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A new method for optimal parameters identification of a PEMFC using an improved version of Monarch Butterfly Optimization Algorithm

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HIGHLIGHTS

- A new technique proposed for optimal selection of PEMFC parameters
- The method is based on a new model of Coyote Optimization Algorithm
- The achieved results showed a good confirmation by the experimental data

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ABSTRACT

In this paper, a circuit-based model of proton exchange membrane fuel cell (PEMFC) is developed for optimal selection of the model parameters. The optimization is based on using an improved version of Monarch Butterfly Optimization (IMBO) algorithm for minimizing the Integral Time Absolute Error between the measured output voltage and the output voltage of the achieved model. For validation of the proposed method, two different case studies including 6 kW NedSstack PS6 and 2 kW Nexa FC PEMFC stacks have been employed and the results have been compared with the experimental data and some well-known metaheuristics including Chaotic Grasshopper Optimization Algorithm (CGOA), Grass Fibrous Root Optimization Algorithm (GRA), and basic Monarch Butterfly Optimization (MBO) to indicate the superiority of the proposed method against the compared methods. Final results show a satisfying agreement between the proposed IMBO and the experimental data.

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Circuit-based model
Integral time absolute error

Introduction

A set of different factors such as fossil resource constraints, negative environmental impacts, hydrocarbon utilization, rising fossil fuel prices, political conflicts and its effects on sustainable energy supply force the policy makers and experts to move towards the creation of a new technology with higher security of energy supply, environmental protective, and higher energy system efficiency [1–3]. Accordingly, hydrogen is one of the best options to play as a safe alternative in this new energy delivery system. Hydrogen as the most abundant element on Earth is produced in various ways. The provided electricity from renewable sources such as wind, solar, and geothermal can be used for hydrogen generation [4–6]. The generated hydrogen is then saved and transferred to the locations to be used in a variety of applications, including small electronics, transportation industry, and power plants. However, many people believe that the ultimate fuel for the human society is hydrogen and that human will be experienced the hydrogen era in a not too distant future. Some prominent features of the hydrogen that distinguish it from other fuel options are its abundance, almost unique consumption, negligible emission of pollutants, reversibility of its production cycle, and reduced greenhouse effects. Hydrogen power system due to independence from primary energy sources, is a permanent, sustainable, immovable, inclusive and renewable system and it is predicted that in the near future, its production and consumption as energy carrier will spread throughout the world economy and stabilize the hydrogen economy. However, one should not expect hydrogen to compete with other energy carriers in terms of cost of production at the beginning step, in the future hydrogen will play a central role in controlling urban pollution. The conversion of chemical energy in hydrogen into electrical energy is carried out by fuel cells. Fuel cells have great potential as one of the future energy sources in hybrid systems due to their many advantages and rapid advancement in their technology [7,8]. Hydrogen, after being extracted from hydrocarbon or water sources, is considered as a sustainable fuel in energy sources by fuel cells. Nowadays, due to the expansion of wind and solar power sources in different countries and the availability of high and low-cost energy, the possibility of hydrogen extraction from the electrolysis process of water has become economical [9]. Therefore, the use of fuel cells in hybrid systems as one of the sources of energy conversion and generation along with solar and wind energy sources is a serious option. A more popular type among fuel cells is proton-exchange membrane fuel cell (PEMFC) [10]. PEMFC are high-efficiency power generators that can achieve 40%–50% electrical efficiency at different power scales. The basis of energy production in PEMFCs is the exothermic reaction between hydrogen and oxygen present in the air. The result of this reaction is electricity, heat and distilled water. The benefits of PEMFCs such as lighter weight, solid electrolyte, short start-up time without noise, variability, and the ability to renew the system in a closed cycle independent of the battery have attracted research into replacing the polymer fuel cell system with satellite batteries [11,12].

Generally, mathematical modeling of the PEMFCs is an important category that can be used for optimal designing the system [13,14]. This modeling is based on considering physical and electrochemical processes to govern the fuel cell efficiency [15–18]. The model includes a differential equation system along with its determined constraints to define the transition processes and their relations. Based on the explained cases and due to the importance of the PEMFC modeling, several researchers have been worked on this subject [19].

Rahman et al. [20] presented both modeling and empirical results for a PEMFC operating based on its open circuit voltage to restricting current conditions. The results were verified by limiting current tests and polarization curves based on different operation conditions. Simulations showed that the proposed 1-D dry model has a good agreement with experimental results.

Yang et al. [21] employed an adaptive neuro-fuzzy inference system (ANFIS) for modeling a 250 W PEMFC that is placed on an electric bicycle. To determine the system configuration, humidity, temperature, hydrogen, oxygen flowrate, and current were adopted as the inputs and the efficiency and the voltage were considered as the outputs of the ANFIS. Simulation results showed that using ANFIS for modeling the PEMFC gives a reliable and accurate result to predict the PEMFC performance. However, the classic methods and the ANN gave logical results, by introducing the metaheuristics, the researchers were attracted to use these types of solvers to resolve the modeling problem with a simple and time saving procedure. For example, Yang et al. [21] proposed a hybrid neural network and metaheuristic for parameter estimation of a proton exchange membrane fuel cell (PEMFC). They used a new hybrid optimization algorithm, called hybrid world cup optimization (WCO) and fluid Search Optimization (FSO) algorithm to optimize the efficiency of an improved version of Elman neural network. The method was also verified based on four different operational conditions. Simulation results were compared with some well-known metaheuristics and the results showed higher efficiency with good agreement with the experimental data of the PEMFC.

Yin and Razmjooy [22] proposed another optimal method based on deer hunting optimization (DHO) algorithm to estimate the PEMFC parameters. The DHO algorithm has been adopted to improve PEMFC parameters identification. The method was then verified based on different operational conditions and the results were compared with different

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algorithms. Final results indicated the superiority of the method in achieving the PEMFC model parameters.

Cao et al. [15] presented another optimized model for parameter identification of the PEMFCs. The main objective was to propose a developed model of seagull optimization algorithm to optimal selection of the PEMFC stack parameters. Two experimental-based data including BCS 500-W and NedStack PS6 were used for algorithm verification and the results were compared with some different optimization algorithms to show the method's higher efficiency.

This study presents a new developed metaheuristic technique with desirable search ability with the ability of making good trade-off between exploration and exploitation search for optimal selection of the PEMFC stack model parameters, i.e. the proposed developed algorithm improves the basic algorithm in terms of diversity and balance of exploitation and exploration. The algorithm also attempts to resolve the basic algorithm premature convergence shortcoming. The total contributions of the algorithm are briefly given below:

- Designing a new improved metaheuristic for parameter estimation of PEMFC.
- The method is based on a new model of Monarch Butterfly Optimization Algorithm.
- The method is verified by two empirical data, NedSstack PS6 and Nexa FC.
- The final configuration is compared with empirical data and some well-known algorithms.

The rest of the paper is organized as follows: Dynamic mechanism of model of proton exchange membrane fuel cell discusses about the model of the PEMFC, in Monarch Butterfly Optimization algorithm, the improved version of Monarch Butterfly Optimization as one contribution of this paper is briefly explained. Simulation results illustrates the simulation results of the proposed method on two experimental case studies and the paper is concluded in Conclusion.

Dynamic mechanism of model of proton exchange membrane fuel cell

PEMFC modeling

PEMFCs consist of a series of electrode membranes including electrodes, electrolytes and catalysts, and gas diffusion layers. A layer of catalyst, carbon, and electrode is sprayed onto the solid electrolyte and a carbon sheet is pressed on each side to protect the cell and act as the electrode [23]. The most basic part of the triple phase boundary cell (TPB) is where the electrolyte, the catalyst, and the reactants are fused together or where the cell's primary reaction occurs. The important point is that the membrane should not be electrically conductive so that half the reactions are not mixed. A fuel cell with a polymer membrane converts the chemical energy released during the electrochemical reaction of hydrogen and oxygen into electrical energy, in contrast to the direct combustion process of hydrogen and oxygen gases that generate thermal energy. The hydrogen gas enters the fuel cell from the anode side. At the anode and adjacent to the catalyst it becomes a proton and an electron. Hydrogen oxidation is expressed as follows:

$$H_2 \rightarrow 2H^+ + 2e^- \quad (1)$$

The proton penetrates the cathode through the electrolytic membrane. The electrons also move to the cathode through the outer charge circuit, which generates the electrical current of the fuel cell output. In the meantime, a stream of oxygen enters the fuel cell through the cathode, forming a chemical reaction with water molecules in combination with protons transported from the anode and electrons through the outer orbit. This oxygen resuscitation reaction is formulated below:

$$\text{Cathode: } 2H^+ + \frac{1}{2}O_2 + 2e^- \rightarrow H_2O \quad (2)$$

And the overall reaction is as follows:

$$\text{Overall: } H_2 + \frac{1}{2}O_2 \rightarrow H_2O \quad (3)$$

The reverse reaction is expressed in the above equations, showing the re-fusion of the protons of hydrogen and electron together with the oxygen molecule and the production of the water molecule. Fig. (1) shows a basic structure of a PEMFC.

To provide a basic perception about PEMFC for analyzing its output parameters including current density and output voltage, the mathematical model has been required. The output voltage of a PEMFC stack can be formulated as follows.

$$V_{FC} = E_{Nerst} - V_{act} - V_{con} - V_{\Omega} \quad (4)$$

where, V_{Ω} represents the ohmic overpotential voltage, V_{con} describes the concentration overpotential, V_{act} determines the activation overvoltage, and E_{Nerst} represents the Nernst potential and is obtained as following:

$$E_{Nerst} = V^* - k_E T_{FC} - \lambda_e I(s)\frac{\tau_e s}{\tau_e s + 1} + \frac{RT}{2F}\left(\ln pH_2 + \frac{1}{2}\ln P_{O_2}\right) \quad (5)$$

where, V^* represents the reference voltage, T_{FC} determines the temperature of fuel cell (°C), λ_e is a constant factor (Ω), F stands for the Faraday constant, k_E represents the empirical constant (V/K), and P_{O_2} and pH_2 determine the oxygen and hydrogen partial pressures (Pa). Fig. (2), shows a circuit model of the output voltage for PEMFC.

If n cells accumulated with a fuel cell system, the voltage V_{out} is achieved as follows:

$$V_T = N \times V_{FC} \quad (6)$$

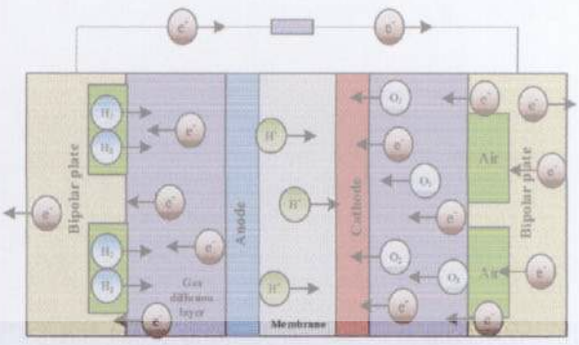

Fig. 1 – The basic structure of a PEMFC.

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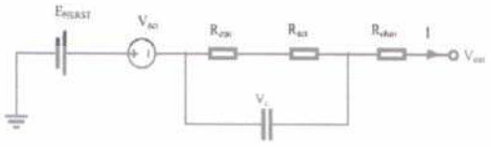

Fig. 2 – The circuit-model of a PEMFC.

Based on literature review, there are some research works with determinative differences between the membrane-electrode connection voltage levels of identical fuel cells at the same conditions that makes V^* as a parameter that should be selected optimally [24]. τ_e and λ_e are two other parameters in model that should be optimally selected. Another part of model that needs optimization for its unknown parameters is ohmic resistance. Based on the electrical modeling from Fig. (2), this term can be achieved by the following equation:

$$R_{ohm} = R_m + R_t \tag{7}$$

where, R_t stands for the equivalent resistance for the transferred protons through the membrane, and R_m represents the membrane resistance that is achieved as follows [25]:

$$R_m = \frac{181.6 \times l \times \left[1 + 0.03 \times \frac{I}{A} + 0.062 \times \left(\frac{T_{FC}}{303}\right)^2 \times \left(\frac{I}{A}\right)^{2.5}\right]}{A \times \left(\phi - 0.634 - \frac{3I}{A}\right) \times e^{\left(4.18 \times \frac{T_{FC}-30}{T_{FC}}\right)}} \tag{8}$$

where, l describes the fuel cell thickness, and ϕ represents an adjustable parameter that depends to the relative humidity, the membrane age, and the anode gas stoichiometric ratio. Here, l and ϕ are also considered as two unknown parameters that should be optimized.

Also, the mass transport losses decrease the concentration of the reactant on the surface of electrodes. This term can be formulated as follows [26].

$$R_{con} = B \times I^{-1} \times \ln\left(\frac{I_{mr}}{I_{mr} - I}\right) \tag{9}$$

where, B represents an experimentally value which depends to the operation state of the cell, and I_{mr} describes the maximum current ratio of the electrode and is obtained by the following Eq. (26).

$$I_{mr} = D \times N_r \times F \times C_b \times \tau^{-1} \tag{10}$$

where, D describes the reacting effective diffusion, N_r represents the number of electrons that are adopted for the reaction, C_b determines the bulk concentration, and τ stands for the thickness of the diffusion layer.

From Fig. (2), model contains a capacitor to simulate the effect of double-layer charging between the membrane and porous cathode. This voltage is obtained by the following equation:

$$V_c = \left(I - C\frac{dV_c}{dt}\right) \times (R_{con} + R_{act}) \tag{11}$$

Since the capacitance parameter (C) has some uncertainties due to the porous behavior of PEMFC, this term has been assumed as an unknown parameter for optimization.

Another term of the model based on Fig. (2) is the activation loss that decreases the speed of the reactions on the surface of electrode. This term is mathematically formulated as follows:

$$V_{act} = \xi_1 + \xi_2 \times T + \xi_3 \times T_{FC} \times \ln(CO_2) + \xi_4 \times T_{FC} \times \ln(I) \tag{12}$$

where, ξ_i points to pseudo-experimental values, and CO_2 defines the oxygen concentration at the cathode/gas interface ($mol.cm^{-3}$) and is achieved as follows:

$$CO_2 = pO2 \times 5.08 \times 108 \times e - 498T - 1 \tag{13}$$

And CH_2 defines the Hydrogen concentration at the anode membrane/gas interface ($mol.\ cm^{-3}$) as follows:

$$CH_2 = p_{H_2} \times \left[10.9 \times 10^7 \times e^{\left(\frac{T}{T}\right)}\right]^{-1} \tag{14}$$

The main parameter values for the PEMFC model are given in Table 1 [24,27,28].

PEMFC model parameters optimization

For optimal selection of the aforementioned unknown parameters, a new optimization algorithm has been employed. The purpose of this algorithm is to minimize the Integral of Absolute Error (IAE) value between the optimized model voltage and the actual voltage that is extracted from experimental data. The IAE minimization as an objective function is given in the following equation:

$$\min \sum_{i=1}^{m} \left| V_{FC}^i - V_{ident}^i \right| \tag{15}$$

where, m stands for the number of empirical data for training, and V_{FC} and V_{ident} describe the actual and the estimated voltages for the PEMFC stack, respectively. Eq. (15) will be performed subject to the following constraints (Table 2):

As can be observed, due to using interval constraints instead of algebraic equations, classic optimization methods fail to achieve the global minimum of this problem. This reason made us to design a metaheuristic-based optimization algorithm to solve the optimal parameter identification problem of the PEMFC stack model.

In recent years, the application of metaheuristic-based methods for solving parameter identification is exponentially increasing [29–33]. Metaheuristic-based methods often have been inspired by different nature phenomena. For

Table 1 – The main parameter values for the PEMFC model [24,27,28].

Parameter	Value	Unit
V^*	1.229	V
λ_e	3.3	Ω
τ_e	80	s
F	96.487	kC/mol
R_t	300	μΩ
ϕ	<23	–

Table 2 – The required limitations for the unknown parameters for optimization.

Parameter	Minimum value	Maximum value	Unit
C	0.1	10	F
A	90	130	cm^2
B	0.01	0.1	V
l	51	89	m
λ_e	0	0.01	Ω
V^*	0.1	2	V
ϕ	1	23	–
ξ_1	0	1	–
ξ_3	0	1×10^{-4}	–
ξ_4	0	1×10^{-3}	–

And, $\xi_2 = 0.003 + 0.0002\ln(A) + 43 \times 10^{-6}\ln(C_{H_2})$.

instance, Emperor Penguin Optimizer (EPO) inspired based on the swarm living of emperor penguins, Coyote Optimization Algorithm (COA) [42] inspired by coyotes survival behavior in the nature, Deer Hunting Optimization Algorithm (DHOA) [43] inspired based on how to hunt the deer.

Among different aforementioned metaheuristics, one of the newest efficient algorithms is Monarch Butterfly Optimization (MBO) that is introduced by Wang et al., in 2019. This algorithm simulates the unique behavior of the monarch butterflies as the only species which migrate to the tropical zones like birds. The main purpose of this paper is to improve this algorithm's efficiency by applying some new mechanisms for PEMFC parameter identification.

Monarch Butterfly Optimization algorithm

Basic Monarch Butterfly Optimization (MBO) algorithm

Monarch Butterfly Optimization (MBO) Algorithm starts with a random and uniform population that is called monarch butterflies population. This population includes the solution candidates of the problem. MBO divides the population into two groups: Land 1 and Land 2. Therefore, the number of monarch butterfly individuals in subpopulation Land 1 and Land 2 are as follows:

$$\text{Land } 1 = NP_1 \times \text{ceil}(p \times NP) \tag{16}$$

$$\text{Land } 2 = NP - NP_1 \times (NP_2) \tag{17}$$

where, NP describes the total number of populations, $ceil(x)$ rounds x to the nearest integer greater than or equal to x, and p determines the monarch butterflies' ratio in Land 1. The new child population in the algorithm is generated by the monarch butterfly parents of both Lands. In the event that the parent has better value than the generated child, to keep the population number constant, it has been replaced with the child. This keeps efficient patents for the next generation. This conception can be formulated as follows:

$$x_{i,k}^{t+1} = x_{r_1,k}^{t} \tag{18}$$

where, $x_{i,k}^{t+1}$ describes the kth element of position (x_i) of monarch butterfly i at generation $t+1$, $x_{r_1,k}^{t}$ defines the kth updated element of x_{r1} for the individual r_1, and t represents the number of current iterations. The individual r_1 is randomly selected from Land 1. If r has less value than or equal to p, r is achieved by the following equation:

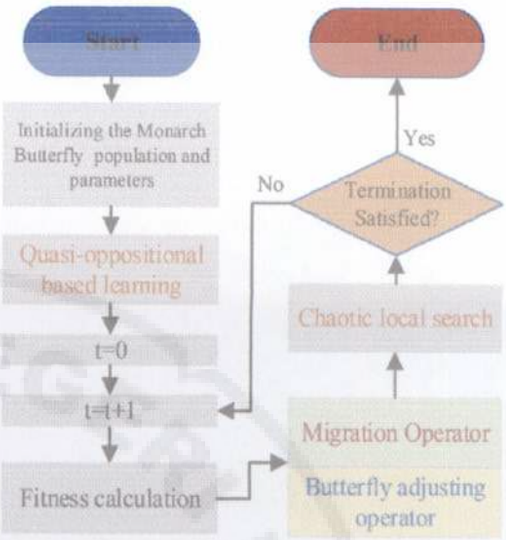

Fig. 3 – The flowchart diagram of the proposed IMBO.

$$r = \rho \times \tau \tag{19}$$

where, τ describes the period of migration, and ρ defines a uniform and random number. In contrast, if the p has a value less than r, the element k for the new butterfly is achieved by the following:

$$x_{i,k}^{t+1} = x_{r_2,k}^{t} \tag{20}$$

where, $x_{r_2,k}^{t}$ describes the kth updated element of x_{r1} for the individual r_1 that is obtained randomly from the Land 2. An interesting advantage of the algorithm is in making a logical trade-off between Land 1 and Land 2 such that when p has bigger value, a large number of populations is selected from Land 1, otherwise, most of population will be selected from Land 2. If the generated child for the monarch butterfly i has smaller value than or equal to p, the position has been updated as follows:

$$x_{i,k}^{t+1} = x_{\text{Best},k}^{t} \tag{21}$$

where, $x_{\text{Best},k}^{t}$ describes the kth individual of x_{Best} that gives the best result in the population.

If p has a value less than ρ, the position has been updated as follows:

$$x_{i,k}^{t+1} = x_{r_3,k}^{t} \tag{22}$$

$$r_3 \in [1, 2, \ldots, NP_2] \tag{23}$$

where, $x_{r_3,k}^{t}$ describes the kth randomly selected member of x_{r_3} from Land 2.

During the algorithm, if the rate of butterfly adjustment (R_{ba}) is less than ρ, the position has been updated as follows:

$$x_{i,k}^{t+1} = x_{i,k}^{t} + \alpha \times (dx_k - 0.5) \tag{24}$$

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where, dx represents the walk step of the individual i and is achieved as follows:

$$dx = \text{Levy}(x_i^t) \tag{25}$$

where, α points to the weighting coefficient, such that:

$$\alpha = \frac{sm}{t^2} \tag{26}$$

where, sm represents the maximum walk step that is passed by a butterfly in one step.

By considering a big value for α, a long search step has been resulted that increases the impact of dx on $x_{j,k}^{t+1}$ applied to the exploration term. In other hand, if α has small value, short search step will be made for $x_{j,k}^{t+1}$ and will result and exploitation mechanism.

Improved monarch butterfly optimization (IMBO) algorithm

Based on aforementioned explanations, excessive exploration of MBO algorithm during high value of α gives an incompetent time-consuming result after some iterations. For resolving this problem, two different mechanisms have been employed that are explained in the following.

Quasi-oppositional based learning

To understand the conception of Quasi-oppositional mechanism, the oppositional-based learning should be first explained. The oppositional-based learning is a term for improving the precision and the convergence speed by comparing of the considered candidate with its opposite and selecting the best one as the new candidate [34,35]. For better illustration of the opposite number, consider NP as a real number in a D-dimensional search space limited in the interval $[L, U]$. The opposite of the candidate NP is defined by $\widehat{NP}$ and is achieved by the following:

$$\widehat{NP}_i = L_i + U_i - NP_i \tag{27}$$

$$i = 1, 2, \ldots, D \tag{28}$$

By considering the definition of opposite number, the quasi-opposite number is defined by $\widehat{NP}$ as follows [36]:

$$\widehat{NP}_i = \text{rand}\left(\frac{U_i + L_i}{2}, NP_i\right) \tag{29}$$

This mechanism can be briefly explained by the following pseudo-code:

```
for i=1:N
    for j=1:D
        OX(i,j)=l(j)+u(j)-np(i,j);
        c(j)=(l(j)+u(j))/2;
        if OX(i,j)<c(j)
            QOX(i,j)=c(j)+(OX(i,j)-c(j))*rand;
        else
            QOX(i,j)=OX(i,j)+(c(j)-OX(i,j))*rand;
        end
    end
end
```

Chaotic local search

The present study also uses chaotic local search for more modification. This mechanism can be used for resolving the algorithm premature convergence [37,38]. A typical form of chaos theory is as follows:

$$CM_{(l+1)}^n = f(CM_l^n) \tag{30}$$

Where, $l = 1, 2, \ldots, n$, n describes the dimension map and $f(CM_l^n)$ represents the chaotic model.

The present study uses a well-known chaotic mechanism, called logistic map for modification. By applying logistic map to the population,

$$\gamma_{n+1} = \omega \times \gamma_n \times (1 - \gamma_n) \tag{31}$$

where, $\omega = 4$, and γ_n represents the value of the chaotic mechanism in iteration n in the range [0, 1] [37,38]. Accordingly, the chaotic sequence, $\sigma_{o,n,q}$, is formulated as follows:

$$\sigma_{o,n,q} = 4 \times \gamma_{o,n,q}\left(1 - \gamma_{o,n,q}\right) \tag{32}$$

where, o represents the system generators quantity, n describes the population number, and q stands for the iteration number.

By adopting Eq. (31) as the chaotic mechanism for the monarch butterfly individuals,

$$x_{i,k}^{t+1} = x_{i,k}^t + \sigma_{o,n,q} \times (dx_k - 0.5) \tag{33}$$

Fig. (3) shows the diagram flowchart of the proposed IMBO algorithm.

To validate the proposed IMBO, it has been applied to four test functions and the results have been compared with some well-known algorithms. The compared algorithms include Chaotic grasshopper optimization algorithm for global optimization (CGOA) [39], Grass Fibrous Root Optimization Algorithm (GRA) [40], and basic Monarch Butterfly Optimization (MBO) [41] to show its prominence. Table 3 indicates the details of the test functions.

Based on this study, the algorithm will be stopped when the maximum number of evaluated functions are achieved. Table 4 indicates the validation results of the compared algorithms by considering the four defined test functions. The

Table 3 – The utilized functions for the verification.

Formulation	Range	F^*
$F1 = x \times \sin(4x) + 1.1y \times \sin(2y)$	$0<x, y<0$	−18.55
$F2 = 0.5 + \frac{\sin^2(\sqrt{x^2+y^2} - 0.5)}{1 + 0.1(x^2+y^2)}$	$0<x, y<2$	0.5
$F3 = \lvert x\rvert + \lvert y\rvert + (x^2+y^2)^{0.25} \times \sin(30((x+0.5)^2+y^2)^{0.1})$	$[-\infty, \infty]$	−0.25
$F4 = 10n + \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i)),\ n = 9$	[-5.12,5.12]	0

Table 4 – The validation results of the compared algorithms.

		CGOA [39]	GRA [40]	MBO [41]	IMBO
F1	Maximum	−9.85	−11.27	−11.20	−10.35
	Minimum	−18.45	−18.50	−18.48	−18.53
	Median std	−15.48	−16.05	−16.36	−16.54
		4.75	2.31	3.26	2.64
F2	Maximum	0.534	0.542	0.511	0.503
	Minimum	0.500	0.500	0.500	0.500
	Median std	0.536	0.542	0.570	0.563
		0.025	0.003	0.001	0.000
F3	Maximum	−0.064	−0.143	−0.223	−0.237
	Minimum	−0.245	−0.249	−0.253	−0.256
	Median std	−0.125	−0.176	−0.230	−0.241
		0.143	0.204	0.014	0.011
F4	Maximum	17.36	22.43	7.25	1.19
	Minimum	2.016	0.005	0.000	0.000
	Median std	7.391	9.470	0.464	0.095
		4.186	6.954	0.329	0.076

validation is based on evaluating *Median* value, standard deviation (std) value, minimum, and the maximum values of the objective function.

Fig. (4) shows the convergence profile of the compared algorithms during the validation on the test functions. Form the results, it is obvious that the proposed IMBO algorithm has the best accuracy among different compared algorithms. The

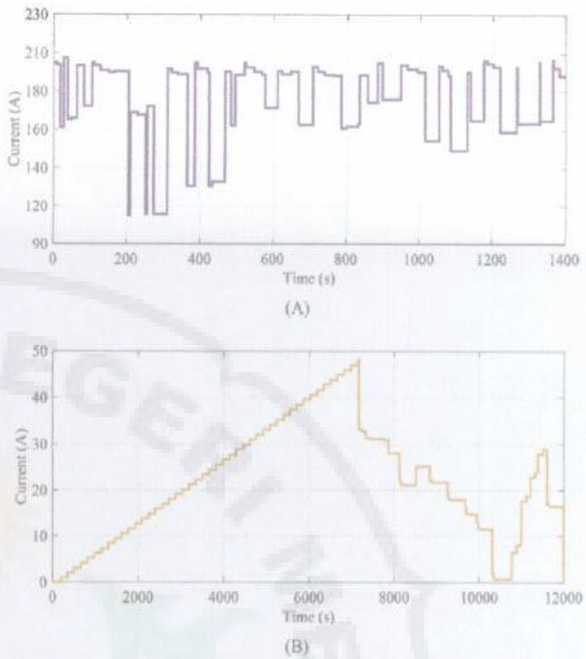

Fig. 5 – The current profile adopted by (A) NedSstack PS6 and (B) 2 kW Nexa for validation.

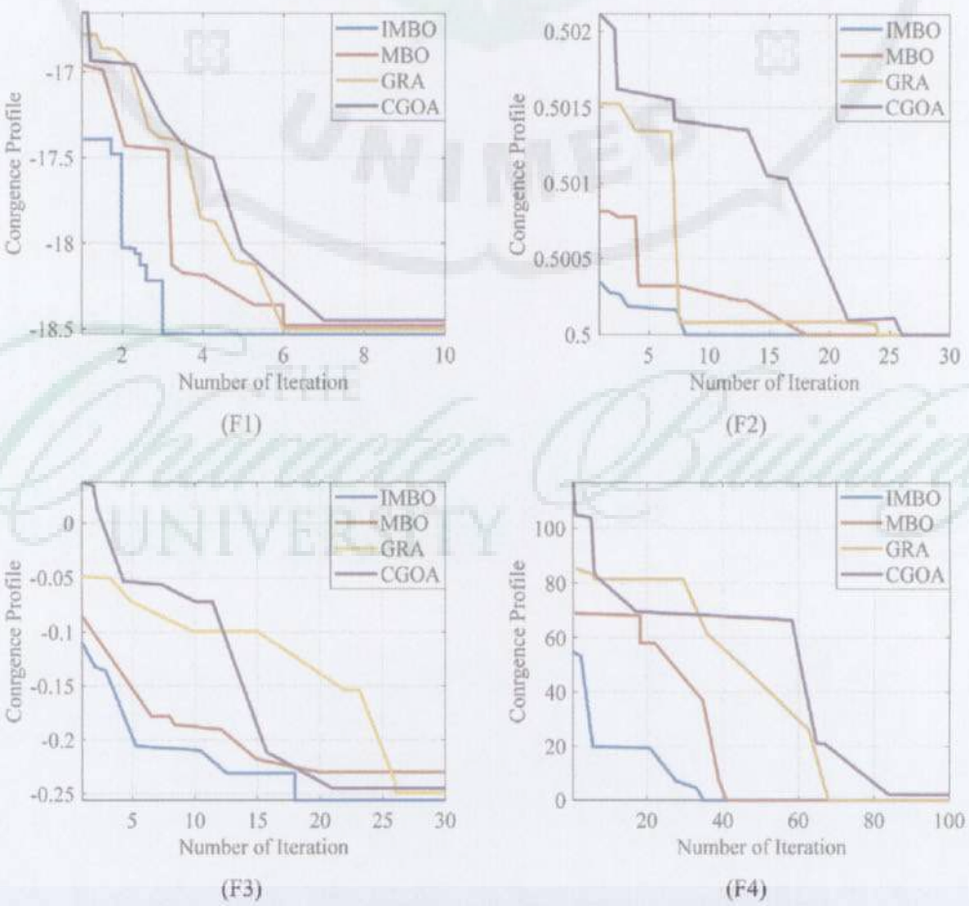

Fig. 4 – The convergence profile of the compared algorithms.

Table 5 – The validation results of the proposed IMBO algorithm compared with other well-known algorithms for NedSstack PS6 PEMFC.

Parameter	Method				Unit
	IMBO	MBO [41]	GRA [40]	CGOA [39]	
E_0^0	1.29	1.42	1.20	1.32	V
ξ_1	−1.92	−0.897	−1.16	−1.03	–
ξ_2	1.98×10^{-3}	2.31×10^{-3}	1.75×10^{-3}	1.75e10−3	–
ξ_3	7.92×10^{-5}	7.62×10^{-5}	5.93×10^{-5}	7.84×10^{-5}	–
ξ_4	-9.54×10^{-4}	-9.37×10^{-4}	-9.29×10^{-4}	-9.48×10^{-4}	–
A	211.37	237.20	209.15	210.58	cm^2
ϕ	15.80	16.18	14.53	15.93	–
λ_e	0.010	0.008	0.004	0.01	Ω
l	13.25×10^{-6}	15.82×10^{-6}	13.40×10^{-6}	12×10^{-6}	m
B	0.054	0.048	0.039	0.072	V
C	5.57	5.80	4.93	5.17	F

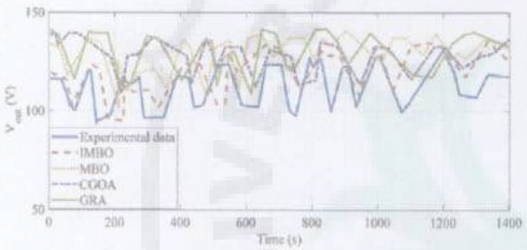

Fig. 6 – The results of different algorithms for NedSstack PS6 parameter identification based on voltage profile.

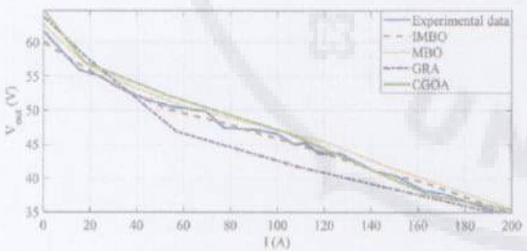

Fig. 7 – The results of different algorithms for NedSstack PS6 parameter identification based on voltage-current profile.

minimum value of the IMBO also shows its higher robustness toward the others.

Simulation results

In this study, two standard benchmarks including 6 kW NedSstack PS6 PEMFC and 2 kW Nexa PEMFC have been adopted for validation the proposed algorithm. Fig. (5) shows the current profile for training the PEMFC models in 6 kW NedSstack PS6 PEMFC (A) and 2 kW Nexa PEMFC (B), respectively.

The system simulation and programming are performed by MATLAB R2017b. The required parameters for the proposed IMBO for optimal parameters selection of the PEMFC are: $N_P = 50$, $N_c = 10$ with 100 iterations. Based on the mentioned assumptions, the results for the two analyzed case studies are given in the following.

6 kW NedSstack PS6 PEMFC

The first case study is based on the information collected by the available data sheet of NedStack PS6 fuel cell, 6 kW [42]. In this case study, the number of cells are considered 65. Each cell contains an area of 240 cm^2 with 178μm thickness. The cell temperature is 343 K and the range of supply pressure is in the

Table 6 – The validation results of the proposed IMBO algorithm compared with other well-known algorithms for Nexa PEMFC.

Parameter	Method				Unit
	IMBO	MBO [41]	GRA [40]	CGOA [39]	
V^*	1.324	1.286	1.319	1.320	V
ξ_1	−0.356	−0.428	−0.376	−1.030	–
ξ_3	6.471×10^{-5}	5.736×10^{-5}	6.137×10^{-5}	7.480×10^{-5}	–
ξ_4	-9.153×10^{-4}	-1.682×10^{-4}	-1.443×10^{-4}	-9.48×10^{-4}	–
A	119.35	116.50	116.76	210.58	cm^2
ϕ	15.76	14.69	14.08	15.930	–
λ_e	0.015	0.008	0.005	0.010	Ω
l	19×10^{-6}	47×10^{-6}	43×10^{-6}	12×10^{-6}	m
B	0.077	0.051	0.064	0.072	V
C	5.24	6.37	5.96	5.170	F

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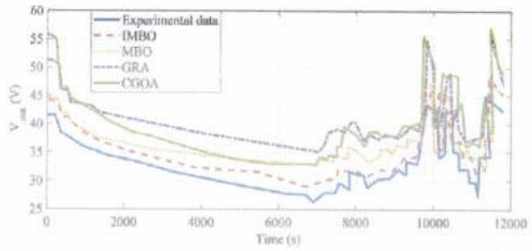

Fig. 8 – The results of different algorithms for Nexa PEMFC parameter identification based on voltage profile.

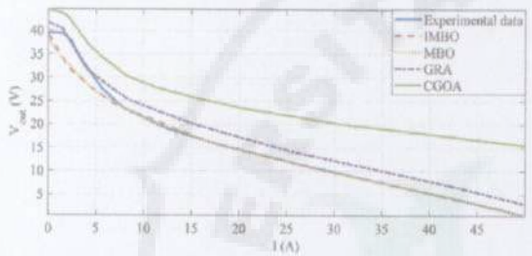

Fig. 9 – The results of different algorithms for Nexa PEMFC parameter identification based on voltage-current profile.

range [0.5, 5] bar. The output voltage of NedSstack is limited between 32 V and 60 V DC, and the range of operation is in the range [0, 225] A. Table 5 indicates the validation results of the proposed IMBO algorithm compared with other well-known algorithms including GRA [40], CGOA [39], and MBO [41]for optimal selection of the NedSstack PS6 PEMFC parameters. The results show the mean value for 30 independent runs.

Fig. (6) shows the output voltage profile for the experimental data, the proposed IMBO algorithm and the other compared algorithms. As can be observed, the proposed IMBO algorithm has the most agreement to the experimental compared with other analyzed algorithms.

Fig. (7) shows the voltage-current profile of the experimental and estimated results for NedSstack PEMFC based on the proposed algorithm and the compared algorithms. As can be observed from Fig. (7), the estimated model based on the proposed IMBO has the best agreement with the experimental profile which shows its prominence than the other compared methods for this case study.

The 2 kW nexa PEMFC

The next case study is to verify the algorithms by the information collected by the available data sheet of 2 kW Nexa PEMFC [43]. Table 6 illustrates the validation results of the proposed IMBO algorithm compared with other well-known algorithms including GRA [40], CGOA [39], and MBO [41] for optimal selection of the 2 kW Nexa PEMFC parameters.

Fig. (8) and Fig. (9) show the voltage and the voltage-current profiles of different algorithms for the Nexa PEMFC parameter identification based on voltage profile. The validation is based on the load profile of the experimental data compared with proposed IMBO and some well-known methods including GRA [40], CGOA [39], and basic MBO [41].

It is observed that the proposed IMBO has the maximum agreement to the experimental data for optimal PEMFC modeling. Fig. (10) shows the value of the Integral Time Absolute Error (ITAE) for the proposed IMBO compared with GRA [40], CGOA [39], and basic MBO [41]. Fig. (10) shows that the presented IMBO algorithm has the minimum value of ITAE for both case srudies.

Conclusions

This study proposed a new procedure for optimal parameter selection of proton exchange membrane fuel cell (PEMFC). The procedure is based on using a new improved version of

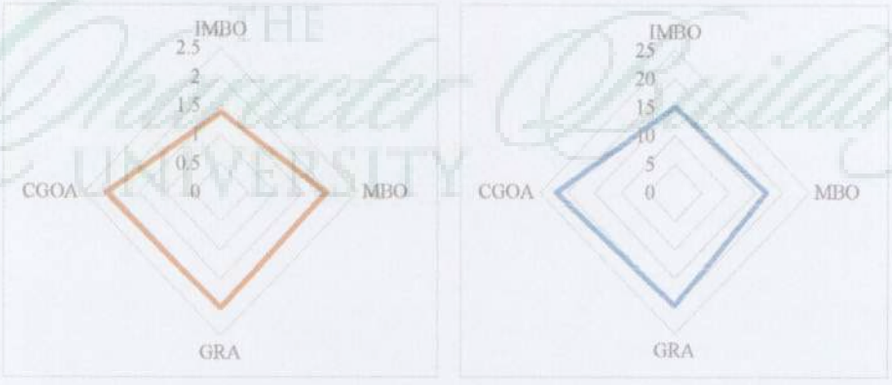

Fig. 10 – The radar plot of ITAE for minimum value for (A) NedSstack PEMFC and (B) Nexa PEMFC.

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Monarch Butterfly Optimization (MBO) for minimizing the Integral Time Absolute Error (ITAE) between the experimental data and the optimal achieved model. 1The system analysis was based on a circuit-based model of the PEMFC and parameters contain data from 2 kW Nexa PEMFC and 6 kW NedSstack PS6 PEMFC. The simulations applied based on MATLAB software and the results of the proposed IMBO were compared with some well-known algorithms including GRA, CGOA, and basic MBO to show the prominence of the presented algorithm.

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