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Effective Parameter Extraction of Different Polymer Electrolyte Membrane Fuel Cell Stack Models Using a Modified Artificial Ecosystem Optimization Algorithm

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ABSTRACT Recently, extracting the precise values of unknown parameters of the polymer electrolyte membrane fuel cell (PEMFC) is considered one of the most widely nonlinear and semi-empirical optimization problems. This paper proposes and applies a Modified Artificial Ecosystem Optimization (MAEO) algorithm to solve the problem of PEMFC parameters extraction. The conventional AEO is a novel optimization technique that is inspired by the energy flow in a natural ecosystem which is defined as abiotic, which includes non-living bodies and elements such as light, water and air. The proposed optimization algorithm, MAEO, is used to enhance the performance of conventional AEO and provide faster convergence rate as well as to be far away from falling into the local optima. In the proposed MAEO, an operator is suggested to improve the balance between exploitation and Exploration phases. The accurate estimation of PEMFC unknown parameters leads to develop a precise mathematical model which simulates the electrochemical and electrical characteristics of PEMFC. The objective function of the studied optimization problem is formulated as the sum of squared errors (SSE) between the measured and simulated stack voltages. To prove the reliability and capability of the proposed MAEO algorithm in solving this problem compared with other recent algorithms, it is tested on four different PEMFC stack models, namely, BCS-500W, SR-12 500W, 250W and Temasek 1 kW stacks. Moreover, statistical measures are performed to assess the superiority and robustness of the proposed algorithm. In addition, the accuracy of optimized parameters is assessed through the dynamic characteristics of PEMFCs under varying the reactants' pressures and temperature of the cell. However, the simulation results confirm that the proposed MAEO algorithm has high accuracy and reliability in extracting the PEMFC optimal parameters compared with the conventional AEO and other effective algorithms.

INDEX TERMS Polymer electrolyte membrane fuel cell, parameters extraction, modified artificial ecosystem optimization, sum of squared errors, polarization curves.

A. ACRONYMS AND ABBREVIATIONS

FC	Fuel cell
PEMFC	Polymer electrolyte membrane fuel cell
SSE	Sum of squared errors
SD	Standard deviation
RE	Relative error
RMSE	Root mean square error

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MAE	Mean absolute error
IAE	Individual Absolute Error
RE	Relative Error
V_{stack}	PEMFC stack voltage (V)
E_{Nernst}	Nernst voltage of a single FC (V)
N_{cells}	Number of cells in the stack
v_{act}, v_{ohm}, and v_{con}	Activation, ohmic, and concentration voltage drop, respectively (V)
T	FC operating temperature (K)
P_{H2} and P_{O2}	Hydrogen and oxygen partial pressures, respectively (atm)
ζ_1, ζ_2, ζ_3, and ζ_4	Parametric adjustable parameters for a particular FC
I_{fc}	PEMFC stack current (A)
$R_c and R_M$	Resistance due to concentration and transfer of proton through membrane electrode, respectively (Ω)
ρ_M	Specific resistance of the membrane (Ω.cm)
l	Membrane thickness (μm)
A	Effective electrode area (cm2)
λ	Adjustable parameter describes the water content in the membrane
b	Parametric coefficient (V)
J and J_{max}	real and maximum current density of the FC stack, respectively (A/cm2)
$\Re and F$	Ideal gas constant and Faraday' constant, respectively
α	Charge transfer coefficient
n	population size
$maxiter$	Maximum number of iterations
L and U	Lower and upper limits of the search space, respectively
r_1, r_2, and r_3	Random numbers between [0, 1]
r	Random vector ranges between [0, 1]
a	Linear weighting coefficient
C and D	Consumption and decomposition factors, respectively

I. INTRODUCTION

FC is become one of the most vital sources of energy among the renewable energy sources, where it is better than the traditional generation sources of energy. Nowadays, FC is used in various applications due to its high efficiency, high reliability, long-term stability, superior durability and less pollution to the surrounding environment. Extensive attention has been directed and focused on the development of FCs [1], [2]. FC is defined as an electrochemical apparatus that converts the chemical energy using hydrogen gas as an input fuel into electric energy and heat using oxygen/air as an oxidant. Among different types of FCs, the PEMFCs are the most widely used kind and have been used in many applications such as mobile, vehicle, transportation, industries applications and distributed residential generation systems [3]–[6]. Generally, the generated output voltage of each single FC is in the range of 0.5-0.9V. Many FCs are connected in series to obtain a huge value of voltage and power, as well as to have the ability to be used in high power generation systems [7], [8].

There are many kinds of FCs are used in real applications, and PEMFCs are considered the most famous and well-known kind among them but still have the lowest electrical efficiency [9], [10]. PEMFCs have several advantages over other traditional sources such as no generated wastes, high electrical efficiency, less emission, low temperature and pressure during their operation that allow fast response to variations of external load and safety cases [1]. To facilitate the testing and design of FCs, modelling of FCs should be demonstrated. Over the last decades, modelling of FCs has gained considerable attention in trying to recognize the mainly phenomena take place inside the FC [11].

To date, several methods of PEMFC modeling have been provided in the literature [12]–[18]. Categories of PEMFCs modeling can be divided into two parts, the first part called the mechanical modeling and it sheds the light on simulation of heat and mass transfer as well as the electrochemical phenomena occurred in FCs [15]–[17], the second part called the empirical modeling and it relies on semi-empirical and non-linear equations, which are used to predict the impact of various parameters on the current-voltage (I/V) polarization characteristics of the FC. In [19], Amphlett has suggested a suitable mathematical model for PEMFC modeling. This model has been accepted by many scientific researchers. The PEMFC model is considered a multi-varialble, non-linear and complex model, therefore, the traditional techniques are not efficient to show the real output characteristics of PEMFC models.

Newly, several novel well-known optimization techniques have been provided for solving the problem of PEMFC parameters extraction. These techniques are Harris Hawks Optimization Technique (HHO) and HHO based on the 4th chaotic function (CHHO4) [20], particle swarm optimization (PSO) [21], support vector machine (SVM)[22], genetic algorithm (GA), simple genetic algorithm (SGA)[14], Hybrid Genetic algorithm (HGA) [14], seagull optimization algorithm (SOA) [23], Seeker optimization algorithm (SO) [24], Salp Swarm Algorithm (SSA) [25], Antlion Optimizer (ALO) [26], Grasshopper Optimiser Algorithm (GOA) [27], Vortex Search Algorithm (VSA) and Differential Evolution (DE) [28], Teaching Learning Based Optimization–Differential Evolution algorithm (TLBODE) [29], Differential evolution (DE) [18], Multi-verse optimizer (MVO)[30], Eagle strategy based on JAYA algorithm and Nelder-Mead simplex method (JAYA-NM) [31], Grey Wolf Optimizer [26], Satin Bowerbird optimizer (SBO) [32], shark smell optimizer (SSO)[33], simulated annealing (SA) [13], Atom Search Optimizer (ASO)[34], hybrid adaptive differential evolution algorithm (HADE)[35], and Cuckoo search algorithm with explosion operator (CS-EO) [36].

In this paper, we propose a modified version of AEO (MAEO) to accurately extract the accurate values of the unknown parameters of PEMFC model based on minimizing the sum of squared error between the measured and simulated data. The optimal obtained parameters using MAEO will lead to construct a precise PEMFC model which mimics the electrical and electrochemical characteristics of actual PEMFC stacks under changing the reactants pressure and temperature of cell. Four different PEMFC stacks, namely, BCS-500W, SR-12 500W, 250W and Temasek 1kW are used to prove the efficiency of the proposed MAEO algorithm. Moreover, a statistical analysis is provided to validate the reliability of proposed algorithm. The obtained results of proposed algorithm are compared with those obtained by several recent algorithms reported in literature. The competitive comparison proved the reliability of the proposed algorithm in solving the studied problem.

The rest part of this paper is outlined as follows. Section II describes the mathematical model of PEMFC stacks. The structure of the objective function is presented in Section III. Section IV explains the procedures of the conventional AEO and proposed MAEO algorithms. Section V provides the study cases, simulation results and dynamic operation of PEMFCs. Finally, the main conclusions are emphasized in Section VI.

II. MATHEMATICAL MODEL OF PEMFC

The polarization characteristics of the PEMFC, that describes the behavior of the generated current versus generated voltage of the FC stack can be obtained not only by experimental measurements but also via constructing an accurate model for the FC. The semi-empirical mathematical model introduced by Correa *et al.* [8], has been reported in many studies. It is also used in this paper for simulating the steady state behavior of different PEMFCs. The output stack voltage is mathematically calculated from the following expression:

$$V_{stack} = N_{cells}(E_{Nernst} - V_{act} - V_{ohm} - V_{con}) \tag{1}$$

where, the Nernst potential at standard temperature (25°C) and operating temperature below 100°C is calculated using (2)[8].

$$\begin{aligned} E_{Nernst} &= 1.229 - 8.5 \times 10^{-4} (T - 298.15) \\ &\quad + 4.3085 \times 10^{-5} T \times \left[\ln\left(P_{H_2}\right) + \ln\left(\sqrt{P_{O_2}}\right)\right] \end{aligned} \tag{2}$$

The voltage loss due to the process of activation between the two electrodes of anode and cathode is mathematically calculated as follow:

$$\begin{aligned} v_{act} = -\Bigg[&\xi_1 + \xi_2 T + \xi_3 T \ln\left(\frac{P_{O_2}}{5.08 \times 10^6 \times \exp^{-\left(498/T\right)}}\right) \\ &+ \xi_4 T \ln\left(I_{fc}\right)\Bigg] \end{aligned} \tag{3}$$

The ohmic voltage loss that results from the resistance of the membrane electrolyte can be expressed as follows:

$$V_{ohmic} = I_{fc}\left(R_M + R_C\right) \tag{4}$$

where,

$$R_M = \frac{\rho_M \cdot l}{A} \tag{5}$$

$$\rho_M = \frac{181.6\left[1 + 0.03\left(\frac{I_{fc}}{A}\right) + 0.062\left(\frac{T}{303}\right)^2\left(\frac{I_{fc}}{A}\right)^{2.5}\right]}{\left[\lambda - 0.634 - 3\left(\frac{I_{fc}}{A}\right)\right] \times \exp\left[4.18\left(\frac{T-303}{T}\right)\right]} \tag{6}$$

The final part of voltage loss due to the variation in concentration of the reactants V_{con} can expressed as follows:

$$V_{con} = -b \ln\left(1 - \frac{J}{J_{\max}}\right) \tag{7}$$

From the abovementioned formulation of the PEMFC model, ζ_1, ζ_2, ζ_3, and ζ_4 denote adjustable parametric coefficients which reflect the geometrical dimensions and the material type of the fuel cell components [37], [38]. The reader can notice that the parametric coefficient λ is depending on several factors. In this paper, the coefficient λ is taken as an adjustable parameter, which is an indication of the life time of the FC and relative humidity [15], [37], [38]. b is a parameter included in the Tafel equation described in (8). In most of studies, b is taken as an adjustable parameter.

$$b = \frac{\Re T}{2\alpha F} \tag{8}$$

III. FORMULATION OF PEMFC PARAMETERS' EXTRACTION PROBLEM

Based on the (1) to (8), which describe the mathematical model of the PEMFC stacks, the reader can observe that the model contains a set of unknown parameters that are adjusted empirically. The model includes seven unknown parameters $X_{PEMFC} = (\zeta_1, \zeta_2, \zeta_3, \zeta_4, \lambda, R_c$, and b) which have to accurately determined to obtain the actual voltage at the terminals of the FC stack. In order to identify these seven parameters using an optimization method, it is essential to define an objective function (OF) which will be minimized. In this study, the SSE between the measured and computed data is utilized as the OF, which presents the cumulative performance of the fuel cell as all data points are subjected in this function [21], [33], [34].

$$\begin{aligned} SSE &= OF(X_{PEMFC}) \\ &= \sum_{i=1}^{N}\left[V_{stack-Exp} - V_{stack-Est}(I_{fc}, X_{PEMFC})\right]^2 \end{aligned} \tag{9}$$

where, N denotes the number of measured data points, $V_{stack-Exp}$ is the experimentally measured values of the FC terminal voltage, and $V_{stack-Est}$ is the estimated value of the stack output voltage regarding the stack current and the seven unknown parameters.

Another important part in the studied optimization problem is the constraints, which is utilized to generate feasible values of the parameters. In the case of PEMFC, the seven unknown parameters are controlled according to the following constraints reported in many studies (see Table 1) [26], [27], [33], [34], [39].

TABLE 1. Minimum and maximum allowable values of PEMFC unknown parameters.

Parameter	Minimum allowable value	Maximum allowable value
ξ_1	-1.1997	-0.8532
ξ_2	0.0008	0.006
ξ_3	3.6×10^{-5}	9.8×10^{-5}
ξ_4	-2.6×10^{-4}	-9.54×10^{-5}
λ	10	23
R_c	0.0001	0.0008
b	0..0136	0.5

IV. OPTIMIZATION ALGORITHMS

In this section, the conventional AEO and proposed MAEO are explained in details.

A. AEO

The AEO is inspired by the energy flow in a natural ecosystem was firstly developed by Zhao *et al.* [40]. The ecosystem means a group of living organisms, which live in a certain space, and it explains the environmental relations between these organisms. The ecosystem is divided into two parts, namely, abiotic and biotic ecosystems. The abiotic ecosystem includes non-living bodies and elements such as light, water, air; but the biotic ecosystem includes all living elements. The AEO is a population-based algorithm, which mimics, production, consumption and decomposition behaviors of organisms on the earth. The main force in maintaining the ecological balance in an ecosystem is the energy flow and the nutrients cycling process. The living elements in an ecosystem can be divided into three groups according to their behavior. The first group is the producer, which is categorized as a kind of green plants and gets its energy from the photosynthesis process without depending on other organisms. The second group is the consumer, which includes animals that depend on producers or other consumers (animals) in their nutrients. Based on the type of food, the consumers are divided into three categories; a) herbivores that eat only plants, b) carnivores that eat only animals, c) omnivores that eat both plants and animals. The third category of the living elements is the decomposers, bacteria and fungi, which play a great role after the death of an organism in converting the remains into molecules that will be absorbed again from the soil by the producers (plants) and the cycle will be repeated. The three types of living organism in an ecosystem interact with each other to form a food chain, which describes who feeds whom and shows various levels of eating and forms the path of energy and nutrients through the ecosystem. A food web is the result of a group of overlapped food chains that describes the way of interconnection between the food chains. The flow of energy in an ecosystem is depicted in Fig. 1. Usually, producers (plants) are found at the beginning of the food web. The consumers are the most complicated among the different living organisms. As shown in Fig. 1., the energy flows from the organism with the higher energy to that with the lower one. The energy level decreases transferring from the producers towards the consumers.

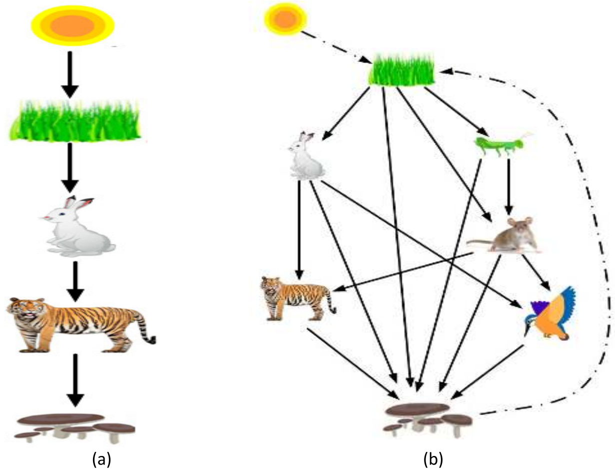


FIGURE 1. Energy flow in an ecosystem: (a) food chain, (b) food web.

Based on the previously described inspiration, the AEO contains three operators; the production that is utilized to improve the balance between the exploration and exploitation processes, consumption for enhancement of exploration, and decomposition to improve the exploitation of the AEO. During the operation of AEO algorithm, it is proposed that in each population there is only one producer and one decomposer, while other individuals are considered consumers from the three predefined types. The level of energy of each element in the population is determined by the fitness function of that individual. The representation of an ecosystem based on the AEO is shown in Fig. 2. The flow of energy is represented by the black arrows. The worst individual x_1 having the highest energy level (producer), while x_n is the best individual (decomposer) having the lowest energy level (fitness value). The other individuals are consumers; x_2 and x_5 taken as herbivores, x_3 and x_7 omnivores and x_4 and x_6 are carnivores.

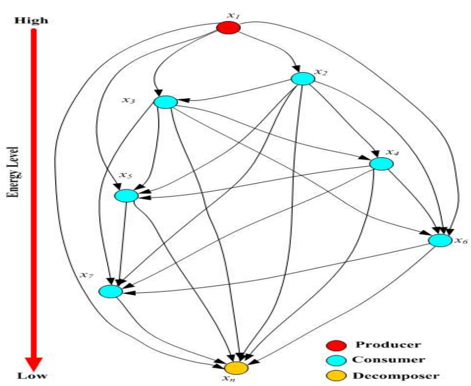


FIGURE 2. Presentation of an ecosystem in AEO technique.

1) PRODUCTION

In AEO, the producer mimics the action of the producer in the ecosystem, which needs sunlight, water and nutrition from the decomposer for generating food. In AEO, the producer with the lowest fitness value is updated based on the search limits of this individual and the best individual (decomposer). Consequently, the other individuals in the population will update their position. Using the production operator, a new individual (producer) will be generated between the best one (x_n) and a randomly generated individual (x_{rand}), which is mathematically expressed as follows [40]:

$$x_1(t+1) = (1-a)x_n(t) + a x_{rand}(t) \tag{10}$$

$$a = \left(1 - \frac{t}{\max iter}\right) r_1 \tag{11}$$

$$x_{rand} = r(U-L) + L \tag{12}$$

2) CONSUMPTION

When the production operator is accomplished from the side of the producer, the consumers start to implement the consumption operator. In this process each consumer may obtain the eating energy from another consumer with lower fitness or from a producer. A mathematical operator called Levy flight mimics the food searching mechanism of many animals and used for improving the exploration stage in many algorithms. A consumption parameter having the feature of the Levy flight is defined by the following expression [40]:

$$C = \frac{1}{2}\frac{v_1}{|v_2|} \tag{13}$$

$$v_1 \sim N(0,1), \quad v_2 \sim N(0,1) \tag{14}$$

where, $N(0, 1)$ represents a normal distribution having a mean of 0 and standard deviation of 1. This consumption factor will help each of the consumers to get food using different hunting strategies.

If the consumer is randomly selected as herbivore, then it will eat only producers and the consumption behavior in this case will be mathematically presented as follows:

$$x_i(t+1) = x_i(t) + C.(x_i(t) - x_1(t)), \quad i \in [2, \ldots, n] \tag{15}$$

When the consumer is selected as a carnivore, it will eat only the consumers with the higher energy level (lower fitness value), and will be mathematically expressed as follow:

$$\begin{cases} x_i(t+1) = x_i(t) + C \cdot (x_i(t) - x_j(t)), & i \in [3, \ldots, n] \\ j = randi([2i-1]) \end{cases} \tag{16}$$

In the other case when the consumer is taken as an omnivore, the consumer has the ability to hunt other consumers with higher energy levels and/or producers. The consumption behavior of an omnivore can be mathematically formulated as follows:

$$\begin{cases} x_i(t+1) = x_i(t) + C.(r_2(x_i(t) - x_j(t)) \\ \qquad + (1-r_2)(x_i(t) - x_j(t))), \quad i = 3, \ldots, n \\ j = randi([2i-1]) \end{cases} \tag{17}$$

3) DECOMPOSION

The decomposer plays a vital role in the ecosystem. After the death of any individual in the population, the decomposer will break down the remains of that individual. The decomposition process is mathematically modeled using a decomposition factor D and two weight variables e and h. The position of the i-th individual x_i in the population can be updated depending on the decomposer x_n and the predefined variables according to the following expression [40]:

$$x_i(t+1) = x_n(t) + D.(e.x_n(t) - h.x_i(t)), \quad i = 1, \ldots, n \tag{18}$$

$$D = 3u, \quad u \sim N(0,1) \tag{19}$$

$$e = r_3 \cdot randi([12]) - 1 \tag{20}$$

$$h = 2 \cdot r_3 - 1 \tag{21}$$

At the beginning of the AEO, a randomly initial population is generated. For each iteration, the position of the first individual (producer) is updated based on (10), while other individuals in the population will update their positions according to (15), (16), and (17) regarding the type of the consumer except if the individual obtains a higher fitness value, then the position of such individual will be updated based on (18). The updating process will continue until the AEO reaches the end criterion. Finally, the optimal solution will be introduced.

B. PROPOSED MAEO

Both exploitation and Exploration are necessary for population-based algorithms, where they are two conflicting milestones. A right balance between these milestones can enhance the performance of metaheuristics algorithms in order to reduce the search space and converge the global optimal solutions [41]. The operator H is suggested to improve the balance between exploitation and Exploration [42]–[44]. In MAEO, the value of operator H decreases linearly from 2 to 0 over the course of iterations as follows:

$$H = 2 \times \left(1 - \frac{iter}{\max iter}\right) \tag{22}$$

where, Iter is the current iteration. The MAEO is suggested to improve performance of the conventional AEO, where the operator H is added in consumption phases in (15), (16), and (17). These equations can be replaced and rewritten as

TABLE 2. Specifications of the studied PEMFC stacks.

PEMFC type	Unit	BCS 500W	AVISTA SR-12 PEM 500W	250 W stack
N cells	-	32	48	24
A	cm^2	64	62.5	27
l	μm	178	25	127
Jmax	mA/cm^2	469	672	860
PH2	atm	1	1.47628	1
Po2	atm	0.2095	0.2095	1
T	K	333	323	343.15

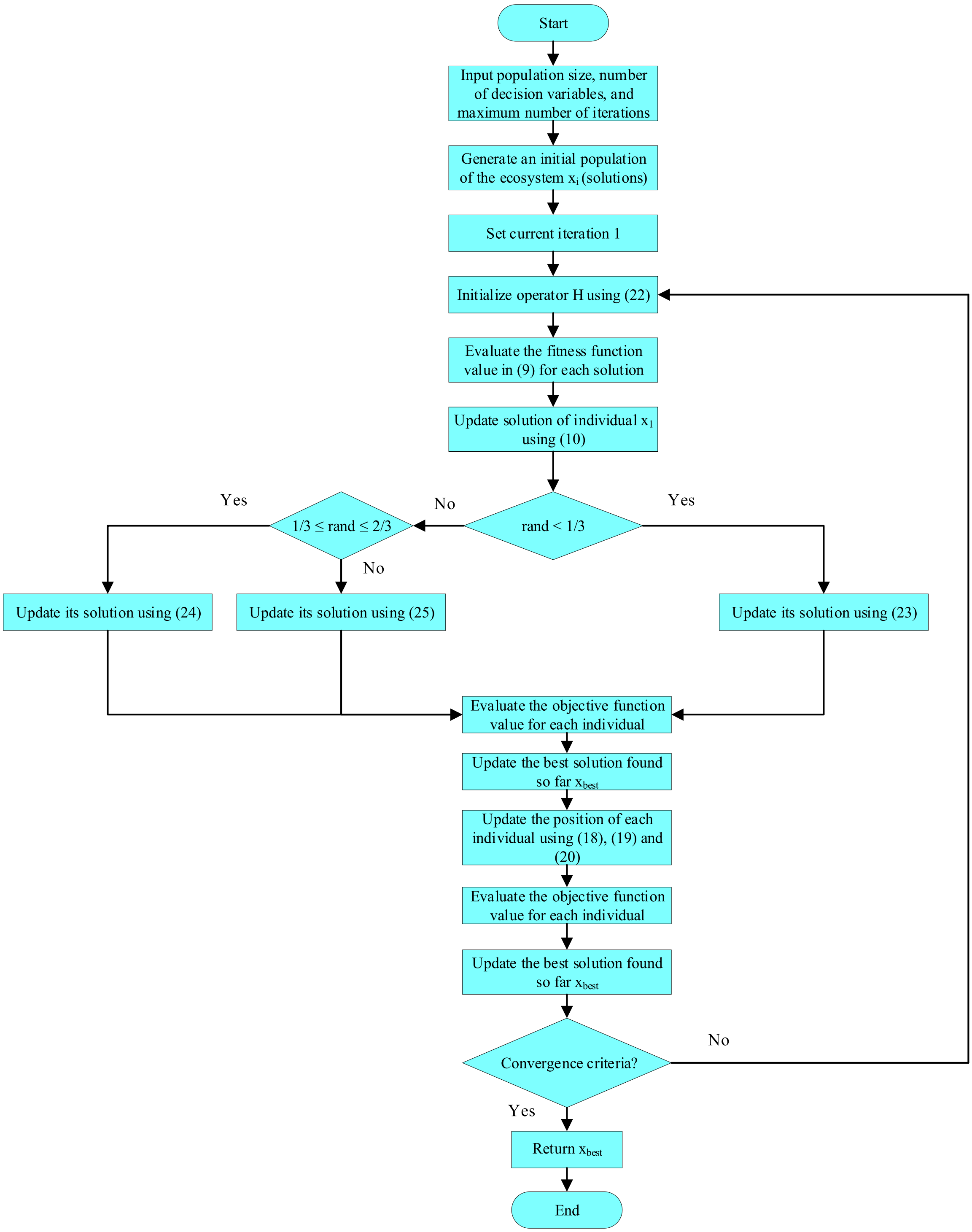


FIGURE 3. Flow chart of the proposed MAEO.

follows:

$$x_i(t+1) = x_i + H \cdot C \cdot (x_i(t) - x_1(t)), \quad i \in [2, \ldots, n] \tag{23}$$

$$\begin{cases} x_i(t+1) = x_i(t) + H \cdot C \cdot (x_i(t) - x_j(t)), \quad i \in [3, \ldots, n] \\ j = randi([2i-1]) \end{cases} \tag{24}$$

$$\begin{cases} x_i(t+1) = x_i(t) + H \cdot C \cdot (\mathrm{r}_2(x_i(t) - x_j(t)) \\ \qquad + (1-\mathrm{r}_2)(x_i(t) - x_j(t))), \quad i = 3, \ldots, n \\ j = randi([2\mathrm{i}-1]) \end{cases} \tag{25}$$

The rest of solution procedures are similar with those of AEO. The overall process of the proposed MAEO is represented graphically in Fig. 3. and summarized in steps asi follows:

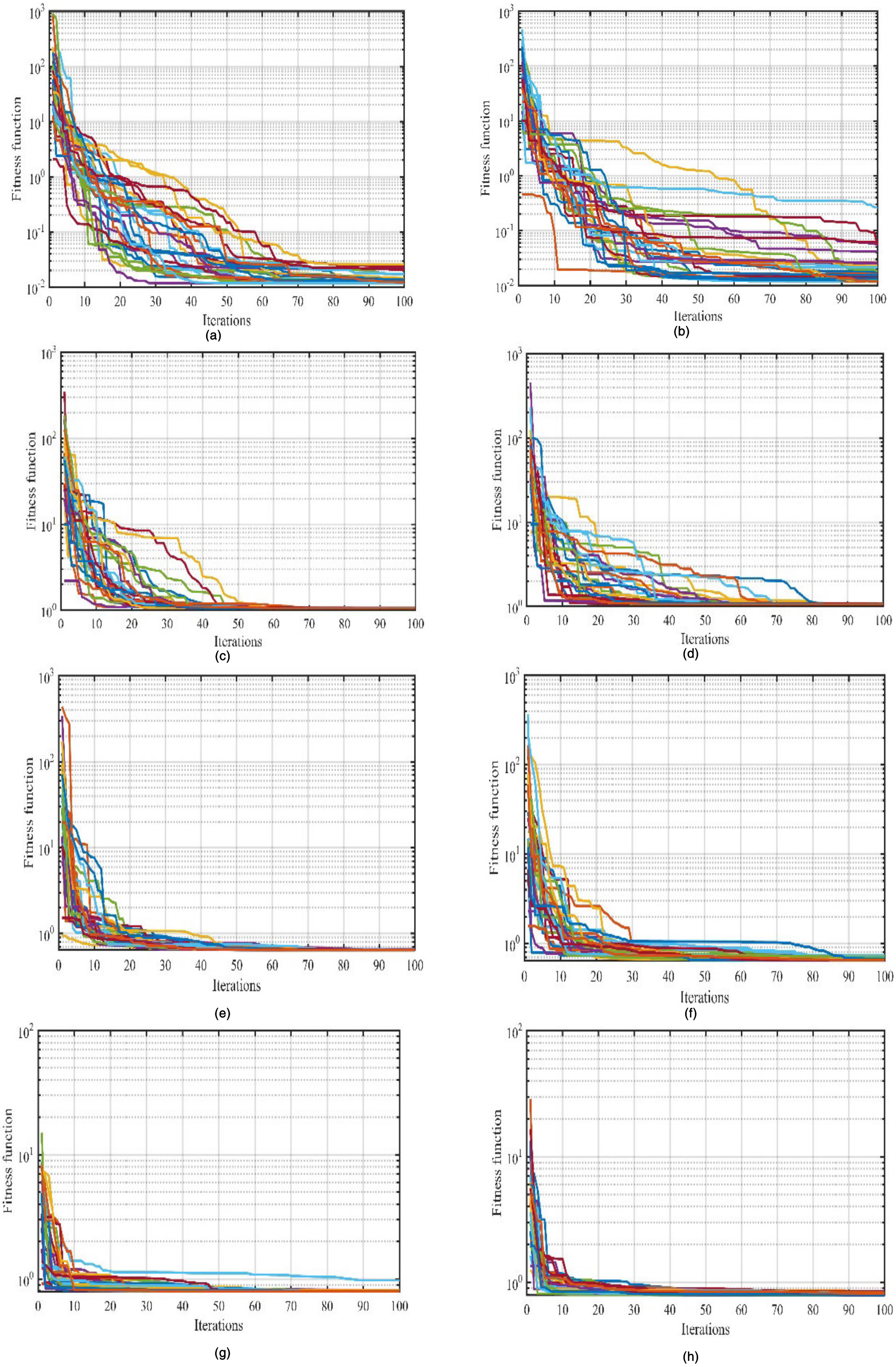


FIGURE 4. Convergence trends of the fitness function over the 30 runs; (a) MAEO for BCS-500 W PEMFC, (b) AEO for BCS-500 W PEMFC, (c) MAEO for SR-12 500W PEMFC, (d) AEO for SR-12 500W PEMFC, (e) MAEO for 250 W PEMFC, (f) AEO for 250 W PEMFC, (g) MAEO for Temasek 1kW PEMFC, (h) AEO for Temasek 1kW PEMFC.

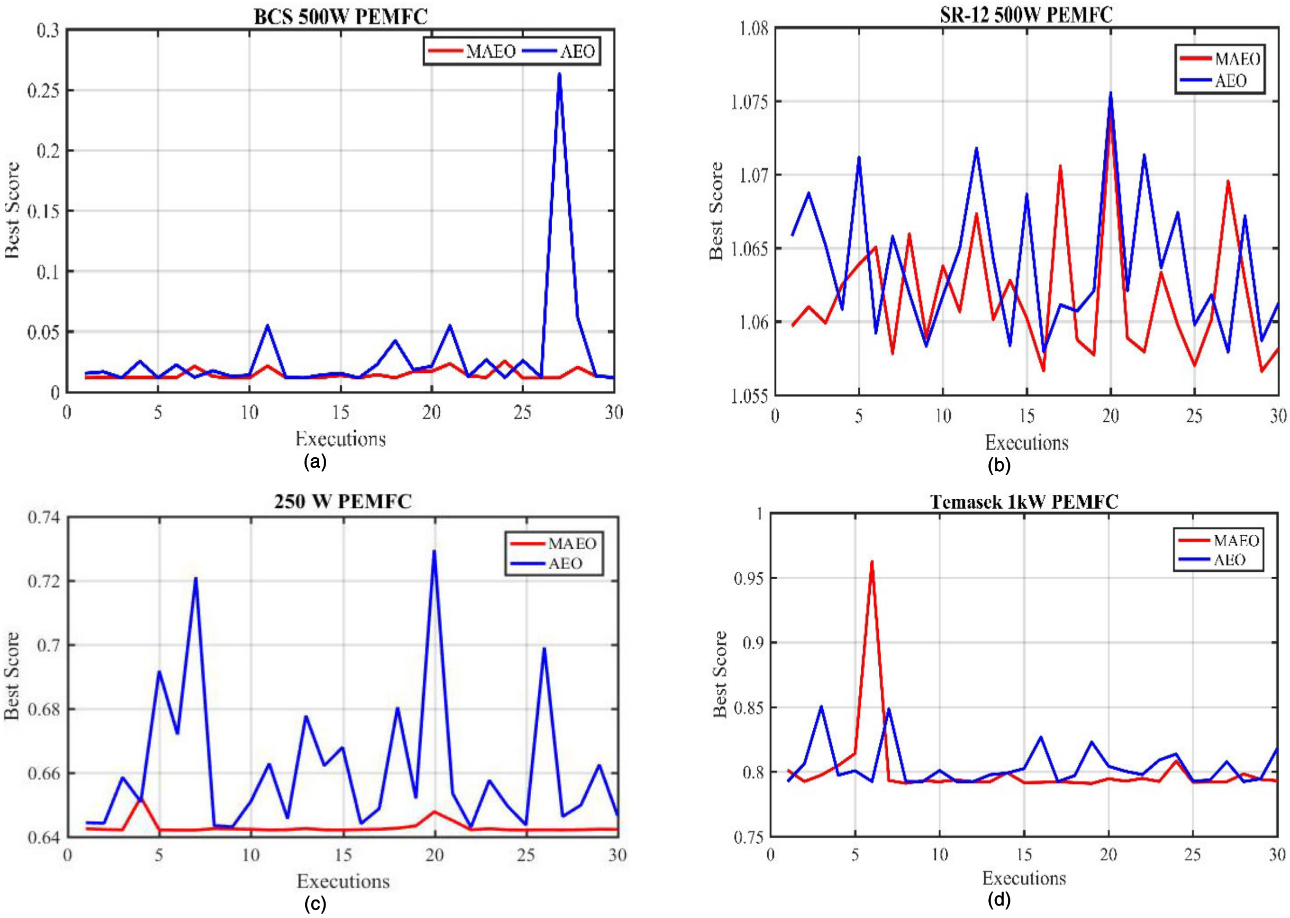


FIGURE 5. Optimal values of the OF over the 30 runs: (a) BCS-500W PEMFC, (b) SR-12 500W PEMFC, (c) 250W PEMFC, and (d) Temasek 1kW PEMFC.

TABLE 3. Statistical analysis of MAEO and AEO for different PEMFC stacks.

PEMFC Type	BCS 500W stack		AVISTA SR-12 500W stack		250W stack		Temasek 1kW stack	
	MAEO	AEO	MAEO	AEO	MAEO	AEO	MAEO	AEO
Min.	0.0115736558	0.011664838	1.056633388	1.057930932	0.642024928	0.642950652	0.790964320	0.792432054
Max.	0.0255420571	0.263553352	1.074281805	1.075554310	0.652231801	0.729502283	0.962584832	0.850493258
Mean	0.0142271678	0.029326168	1.061733649	1.063854061	0.642868957	0.661399709	0.800817602	0.804116978
Median	0.0120147885	0.015454882	1.060196400	1.062107208	0.642206041	0.651454118	0.792936833	0.798480129
SD	0.4075077598	4.637295890	0.434743759	0.468211029	0.209969921	2.277403053	3.103588334	1.549819607
RE	6.8781517916	45.42196791	0.144806922	0.167963582	0.039439071	0.860830784445073	0.373719076	0.442369436
MAE	0.0026535120	0.017661330	0.005100260	0.005923128	0.000844028	0.018449057	0.009853281	0.011684924
RMSE	0.0048056052	0.048894705	0.006654537	0.007501658	0.002230283	0.029012680	0.032065646	0.019202215
Eff.	86.226010523	68.46307680	99.52123436	99.44509496	99.86972729	97.31631127	98.89048758	98.58110659

Step 1) Input population size, number of decision variables, and maximum of iterations;

Step 2) Generate an initial population of an ecosystem x_i (solutions).;

Step 3) Set current iteration 1;

Step 4) Initialize operator H using (22);

Step 5) Evaluate the fitness function value in (9) for each solution;

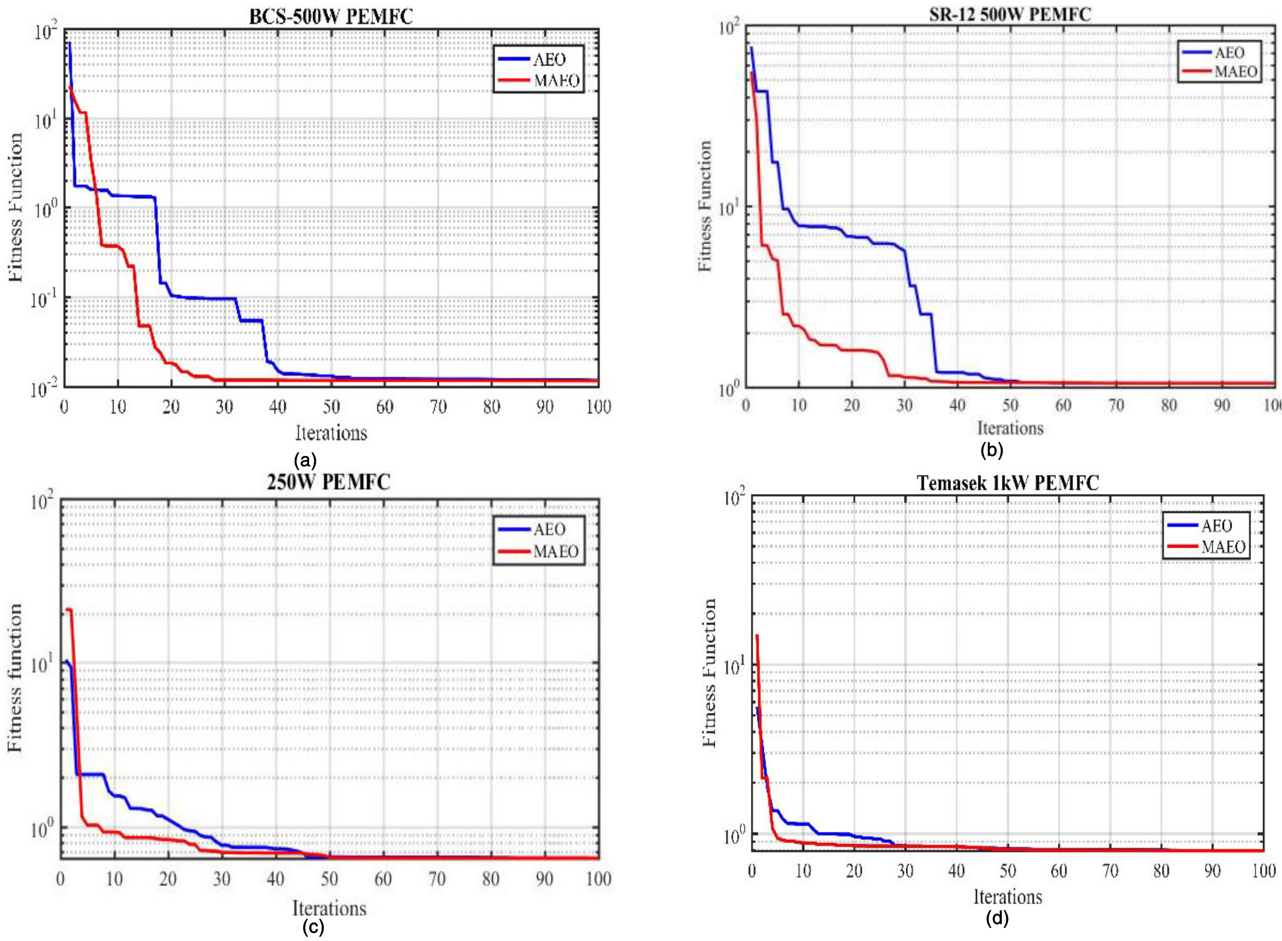


FIGURE 6. Convergence trends for the best execution within 30 individual runs; (a) BCS-500W PEMFC, (b) SR-12 500W PEMFC, (c) 250W PEMFC, and (d) Temasek 1kW PEMFC.

TABLE 4. Optimized parameters of BCS-500W PEMFC stack obtained by different optimization algorithms.

Algorithm	SSE	ξ_1	$\xi_2\times10^{-3}$	$\xi_3\times10^{-5}$	$\xi_4\times10^{-4}$	λ	β	$R_c\times10^{-4}$
MAEO	0.01157	-0.85596	2.73328	6.634280	-1.92816	20.702572	0.016023	1.004526
AEO	0.01167	-1.19106	4.96358	7.01870	-1.28843	22.20886	0.022004	1.86308
HHO	0.08456	-1.12068	3.44419	6.22409	-1.79257	16.19631	0.013601	1.00005
GWO	7.1889	-1.0180	2.3151	5.240	-1.2815	18.8547	0.0136	7.503
SSO	7.1889	-1.018	2.3151	5.240	-1.2815	18.8547	0.0136	7.5036
CS-EO	5.5604	-1.1365	2.9254	3.7688	-1.3949	18.5446	0.013600	8.00
SOA	0.02	-0.75	5.34	9.15	-2.14	22.92	0.02	3.20
SO	0.02	-1.02	5.14	7.96	-2.17	22.86	0.02	3.1
SSA	0.03	-1.01	3.22	5.45	-1.42	20.17	0.01	7.5
GHO [23]	0.02	-0.79	4.12	8.37	-2.12	22.95	0.02	3.7
SBO	7.1902	- 1.1023	2.3212	5.123	- 1.2784	18.8451	0.01321	7.4958

Step 6) Update solution of individual x_1 using (10);

Step 7) If the current iteration is less than the maximum number of iterations, then continue; else end;

Step 8) If $rand < 1/3$ then update its solution using (27);

Step 9) Else If $1/3 \leq rand \leq 2/3$, then update its solution using (28);

Step 10) Else update its solution using (29);

Step 11) End If;

Step 12) End If;

TABLE 5. Optimized parameters of SR-12 500W PEMFC stack obtained by different optimization algorithms.

Algorithm	SSE	ξ_1	$\xi_2\times10^{-3}$	$\xi_3\times10^{-5}$	$\xi_4\times10^{-4}$	λ	β	$R_c\times10^{-4}$
MAEO	1.05663	-0.86068	2.77134	6.19649	-0.954009	22.98870	0.175366	6.70732
AEO	1.05793	-1.19838	1.05009	5.03693	-1.50919	20.04172	0.06079	2.41329
HHO	1.05931	-0.85331	2.41736	4.24879	-0.95412	15.34129	0.17794	3.716654
GWO	1.517	-0.9664	2.2833	3.400	-0.954	15.7969	0.1804	6.6853
SSO	1.517	-0.9664	2.2833	3.400	-0.954	15.7969	0.1804	6.6853
CS-EO	7.5753	-1.0353	3.3540	7.2428	-0.954	10	0.1471	7.1233
VSDE [28]	1.266	−0.8576	3.0100	7.7800	-0.95400	23	0.1516	1.339
SBO	1.496	- 0.9598	2.2901	3.23	- 0.95368	15.8630	0.1812	6.7425

TABLE 6. Optimized parameters of 250W PEMFC stack obtained by different optimization algorithms.

Algorithm	SSE	ξ_1	$\xi_2\times10^{-3}$	$\xi_3\times10^{-5}$	$\xi_4\times10^{-4}$	λ	b	R_c×10-4
MAEO	0.64202	-0.89119	2.264152	3.84106	-1.55950	22.99999	0.05454	1.00019
AEO	0.64295	-1.11090	4.26165	4.98499	-2.13929	19.39091	0.02434	4.78500
HHO	1.02274	-1.16200	4.01800	9.74537	-1.33452	16.68106	0.04784	7.00848
SSO	1.1508	-1.0554	3.7953	9.800	-1.1755	24	0.0136	1.0884
ALO	1.1513	-0.9438	3.4734	9.7898	-1.1811	24	0.0136	1.6530
RGA	8.4854	-1.1568	3.4243	6.4161	-1.1544	12.8989	0.0343	1.4504
MPSO	9.7539	-0.9479	3.0835	7.799	-1.8800	20.7624	0.0296	2.8666
ARNA-GA	2.9518	-0.9470	3.0586	7.6059	-1.8800	23.00	0.0329	1.1026
JAYA-NM	5.2513	-1.19966	3.55	6.00	-1.200	13.2287	0.03334	1.00
HGA	4.8469	-0.94496	3.01801	7.401	-1.880	23.00	0.02914489	1.00
SGA	5.6530	-0.9473	3.0641	7.7134	-1.9390	19.7650	0.0240	2.7197
HADE	7.9908	-0.8532	2.81009	8.09203	-1.2870	14.0448	0.0335374	1.00
TLBO-DE	7.2776677	-0.853200	2.65052	8.001574	-1.360144	15.651416	0.0364609	1.00
VSDE [28]	1.0526	−1.1921	3.199	3.7990	−1.87000	22.8170	0.02903	1.202
MVO	3.5846	−0.9182	3.1299	8.7031	−1.80253	15.1921	0.01800	4.223
GWO [26]	1.1505	−1.0564	3.7953	9.8000	-1.17550	23.000	0. 0136	1.088
SBO [32]	1.1510	−1.0554	3.7953	9.800	−1.1755	24	0.0136	1.0884
ASO [34]	0.7346	- 1.1132	3.6	9.8	-2.00	22.1763	0.0248	1.00

TABLE 7. Optimized parameters of Temasek 1kW PEMFC stack obtained by different optimization algorithms.

Algorithm	SSE	ξ_1	$\xi_2\times10^{-3}$	$\xi_3\times10^{-5}$	$\xi_4\times10^{-4}$	λ	β	Rc×10-4
MAEO	0.79096	-0.85440	3.57655	7.88883	-2.29258	13.00172	0.068260	1.00027
AEO	0.79243	-1.11706	3.82900	4.56767	-2.26309	22.52322	0.11019	1.01920
HHO	0.80553	-0.85320	3.49911	7.21118	-2.44049	22.99963	0.07124	1.826515
GWO	1.6481	-1.0299	2.4105	4.00	-0.9540	10.0005	0.1274	1.0873
SSO	1.6481	-1.0299	2.4105	1.00	-0.9540	10.0005	0.1274	1.0873
SBO	1.6322	-1.0312	2.4095	3.95	- 0.95368	9.9852	0.1269	1.1236

Step 13) Evaluate the objective function value for each individual;

Step 14) Update the best solution found so far x_{best};

Step 15) Update the position of each individual using (18), (19), and (20);

Step 16) Evaluate the objective function value for each individual;

Step 17) Update the best solution found so far x_{best}.

Step 18) End If;

Step 19) Return x_{best}.

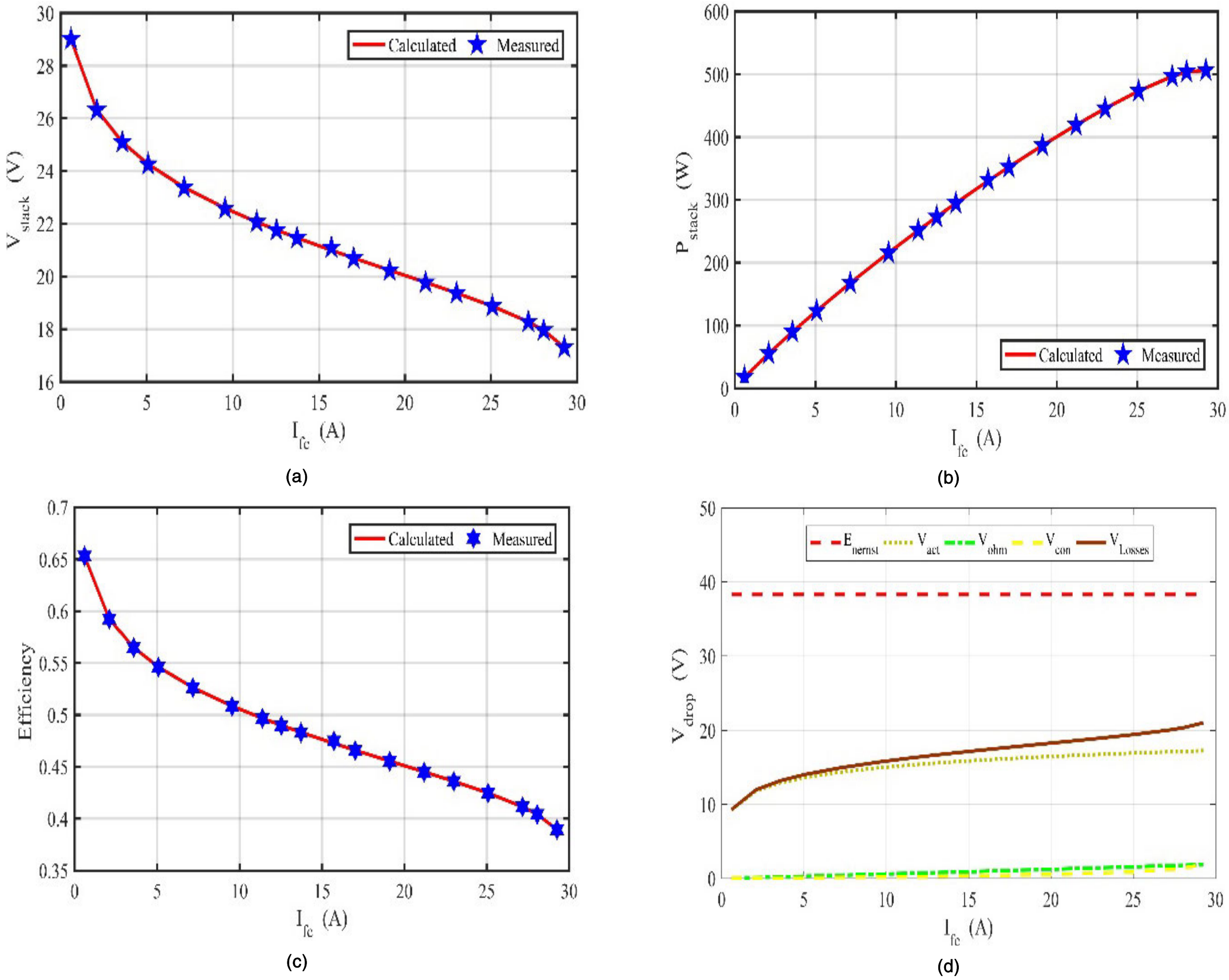


FIGURE 7. Characteristics of BCS 500W PEMFC stack; (a) I-V polarization curve, (b) I-P polarization curve, (c) Efficiency curve, (d) voltage drops of PEMFC stack.

TABLE 8. Calculated and measured values of stack voltages as well as the absolute and relative errors for BCS-500W PEMFC stack.

No.	I_{fc} (A)	Vstack,meas (V)	Vstack,cal (V)	IAE	$(IAE)^2$	RE
1	0.600	29.0000	28.9967	0.0033	0.0000	0.0001
2	2.100	26.3100	26.3075	0.0025	0.0000	0.0001
3	3.580	25.0900	25.0957	-0.0057	0.0000	-0.0002
4	5.080	24.2500	24.2569	-0.0069	0.0000	-0.0003
5	7.170	23.3700	23.3776	-0.0076	0.0001	-0.0003
6	9.550	22.5700	22.5865	-0.0165	0.0003	-0.0007
7	11.390	22.0600	22.0620	-0.0020	0.0000	-0.0001
8	12.540	21.7500	21.7598	-0.0098	0.0001	-0.0004
9	13.730	21.4500	21.4623	-0.0123	0.0002	-0.0006
10	15.730	21.0900	20.9884	0.1016	0.0103	0.0048
11	17.020	20.6800	20.6948	-0.0148	0.0002	-0.0007
12	19.110	20.2200	20.2309	-0.0109	0.0001	-0.0005
13	21.200	19.7600	19.7705	-0.0105	0.0001	-0.0005
14	23	19.3600	19.3653	-0.0053	0.0000	-0.0003
15	25.080	18.8600	18.8658	-0.0058	0.0000	-0.0003
16	27.170	18.2700	18.2746	-0.0046	0.0000	-0.0003
17	28.060	17.9500	17.9539	-0.0039	0.0000	-0.0002
18	29.260	17.3000	17.2959	0.0041	0.0000	0.0002
SSE					0.01157	

V. SIMULATION RESULTS AND DISCUSSION

To check the stability and accuracy of MAEO technique in obtaining the accurate values of unknown parameters of PEMFC stack models, four test cases are carried out on different commercial PEMFC stacks, namely, BCS-500W PEMFC, AVISTA SR-12 500W PEMFC, 250W PEMFC, and

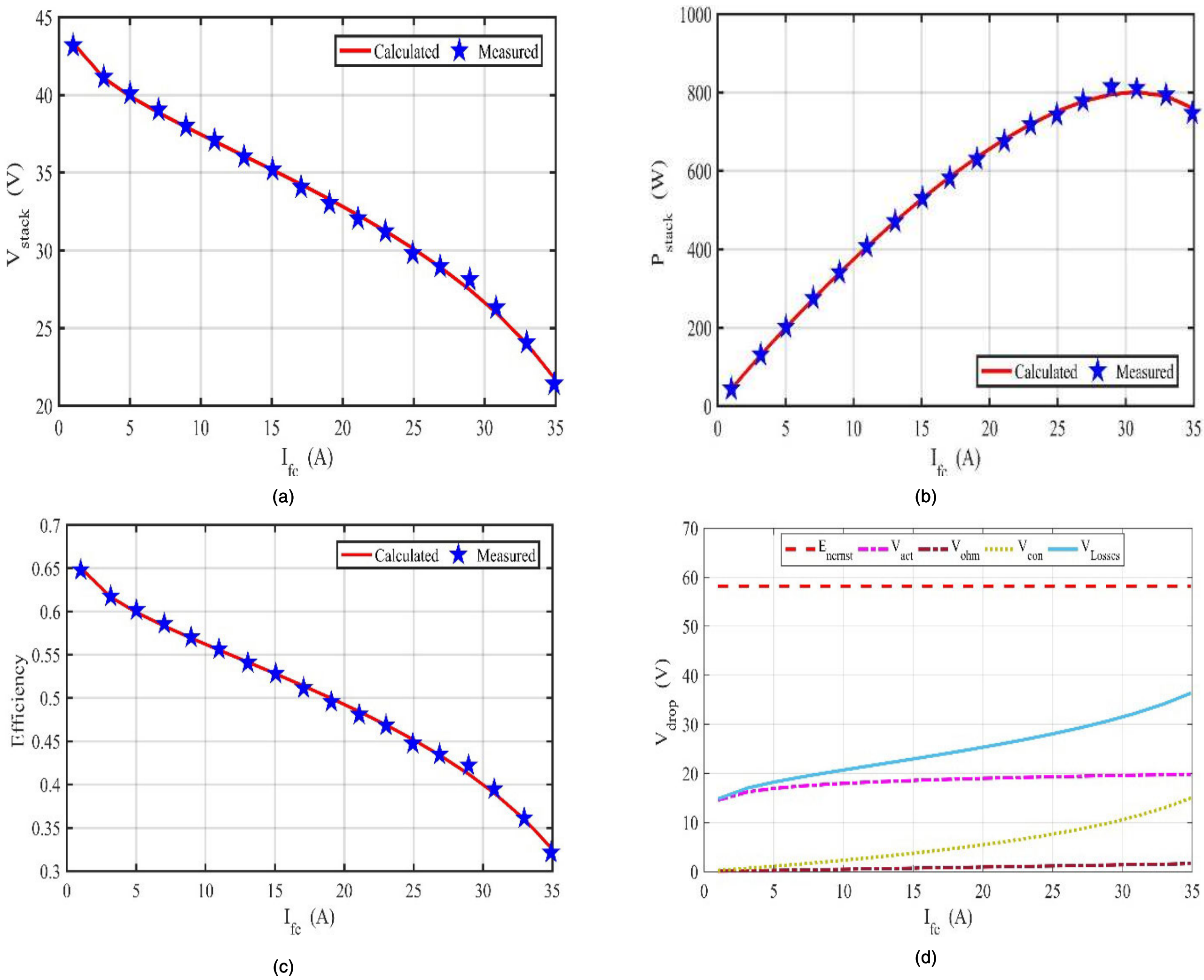


FIGURE 8. Characteristics of SR-12 500W PEMFC stack; (a) I-V polarization curve, (b) I-P polarization curve, (c) Efficiency curve, (d) voltage drops of PEMFC stack.

Temasek 1kW PEMFC stacks. The experimentally measured data of current/voltage (I/V) curves of these FC stacks are utilized to be the input information of the optimization program [24], [30], [31], [33], [45]. The proposed algorithm is used to extract the optimal best parameters of PEMFC stacks which based on the minimum values between these measured data and the calculated ones. The proposed MAEO has been programmed using MATLAB (R2018a) software with personal Laptop which has the following features; Intel Core i3-M370 CPU@2.40GHz with 4.00GB RAM under Microsoft Windows 10. The obtained results of proposed MAEO are compared with the conventional AEO technique and other optimization algorithms used for solving the same studied optimization problem. The optimization algorithm is executed 30 individual runs and the optimized parameters based on the minimum value of the OF are reported. The control variables for both MAEO and AEO techniques in every individual run are adjusted as follows; the max iterations number equals 100 and the population size number equals 20. The main specifications of the four different commercial PEMFC stacks are provided in Table 2. All convergence curves in this study are plotted in semi logy graphs.

A. STATICAL MEASURES AND CONVERGENCE TRENDS

In order to appreciate the stability and accurateness as well as give a clear assessment of the proposed MAEO in obtaining the exact values of PEMFC unknown parameters, a sensitivity and statistical analysis is studied for all studied PEMFC stacks. The statical results of MAEO algorithm are compared with the conventional AEO algorithm with respect to many metrics, basically the best and worst values of the objective function, mean value of the objective function, Median, SD, RE, RMSE, MAE and efficiency. These metrics can be mathematically represented as given in (26) to (30):

$$SD = \sqrt{\frac{\sum_{i=1}^{30}\left(SSE_i - \overline{SSE}\right)}{30-1}} \tag{26}$$

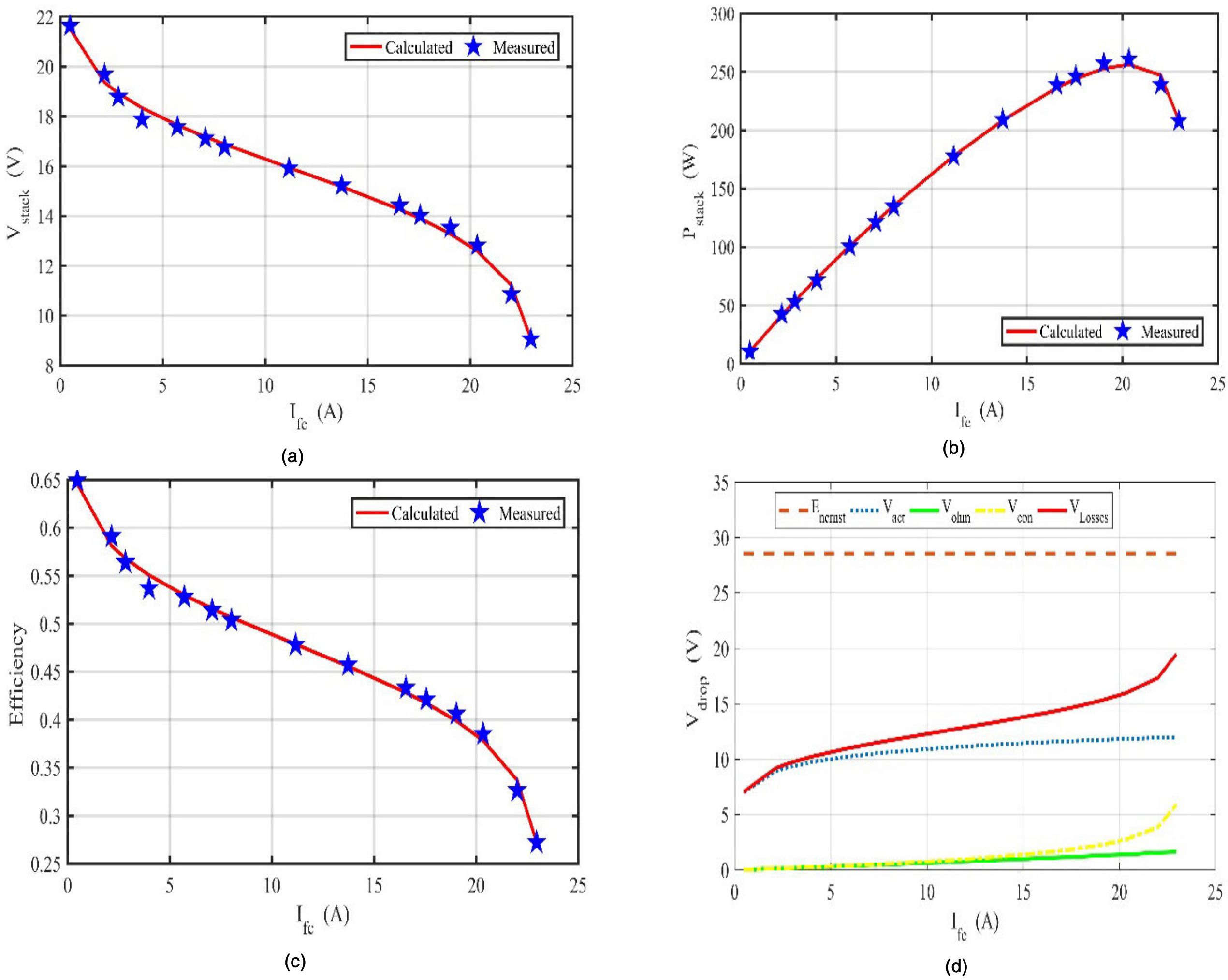


FIGURE 9. Characteristics of 250 W PEMFC stack; (a) I-V polarization curve, (b) I-P polarization curve, (c) Efficiency curve, (d) voltage drops.

$$RE = \frac{\sum_{i=1}^{30} (SSE_i - SSE_{\min})}{SSE_{\min}} \tag{27}$$

$$MAE = \frac{\sum_{i=1}^{30} (SSE_i - SSE_{\min})}{30} \tag{28}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{30} (SSE_i - SSE_{\min})^2}{30}} \tag{29}$$

$$efficiency = \frac{SSE_{\min}}{SSE_i} \times 100\% \tag{30}$$

where, SSE_i denotes the obtained value of OF at the end of each run. SSE_{min} is the minimum optimal value of objective function overall. SSE is the mean value of objective function over the 30 runs of optimization algorithm. The statistical measures values of proposed MAEO compared with AEO for the four commercial PEMFC stacks listed in Table 3. From this table. it is noticed that the proposed AEO gives the minimum values of the objective function compared with the conventional AEO for all types of PEMFC stacks. Therefore, the results obtained from the statistical analysis (the insignificant values of the Min., MAE and RMSE) revealed the robustness and stability of the proposed MAEO in extracting the accurate parameters of all commercial PEMFC stacks included in this study.

The proposed MAEO and AEO have been implemented 30 individual times, and the final values of OF in each individual run have been reported. The convergence characteristics of OF for all PEMFC stacks over the 30 individual runs are provided in Fig. 4., while the final values of OF over each implementation are presented in Fig. 5.

From Fig. 5., it is observed that best minimum values of the cost function obtained by the MAEO oscillate in a very small range with few numbers of overshoots compared with those obtained by the conventional AEO algorithm. Therefore, the calculated results prove the stability and superiority of the MAEO algorithm in solving the studied optimization problem.

The convergence trends based on the best OF value within the 30 individual runs for all studied PEMFC stacks by the application of MAEO and conventional AEO algorithms are

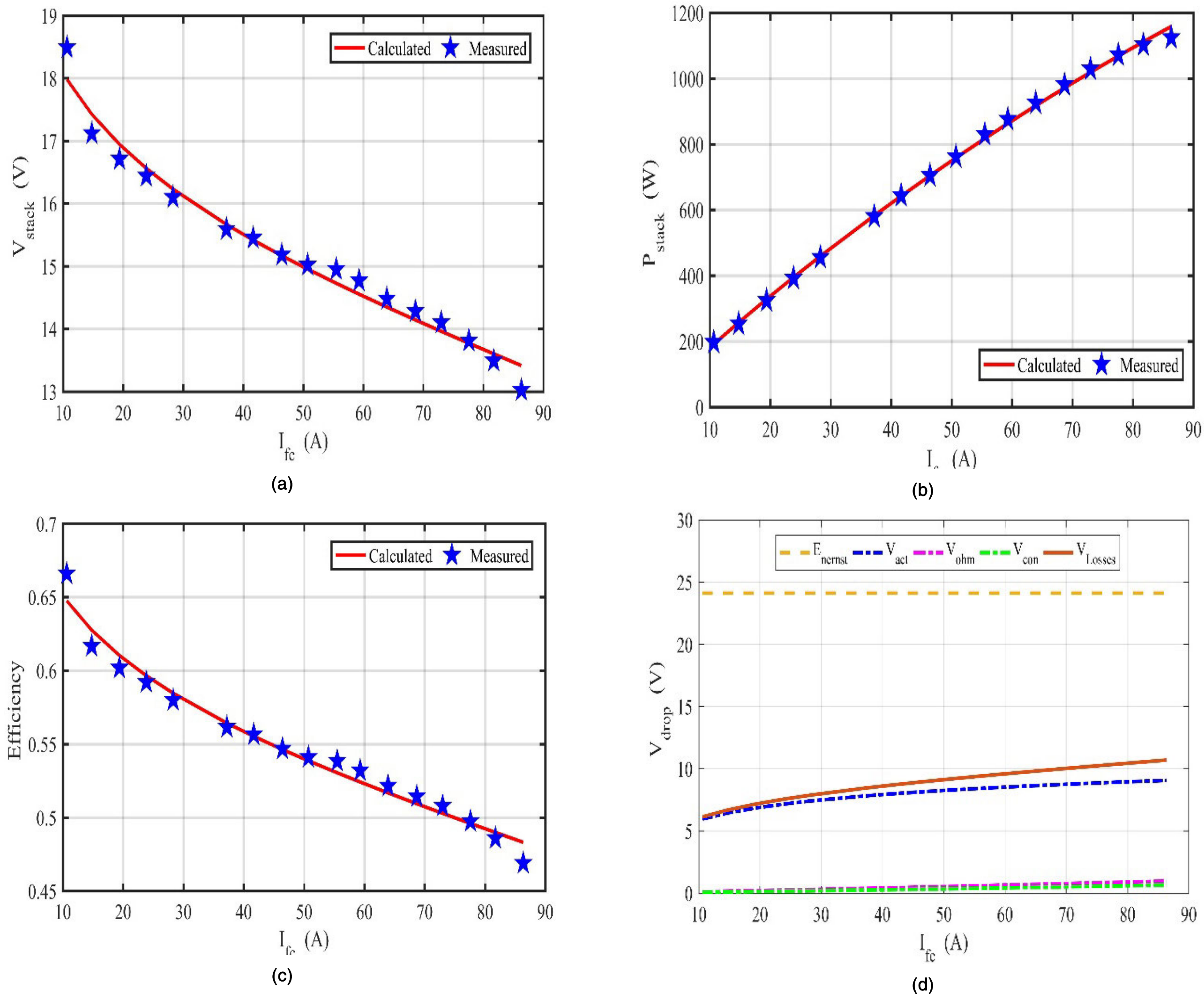


FIGURE 10. Characteristics of Temasek 1kW PEMFC stack; (a) I-V polarization curve, (b) I-P polarization curve, (c) Efficiency curve, (d) voltage drops of PEMFC stack.

shown in Fig. 6(a) to Fig. 6(d). It is clearly noticed that the convergence curves obtained by the MAEO is faster than that obtained from the conventional AEO as well as gives the minimum value of the objective function.

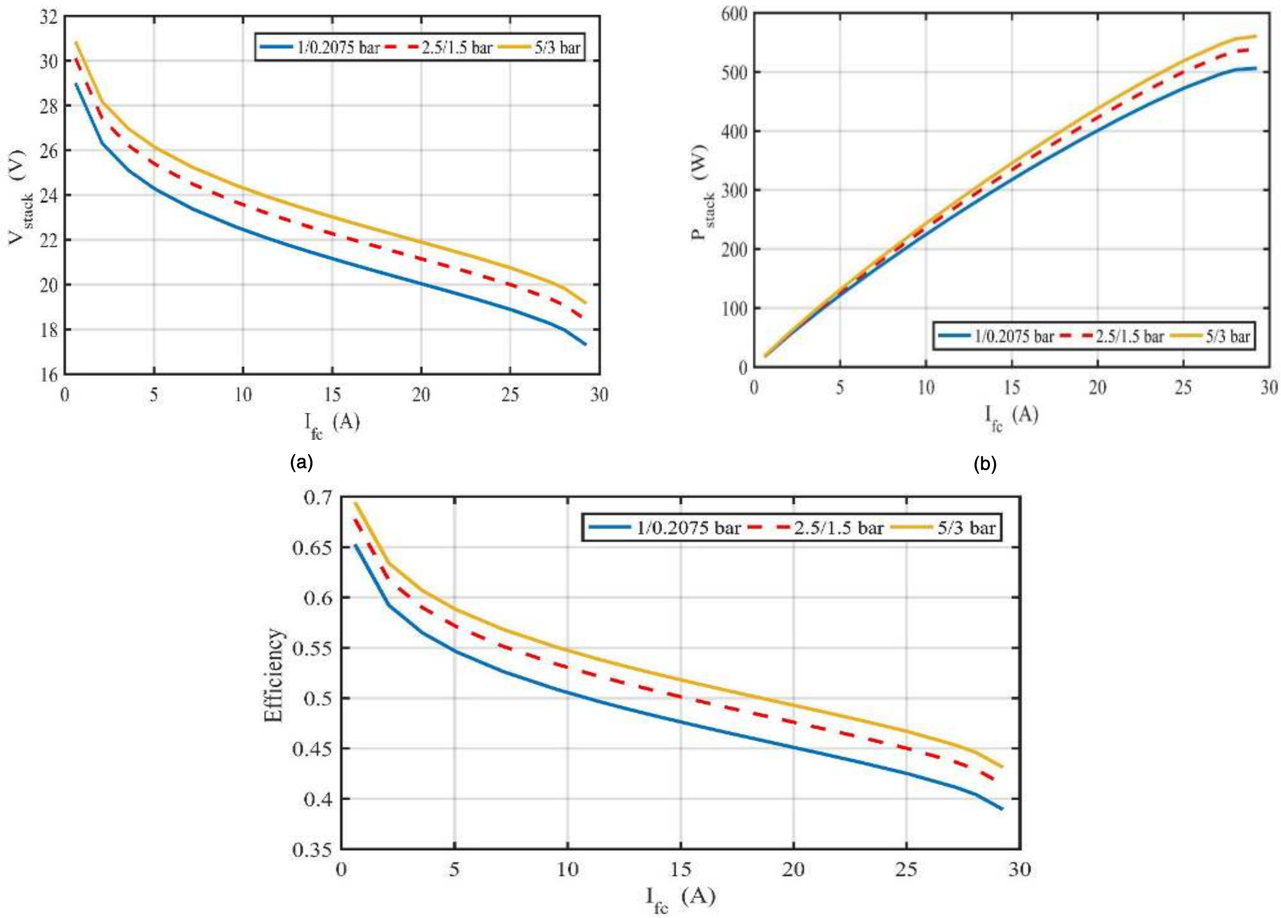
B. EXTRACTION OF PEMFC SEVEN PARAMETERS

In this subsection, the simulation results are performed based on the best minimum value of OF within the 30 individual runs. The optimized values of the seven unknown parameters of different commercial PEMFC stacks obtained from the MAEO algorithm and compared with other optimization algorithms. These optimized parameters as well as the minimum OF values of BCS-500W PEMFC, SR-12 500W PEMFC, 250W PEMFC and Temasek 1Kw PEMFC are listed in Tables 4, 5, 6, and 7, respectively. From these tables, it is observed that the MAEO algorithm gives the best value of fitness function compared with the conventional AEO algorithm and other optimization algorithms.

The efficiency of the PEMFC stack can be expressed as [8]:

$$\eta_{stack} = \mu_F \times \frac{V_{stack}}{v_{\max} \times V_{stack}} \tag{31}$$

where, $v_{\max}$ represents the maximum generated voltage under high temperature conditions, and μ_{F} denotes the factor of utilization, which depends on the flow rate hydrogen gas. According to the values listed in [8], the maximum output voltage per cell is 1.48 volt and the factor of utilization is taken as 95%. The polarization curves (*I-V, P-I and Efficiency*) as well as the voltage losses occurred inside the stack which obtained by MAEO are compared with the measured curves of BCS-500W, SR-12 500W, 250W and Temasek 1kW PEMFC stacks and shown in Figs. 7 to 10., respectively. From these figures, it is clearly observed that the simulated polarization curves provide a good matching with the experimentally measured curves, which confirm the reliability of the proposed algorithm.



(a) (b) (c)

FIGURE 11. Characteristics of BCS 500W PEMFC stack under variation of hydrogen /oxygen pressures; (a) I-V curve, (b) I-P curve, (c) Efficiency curve.

TABLE 9. Calculated and measured values of stack voltages as well as the absolute and relative errors for 250W PEMFC stack.

No.	I_{fc} (A)	Vstack,meas (V)	Vstack,cal (V)	IAE	$(IAE)^2$	RE
1	0.4717	21.63	21.5099	0.1201	0.0144	0.0056
2	2.149	19.68	19.3622	0.3178	0.1010	0.0164
3	2.83	18.78	18.9245	-0.1445	0.0209	-0.0076
4	3.983	17.88	18.3389	-0.4589	0.2106	-0.0250
5	5.713	17.58	17.6445	-0.0645	0.0042	-0.0037
6	7.075	17.12	17.1771	-0.0571	0.0033	-0.0033
7	8.019	16.77	16.8763	-0.1063	0.0113	-0.0063
8	11.16	15.92	21.5099	-0.0185	0.0003	-0.0012
9	13.73	15.22	19.3622	0.0425	0.0018	0.0028
10	16.56	14.42	18.9245	0.1572	0.0247	0.0110
11	17.56	14.02	18.3389	0.1230	0.0151	0.0089
12	19.03	13.52	17.6445	0.2371	0.0562	0.0179
13	20.34	12.82	17.1771	0.2214	0.0490	0.0176
14	22.01	10.86	16.8763	-0.3592	0.1291	-0.0320
15	22.96	9.058	21.5099	-0.0101	0.0001	-0.0011
SSE					0.64202	

To ensure more validation, the calculated values of stack voltages are compared with the experimentally measured stack voltages. The deviation between the calculated and measured stack voltages is appreciated through IAE and RE. These errors can be computed as expressed in (32) and (33), respectively. The computed voltage values of IAE and RE of

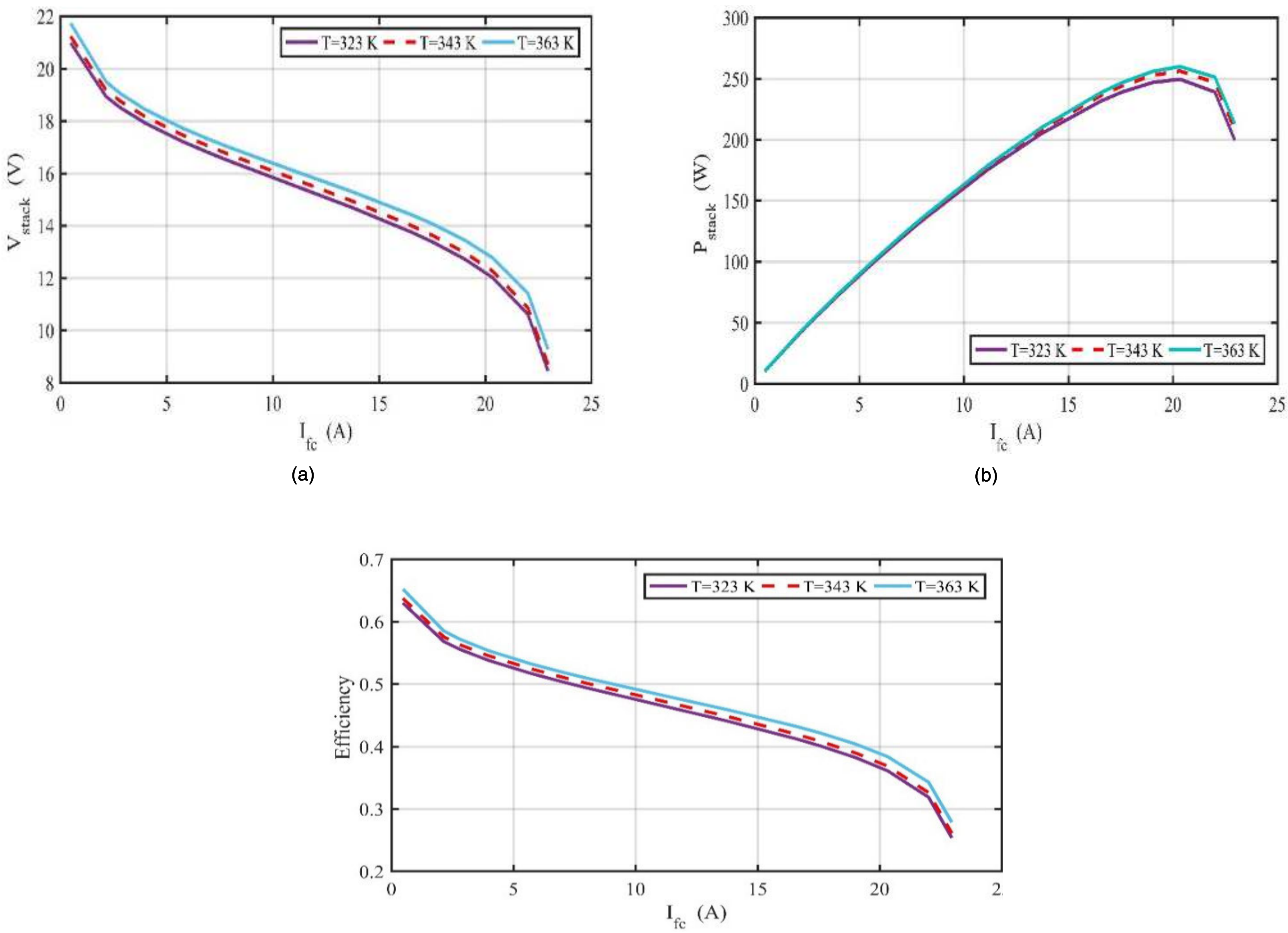


FIGURE 12. Characteristics 250 W PEMFC stack under variation of cell temperature; (a) I-V curve, (b) I-P curve, (c) Efficiency curve.

BCS-500W PEMFC and 250W PEMFC stacks are provided in Table 8 and Table 9, respectively.

$$IAE = \left|V_{stack,meas} - V_{stack,cal}\right| \tag{32}$$

$$RE = \left(V_{stack,meas} - V_{stack,cal}\right)/V_{stack,cal} \tag{33}$$

C. DYNAMIC OPERATION OF PEMFCS STACKS

In order to check the stability and accuracy of the proposed optimization algorithm, the effect of changing the cell temperature and reactants pressures is studied. To avoid duplication of drawn figures, based on the optimized parameters obtained by MAEO, the polarization curves of 250W PEMFC stack at different values of cell temperature are reported, whereas the influence of H_2 and O_2 pressures variation is studied for BCS-500W PEMFC stacks. The polarization curves (*I-V, I-P and efficiency*) of the BCS-500 W PEMFC stack at different pressures of 1/0.2075bar, 2.5/1.5bar and 5/3bar are shown in Fig. 11., while the values of cell temperature are kept constant at the value provided in the manufacturer datasheet. The polarization curves of the 250 W PEMFC stack at different temperatures at 323K, 343K, and 363K with constant cell temperature at 343.15K are shown in Fig. 12., while the values of H_2 and O_2 pressure are maintained constants at the values listed in the manufacture datasheet of 250W PEMFC stack. From Fig. 11. and Fig. 12., it is clearly observed that with increasing the reactants pressures and cell temperature, the generated power and voltage as well as the efficiency of PEMFC stack are increased.

VI. CONCLUSION

In this study, the MAEO algorithm has been proposed and applied to extract the optimized values of unknown parameters of different commercial PEMFC stacks. MAEO has been proposed to improve the performance of the conventional AEO. The stability of proposed algorithm has been validated through testing on four various commercial PEMFC stacks. A comprehensive statistical analysis has been studied to confirm the reliability and robustness of the proposed algorithm. In addition, the optimized parameters have been used to show the impact of cell temperature and oxygen/hydrogen pressures variations of different PEMFC stacks. The obtained results have been comprehensively compared with some well-known optimization algorithms. Moreover, the polarization curves obtained by the application of proposed MAEO algorithm have been emphasized a good matching with the experimental curves. Based on the simulation results, it was observed that the proposed optimization algorithm confirmed its reliability and efficiency in extracting the precise parameters of complex and semi-empirical PEMFC stack models compared with other recent algorithms. In the future study, the proposed algorithm can be used to solve other complex optimization problems.

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