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## Article

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## Research Paper

# Parameter estimation of PEMFC based on Improved Fluid Search Optimization Algorithm



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## ABSTRACT

This paper presents a new optimal method for model estimation of the unknown parameters of circuit-based proton exchange membrane fuel cells (PEMFCs). The main idea is to minimize the sum of squared error (SSE) value between the actual data and the estimated results. The optimization process here is based on an Improved Fluid Search Optimization Algorithm (IFSO). For verification of the suggested method, it is applied to three practical case studies including Horizon H-12 stacks, NedStack PS6, and Ballard Mark V 5 kW under different operating conditions with temperature variations between 30 °C and 55° C and pressure variations between 1.0/1.0 Bar and 3.0/3.0 Bar. The results of these case studies are also compared with CGOA, MRFO, and basic FSO algorithm to show the proposed method's effectiveness. The results show that the minimum value of SSE among different algorithms is 0.7845, 2.15, and 0.084, respectively that are reached by the suggested IFSO algorithm.

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## 1. Introduction

Energy has long been recognized as the driving force of human societies and has been added to human importance and influence in human development. For this reason, one of the most important things in today's world that has a great impact on international relations and the development of countries is energy supply. The current pattern of energy consumption, over the past centuries and decades and in the recently industrialized world, has relied on the use of fossil fuels on a large scale so that these sources of energy provide about 90 percent of the world's required energy (Cao et al., 2019; Eslami et al., 2019). The excessive use of fossil fuels has created problems that endanger human health and well-being on a global scale, so it is feared that it will suffer irreparable damage soon (Liu et al., 2017; Gollou and Ghadimi, 2017). The biggest problem with the use of fossil fuels is that the recovery of energy and carbon dioxide that have been out of the world's energy and energy cycle over millions of years. This direct energy releasing and the resulting greenhouse gases increase the Earth's temperature and cause abnormal environmental changes such as polar ice melting and rising ocean water levels, flooding, storms, droughts and famine, outbreaks of pests, parasites and infectious diseases (Mirzapour et al., 2019; Hosseini Firouz and Ghadimi, 2016). On the other hand, unintentional and irresponsible use of these energy sources

has exacerbated environmental problems and pollution (Hekler et al., 2019; Gong and Razmjoo, 2020). Another problem with the use of fossil fuels is their deterioration. So, according to the above, clean energy production and renewable energy sources that are inexhaustible and have no problems with fossil fuel sources and, most importantly, are available free of charge in most parts of the world. Fuel cells are part of clean, voiceless, and inexpensive power generation systems whose applications are expanding worldwide. The fuel cell system consists of some cells that are assembled with its lateral system. A fuel cell converts chemical fuel energy directly into electricity (Akbari et al., 2019). The energy storage function of a fuel cell is not like a battery; a fuel cell converts energy from one state to another so that the materials in the cell are not consumed. Hydrogen gas is used as an ideal fuel in fuel cells due to its high reactivity, abundance, and environmental pollution. The topic of renewable energies is a fascinating and up-to-date discussion and the near future will replace fossil fuels. Fuel cell systems are rapidly growing and commercializing (Fei et al., 2019; Fawzi et al., 2019). The smallest unit of a fuel cell system is a single fuel cell composed of anode, cathode, and electrolyte (Yin and Razmjoo, 2020; El-Hay et al., 2019; El-Fergany, 2017). This conversion is straightforward and has a high return. The most popular type of fuel cell is the proton-exchange membrane fuel cell (PEMFC) (Chugh et al., 2020; Agwa et al., 2019; El-Hay et al., 2018). PEMFC is a high-efficiency power generation system with an efficiency of about 40% to 50% for different power scales (Mir et al., 2020). The main process in PEMFC is applying the exothermic reaction between

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hydrogen and oxygen in the air to generate electricity, distilled water, and heat (Ebrahimian et al., 2018). Among the profits of PEMFC over other fuel cells, 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 are some characteristics (Chevalier et al., 2013; Rasheed et al., 2017). As can be explained from the literature, using the classic methods usually fails to achieve a good model of the PEMFC. Besides, the simple metaheuristics sometimes stuck in the local minimum. Therefore, the main purpose of the present study is to develop a new metaheuristic method for optimal selection of a PEMFC stack model parameters. The idea is to improve the optimization algorithm to resolve the diversity and the premature convergence of the method. The main contributions of the paper are briefly addressed in the following:

- New optimal method for model estimation of a circuit-based PEMFCs is proposed
- The idea is to minimize the SSE value between the actual data and the estimated results
- Improved version of Fluid Search Optimization Algorithm (IFSO) is proposed for minimizing the SSE
- Three practical case studies under different operating conditions are used for the analysis
- The results compared with CGOA, GRA, and basic FSO algorithms

The rest of the study is organized as follows: Section 2 declares some works from the literature about the PEMFC model identification. Section 3 presents a general model of PEMFCs. In Section 4, the method of improving the Fluid Search Optimization Algorithm has been explained. Section 5 indicates the problem formulation of the study. Section 6 gives the simulation results of the proposed method and the paper is finally concluded in Section 7.

## 2. Related works

Typically, the mathematical model of PEMFCs is a significant case that should be adopted for optimal designing the system. The mathematical modeling considers the electrochemical and the physical reactions to analyze the fuel cell performance (Firouz and Ghadimi, 2016). due to the importance of system modeling, numerous research works are introduced (Fan et al., 2020).

Chakraborty (2019) introduced a modified version of Improved Jaya Algorithm for the optimal designing of a PEMFC Stack. The study addressed a constrained optimization to the optimal selection of the number of PEMFCs to be connected in series, in parallel, and the cell area to decrease the construction cost as low as possible. The final simulation was compared with four well-known and the results showed the superiority of the proposed algorithm (Zhang et al., 2020; Gheydi et al., 2016).

Shao et al. (2019) proposed a one-dimension dynamic PEMFC model to decrease its complexity of evaluation based on the Matlab-Simulink environment. The model contains five interconnected subsystems. For optimal parameter estimation of the PEMFC with avoiding premature convergence, a hybrid GA-PSO optimization algorithm was used. The simulation result indicated that the error value between the actual data and the estimated value is less than 1%. The results also were compared with some literature works.

Cao et al. (2020) presented an optimized version of PEMFC to the proper arrangement of the PEMFC system. They also used an LQR optimal procedure for controlling the PEMFC system. To improve the performance of the controller, a modified version of the whale optimization algorithm was adopted. Simulation

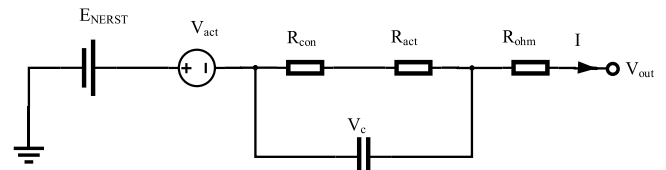


Fig. 1. The circuit-model of a PEMFC.

results were compared with some other approaches to show the method's effectiveness.

Yuan et al. (2020) proposed an optimized method for optimal selection of PEMFCs parameters. The main idea is to minimize the sum of squared error (SSE) value between the experimental data and the estimated results. The optimization was performed based on an improved version of the Sunflower Optimization Algorithm (DSFO). The simulations were applied to two benchmarks. The results were compared with experimental data and also some literature research works.

## 3. Dynamic mechanism of model of the PEMFC

As aforementioned, for proper optimizing of the PEMFC, we need to model and simulate before construction. The general  $I$ - $V$  polarization profile of a PEMFC is mathematically modeled with three voltage losses including ohmic overpotential voltage ( $V_{\Omega}$ ), concentration overpotential ( $V_{con}$ ), and activation overvoltage ( $V_{act}$ ). Fig. 1 shows the circuit-based model of a PEMFC.

Therefore, based on Fig. 1, the explanations, and the assumption that the reference temperature value during the operating changes is assumed 25 °C, the output terminal voltage of  $N$  connected PEMFC can be formulated as follows:

$$V_{FC} = N \times (E_{Nerst} - V_{con} - V_{\Omega} - V_{act}) \quad (1)$$

where,  $E_{Nerst}$  describes the Nernst potential and is achieved by the following equation:

$$E_{Nerst} = 1.23 - 8.5 \times 10^{-4} (T_{PEM} - 298.15) + 4.31 \times 10^{-5} \times T_{PEM} \times \ln(P_{H_2} \sqrt{P_{O_2}}) \quad (2)$$

where,

$$P_{H_2} = \frac{R_{ha} \times P_{H_2O}}{2} \left[ \frac{1}{\frac{R_{ha} \times P_{H_2O}}{P_a} \times e^{\frac{1.635I_{PEM}/A}{T^{1.334}I_{PEM}}} - 1} \right] \quad (3)$$

$$P_{O_2} = R_{hc} \times P_{H_2O} \left[ \frac{1}{\frac{R_{hc} \times P_{H_2O}}{P_c} \times e^{\frac{1.635I_{PEM}/A}{T^{1.334}I_{PEM}}} - 1} \right] \quad (4)$$

$$\log_{10}(P_{H_2O}) = 2.95 \times 10^{-2} T_c - 9.18 \times 10^{-5} T_c^2 + 1.4 \times 10^{-7} T_c^3 - 2.18 \quad (5)$$

$$T_c = T_{PEM} - 273.15 \quad (6)$$

where,  $T_{PEM}$  describes the operating cell temperature (K),  $P_a$  and  $P_c$  determines the inlet pressure for the anode and the cathode,  $R_{ha}$  and  $R_{hc}$  represent the vapor relative humidity at anode and cathode, respectively,  $P_H$ ,  $P_{O_2}$ , and  $P_{H_2O}$  define the partial pressure of Hydrogen, Oxygen, and water, respectively. The concentration overpotential ( $V_{con}$ ) of the PEMFC is achieved as follows:

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

where,  $\beta$  stands for a parametric coefficient,  $J$  defines a real current density, and  $J_{max}$  describes the maximum value of  $J$ .

The mathematical model of the activation overvoltage ( $V_{act}$ ) is achieved as follows:

$$E_{op} = -[\gamma_1 + \gamma_2 \times T_{PEM} + \gamma_3 \times T_{PEM} \times \ln(C_{O_2}) + \gamma_4 \times T_{PEM} \times \ln(I_{PEM})] \quad (8)$$

where,  $\gamma_i$  determines the  $i$ th experimental coefficients and  $C_{O_2}$  and  $C_{H_2}$  represent the Oxygen and the Hydrogen saturation in the cathode's catalytic interface (mol/cm<sup>3</sup>) and are obtained by the following equation:

$$C_{O_2} = \frac{P_{O_2}}{5.1 \times 10^6} \times e^{\frac{498}{T_{PEM}}} \quad (9)$$

$$C_{H_2} = \frac{P_{H_2}}{1.1 \times 10^6} \times e^{\frac{-77}{T_{PEM}}} \quad (10)$$

Finally, the ohmic overpotential voltage ( $V_{\Omega}$ ) in the cells is formulated as follows:

$$V_{\Omega} = I_{PEM} \times (R_m + R_c) \quad (11)$$

where,  $I_{PEM}$  describes the operating current of the PEMFC,  $R_c$  is the resistance of the connection, and  $R_m$  defines the membrane resistance and is achieved as follows,

$$R_m = \rho_m l S^{-1} \quad (12)$$

$$\rho_m = \frac{181.6 \left[ 0.062 \left( \frac{T_{PEM}}{303} \right)^2 \left( \frac{I_{PEM}}{5} \right)^{2.5} + 0.03 \left( \frac{I_{PEM}}{5} \right) + 1 \right]}{\left[ \lambda - 0.063 - 3 \left( \frac{I_{PEM}}{5} \right) \right] \times e^{\frac{T_{PEM}-303}{T_{PEM}}}} \quad (13)$$

where,  $\rho_m$  stands for the membrane resistivity,  $l$  describes the membrane thickness,  $\lambda$  defines a tunable parameter, and  $S$  describes the membrane surface (cm<sup>2</sup>).

With a close look at the above equations, seven parameters including  $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \lambda, R_c$ , and  $\beta$  can be considered for optimal parameter identification of the PEMFC (Aghajani and Ghadimi, 2018). Generally, the above-mentioned parameters are usually does not give in the PEMFCs builder's datasheet. This subject made the researchers work on the optimal selection of these parameters. Therefore, the main purpose of this paper is to propose a new methodology to develop system identification.

#### 4. Fluid search optimization algorithm

Optimization is a key part of this study. As can be described before, the main idea is to utilize a method for modeling the PEMFCs by minimizing the error value between the actual output value and the model output value. There are different methods for minimizing the optimization problems. especially, classic methods like gradient descent (Yu and Ghadimi, 2019) or HJB (Hosseini Firouz and Ghadimi, 2016) methods that give an exact solution for the problem. A big shortcoming of using these methods is that in some cases, using them for solving complicated problems is so time-consuming or completely impossible. In such cases, the best alternative is to use metaheuristic methods. A prominent advantage of Meta-heuristic methods is that they are not problem-dependent. Besides, they can solve any constrained and unconstrained problem without needing a big time-wasting. Metaheuristic methods often inspired by different natural phenomena. For example, some of the meta-heuristic methods are like genetic algorithm (Hamian et al., 2018) that simulates Darwin's principles of selection to find the optimal formula, Grass Fibrous Root Optimization Algorithm (GRA) that simulates the Fibrous Root behavior (Leng et al., 2018), Butterfly Optimization Algorithm (BOA) (Khodaei et al., 2018) that simulates the butterflies' migration from the cold areas to the warmer places in the cold seasons, Teaching-Learning-Based Optimization Algorithm (Bagal et al., 2018) that simulates the relations between

Teaching and Learning. Another new metaheuristic method is Fluid Search Optimization (FSO) algorithm which is recently introduced by Dong et al. The FSO algorithm simulates Bernoulli's principle in fluid mechanics.

##### 4.1. The basic fluid search optimization algorithm

The principle of Bernoulli is to determine how the speed of a fluid depends on the fluid pressure such that enhancing the fluid speed, decreases the fluid pressure and the potential energy. the formulation of the Bernoulli principle is as follows.

$$p + \frac{1}{2} \rho v^2 = p_0 \quad (14)$$

where,  $p$  describes the pressure of a selected point on a streamline,  $p_0$  represents a constant pressure for the system,  $v$  determines the fluid flow speed at the point, and  $\rho$  represents the fluid density at each point in the fluid. Dong and Wang reformulated this equation as follows:

$$v = \sqrt{\frac{2(p_0 - p)}{\rho}} \quad (15)$$

Based on this equation, the new position of the solution is achieved by the following recursive equation,

$$x_{new} = x_{old} + v \quad (16)$$

where,  $x_{new}$  and  $x_{old}$  represent the new and the previous position of the infinitesimals.

Here, the fluid infinitesimal pressure is assumed as the objective function value such that enhancing the pressure, decreases the fluid infinitesimal velocity. The fluid infinitesimal optimization depends on the fluid flowing inverse process from the high pressure to the low pressure involuntary. The fluid infinitesimals have been converged if the point with the highest pressure has been reached.

The algorithm starts with  $n$  number of random population (infinitesimals), i.e.  $X = [x_1, x_2, \dots, x_n]$ . With this assumption, the infinitesimal pressure  $p_i$  is achieved as follows:

$$p_i = \frac{(y_{worst} - y_i)}{(y_{worst} - y_{best})} \quad (17)$$

$$P_0 = 1$$

where,  $y$  describes the fitness function,  $p_i$  defines a normalized value in the range [0, 1] to consider the effect of different cost functions on the algorithm, and  $y_{worst}$  and  $y_{best}$  represent the worst and the best results of  $y$  after optimization, respectively. Infinitesimal density is another mechanism of the algorithm that shows the overall neighbor infinitesimals of the cell of the current infinitesimal and is achieved by the following equation:

$$\rho = m \times l^{D-1} \quad (18)$$

where,  $D$  stands for the dimension of the hypercube,  $m$  defines the value of the infinitesimals, and  $l$  describes the length for the cell side.

For increasing the convergence ability, the algorithm uses the normalized value of the pressure by the following equation:

$$\vec{p}_i = \sum_{\substack{j=1 \\ j \neq i}}^n rand \otimes p_j \frac{(X_j - X_i)}{|(X_j - X_i)|_2} + rand \otimes p_{best} \times 2 \times \frac{(X_{best} - X_i)}{|(X_{best} - X_i)|_2} \quad (19)$$

where,  $\vec{p}_i$  describes a vector value. And the new direction is achieved as follows:

$$D_n = \gamma \times D_l + \vec{p}_i \times |\vec{p}_i|_2^{-1} \quad (20)$$



where,  $\gamma$  describes the inertial factor,  $D_n$  and  $D_l$  represents the new and the previous directions, respectively.

With all this, the basic FSO algorithm has a significant drawback in terms of premature convergence. In the next section, a mechanism is applied to resolve this problem.

#### 4.2. Fluid search optimization algorithm based on chaos theory (IFSO)

In this part, two improvement mechanisms have been used for developing the FSO algorithm. The first mechanism for algorithm improvement is Quasi-oppositional based learning. For more clarification of this conception, oppositional-based learning should be first clarified. The oppositional-based learning is a mechanism to modify the system convergence speed based on comparing every single member of the population with their opposite value and to choose the best one as the new candidate (Saeedi et al., 2019; Haixiong et al., 2020). To do so, consider  $x$  as a real number in a solution space with  $D$  dimension that is ranged in the interval  $[\alpha, \beta]$ . The opposite of the candidate  $x$  is defined by  $\check{x}$  and is achieved by the following:

$$\check{x}_i = \alpha_i + \beta_i - x_i \quad (21)$$

$$i = 1, 2, \dots, D \quad (22)$$

Based on the above definition, the quasi-opposite number can be defined by  $\hat{x}$  by the following (Liu et al., 2020):

$$\hat{x}_i = \text{rand} \left( \frac{\alpha_i + \beta_i}{2}, \check{x}_i \right) \quad (23)$$

Another mechanism for algorithm improvement is based on the chaotic conception. The chaotic mechanism considers random and unpredictable processes in any system. Generally, the nature of some systems is nonlinear and so complicated which is originated due to their chaotic nature. This leads us to use this mechanism for increasing the population diversity in the FSO algorithm. this mechanism also develops the FSO algorithm in terms of convergence speed and escaping from falling into the local optimal point (Meng et al., 2020; Cai et al., 2019). In this paper, the logistic map is adopted as a popular type of chaotic functions for algorithm improvement. Based on the logistic map mechanism,

$$\delta_{o,n}^{q+1} = 4\delta_{o,n}^q(1 - \delta_{o,n}^q) \quad (24)$$

where,  $o$  represents the system generators quantity,  $n$  describes the population number,  $q$  stands for the iteration number,  $\delta_n$  describes the chaotic mechanism value in iteration  $n$  which is ranged in the interval  $[0, 1]$  (Meng et al., 2020; Cai et al., 2019). By considering the logistic map mechanism and the chaotic conception, the new direction for the proposed FSO is achieved as follows:

$$D_n^{q+1} = D_n^q + \delta_{o,n}^q \times D_l^q \quad (25)$$

Fig. 2 shows the flowchart diagram of the IFSO algorithm.

For verifying the proposed IFSO algorithm, it is applied to four different test functions and the results are compared with some different metaheuristics including CGOA (Arora and Anand, 2018), GRA (Leng et al., 2018), and basic FSO (Leng et al., 2018). Table 1 illustrates the adopted functions for the compared algorithms validation.

The results of the algorithms by considering the above benchmarks are given in Table 2. The verification is based on analyzing the median value, standard deviation (std) value, minimum, and the maximum values of the cost function.

As can be observed from Table 2, the presented IFSO algorithm has the best accuracy compared with CGOA (Arora and Anand,

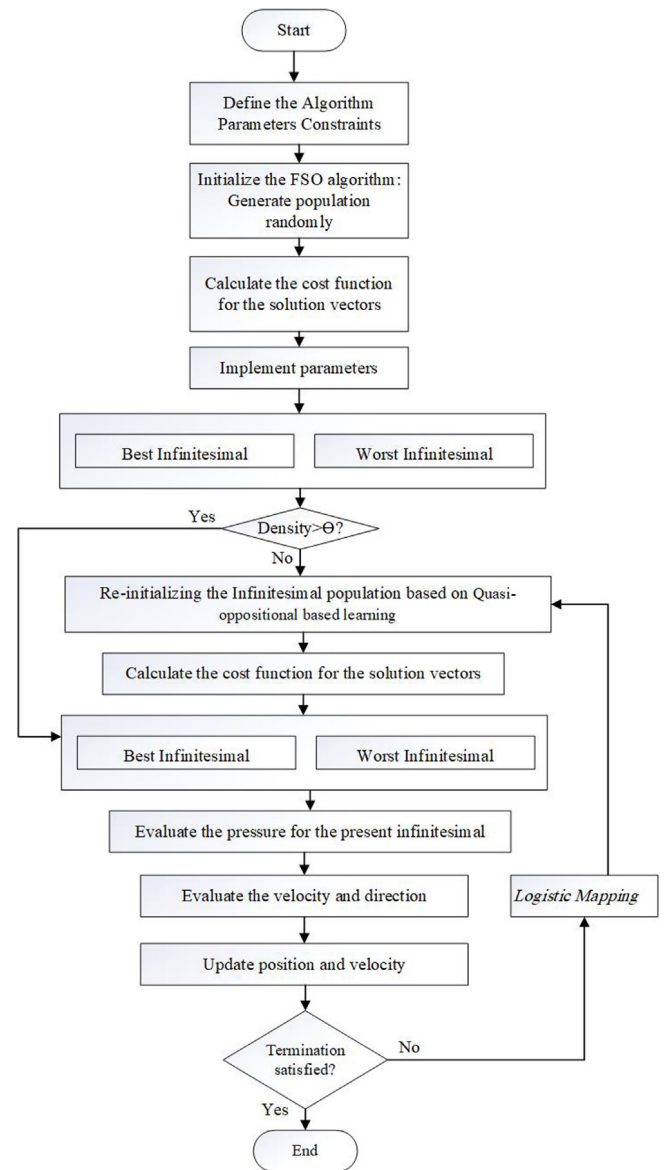


Fig. 2. The diagram flowchart of the IFSO.

2018), GRA (Leng et al., 2018), and basic FSO for the analyzed test functions. The results of the standard deviation value show also that the proposed IFSO algorithm with the minimum std has the best condition among the others in terms of robustness.

### 5. Problem formulation

Based on the before mentioned explanations, the main idea of the present research is to use the IFSO algorithm for optimal selection of the seven presented unknown parameters of PEMFCs stacks as a nonlinearly constrained optimization problem. To achieve the best parameter selection, the sum of squared error (SSE) between the actual output voltage and the estimated output voltage should be minimized. The SSE formulation is given below:

$$F_{SSE} = \min (SSE) = \min \left\{ \sum_{i=1}^n (V_e(i) - V_{FC}(i))^2 \right\} \quad (26)$$

where,  $V_{FC}$  and  $V_e$  describe the experimental and the estimated values for the output voltage.

**Table 1**  
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
$F3 =  x  +  y  + (x^2 + y^2)^{0.25} \times \sin(30((x + 0.5)^2 + y^2)^{0.1})$	$[-\infty, \infty]$	-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 2**  
The validation results of the compared algorithms.

		CGOA (Arora and Anand, 2018)	GRA (Leng et al., 2018)	FSO (Leng et al., 2018)	IFSO
$F_1$	Maximum	-8.19	-9.83	-10.32	-10.85
	Minimum	-18.58	-18.41	-18.56	-18.67
	Median	-16.37	-15.74	-16.42	-16.84
	std	4.62	3.51	3.46	2.19
$F_2$	Maximum	0.541	0.538	0.520	0.509
	Minimum	0.500	0.500	0.500	0.500
	Median	0.526	0.519	0.512	0.502
	std	0.067	0.007	0.005	0.000
$F_3$	Maximum	-0.152	-0.213	-0.219	-0.345
	Minimum	-0.316	-0.307	-0.320	-0.337
	Median	-0.227	-0.219	-0.241	-0.340
	std	0.314	0.357	0.096	0.017
$F_4$	Maximum	16.28	21.49	19.08	6.37
	Minimum	4.08	0.009	0.000	0.000
	Median	10.35	11.43	9.27	3.16
	std	5.284	6.281	0.628	0.028

**Table 3**  
The search ranges of the parameters for all the case studies.

Parameter	$\gamma_1$	$\gamma_2$	$\gamma_3$	$\gamma_4$	$\beta$	$\lambda$	$R_c$
Minimum	-1.20	1	3.6	-26	0.014	13	1E-4
Maximum	-0.85	5	9.8	-9.54	0.50	23	8E-4

**Table 4**  
The main parameters of Ballard Mark V.

Parameter	Value	Unit
Power	5	kW
Maximum cell current	70	A
$T_{PEM}$	343	K
Number of cells	35	-
membrane area	50.6	cm <sup>2</sup>
ultimate Jmax	1500	mA/cm <sup>2</sup>
$l$	178	$\mu$ m

**6. Simulation results**

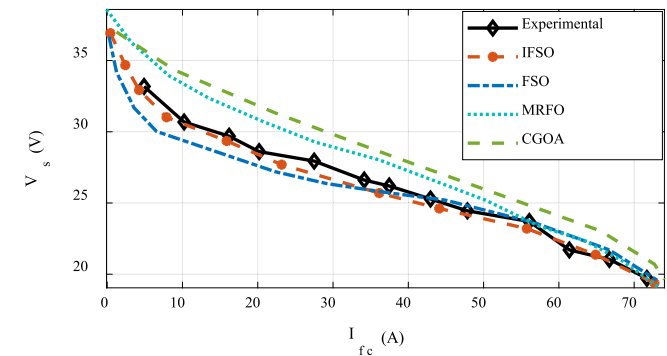
After explaining the structure of the proposed system parameter, the method has been validated on three well-known practical PEMFC stacks including Horizon H-12 stacks, NedStack PS6, and Ballard Mark V 5 kW. The parameters values and operating conditions for the considered PEMFC stacks have been collected from El-Fergany et al. (2019), El-Fergany (2018) and Ali et al. (2017). For performing a fair analysis, the search ranges for all case studies are assumed identical. For both test cases, the maximum ratio of the density ( $\theta$ ) is considered as 20% and the ratio of diversification search ( $M'$ ) is assumed 70% (Dong and Wang, 2018). Table 3 illustrates these ranges.

**6.1. Case study 1: Ballard Mark V**

The first case study is a 5 kW Ballard Mark V PEMFCs stack. Table 4 illustrates the main parameters of this PEMFC stack. For better validation of the algorithm, in addition to comparing the proposed IFSO with the experimental data, it has compared with GRA, CGOA, and the basic FSO algorithms with 30 runs for each algorithm to have a fair comparison among them.

The current-voltage curve of the Ballard Mark V for the experimental curve and model curve using GRA, CGOA, the basic FSO, and the proposed IFSO algorithms are shown in Fig. 3. Fig. 3 shows a good agreement among measured and model voltage points.

Table 5 illustrates the estimated parameters of Ballard Mark V, SSE validation, and running time for the CGOA (Arora and Anand,



**Fig. 3.** The current–voltage curve for the Ballard Mark V.

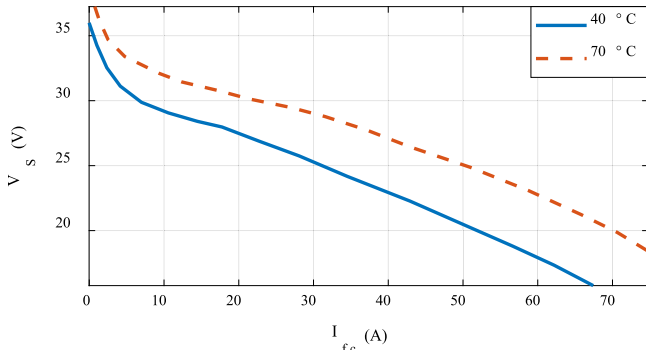
2018), MRFO (Selem et al., 0000), basic FSO (Leng et al., 2018), and the proposed IFSO.

As can be observed from Fig. 3 and the records of Table 5, the proposed IFSO algorithm has the minimum value of SSE (0.7845) with a fast convergence characteristic compared with other algorithms. The results also show how the presented modification effects on the accuracy and convergence of the FSO algorithm.

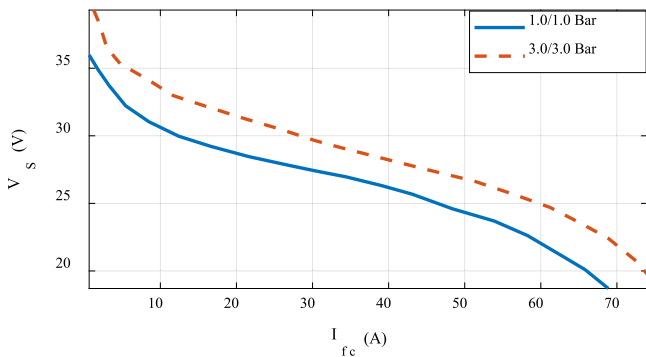
To show the reliability of the proposed model based on IFSO, it is analyzed under different conditions, i.e. temperature variations

**Table 5**  
The estimated parameters of Ballard Mark V, SSE validation, and running time for the analyzed algorithms.

Parameter	Algorithm			
	CGOA (Arora and Anand, 2018)	MRFO (Selem et al., 0000)	FSO (Leng et al., 2018)	IFSO
$\gamma_1$	-2.12	-1.09	-0.95	-1.12
$\gamma_2 \times 10^{-3}$	3.80	3.82	3.36	3.57
$\gamma_3 \times 10^{-5}$	7.19	7.73	7.42	8.01
$\gamma_4 \times 10^{-5}$	-17.03	-16.28	-15.83	-15.94
$\lambda$	23.00	23.00	22.00	22.00
$R_c \times 10^{-4}$	1.00	1.00	1.00	1.00
$\beta$	0.042	1.36	0.029	0.015
SSE	2.613	0.85	0.952	0.784
Elapsed time (s)	5.61	6.19	6.13	3.80



**Fig. 4.** The temperatures variations in 40 °C and 70 °C.



**Fig. 5.** The partial pressures variations in 1.0/1.0 Bar and 3.0/3.0 Bar.

and partial pressure variations. Fig. 4 shows the temperature variations in 40 °C and 70 °C and Fig. 5 shows the variations of the partial pressure during 1.0/1.0 Bar and 3.0/3.0 Bar.

6.2. Case study 2: NedStack PS6

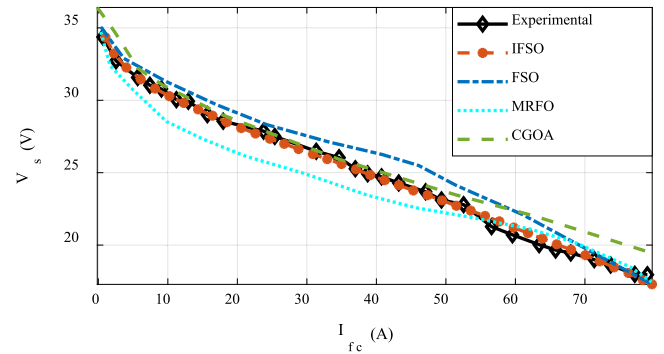
The second case study is a NedStack PS6 with a rated power of 6 kW PEMFCs stack. The information for the NedStack PS6 has been extracted from N.F.C. Technology and El Monem et al. (2014). Table 6 illustrates the required parameters of the NedStack PS6.

The current–voltage curve of the NedStack PS6 for the empirical curve and model curve based on GRA, CGOA, the basic FSO, and the proposed IFSO algorithms have been shown in Fig. 6 which shows a satisfying agreement among measured and model voltage points.

By applying the proposed IFSO algorithm to the NedStack PS6 system, the optimal value for the seven unknown parameters have been identified. Table 7 indicates the results of the GRA, CGOA, and basic FSO algorithms by illustrating the estimated parameters, SSE validation, and running time.

**Table 6**  
The main parameters of NedStack PS6.

Parameter	Value	Unit
$N_{cells}$	65	-
Power	6	kW
Maximum cell current	225	A
$T_{PEM}$	343	K
Partial pressure	[1, 5]	Bar
Membrane area	240	cm <sup>2</sup>
Ultimate Jmax	1200	mA/cm <sup>2</sup>
$l$	178	μm



**Fig. 6.** The current–voltage curve for the NedStack PS6.

Fig. 7 shows the temperature variations between 30 °C and 55 °C. As can be clear from Fig. 7 and Table 7, in this case, study, the proposed IFSO algorithm gives the best results with minimum SSE (2.15) as the fastest convergence again compared with other algorithms. To show the reliability of the proposed model based on IFSO, it is analyzed under different conditions, i.e. temperature variations and partial pressure variations. Fig. 4 shows the temperature variations in 40 °C and 70 °C and Fig. 5 shows the variations of the partial pressure during 1.0/1.0 Bar and 3.0/3.0 Bar. (See Fig. 8.)

6.3. Case study 3: Horizon H-12

The final case study is Horizon H-12 PEMFC stack. The system information is given in Table 8. The information for the Horizon H-12 has been extracted from Ondrejčička et al. (2019). Table 8 indicates the required parameters of the Horizon H-12.

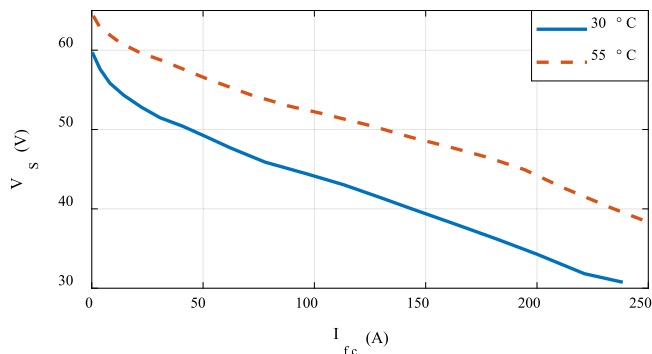
The current–voltage curve of the Horizon H-12 for the empirical curve and model curve based on GRA, CGOA, the basic FSO, and the proposed IFSO algorithms have been shown in Fig. 9 which shows a satisfying agreement among measured and model voltage points.

By implementing the presented IFSO algorithm to the Horizon H-12 system, the optimal value for the seven unknown parameters has been estimated. Table 8 indicates the results of the GRA,

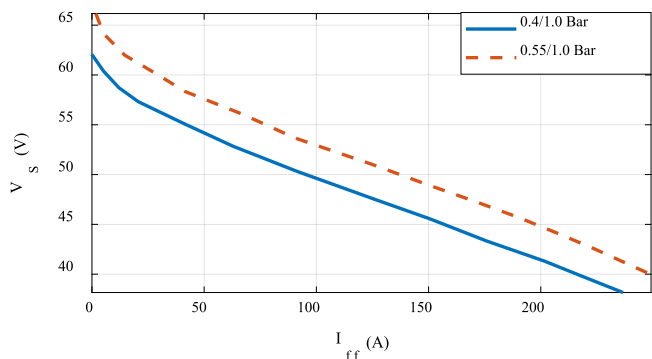
**Table 7**

The estimated parameters of NedStack PS6, SSE validation, and running time for the analyzed algorithms.

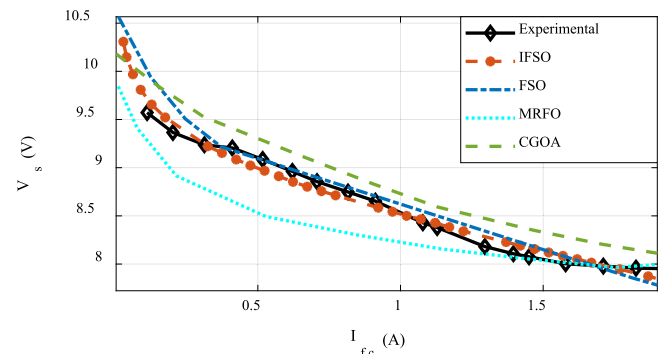
Parameter	Algorithm			
	CGOA (Arora and Anand, 2018)	MRFO (Selem et al., 0000)	FSO (Leng et al., 2018)	IFSO
$\gamma_1$	-1.19	-0.94	-0.92	-0.92
$\gamma_2 \times 10^{-3}$	3.32	3.49	3.51	3.46
$\gamma_3 \times 10^{-5}$	4.19	9.51	7.46	7.59
$\gamma_4 \times 10^{-5}$	-9.61	-9.54	-9.57	-9.62
$\lambda$	12.41	13.09	13.10	13.15
$R_c \times 10^{-4}$	0.11	1.00	0.08	0.10
$\beta$	0.05	0.01	0.05	0.04
SSE	2.53	2.26	2.32	2.15
Elapsed time (s)	5.18	7.54	4.82	1.28



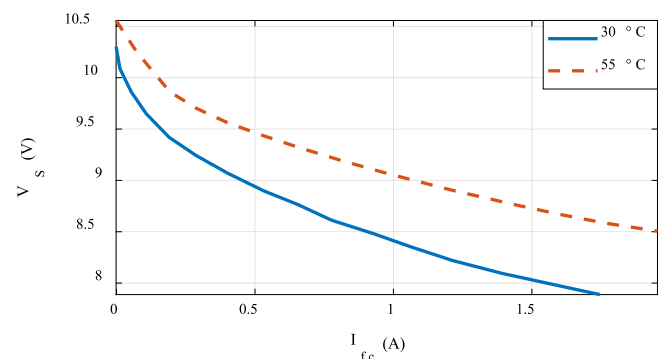
**Fig. 7.** The temperatures variations in 30 °C and 55 °C.



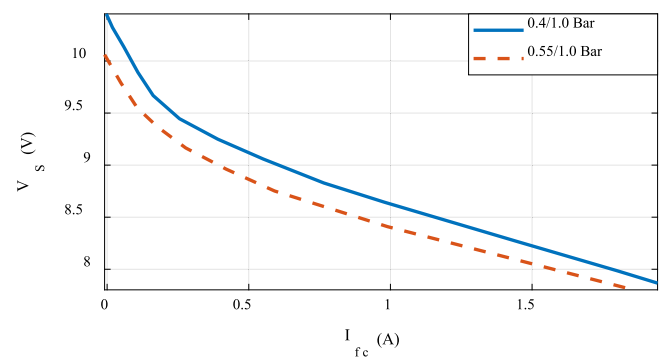
**Fig. 8.** The partial pressures variations in 0.4/1.0 Bar and 0.55/1.0 Bar.



**Fig. 9.** The current–voltage curve for the H-12 PEMFC.



**Fig. 10.** The temperatures variations in 30 °C and 55 °C.



**Fig. 11.** The partial pressures variations in 0.4/1.0 Bar and 0.55/1.0 Bar.

**Table 8**

The main parameters of Horizon H-12.

Parameter	Value	Unit
$N_{cells}$	13	-
Power	12	W
$T_{PEM}$	328.15	K
Partial pressure	[0.4, 0.55]	Bar
Membrane area	8.1	cm <sup>2</sup>
Ultimate $J_{max}$	246.9	mA/cm <sup>2</sup>

CGOA, and basic FSO algorithms by illustrating the estimated parameters, SSE validation, and running time.

As can be clear from Figs. 10, 11, and Table 9, in this case, study, the proposed IFSO algorithm gives the best results with minimum SSE (0.084) as the fastest convergence again compared with other algorithms. To show the reliability of the proposed model based on IFSO, it is analyzed under different conditions, i.e. temperature variations and partial pressure variations. Fig. 10 shows the temperature variations in 30 °C and 55 °C and Fig. 11 shows the variations of the partial pressure during 0.4/1.0 Bar and 0.55/1.0 Bar.

## 7. Conclusions

In the present study, a new improved version of the Fluid Search Optimization Algorithm (IFSO) was presented for the optimal selection of unknown parameters of PEMFS stack models.



**Table 9**

The estimated parameters of H-12 PEMFC, SSE validation, and running time for the analyzed algorithms.

Parameter	Algorithm			
	CGOA (Arora and Anand, 2018)	MRFO (Selem et al., 0000)	FSO (Leng et al., 2018)	IFSO
$\gamma_1$	−1.14	−1.06	−1.15	−1.08
$\gamma_2 \times 10^{-3}$	2.56	2.36	2.49	2.34
$\gamma_3 \times 10^{-5}$	4.01	4.33	3.28	3.76
$\gamma_4 \times 10^{-5}$	−9.54	−9.54	−9.54	−9.54
$\lambda$	14.27	19.81	14.85	19.92
$R_c \times 10^{-4}$	7.47	2.85	8.00	7.97
$\beta$	0.16	0.18	0.17	0.18
SSE	0.117	0.11	0.121	0.084
Elapsed time (s)	6.19	6.38	4.19	3.54

The main purpose was to minimize the sum of squared error (SSE) between the actual output voltage and the estimated output voltage. The research adopts three practical case studies including Horizon H-12 stacks, NedStack PS6, and Ballard Mark V 5 kW under different operating conditions and the results were compared with three different metaheuristics including CGOA, MRFO, and basic FSO algorithms to show the superiority of the presented algorithm. In future research, we will work on a more accurate model of the PEMFC by considering the model uncertainties by robust modeling based on the affine analysis.

### CRedit authorship contribution statement

**Fuzhen Qin:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Peixue Liu:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Haichun Niu:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Haiyan Song:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Nasser Yousefi:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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