*J. Electrochem. Sci. Eng.* **14(2)** (2024) 177-192; http://dx.doi.org/10.5599/jese.1991

Open Access : : ISSN 1847-9286
https://pub.iapchem.org/ojs/index.php/JESE

*Original scientific paper*

# Moth flame-random search optimization of a zero-dimensional model of a proton exchange membrane fuel cell

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Received: July 21, 2023; Accepted: January 8, 2024; Published: February 16, 2024

***Abstract***

*Modelling of proton exchange membrane fuel cell (PEMFC) is important for better understanding, simulation, and design of high-efficiency fuel cell systems. PEMFC models are often multivariate with several nonlinear elements. Metaheuristic algorithms that are successful in solving nonlinear optimization problems are good candidates for this purpose. This study proposes a new metaheuristic algorithm called MFORS that uses the advantages of the moth-flame optimization algorithm in global search and the non-deterministic properties of the random search algorithm to identify the optimal parameters of the PEMFC model. The sum of squared errors between the estimated and measured voltage is a quality of fit criterion. To show the effectiveness of the proposed algorithm, two case studies of zero-dimensional models of SR-12 Modular PEM Generator and Ballard Mark V fuel cell are considered. The sum of squared errors for the parameter estimated of electrical PEMFCs by the proposed MFORS algorithm is compared with recent works. The results showed that by the MFORS algorithm, the minimum sum of absolute errors of the actual stack voltage and the simulated stack voltage in the two PEMFC are 0.095037 and 0.018019, compared with the second-best algorithm results giving 0.09681 and 0.8092, respectively.*

**Keywords**
Fuel cell system; parameters estimation; global optimization algorithm; chemical energy; hybrid algorithm

## Introduction

The energy demand, environmental pollution, global warming and limited amount of fossil fuel sources are reasons to encourage researchers to study fuel cells (FCs) [1,2]. Fuel cells (FC) are an emerging technology used in portable power generation, electrification to island areas, *etc*. [3,4]. The proton exchange membrane fuel cell (PEMFC) converts most of the chemical energy of the hydrogen and oxygen reactions into electrical energy (along with the production of water and a heat release) near room temperature without pollutant emissions [5]. Other advantages of PEMFC include low noise, high specific power and good energy efficiency [6,7].

Recently, evolutionary and metaheuristic algorithms have been applied for optimizing the parameters of FCs. A moth-flame optimization algorithm is employed in [8] to estimate the optimal parameters of solid oxide fuel cells to improve the output power of this model. They compared the study with a genetic algorithm (GA), radial movement optimizer (RMO) and social spider optimizer (SSO). Abdullah *et al*. proposed a moth flame optimization algorithm for optimal modeling of the PEMFC [9]. To show the approach efficiency, the results were validated by comparing with the particle swarm optimization(PSO) algorithm and sine cosine algorithm (SCA). The hybrid water cycle moth-flame optimization (WCMFO) was applied to lessen the sum of squared errors (SSE) between the measured and the experimental stack voltage of PEMFC [10]. A comparative study was proposed on the optimal estimation of the PEMFC parameters based on two different metaheuristics. The results indicated that using MFO gives better results than methods in [11].

Diab *et al*. [12] proposed a PEMFC numerical model using metaheuristic tools to estimate model parameters. Houssein *et al.* applied Archimedes optimization algorithm (AOA) using orthogonal learning to identify PEMFC parameters [13]. A robust method based on the gradient-based optimizer (GBO) was proposed to identify unknown parameters of PEMFC [14]. During the optimization process, the unknown parameters of PEMFC were used as decision variables, whereas the objective function needs to be minimum is presented by the SSE between the estimated and measured production voltage of the PEMFC.

Three algorithms, namely the imperialist competitive algorithm (ICA), firefly optimization algorithm (FOA), and shuffled frog-leaping algorithm (SFLA), have been employed for the extraction of unknown BCS 500-W, Horizon 500-W FC and NedStack PS6 parameters [15]. A flower pollination algorithm (FPA) has been used to estimate the optimal parameters of different PEMFCs by selecting SSE as an objective function [16]. A combination of the two algorithms, including the JAYA algorithm and the Nelder-Mead simplex search algorithm (JAYA-NM), was presented to estimate the optimal parameters of PEMFC [17]. A hybrid of vortex search algorithm and differential evolution has been used for extracting the parameters of FC under different conditions [18]. A cuckoo search algorithm with an explosion operator (CS-EO) was proposed for solving unknown parameters of PEMFC. CS-EO has the ability to obtain better performance and avoid precipitate convergence [19]. The transient search optimization (TSO) algorithm was used to estimate the parameters by minimizing the SSEs between the calculated and measured voltages [20]. The chimp optimization algorithm (ChOA) has also been presented to determine the unknown parameters of the PEMFC [21].

Many optimization alghoritms have been used to identify parameters of PEMFC (Table 1).

However, the accuracy of the previous algorithms is not satisfactory. Some algorithms converge to suboptimum solutions. Thus, a new algorithm that could improve the quality of the solution is needed. Recently, a new metaheuristic algorithm called moth-flame optimization (MFO) was presented [22]. This algorithm has a promising performance in solving optimization problems [22]. An MFO was applied for the problem related to the strategic accommodation of fuel cells in an active distribution network that consists of wind turbines and photovoltaic modules [23].

An MFO was applied for the artificial neural network to improve its operational accuracy for providing an accurate predicting control scenario for the integration of fuel cells with photovoltaic and wave energy sources using the field programmable gate array (FPGA) technology [24]. An MFO based on sine mapping and Gaussian mutation was used for the economic optimization dispatch of the microgrid [25].

***Table 1**. Some of algorithms utilized in recent years in PEMFC case studies*

| Optimization algorithm | Case studies | | | | | | | | | Year | Ref. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ballard Mark V | BCS 500 W | SR-12 500 W | NedStack PS6 | 250-W PEMFC | Temasek 1 kW | Horizon 500-W | H-12 stack | 250W stack | | |
| Shuffled frog-leaping algorithm (SFLA), firefly optimization algorithm (FOA), and imperialist competitive algorithm (ICA) | + | | | + | | | + | | | 2019 | [15] |
| Transient search optimization (TSO) | + | | | + | | | | + | | 2022 | [20] |
| Heap-based optimizer (HBO) | | + | + | + | | | | + | | 2021 | [27] |
| Simplified teaching-learning-based optimization algorithm (STLBO) | | | | | | | | | + | 2014 | [28] |
| Aging and challenging P systems-based optimization algorithm (AC-POA) | | | | | | | | | + | 2016 | [29] |
| Harris Hawks optimizer (HHO) | + | + | + | + | | | | + | | 2021 | [30] |
| Gravitational search algorithm (GSA), grey wolf optimizer (GWO), differential evolution (DE), sine cosine algorithm (SCA), RSA algorithm, and arithmetic optimization algorithm (AOA) | | + | | + | | | | | | 2022 | [31] |
| Pathfinder algorithm (PA) | + | | | | | | | + | | 2021 | [32] |
| Salp Swarm algorithm (SSA) | | + | + | | + | + | | | | 2020 | [33] |
| Flower pollination algorithm (FPA) | + | + | | + | | + | | | | 2019 | [16] |
| Sparrow search algorithm (SSA) | + | | | + | | | | + | | 2021 | [34] |
| Bald eagle search (BES) | | + | | + | | | | + | + | 2022 | [35] |
| Black widow optimization (BWO) | + | | + | | | | | | | 2021 | [36] |
| Whale optimization algorithm (WOA) | + | | + | | | | | + | + | 2019 | [37] |
| Artificial bee colony differential evolution shuffled complex (ABCDESC) | + | + | | + | | | | + | + | 2022 | [38] |
| Artificial bee colony differential evolution optimizer (ABCDE) | + | + | + | + | | | + | + | | 2022 | [39] |
| Bonobo optimizer (BO) | | + | + | | | | | | + | 2020 | [40] |
| Jellyfish search algorithm (JSA) | | + | | + | | | | | + | 2021 | [41] |
| Ecosystem optimization (AEO) | | + | + | | | + | | | + | 2020 | [42] |
| Marine predators algorithm (MPA) | | + | + | | | | | | + | 2020 | [43] |
| Shark smell optimizer (SSO) | + | + | + | | | + | | | | 2019 | [44] |
| Grey wolf optimization (GWO) | | + | + | | | | | | + | 2022 | [45] |

The MFO algorithm searches the solution space rapidly. However, sometimes, it cannot find the correct solution for a highly nonlinear problem and contains many local minima. A random search algorithm (RS) can obtain the global optimum solution for highly nonlinear functions [26]. However, it is slow in convergence. Unlike other heuristic algorithms inclined to close the best current solutions, the RS algorithm explores the space randomly without considering the best solutions [26]. In this study, a new optimization algorithm called MFORS is introduced. This algorithm uses the ability of the MFO algorithm in global search and non-deterministic properties of RS to obtain the optimal parameters of the PEMFC model.

The remainder of this paper is organized as follows: the problem formulation of PEMFC is presented in the Problem description section, and the basic MFO and RS algorithm are presented in the next section. After that, simulations and discussions about PEMFC are provided, followed by conclusions.

## Problem description

### *The theory of PEMFC*

A PEMFC is electrochemical device that converts the chemical energy of oxygen and hydrogen into electrical and thermal energy. The chemical reactions that occur at PEMFC cathode and anode are defined as follows [46]:

Anode side: $H_{2(g)} \rightarrow 2H^+ + 2e^-$ (1)

Cathode side: $2H^+ + 2e^- + 1/2O_2 \rightarrow H_2O$ (2)

Overall reaction: $H_{2(g)} + 1/2O_2 \rightarrow H_2O$ (3)

The overall reaction (3) between oxygen ($O_2$) and hydrogen ($H_2$) has a large negative Gibbs energy change, which dictates a theoretical open circuit voltage of ~1.23 V. During the overall reaction, the products are liquid water, electricity, and heat. To provide the required amount of power, many single cells can be assembled into a fuel cell stack system [47]. The operating temperature of PEMFC typically ranges from 70 to 85 °C. Figure 1 illustrates a basic scheme of a single PEMFC [46].

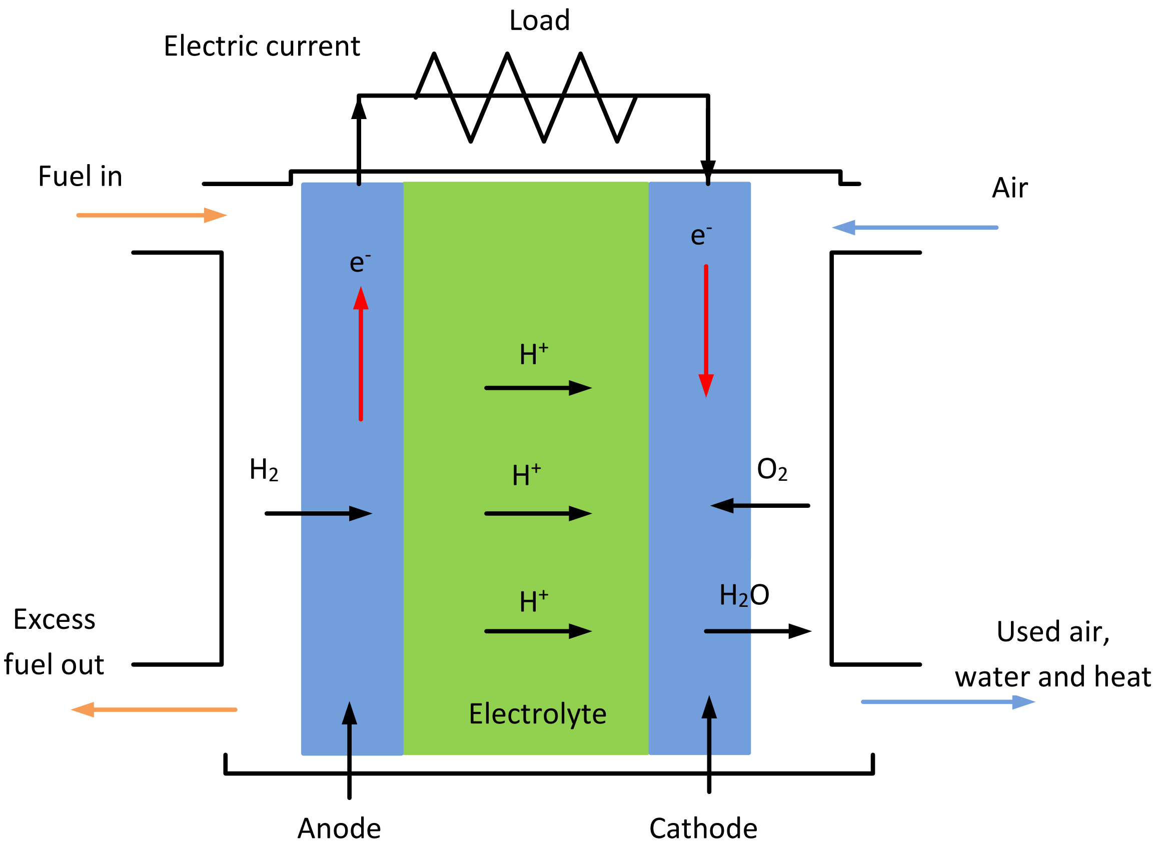


***Figure 1.*** *Basic PEMFC operation*

*The mathematical model of PEMFC*

In the present study, a zero-dimensional PEMFC model described earlier in [46] was employed. The value of the equilibrium potential voltage $E_{\text{Nernst}}$ is obtained by the Nernst equation. Many factors cause voltage losses, including activation voltage drop ($V_{\text{act}}$), ohmic voltage drop ($V_{\text{ohmic}}$), and concentration voltage drop ($V_{\text{con}}$). The production voltage of the FC is given by equations (4-8) [48,49]:

$$V_{\text{STACK}} = N_{\text{S}}(E_{\text{Nernst}} - V_{\text{act}} - V_{\text{ohmic}} - V_{\text{con}}) \tag{4}$$

$$E_{\text{Nernst}} = 1.229 + 4.3085\times10^{-5} T_{\text{FC}} \ln\left(P_{\text{H}_2}\sqrt{P_{\text{O}_2}}\right) - 0.846\times10^{-3}\left(T_{\text{FC}} - 298.15\right) \tag{5}$$

$$V_{\text{act}} = I_{\text{fc}}\left(R_{\text{C}} + \frac{L}{A}\frac{181.6\left[1+0.03\frac{I_{\text{fc}}}{A}+0.062\left(\frac{T_{\text{FC}}}{303}\right)^2\left(\frac{I_{\text{fc}}}{A}\right)^{2.5}\right]}{\left[\lambda - 0.634 - 3\frac{I_{\text{fc}}}{A}\right]\exp\left(4.18\left[\frac{T_{\text{FC}}-303}{T_{\text{FC}}}\right]\right)}\right) \tag{6}$$

$$V_{\mathrm{ohmic}} = \xi_1 + \xi_2 T + \xi_3 T \ln\left(\frac{P_{\mathrm{O_2}}}{5.08\times 10^6 \exp\left(-\frac{498}{T_{\mathrm{FC}}}\right)}\right) + \xi_4 T \ln I_{\mathrm{fc}} \tag{7}$$

$$V_{\mathrm{con}} = b \ln\left(1\text{-}\frac{j}{j_{\mathrm{max}}}\right) \tag{8}$$

In the above equations, the fuel cell temperature ($T_{FC}$), the hydrogen partial pressure ($P_{H_2}$) and the oxygen partial pressure ($P_{O_2}$) are dependent on the operating conditions of the system and are measurable. $I_{fc}$ and $N_s$ are the cell current and number of cells, $j$ is the current, and $j_{max}$ is the maximum current density.

The other parameters ($\xi_1$, $\xi_2$, $\xi_3$, $\xi_4$, $R_c$, $b$, $\lambda$) are unknown parameters that need to be extracted for designing and simulation of the PEMFC model.

The sum square error (SSE) between the measured and experimental production voltage of the PEMFC stack model can serve as an objective function (*OF*) to determine unknown parameters, which is represented by equations (9) and (10):

$$OF = \mathrm{SSE} = \sum_{n=1}^{N}\left(V_{\mathrm{measured}} - V_{\mathrm{stack}}\right)^2 \tag{9}$$

Subject to:

$$\begin{gathered} \xi_{k_{\min}} \le \xi_k \le \xi_{k_{\max}} \quad k = 1:4 \\ \lambda_{\min} \le \lambda \le \lambda_{\max} \\ R_{c_{\min}} \le R_c \le R_{c_{\max}} \\ b_{\min} \le b \le b_{\max} \end{gathered} \tag{10}$$

where $N$ is the sampling rate of data points, $V_{measured}$ is the measured output voltage PEMFC stack, $V_{stack}$ is the computed output voltage by equation (2). Table 2 represents the lower and upper bounds of these parameters.

***Table 2**. Lower and upper bounds of PEMFC parameters*

| Parameter | $\xi_1$ | $\xi_2\times10^3$ | $\xi_3\times10^5$ | $\xi_4\times10^4$ | $R_c$ / mΩ | $\lambda$ | b(V) |
|---|---|---|---|---|---|---|---|
| Max | -0.5832 | 5 | 9.8 | -0.954 | 0.8 | 24 | 5.0000 |
| Min | -1.1997 | 1 | 3.6 | -2.600 | 0.1 | 10 | 0.0136 |

*Proposed algorithm for optimizing the parameters of a PEMFC model*

This section presents the main conceptions of moth-flame optimization (MFO) and random search.

1. Moth-flame optimization (MFO algorithm)

Moth-flame optimization (MFO) is a promising optimization algorithm that is inspired by moth navigation at night when moths use moonlight for navigation. Moths are flying at an angle to the direction of the Moon. The orientation of moth travel during the night is shown in Figure 2. Since the distance between the Moon and the moth is long, the moth moves in a linear path [22]. However, when the light source is close to the moth flying at a constant angle toward the light, a spiral trajectory is observed. The model of a flying path surrounding flame or light by moths is depicted in Figure 3 [22]. It can be concluded from Figure 3 that the moth lastly converges near the flame or light source.

This is formulated mathematically to arrive at an optimizer termed the moth-flame optimization algorithm. In this method, candidate solutions are represented by the moths and parameters of the problems are described by moth positions. This approach allows moths to move in one or more dimensions by replacing their position vectors. The moth population is represented as a matrix (11):

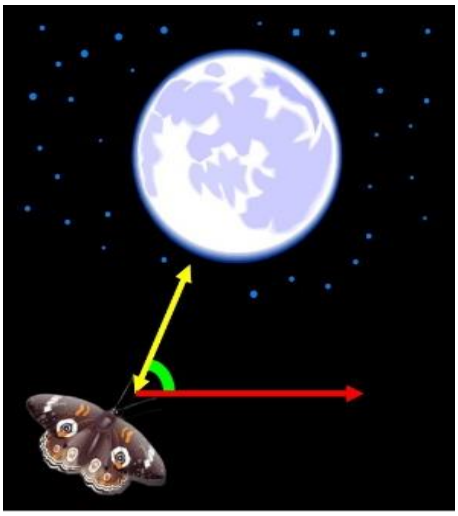

***Figure 2.*** *Moth orientation toward the light*

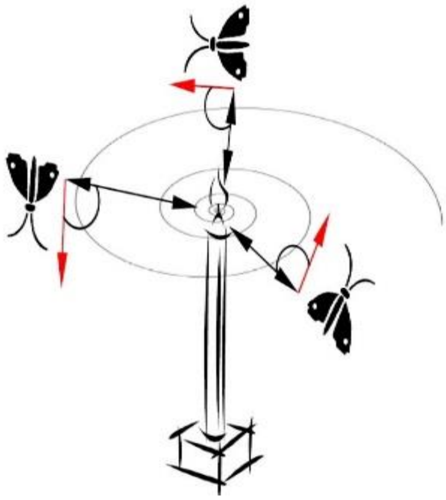

***Figure 3.*** *Spiral flying path of moth around the light*

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \dots & \dots & m_{1,d} \\ m_{2,1} & m_{2,2} & \dots & \dots & m_{2,d} \\ & & \vdots & & \\ m_{n,1} & m_{n,2} & \dots & \dots & m_{n,d} \end{bmatrix} \tag{11}$$

where $n$ is the number of moths, and the number of variables is $d$. The array $OM$ stores the corresponding fitness values for moths, equation (12).

$$OM = [OM_1, OM_2, OM_3] \tag{12}$$

The fitness value is the value of the objective function for each moth. Another main element of the algorithm is the flame matrix:

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \dots & \dots & F_{1,d} \\ F_{2,1} & F_{2,2} & \dots & \dots & F_{2,d} \\ & & \vdots & & \\ F_{n,1} & F_{n,2} & \dots & \dots & F_{n,d} \end{bmatrix} \tag{13}$$

Size of matrices $M$ and $F$ are equal. For storing the fitness values of the flames, the array OF is defined by equation (14):

$$OF = [OF_1, OF_2, OF_3] \tag{14}$$

It is notable that moths and flames are both solutions, but how they are updated and generated differs. The moths are considered to be search candidates that explore the search space. The best positions of moths during the search are considered flames. Thus, a flame can be updated by a better solution obtained by a moth that searches around the flame. This mechanism keeps the best solution found by a moth. The MFO can be defined as tree-tuple approximation functions as follows. A random population and their corresponding fitness value are generated by $I$. Moths are moved around search space by the $P$ function. The matrix $M$ is the input of function $P$ and the output is its updated one, equation (15).

$$\text{MOF} = (I,P,T);\ I:\phi \rightarrow \{M,OM\};\ P:M \rightarrow M \tag{15}$$

The $T$ function output is true when termination criteria are satisfied, otherwise, it is false, equation (16).

$$T:M\{\text{true, false}\};\ M_\text{i} = S\,(M_\text{i}, F_\text{j}) \tag{16}$$

The updated formula for the moth position with respect to the flame position is as presented by equation (17):

$$S\,(M_\text{i}, F_\text{j}) = D_\text{i}\,\text{e}^{\text{bt}}\cos(2\pi t) \tag{17}$$

where $M_\text{i}$ and $F_\text{j}$ are i$^\text{th}$ moth and j$^\text{th}$ flame, respectively. The $t$ is a random variable belonging to [-1,1]. The spiral shape is defined by $b$. The $D_\text{i}$ (equation (18)) is the distance between the i$^\text{th}$ moth and j$^\text{th}$ flame.

$$D_\text{i} = |F_\text{j} - M_\text{i}| \tag{18}$$

The number of flames is reduced during the iterations as equation (19):

$$\text{Number of flame} = \text{round}\left(\text{N-}L\,\frac{\text{N-1}}{T}\right) \tag{19}$$

where the maximum number of the flame population is $N$, the current iteration is $L$ and $T$ is the maximum number of iterations.

2. Random search (RS) algorithm

A global optimization problem with continuous variables may be highly nonlinear or contain several local optima. Heuristic algorithms like random search can obtain the global optimum solution [26]. A random search (RS) algorithm uses a stochastic approach for randomness. A random search method has the ability to solve large-scale problems efficiently with respect to the deterministic approaches. It is a derivation-free algorithm and easy to implement on problems without knowing about the gradient information of the problem functions [50]. The main advantages of the RS method are: a) simple algorithm and easy implementation, b) robustness to the noise in the objective function, c) insensitivity to irregularity of the objective function behavior and increasing dimension of the problem.

The procedure for this algorithm can be summarized as follows. In the initial step, a feasible solution is randomly chosen from the search space as the optimal solution. Then, other solutions are randomly generated in the feasible region and any solution with better fitness than the optimal solution updates it. After some iterations, the optimal solution can be shrunk around the optimal solution. The RS algorithm with more details has been described in [51,52].

3. Hybrid MFO and RS algorithm (MFORS)

Usually, some optimization algorithms are good in global exploration, while others are good in local exploitation [53]. The MFO is a promising optimization algorithm with high performance in global optimization problems [54-56]. The hybrid of MFO and RS, which is called MFORS, has been applied to keep a balance between exploitation and exploration search space. In this study, RS has been used for exploiting the best solution around the initial solution obtained by MFO. MFO shows good performance in global optimization, while RS is good in local exploitation. Thus, by a hybrid of these two algorithms, the advantages of both can be utilized. Figure 4 shows the pseudo-code of the RS algorithm, while Figure 5 shows the stages of the proposed MFORS algorithm.

```
Step0: Initialize:
Select initial optimal solution x0 from the region x0 ∈[LB UB] where LB and UB are
upper and lower bound of solutions, initialize the refining region factor (KRef), period of
region refining T, dimension of the solutions Dim, and initial iteration number (Iter) to
zero
While stop condition is not true:
        Iter=Iter+1
        Step1: Random Move: Select a randomly solution in the solution space
                for i=1:Dim
                  x(i) = LB(i) + rand * (UB(i) - LB(i))
                End
        Step2: Optimal Solution Update: update optimal solution (x0) when new solution
        (x) better than    optimal solution
                If( f(x) < f(x0) )
                x0 = x
                End
        Step3: Refine solution space: Refine the region in the respect with the optimal
        solution every T times
                If( mod(Iter, T) equal to zero)
                     For i=1 to Dim
                        Width(i)= (UB(i)-LB(i))* KRef;
                        If( x0(i)-Width(i)/2< LB (i) )
                                LB (i)= LB (i);
                                UB(i)=  UB(i)- Width(i)/2
                        Else If( x0(i)+Width(i)/2 > UB (i) )
                                LB(i)=  LB(i)+ Width(i)/2
                                UB(i)= UB (i);
                        Else
                                LB (i)= x0(i)-Width(i)/2
                                UB(i)=  x0(i)+Width(i)/2
                        End If
                      End for
                End If
End While
x0 is the refined optimization solution
```

***Figure 4***. *The pseudo code of RS algorithm*

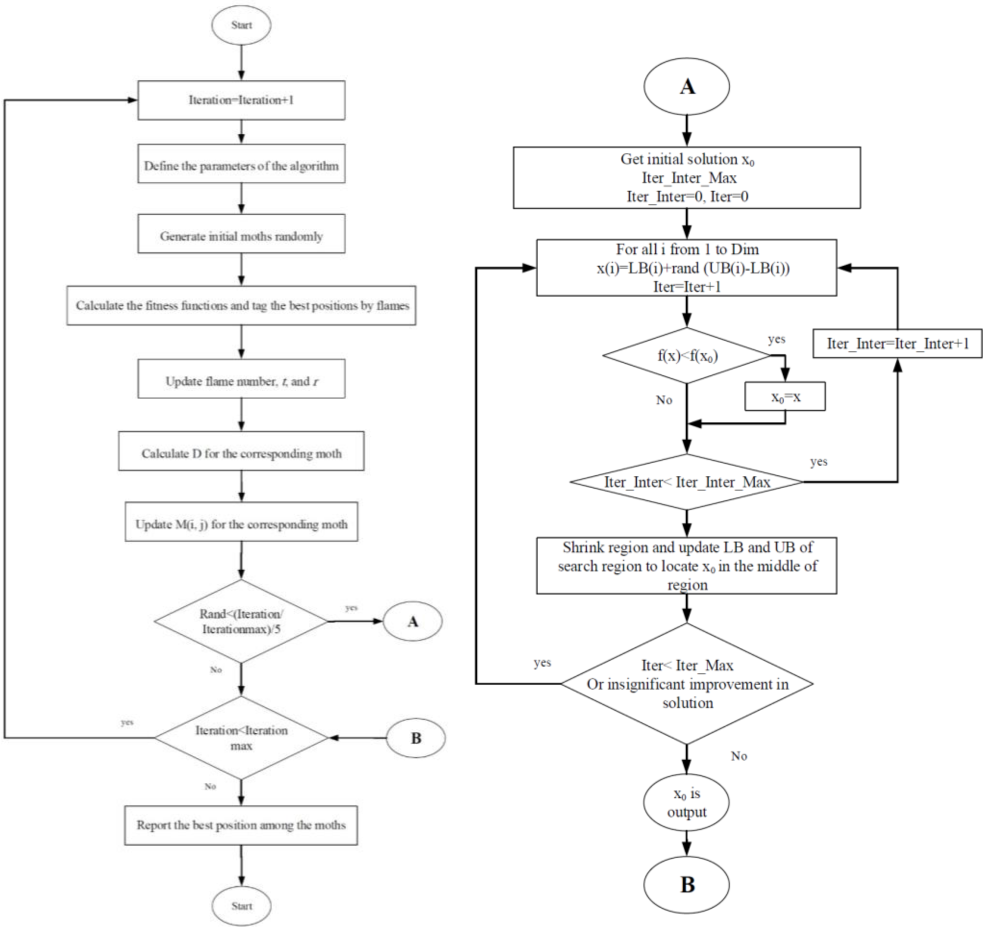


***Figure 5.*** *The flowchart of proposed MFORS algorithm*

## Results and discussion

### *Simulation of PEMFC*

In this subsection, the simulation results are presented in order to validate the proposed MFORS algorithm for estimating the PEMFC parameters. The MFORS and other algorithms were implemented under MATLAB 2014 and simulations have been done on an Intel, core i5 CPU, 6 GB RAM and 2.4 GHz computer. In this study, the population size for MFORS and other algorithms is equal to 30 and the maximum iteration is 5000 [47]. Simulations have been done for two case studies, including the SR-12 modular PEM generator and the Ballard Mark V FC [46,57,58].

### *Case study 1: SR-12 modular PEM generator*

The SR-12 Modular PEM Generator was used as the first case study. Its rated power is 500W. The operating conditions parameters are $T$ = 323 K, $P_{H_2}$=149.584 Pa (1.47628 atm), $P_{O_2}$= 21.228 Pa (0.2095 atm), $N_s$ = 48, $J_{max}$ = 672 mA/cm$^2$ maximum current density [37,46,57].

Table 3 shows the optimal parameters related to the optimum implementation of the algorithms and a comparison of the proposed MFO and MFORS with other metaheuristic algorithms. The algorithms studied in Table 3 are as follows: Shark smell optimizer (SSO) [44], Cuckoo search (CS) [19], Cuckoo search algorithm with explosion operator (CS-EO) [19], Vortex search algorithm and differential evolution (VSDE) [18], Bonobo optimizer (BO) [40], Harris hawks optimization (HHO) [40], Chaotic Harris Hawks optimization (CHHO) [40], Grey Wolf optimization (GWO) [45], Improved Grey Wolf optimization (IGWO) [45], Multi-verse optimization (MVO) [45], Selective opposition-based Grey Wolf optimization (SOGWO) [45], Dragonfly algorithm (DA) [45], Atom search optimization (ASO) [45], Ant lion optimization (ALO) [44, 45], Sparrow search algorithm (SSO) [34], Salp swarm optimization (SSO) [34], Flower pollination algorithm (FPA) [59], Shuffled frog-leaping algorithm (SFLA), Firefly algorithm (FA), Artificial bee colony (ABC), Moth-flame optimization (MFO).

***Table 3.*** *The optimal parameters for different algorithms of Sr-12*

| Algorithm | $\xi_1$ | $\xi_2\times10^3$ | $\xi_3\times10^5$ | $\xi_4\times10^4$ | $\lambda$ | $b$ / V | $R_c$ / mΩ | SSE | Year | Ref. |
|---|---|---|---|---|---|---|---|---|---|---|
| SSO | -0.9664 | 2.2833 | 2.2833 | -0.954 | 15.796 | 0.1804 | 0.66853 | 1.15080 | 2019 | [44] |
| SC | 1.0782 | 3.7309 | 8.8207 | 0.9540 | 10.0 | 0.1471 | 0.71274 | 7.57590 | 2019 | [19] |
| SC-EO | -1.0353 | -1.0353 | 3.354 | -0.954 | 10.0 | 0.1471 | 0.71233 | 7.57530 | 2019 | [19] |
| VSDE | −0.8576 | 3.0100 | 7.7800 | 9.5400 | 23 | 0.1339 | 0.01516 | 1.26600 | 2019 | [18] |
| BO | -1.0972 | 3.80925 | 9.8000 | -0.95 400 | 23 | 0.175320 | 0.67231 | 1.05663 | 2020 | [40] |
| CHHO | -0.8532 | 3.0918 | 8.2387 | -0.9540 | 22.91 | 0.17623 | 0.62468 | 1.05716 | 2020 | [40] |
| HHO | -0.8533 | 2.4173 | 4.2487 | -0.95412 | 15.34 | 0.17794 | 0.37166 | 1.05931 | 2020 | [40] |
| IGWO | -1.14361 | -0.14361 | 3.5748 | -0.95405 | 22.87 | 0.17533 | 0.66936 | 1.05660 | 2022 | [45] |
| MVO | -0.90495 | -0.90495 | 3.4871 | -0.9540 | 22.87 | 0.1757 | 0.64633 | 1.05680 | 2022 | [45] |
| GWO | -1.17592 | -1.1759 | 3.3486 | -0.9540 | 21.93 | 0.1755 | 0.64448 | 1.057000 | 2022 | [45] |
| SOGWO | -1.1759 | -1.1759 | 3.34861 | -0.9540 | 21.93 | 0.1755 | 0.64448 | 1.05702 | 2022 | [45] |
| DA | -1.07150 | -1.0715 | 3.55304 | -0.9540 | 23.0 | 0.1743 | 0.72377 | 1.05724 | 2022 | [45] |
| ASO | -0.9940 | -0.9940 | 3.40927 | -0.9540 | 21.142 | 0.1751 | 0.64766 | 1.05724 | 2022 | [45] |
| ALO | -1.10334 | -1.1033 | 4.1130 | -0.954 | 22.722 | 0.173 | 0.76773 | 1.05895 | 2022 | [45] |
| SSO | -1.03331 | 3.72 | 9.57 | -9.58 | 14.301 | 0.799 | 0.01421 | 0.09681 | 2021 | [34] |
| ALO | -0.9438 | 3.4734 | 9.7898 | 1.1811 | 24.0 | 0.0136 | 0.03000 | 1.15130 | 2019 | [44] |
| FPA | −0.85320 | 31.0 | 9.15 | −0.954 | 13.00 | 0.571 | 0.01455 | 0.15982 | 2019 | [59] |
| ABC | -1.082 | 3.4956 | 7.5015 | -0.954 | 24 | 0.1711 | 0.17882 | 0.70821 | - | This study |
| SFLA | -0.9569 | 3.10183 | 7.45219 | -0.954 | 24 | 0.171489 | 0.10000 | 0.70800 | - | This study |
| FA | -1.0882 | 3.7288 | 8.8773 | -0.954 | 24 | 0.17149 | 0.10001 | 0.70800 | - | This study |
| MFO | -1.1733 | 3.18622 | 3.66397 | -0.954 | 10 | 0.171487 | 0.10001 | 0.70801 | - | This study |
| **MFORS** | **-1.1103** | **3.1041** | **3.75906** | **-0.954** | **15.532** | **0.2246** | **0.35008** | **0.09503** | - | **This study (proposed)** |

As shown in Table 3, the proposed MFORS could achieve the best results compared with the other algorithms. The average time to obtain parameters by the MFORS algorithm is 809 seconds. Current-

Voltage dataset values, together with results of estimated voltage ($V_{measured}$) and SSE values obtained by proposed MFORS, are given in Table 4.

***Table 4.*** *The I/V datasets of SR-12 found by the MFORS and voltage stack*

| Sampling number | $I_{stack}$ / A | $V_{measured}$ / V | $V_{stack}$ / V | $(V_{measured} - V_{stack})^2$ / V$^2$ |
|---|---|---|---|---|
| 1 | 0 | 41.7791 | 42.1705 | 0.1532 |
| 2 | 1.0188 | 41.1145 | 41.2848 | 0.0290 |
| 3 | 1.9303 | 40.5010 | 40.6568 | 0.0243 |
| 4 | 2.9491 | 40.0409 | 40.0512 | 0.0001 |
| 5 | 3.9678 | 39.6319 | 39.5069 | 0.0156 |
| 6 | 4.9330 | 38.9162 | 39.0276 | 0.0124 |
| 7 | 6.0054 | 38.5583 | 38.5228 | 0.0013 |
| 8 | 6.8633 | 38.1493 | 38.1335 | 0.0003 |
| 9 | 7.9893 | 37.8425 | 37.6357 | 0.0427 |
| 10 | 8.9544 | 37.3824 | 37.2171 | 0.0273 |
| 11 | 9.8659 | 36.8712 | 36.8256 | 0.0021 |
| 12 | 10.9383 | 36.2065 | 36.3674 | 0.0259 |
| 13 | 11.9035 | 35.9509 | 35.9551 | 0.0000 |
| 14 | 12.9759 | 35.4397 | 35.4950 | 0.0031 |
| 15 | 13.8874 | 35.2352 | 35.1010 | 0.0180 |
| 16 | 14.9598 | 34.7239 | 34.6322 | 0.0084 |
| 17 | 15.8713 | 34.1616 | 34.2281 | 0.0044 |
| 18 | 16.9437 | 34.1104 | 33.7446 | 0.1338 |
| 19 | 17.9088 | 33.3947 | 33.3006 | 0.0089 |
| 20 | 18.8204 | 33.0368 | 32.8725 | 0.0270 |
| 21 | 19.8928 | 32.5256 | 32.3563 | 0.0287 |
| 22 | 20.9651 | 31.9632 | 31.8250 | 0.0191 |
| 23 | 21.9303 | 31.5031 | 31.3320 | 0.0293 |
| 24 | 22.9491 | 30.9918 | 30.7947 | 0.0388 |
| 25 | 23.9142 | 30.0716 | 30.2678 | 0.0385 |
| 26 | 24.9866 | 29.4581 | 29.6596 | 0.0406 |
| 27 | 26.0054 | 29.3047 | 29.0567 | 0.0615 |
| 28 | 27.0241 | 27.7710 | 28.4266 | 0.4298 |
| 29 | 27.9893 | 27.3108 | 27.8011 | 0.2404 |
| 30 | 28.9544 | 27.3620 | 27.1447 | 0.0472 |
| 31 | 30.0268 | 26.9530 | 26.3740 | 0.3353 |
| 32 | 30.9383 | 26.0838 | 25.6799 | 0.1631 |
| 33 | 31.9035 | 24.3967 | 24.9003 | 0.2536 |
| 34 | 32.9759 | 23.0164 | 23.9716 | 0.9125 |
| 35 | 34.0483 | 22.9952 | 22.9657 | 0.0009 |
| 36 | 34.9598 | 21.9916 | 22.0384 | 0.0022 |
| 37 | 35.9786 | 21.4871 | 20.9074 | 0.3360 |
| SSE | | | | **0.095037** |

*Case study 2: Ballard Mark V FC*

In this section, simulation has been done for Ballad Mark V FC, made by the Canadian company, with a rated power of 5 kW and operating conditions are $T$ = 343 K, $P_{H_2}$=101 kPa (1 atm), $P_{O_2}$ = 101 kPa (1 atm), $N_s$ = 1, and $J_{max}$ = 1500 mA/cm$^2$ [46,58]. Table 5 shows the optimal results obtained *via* the proposed and other algorithms [21].

The simulation results and experimental polarization curves *I-V* data for the SR-12 modular PEM generator and Ballard Mark V FC are illustrated in Figures 6 and 7. These results show that the model obtained by the proposed MFORS matches well with the experimental data. Figures 8 and 9 show convergence curves of MFORS and other algorithms for minimizing SSE. The algorithms studied in Table 5 are as follows: Whale optimization algorithm (WOA) [37], Grasshopper optimizer (GHO) [37], Enhanced transient search optimization (ETSO) [20], Lightning search algorithm (LSA) [60], Dandelion optimizer (DO) [61], Artificial rabbits optimization (ARO) [62], Transient search optimization (ETSO)

[20], Harris hawks optimization (HHO) [20], Artificial bee colony (ABC), Shuffled frog-leaping algorithm (SFLA), Firefly algorithm (FA), Moth-flame optimization (MFO).

These results show that the convergence behavior of MFO is improved by using the RS algorithm, showing that MFORS could converge to better results. The average time to obtain parameters by the MFORS algorithm is 455 seconds. Furthermore, we ran the algorithm many times. When the obtained solution did not change much during different runs, the data variance was low and better results could be achieved from other algorithms. This shows the robustness of the algorithm, which is an advantage of RS in the proposed algorithm.

***Table 5**. The optimal parameters for different algorithms of Ballard V Fc*

| Algorithm | $\xi_1$ | $\xi_2\times10^3$ | $\xi_3\times10^5$ | $\xi_4\times10^4$ | $\lambda$ | $b$ / V | $R_c$ / m$\Omega$ | SSE | Year | Ref. |
|---|---|---|---|---|---|---|---|---|---|---|
| WOA | -1.1978 | 4.4183 | 9.72 | -16.27 | 23.0 | 1.002 | 0-1002 | 0.8537 | 2019 | [37] |
| GHO | -0.8532 | 3.4173 | 9.8 | -15.95 | 22.84 | 1.000 | 0.1000 | 0.871 | 2019 | [37] |
| ETSO | -0.8534 | 2.5591 | 3.61 | -16.28 | 23.0 | 1.000 | 0.1000 | 0.8536 | 2022 | [20] |
| LSA | -1.0624 | 3.597 | 6.65 | -16.49 | 23.00 | 1.030 | 0.1030 | 0.8140 | 2022 | [60] |
| DO | -0.8532 | 2.8687 | 5.93 | -14.75 | 23.00 | 1.000 | 0.1000 | 0.8092 | 2023 | [61] |
| ARO | -1.1588 | 3.5208 | 4.05 | -16.72 | 23.99 | 1.000 | 0.1000 | 0.81391 | 2023 | [62] |
| TSO | -0.8741 | 3.0843 | 7.96 | -9.77 | 2.713 | 7.636 | 0.7636 | 1.721 | 2022 | [20] |
| HHO | -1.0098 | 3.492 | 7.82 | -11.00 | 22.98 | 5.5000 | 0.5500 | 1.418 | 2022 | [20] |
| ABC | -1.1985 | 1.5000 | 0.0001 | -1.19 | 24 | 1.000 | 0.1000 | 1.7426 | - | This study |
| SFLA | -1.1077 | 1.4505 | 8.73 | -1.03 | 19.97 | 1.944 | 0.1944 | 2.0138 | - | This study |
| FA | -1.0876 | 1.4408 | 8.62 | -1.17 | 19.21 | 3.053 | 0.3053 | 2.9369 | - | This study |
| MFO | -1.0768 | 1.2329 | 7.83 | -1.02 | 18.55 | 2.532 | 0.2532 | 1.9731 | - | This study |
| **MFORS** | **-1.0593** | **2.9279** | **3.737** | **-1.3920** | **23.025** | **1.1815** | **0.1002** | **0.01802** | **-** | **This study (proposed)** |

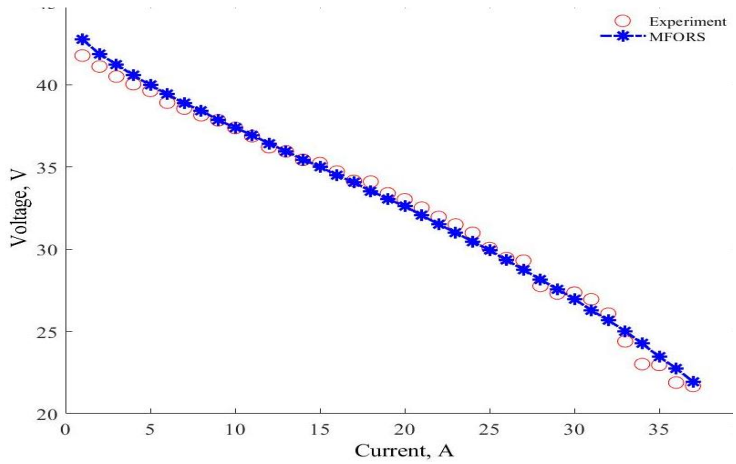


***Figure 6.** I-V characteristic for experimental and simulation results of sr-12 problem*

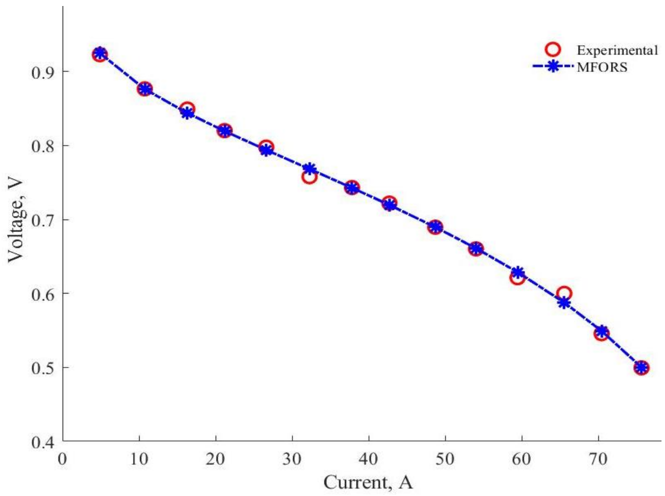


***Figure 7**. I-V characteristic for experimental and simulation results of Ballard V FC*

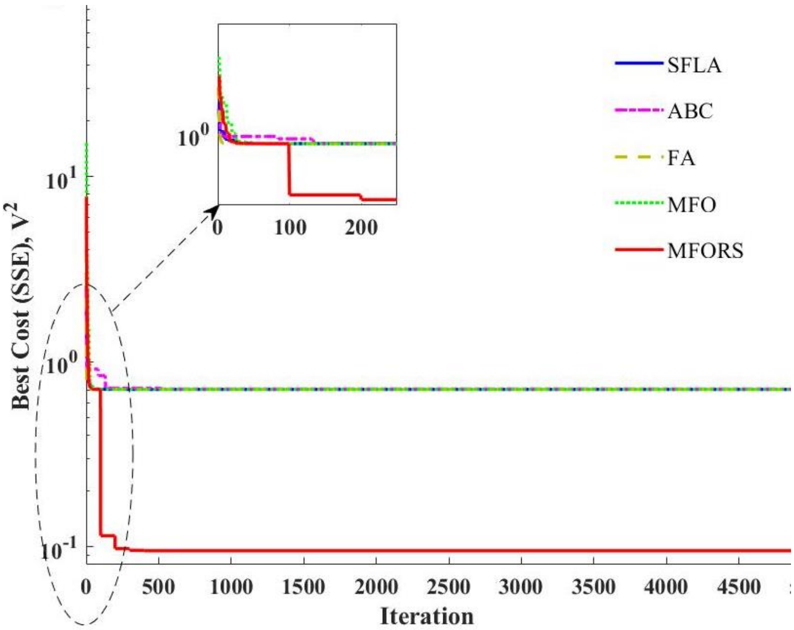


***Figure 8***. *The convergence behavior of MFO and proposed MFORS for SR-12*

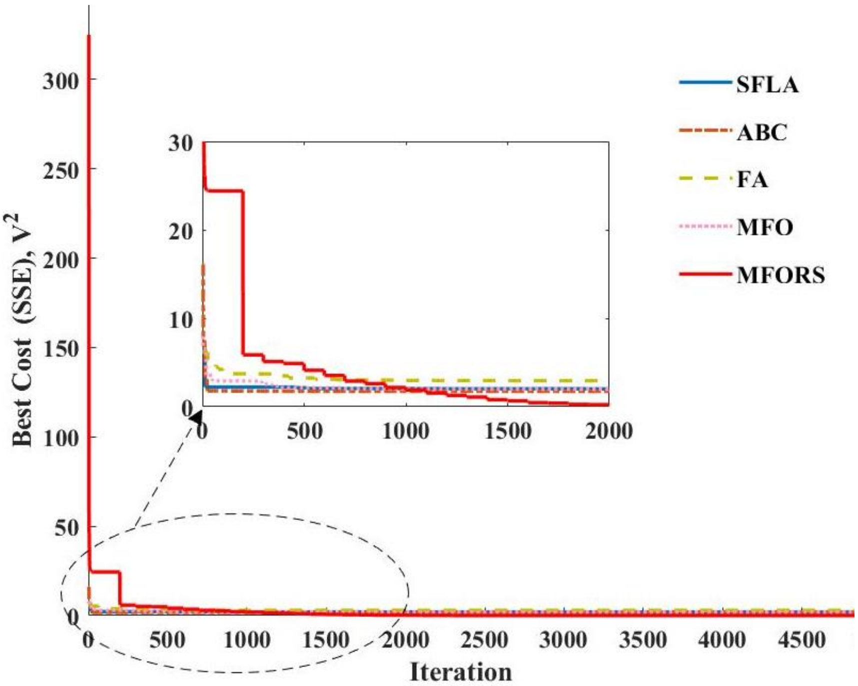


***Figure 9.*** *The convergence behavior of MFO and proposed MFORS for Ballard V FC*

## Conclusion

An accurate mathematical model of the FC system is suitable for control, evaluation, simulation and optimal operation of the FC system. However, the I-V characteristic of FC is nonlinear and an optimization algorithm is needed to find optimal parameters of its model. In this study, a new hybrid optimized algorithm called moth flame optimization-random search (MFORS) was proposed to identify the optimal parameters of PEMFC. This algorithm used the power of MFO in global exploration and the advantage of RS in the exploitation of the search space around the solutions. Simulation results showed that the proposed algorithm could achieve less SSE in comparison with the other algorithms. Based on the performance of this algorithm, using MFORS for complex energy problems, such as optimization in active distribution with microgrids, is proposed for future works.

Another direction for future work is considering uncertainty in modeling energy systems and adopting MFORS to solve these problems.

***Acknowledgements***: *This work has been financially supported by the University of Torbat Heydarieh. The grant number is UTH1401/10/05147.*

***Conflicts of interest***: *The authors have no potential conflict of interest.*

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