.99 imes10^{-15}$	1.1531	1.1531	1.1531	$4.03 imes10^{-30}$	4.14063
MPA [53]	1.1415	$1.11  imes 10^{-15}$	1.1415	1.1415	1.1415	$1.245  imes 10^{-30}$	0.8052
GOA [51]	1.0897	133.37	87.573	33.951	871.03	17968.8	5.3231
IGWO [52]	1.0006	0.00605587	1.010265	1.0088	1.0262	$3.704 imes10^{-5}$	0.986453905
CBO [43]	0.84042	0.005467	0.845162	0.841525	0.85763	$3.019  imes 10^{-5}$	0.387034

An additional statistical non-parametric analysis using the Wilcoxon signed rank test was performed to compare the results of the nearest competitors (CBO, IGWO, and GOA), in which the medians of the best fitness results of 100 separate runs were compared based on a significant value of 0.05. The analysis output of the related pairs' comparison (*p*-values, positive rank, and negative rank) is listed in Table 6, taking into consideration the CBO's

superior performance. It was deduced from the analysis outputs that there were statistically significant differences between the frequency results of the compared algorithms. This means the contrastive performance of each.



Figure 4. Boxplot describing the results' distribution of the state-of-the-art competing algorithms.

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Table 6. Statistical non-parametric Wilcoxon analysis for CBO and nearest competitors.

Comparison	CBO-EO	CBO-GOA	IGWO-GOA
<i>p</i> -value	0	0	0
Positive rank	0	0	0
Negative rank	100	100	100
Decision	Reject the null hypotheses	Reject the null hypotheses	Reject the null hypotheses

In regard to the nearest competitors in terms of the solution accuracy, further investigations were performed as shown in Figure 5a–c, which depict the convergence curves of the CBO, IGWO, and GOA, respectively. The convergence curves proved that the performances of the CBO and IGWO were very close in terms of the fast convergence rate towards the optimal solution with the least convergence time compared to the nearest competitor, the GOA. The corresponding histograms of the frequent results of the CBO, IGWO, and GOA are displayed in order in Figure 5d–f, where the GOA's fitness frequencies were distributed in a wide range between (1.0897 and 871.03). This resulted in bad expectations about its reliability for every run. On the other hand, the majority of the IGWO's frequencies were concentrated about the median in a narrow range between 1.0006 and 1.0262. In a better situation, almost all of the CBO frequencies were approximately confined between the values of 0.84042 and 0.85763. It was concluded from these histograms that the CBO and IGWO were more trusted in terms of the accuracy of the solution for every run. Consequently, there was a need for a crucial factor that would give the preference for one of the two algorithms to be qualified for the second stage of study.



**Figure 5.** Convergence curves for (**a**) CBO; (**b**) IGWO; (**c**) GOA and histograms of the corresponding results in (**d**), (**e**), (**f**), respectively.

A newly added factor, the average elapsed computational time, was considered as a judgement factor. This represents the core of this study to propose an effective PEMFC modeling strategy suitable for real-time implementation. According to the results, it gave the weight of the CBO-based approach with a difference of 0.59 s less than the nearest

competitor, the IGWO approach. This all revealed that the CBO outperformed the nearest competitor (the IGWO algorithm) and validated it for implementation in real-time fuel cell applications due to the accuracy, fastness, and less computational burden.

The developed model of the 250 W PEMFC under study by the CBO-based approach and relevant verification data are shown in Figure 6. The process was carried out through the data of four different operating conditions. The perfect match between the estimated V–I curves and the actual data points in the figure revealed how well the proposed technique resolved the problem.



**Figure 6.** The first stage of study, the 250 W PEMFC's developed models: (**a**) estimation data; (**b**) verification data.

The second stage of study was designed to verify the performance of the qualified approach (CBO) by dealing with five commercial PEMFCs. The CBO-based technique was adapted to the Ballard Mark-V 5 kW PEMFC's modeling, where the estimated model parameters, the fitness of the solution, and the computational time are described in the Ballard Mark-V part of Table 7. Next to them are the results of the competing methods in the literature. It was obvious that the CBO approach achieved the best fitness value of 0.00061592, surpassing the nearest competitor by a value of  $4.48 \times 10^{-6}$ . On the other hand, from the viewpoint of the computational time elapsed during the optimization process, the CBO surpassed the reported measured time of the IFSO approach [35] by a significant difference of 3.55 s. The estimated model V–I and P–I curves are depicted in Figure 7a,b, respectively. The figures reflect the perfect match between the model estimated by the CBO-based approach and the actual measured data of the Ballard Mark-V.

Similarly, the CBO-based technique was applied to model the commercial PEMFC device named Nedstack-PS6 6 kW. The results emphasized the same effectiveness as listed in the Nedstack-PS6 part of Table 7. In addition, the estimated V–I and P–I curves are depicted in Figure 8a,b, respectively. The CBO-based approach recorded a fitness value of 1.5734 with a difference from the nearest competitor of 0.51509. On the other hand, the proposed technique consumed very little computational time, 0.35 s, and no data on the elapsed time are reported for the other competitors dealing with the same device model.

Device	Approach	Fitness	Elapsed Time	ξ1	ξ2	ξ3	ξ4	Ψ	R <sub>c</sub>	В
	СВО	0.00061592	0.25	-1.1788	0.0028743	$3.64 imes10^{-5}$	$-1.195 imes10^{-4}$	12.08	0.0008	0.0136
Ballard-	FPO [17]	0.0006204	NR <sup>a</sup>	-1.0257	$3.4 imes10^{-3}$	$6.79 \times 10^{-5}$	$-1.285 imes10^{-4}$	15.644	$5.2906 \times 10^{-4}$	0.0614
Mark-V	GWO [21]	0.002067	NR <sup>a</sup>	-1.1827	$3.7080 \times 10^{-3}$	$9.36  imes 10^{-5}$	$-1.192 imes10^{-4}$	11.76	$7.8773  imes 10^{-4}$	0.0136
3 KW	IFSO [38]	0.784	3.80	-1.12	$3.57  imes 10^{-3}$	$8.01 imes10^{-5}$	$-1.59 imes10^{-4}$	22.00	$1.00 imes10^{-4}$	0.015
	CBO	1.5734	0.35938	-1.0945	$2.8818 \times 10^{-3}$	$5.66  imes 10^{-5}$	$-1.162 imes10^{-4}$	16.287	$1.0125 imes10^{-4}$	0.1148
Nedstack-	VSDE [28]	2.08849	NR <sup>a</sup>	1.1212	$3.3487  imes 10^{-3}$	$4.67  imes 10^{-5}$	$9.54 imes10^{-5}$	13.000	$1 imes 10^{-4}$	0.0494
PS6	SSO [33]	2.18067	NR <sup>a</sup>	0.9719	$3.3487  imes 10^{-3}$	$7.91 imes10^{-5}$	$9.5435  imes 10^{-5}$	13.000	$1 imes 10^{-4}$	0.0534
6 kW	GOA [28]	2.18586	NR <sup>a</sup>	1.1997	$3.5505  imes 10^{-3}$	$4.61 \times 10^{-5}$	$9.54 \times 10^{-5}$	13.009	$1.01  imes 10^{-4}$	0.0579
	VSA [28]	2.34260	NR <sup>a</sup>	0.8946	$3.3480  imes 10^{-3}$	$9.75 \times 10^{-5}$	$9.54 \times 10^{-5}$	13.000	$1.03 imes10^{-4}$	0.0429
Toursel	CBO	0.15204	0.29688	-0.9421	$2.8427  imes 10^{-3}$	$8.70 imes10^{-5}$	$-9.54 imes10^{-5}$	10	0.00059487	0.1319
1 LW	FPO [17]	0.1881	NR <sup>a</sup>	-0.4838	$1.0 imes10^{-3}$	$2.77 \times 10^{-5}$	$-7.578 \times 10^{-5}$	11.322	$1.1091  imes 10^{-4}$	0.1287
1 KVV	GWO [21]	1.6481	NR <sup>a</sup>	-1.0299	$2.4105 \times 10^{-3}$	$4.00  imes 10^{-5}$	$-9.54 imes10^{-5}$	10.000	$1.0873  imes 10^{-4}$	0.1274
	CBO	1.1171	0.29688	-0.8863	0.0027936	$8.92  imes 10^{-5}$	$-9.54 imes10^{-5}$	10	0.00067766	0.1631
SR-12PEM-	VSDE [28]	1.266	NR <sup>a</sup>	-0.8576	$3.0100 \times 10^{-3}$	$7.78  imes 10^{-5}$	$-9.54 imes10^{-5}$	23.000	$1.339 \times 10^{-4}$	0.1516
500 W	Shark smell [34]	1.517	NR <sup>a</sup>	-0.9664	$2.2833 \times 10^{-3}$	$3.4 imes10^{-5}$	$-9.54 imes10^{-5}$	15.797	$6.685  imes 10^{-4}$	0.1804
	GWO [21]	1.517	NR <sup>a</sup>	-0.9664	$2.2833  imes 10^{-3}$	3.40	$-9.54 imes10^{-5}$	15.796	$6.6853  imes 10^{-4}$	0.1804
	CBO	0.01161	0.5468	-1.0922	0.0028264	$6.97  imes 10^{-5}$	$-1.212 imes10^{-4}$	23.154	$1.4445  imes 10^{-4}$	0.0141
	VSDE [28]	0.01214	NR <sup>a</sup>	-1.1970	$4.2330 \times 10^{-3}$	$9.79  imes 10^{-5}$	$-1.9201 \times 10^{-5}$	20.194	$1.108  imes 10^{-4}$	0.0157
BCS 500 W	SSO [33]	0.01219	NR <sup>a</sup>	-0.8532	$4.8115 \times 10^{-5}$	$9.43  imes 10^{-5}$	$-1.9205  imes 10^{-4}$	23.000	$3.49 imes10^{-4}$	0.0159
	Shark smell [34]	7.18890	NR <sup>a</sup>	-1.0180	$2.3151 \times 10^{-3}$	$5.24 \times 10^{-5}$	$-1.2815  imes 10^{-4}$	18.855	$7.50  imes 10^{-4}$	0.0136
	GWO [21]	7.1889	NR <sup>a</sup>	-1.0180	$2.3151  imes 10^{-3}$	$5.24 imes10^{-5}$	$-2.6 imes10^{-4}$	18.854	$7.5036 imes10^{-4}$	0.0136

Table 7. Modeling of commercial PEMFC devices by CBO for further investigations.

<sup>a</sup> NR means not reported in the original reference.



Figure 7. The second stage of study, the Ballard-Mark-V 5 kW's model characteristics: (a) V-I; (b) P-I.

In the same manner, the Temasek 1 kW PEMFC's actual data were entered into the proposed CBO-based technique, obtaining promising results, as shown in the Temasek part of Table 7. It consumed only 0.29 s to finish the optimization process with a very good fitness of 0.15204, in addition to the perfect match between the experimental data and the developed model's V–I and P–I curves shown in Figure 9a,b, respectively.

Correspondingly, the CBO-based technique was designated to develop the models for the SR-12PEM 500 W and BCS 500 W fuel cells for further investigations. The resulting models' parameters are given in Table 7 in the SR-12PEM and BCS 500 W parts, respectively, in comparison with competing studies' results. As can be seen, the fitness of the estimated parameters of the SR-12PEM 500 W device recorded a value of 1.1171, and this revealed the quality of the solution compared to the results reported in the literature. The elapsed time through the estimation process was recorded as 0.29 s, which confirmed the speed of the proposed technique. The characteristic curves for the SR-12PEM 500 W are depicted in Figure 10, expressing a perfect match with the experimental data.



Figure 8. The second stage of study, the Nedstack 6 kW's model characteristics: (a) V-I; (b) P-I.



Figure 9. The second stage of study, the Temasek 1 kW's model characteristics: (a) V-I; (b) P-I.



Figure 10. The second stage of study, the SR-12 500 W's model characteristics: (a) V-I; (b) P-I.

Taking a closer look at the BCS 500 W portion of Table 7, it is clear that the CBO surpassed the closest competitor, the VSDE, and achieved a fitness value of 0.01161, in addition to consuming a very short time of 0.54 s during the estimation process. The developed characteristic curves are displayed in Figure 11, which confirmed the quality and reliability of the proposed approach.



Figure 11. The second stage of study, the BCS 500 W's model characteristics: (a) V-I; (b) P-I.

#### 6. Conclusions

A novel adaptive quasi-empirical modeling technique for PEMFCs was proposed in this work based on the nature-inspired CBO algorithm and accumulated data. Eight recent algorithms were implemented to measure their suitability for this task. The impact of the solution accuracy (fitness) and computational burden was a crucial factor in nominating the best algorithm. In the first stage of study, the CBO approach surpassed the closest competitor (the IGWO algorithm) by a difference of 16.01% and 62.53% in terms of the accuracy and computational speed, respectively. The second stage was set as a verification test for the CBO-based technique for modeling five commercial PEMFC devices, namely: Ballard Mark-V, Nedstack-PS6 6 kW, Temasek 1 kW, SR-12-PEM 500 W, and BCS 500 W. The results confirmed the validity of the CBO-based technique for the goal of high-accuracy PEMFC modeling with minimal computational burden. The proposed technique is an effective tool for real-time PEMFC applications, and it can reflect the cell's dynamic changes in the polarization curve and performance aberrations caused by aging throughout its lifetime.

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15119017/s1, Figure S1. PEMFC layout; Figure S2. PEMFC Polarization (or characteristic) curve.

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# Nomenclature

$V_{FC}$	:	PEMFC output voltage
N <sub>cells</sub>	:	Total number of cells in the PEMFC stack
E <sub>Nernst</sub>	:	Nernst or reversible voltage
V <sub>Act</sub>	:	PEMFC activation voltage
V <sub>Ohmic</sub>	:	PEMFC ohmic losses
V <sub>Conc</sub>	:	PEMFC concentration losses
$p_{H_2}$	:	Partial pressure of hydrogen
$p_{O_2}$	:	Partial pressure of oxygen
$p_{H_2O}$	:	Membrane water saturation pressure
Т	:	Operating temperature
$RH_a$	:	Relative humidity of vapor at anode
$RH_c$	:	Relative humidity of vapor at cathode
$I_{FC}$	:	PEMFC operating current
p <sub>a</sub>	:	PEMFC anode inlet pressure
p <sub>c</sub>	:	PEMFC cathode inlet pressure
Α	:	PEMFC membrane active area
$\xi_i$	:	Parametric coefficients of the activation voltage of the PEMFC ( $i \in \{1:4\}$ )
$C_{O_2}$	:	Concentration of oxygen
$R_c$	:	Constant part of PEMFC membrane resistance
$R_m$	:	Variable part membrane resistance
Ψ	:	PEMFC membrane saturation index
1	:	Thickness of PEMFC membrane
$ ho_m$	:	Specific membrane resistance
$i_L$	:	Maximum current density
В	:	Parametric coefficient
i <sub>d</sub>	:	Current density driven from the cell
$N_{Pop}$	:	CBO total flock population
N <sub>leader</sub>	:	CBO total number of flock leaders
N <sub>coot</sub>	:	CBO total number of flock subordinate coots
rand <sub>coot</sub>	:	Initial random positions of coots
rand <sub>leader</sub>	:	Initial random positions of leaders
Pos <sub>coot</sub>	:	Flock leaders' positions
Pos <sub>leader</sub>	:	Flock subordinate positions
$U_{\rm b}$	:	Problem upper boundary
L <sub>b</sub>	:	Problem lower boundary
Fit <sub>coot</sub>	:	Fitness of each subordinate coot
Fit <sub>leader</sub>	:	Fitness of each leader coot
F <sub>obj</sub>	:	CBO fitness function of each coot
Optim <sub>score</sub>	:	Optimal score
Optim <sub>pos</sub>	:	Optimal position
It(L)	:	Current iteration index
It <sub>max</sub>	:	Maximum number of iterations
Obj		Optimization process objective function
V <sub>actual,j</sub>	:	Actual measured voltage of PEMFC stack
$V_{mdl,j}$	:	Model-estimated voltage
j	:	The number of data points of PEMFC characteristics

# References

- 1. Kaur, G. PEM Fuel Cells: Fundamentals, Advanced Technologies, and Practical Application, 1st ed.; Elsevier: Amsterdam, The Netherlands, 2021; ISBN 9780128237083. [CrossRef]
- 2. Dimitrova, Z.; Nader, W.B. PEM fuel cell as an auxiliary power unit for range extended hybrid electric vehicles. *Energy* **2022**, 239, 121933. [CrossRef]
- 3. Amphlett, J.C.; Baumert, R.M.; Mann, R.F.; Peppley, B.A.; Roberge, P.R.; Harris, T.J. Performance modeling of the Ballard mark-IV solid polymer electrolyte fuel cell. *J. Electrochem. Soc.* **1995**, *142*, 9–15. [CrossRef]

- Hoelzen, J.; Silberhorn, D.; Zill, T.; Bensmann, B.; Hanke-Rauschenbach, R. Hydrogen-powered aviation and its reliance on green hydrogen infrastructure—Review and research gaps. *Int. J. Hydrogen Energy* 2022, 47, 3108–3130. [CrossRef]
- 5. Maden, T.; Şahin, M. Modeling of The PEM Type Fuel Cells. Turk. J. Mater. 2019, 4, 1–10.
- 6. Fletcher, T.; Thring, R.; Watkinson, M. An Energy Management Strategy to concurrently optimise fuel consumption & PEM fuel cell lifetime in a hybrid vehicle. *Int. J. Hydrogen Energy* **2016**, *41*, 21503–21515. [CrossRef]
- Shah, S.A.; Najam, T.; Bashir, M.S.; Peng, L.; Nazir, M.A.; Javed, M.S. Single-atom catalysts for next-generation rechargeable batteries and fuel cells. *Energy Storage Mater.* 2022, 45, 301–322. [CrossRef]
- Singh, R.; Sui, P.; Wong, K.; Kjeang, E.; Knights, S.; Djilali, N. Modeling the effect of chemical membrane degradation on pemfc performance. J. Electrochem. Soc. 2018, 165, 3328–3336. [CrossRef]
- 9. Najam, T.; Shah, S.A.; Ibraheem, S.; Cai, X.; Hussain, E.; Suleman, S.; Javed, M.S.; Tsiakaras, P. Single-atom catalysis for zinc-air/O<sub>2</sub> batteries, water electrolyzers and fuel cells applications. *Energy Storage Mater.* **2022**, *45*, 504–540. [CrossRef]
- Javed, M.S.; Zhang, X.; Ali, S.; Abdul Mateen Idrees, M.; Sajjad, M.; Batool, S.; Ahmad, A.; Imran, M.; Najam, T.; Han, W. Heterostructured bimetallic–sulfide@layered Ti<sub>3</sub>C<sub>2</sub>T<sub>x</sub>–MXene as a synergistic electrode to realize high-energy-density aqueous hybrid-supercapacitor. *Nano Energy* 2022, 101, 107624. [CrossRef]
- Javed, M.S.; Shaheen, N.; Hussain, S.; Li, J.; Shah, S.; Abbas, Y.; Ahmad, M.; Raza, R.; Mai, W. An ultra-high energy density flexible asymmetric supercapacitor based on hierarchical fabric decorated with 2D bimetallic oxide nanosheets and MOF-derived porous carbon polyhedral. *J. Mater. Chem. A* 2019, *7*, 956–957. [CrossRef]
- 12. Dannenberg, K.; Ekdunge, P.; Lindbergh, G. Mathematical model of the PEMFC. J. Appl. Electrochem. 2000, 30, 1377–1387. [CrossRef]
- 13. Jiang, M.; Meng, X.; Zhang, W.; Huang, H.; Wang, F.; Wang, S.; Ouyang, Y.; Yuan, W.; Zhang, L. Facile synthesis of heterophase sponge-like Pd toward enhanced formic acid oxidation. *Electrochem. Commun.* **2021**, *126*, 107004. [CrossRef]
- Yang, Q.; Lin, H.; Wang, X.; Zhang, L.; Jing, M.; Yuan, W.; Li, C. Dynamically self-assembled adenine-mediated synthesis of pristine graphene-supported clean Pd nanoparticles with superior electrocatalytic performance toward formic acid oxidation. *J. Colloid Interface Sci.* 2022, 613, 515–523. [CrossRef] [PubMed]
- Fan, X.; Yuan, W.; Zhang, D.; Li, C. Heteropolyacid-Mediated Self-Assembly of Heteropolyacid-Modified Pristine Graphene Supported Pd Nanoflowers for Superior Catalytic Performance toward Formic Acid Oxidation. ACS Appl. Energy Mater. 2018, 1, 411–420. [CrossRef]
- 16. Xing, Y.; Costa-Castelló, R.; Na, J.; Renaudineau, H. Control-oriented modelling and analysis of a solid oxide fuel cell system. *Int. J. Hydrogen Energy* **2020**, *45*, 20659–20672. [CrossRef]
- 17. Priya, K.; Rajasekar, N. Application of flower pollination algorithm for enhanced proton exchange membrane fuel cell modelling. *Int. J. Hydrogen Energy* **2019**, *44*, 18438–18449. [CrossRef]
- Seleem, S.I.; Hasanien, H.M.; El-Fergany, A.A. Equilibrium optimizer for parameter extraction of a fuel cell dynamic model. *Renew. Energy* 2021, 169, 117–128. [CrossRef]
- 19. Turgut, O.E.; Coban, M.T. Optimal proton exchange membrane fuel cell modelling based on hybrid Teaching Learning Based Optimization-Differential Evolution algorithm. *Ain Shams Eng. J.* **2016**, *7*, 347–360. [CrossRef]
- 20. Jia, J.; Li, Q.; Wang, Y.; Cham, Y.; Han, M. Modeling and dynamic characteristic simulation of a Proton Exchange Membrane Fuel Cell. *IEEE Trans. Energy Convers.* **2009**, *24*, 283–291. [CrossRef]
- 21. Ali, M.; El-Hameed, M.A.; Farahat, M.A. Effective parameters' identification for polymer electrolyte membrane fuel cell models using grey wolf optimizer. *Renew. Energy* 2017, 111, 455–462. [CrossRef]
- 22. Yang, B.; Wang, J.; Yu, L.; Shu, H.; Yu, T.; Zhang, X.; Yao, W.; Sun, L. A critical survey on proton exchange membrane fuel cell parameter estimation using meta-heuristic algorithms. *J. Clean. Prod.* **2020**, *265*, 121660. [CrossRef]
- 23. Mo, Z.; Zhu, X.; Wei, L.; Cao, G. Parameter optimization for a PEMFC model with a hybrid genetic algorithm. *Int. J. Energy Res.* **2006**, *30*, 585–597. [CrossRef]
- Ohenoja, M.; Leiviskä, K. Validation of genetic algorithm results in a fuel cell model. Int. J. Hydrogen Energy 2010, 35, 12618–12625. [CrossRef]
- 25. Zhang, L.; Wang, N. An adaptive RNA genetic algorithm for modeling of proton exchange membrane fuel cells. *Int. J. Hydrogen Energy* **2013**, *38*, 219–228. [CrossRef]
- Ye, M.; Wang, X.; Xu, Y. Parameter identification for proton exchange membrane fuel cell model using particle swarm optimization. *Int. J. Hydrogen Energy* 2009, 34, 981–989. [CrossRef]
- Gong, W.; Yan, X.; Liu, X.; Cai, Z. Parameter extraction of different fuel cell models with transferred adaptive differential evolution. Energy 2015, 86, 139–151. [CrossRef]
- Fathy, A.; Abd Elaziz, M.; Alharbi, A.G. A novel approach based on hybrid vortex search algorithm and differential evolution for identifying the optimal parameters of PEM fuel cell. *Renew. Energy* 2020, 146, 1833–1845. [CrossRef]
- 29. Yang, S.; Wang, N. A novel P system based optimization algorithm for parameter estimation of proton exchange membrane fuel cell model. *Int. J. Hydrogen Energy* **2012**, *37*, 8465–8476. [CrossRef]
- 30. Askarzadeh, A.; Rezazadeh, A. A grouping-based global harmony search algorithm for modeling of proton exchange membrane fuel cell. *Int. J. Hydrogen Energy* **2011**, *36*, 5047–5053. [CrossRef]
- Niu, Q.; Zhang, H.; Li, K. An improved TLBO with elite strategy for parameters identification of PEM fuel cell and solar cell models. *Int. J. Hydrogen Energy* 2014, 39, 3837–3854. [CrossRef]

- 32. Guarnieri, M.; Negro, E.; Noto, V.D.; Alotto, P. A selective hybrid stochastic strategy for fuel-cell multi-parameter identification. *J. Power Sources* **2016**, 332, 249–264. [CrossRef]
- El-Fergany, A.A. Extracting optimal parameters of PEM fuel cells using Salp Swarm Optimizer. Renew. *Energy* 2018, 119, 641–648. [CrossRef]
- 34. Rao, Y.; Shao, Z.; Ahangarnejad, A.H.; Gholamalizadeh, E.; Sobhani, B. Shark Smell Optimizer applied to identify the optimal parameters of the proton exchange membrane fuel cell model. *Energy Convers. Manag.* **2019**, *182*, 1–8. [CrossRef]
- Yang, B.; Zeng, C.; Wang, L.; Guo, Y.; Chen, G.; Guo, Z.; Chen, Y.; Li, D.; Cao, P.; Shu, H.; et al. Parameter identification of proton exchange membrane fuel cell via Levenberg-Marquardt backpropagation algorithm. *Int. J. Hydrogen Energy* 2021, 46, 22998–23012. [CrossRef]
- 36. Yang, B.; Li, D.; Zeng, C.; Chen, Y.; Guo, Z.; Wang, J.; Shu, H.; Yu, T.; Zhu, J. Parameter extraction of PEMFC via Bayesian regularization neural network based meta-heuristic algorithms. *Energy* **2021**, *228*, 120592. [CrossRef]
- Legala, A.; Zhao, J.; Li, X. Machine learning modeling for proton exchange membrane fuel cell performance. *Energy AI* 2022, 10, 100183. [CrossRef]
- Qin, F.; Liu, P.; Niu, H.; Song, H.; Yousefi, N. Parameter estimation of PEMFC based on Improved Fluid Search Optimization Algorithm. *Energy Rep.* 2020, 6, 1224–1232. [CrossRef]
- Yakout, A.H.; Hasanien, H.M.; Kotb, H. Proton Exchange Membrane Fuel Cell Steady State Modeling Using Marine Predator Algorithm Optimizer. *Ain Shams Eng. J.* 2021, 12, 3765–3774. [CrossRef]
- 40. Ćalasan, M.; Abdel Aleem, S.; Hasanien, H.M.; Alaas, Z.M.; Ali, Z.M. An innovative approach for mathematical modeling and parameter estimation of PEM fuel cells based on iterative Lambert W function. *Energy* **2023**, *264*, 126165. [CrossRef]
- 41. Wilberforce, T.; Rezk, H.; Olabi, A.G.; Epelle, E.I.; Abdelkareem, M.A. Comparative analysis on parametric estimation of a PEM fuel cell using metaheuristics algorithms. *Energy* **2023**, *262 Pt B*, 125530. [CrossRef]
- 42. Wolpert, D.H.; Macready, W.G. No free lunch theorems for optimization. IEEE Trans. Evol. Comput. 1997, 1, 67–82. [CrossRef]
- 43. Naruei, I.; Keynia, F. A new optimization method based on COOT bird natural life model. *Expert Syst. Appl.* **2021**, *183*, 115352. [CrossRef]
- 44. Lyon, B.E.; Shizuka, D. Extreme offspring ornamentation in American coots is favored by selection within families, not benefits to conspecific brood parasites. *Proc. Natl. Acad. Sci. USA* 2020, 117, 2056–2064. [CrossRef] [PubMed]
- 45. Salaia, K.E.; Mansouri, I.; Squalli, W.; El Hassani, A.; Dakki, M.; Zine, N.E. Nesting features and breeding chronology of the crested coot (*Fulica cristata*) in two North African high altitude wetlands. *J. Anim. Behav. Biometeorol.* **2021**, *9*, e2129. [CrossRef]
- 46. Gouda, E.A.; Kotb, M.F.; Ghoneim, S.S.M.; Al-Harthi, M.M.; El-Fergany, A.A. Performance assessment of solar generating units based on coot bird metaheuristic optimizer. *IEEE Access* **2021**, *9*, 111616–111632. [CrossRef]
- Mohammad, H.; Nadimi-Shahraki Taghian, S.; Mirjalili, S.; Faris, H. MTDE: An effective multi-trial vector-based differential evolution algorithm and its applications for engineering design problems. *Appl. Soft Comput.* 2020, 97 Pt A, 106761. [CrossRef]
   Mirjalili, S. The ant lion optimizer. *Adv. Eng. Softw.* 2015, *83*, 80–98. [CrossRef]
- 49. Mirjalili, S. Dragonfly algorithm: A new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems. *Neural Comput. Appl.* **2015**, *27*, 1053–1073. [CrossRef]
- 50. Zhao, W.; Wang, L.; Zhang, Z. Atom search optimization and its application to solve a hydrogeologic parameter estimation problem. *Knowl.-Based Syst.* **2019**, *163*, 283–304. [CrossRef]
- 51. Saremi, S.; Mirjalili, S.; Lewis, A. Grasshopper Optimisation Algorithm: Theory and application. *Adv. Eng. Softw.* **2017**, *105*, 30–47. [CrossRef]
- 52. Mohammad, H.; Nadimi-Shahraki Taghian, S.; Mirjalili, S. An improved grey wolf optimizer for solving engineering problems. *Expert Syst. Appl.* **2021**, *166*, 113917. [CrossRef]
- 53. Faramarzi, A.; Heidarinejad, M.; Mirjalili, S.; Gandomi, A.H. Marine Predators Algorithm: A nature-inspired metaheuristic. *Expert Syst. Appl.* **2020**, *152*, 113377. [CrossRef]
- 54. Matlab (R2020a) Is a Product of the MathWorks. Available online: http://www.mathworks.com (accessed on 5 January 2023).
- 55. IBM SPSS (Version 22) Is a Product of the IBM Corporation. Available online: http://www.ibm.com/analytics/us/en/technology/spss/ (accessed on 9 January 2023).

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