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## Article

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## Research paper

# New optimized technique for unknown parameters selection of SOFC using Converged Grass Fibrous Root Optimization Algorithm

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## ABSTRACT

This paper presents an optimal technique for parameter estimation of a Solid Oxide Fuel Cell (SOFC) model. The idea is to minimize the Sum of Squared Error (SSE) between the output voltage and the experimental data. To achieve this purpose, a new metaheuristic, called the Converged Grass Fibrous Root Optimization Algorithm (CGRA) is presented and is validated by comparing it with some well-known algorithms. The method is then applied to the optimal parameter estimation of the model. To analyze the method accuracy and its robustness, the proposed model is verified under different pressure and temperature operating conditions and the results have been compared with some different methods from the literature. Simulation results indicate a good confirmation between the experimental results and the model designed based on the proposed CGRA. The results for the CGRA show that the SSE results for 3 atm constant pressure and 563.85°C, 649.85°C, 699.85°C, 749.85°C, and 799.85°C are 1.67E−4, 1.84E−4, 9.42E−4, 1.87E−3, and 1.62E−3, respectively and for 799.85°C constant temperature with 1 atm, 2 atm, 3 atm, 4 atm, and 5 atm, are 1.68E−3, 1.84E−3, 9.42E−3, 1.87E−3, and 1.62E−3, respectively that are the minimum values among the other analyzed methods that indicate that the suggested technique gives better efficiency with the highest robustness and convergence speed compared with the other methods.

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## 1. Introduction

In recent years, the use of fossil fuels has been increased, while these resources are running out, and activists around the world and environmental experts and economists are considering replacing clean fuels with various methods for use as an alternative energy source (Fan et al., 2020; Leng et al., 2018; Akbary et al., 2019). A range of different factors including fossil resources limitations, their negative effects on the environment, utilization of hydrocarbon resources, rising fossil fuel prices, political strife and their effects on sustainable energy, have led many politicians, energy experts and environmentalists to move toward presenting a new security-based structure to supply energy, preserve the environment and to enhance the energy system efficiency (Hosseini Firouz and Ghadimi, 2016; Hamian et al., 2018; Eslami et al., 2019; Saeedi et al., 2019). Hydrogen is one of the best options for playing the role of energy carrier (Yin and Razmjoo, 2020; Yuan et al., 2020; Yu and Ghadimi, 2019). Hydrogen is known as one of the abundant elements on the world (Liu et al., 2017). In a hydrogen-based energy ideal system,

hydrogen has been produced by surplus electricity produced by the renewable energy sources like solar, wind, and geothermal for guaranteeing of a safe energy supply, preserving the environment and improving the energy system efficiency (Gollou and Ghadimi, 2017; Mirzapour et al., 2019). With this approach, most of researchers believe that hydrogen will be the ultimate fuel for human in not-so-distant future. The fuel cell is the latest technology in the world to direct convert of chemical energy into the electricity (Ebrahimi et al., 2018; Bagal et al., 2018). Fuel cells have been considered as an interesting technology in many countries around the world due to their high efficiency and very low pollution characteristics (Gheydi et al., 2016). Hydrogen is the main fuel of fuel cells that can be produced in various ways (Yuan et al., 2020). Hydrogen generation from natural gas is the most important and economical method. Fuel cell technology, in which hydrogen produces oxygen, electricity, and heat during a series of electrochemical tests, is one of the best options for energy production (Aghajani and Ghadimi, 2018). Due to their efficient, non-emission of environmental pollutants, high density, lack of moving parts and lack of vibration and sound, fuel cells are desirable equipment for energy production.

One of the most important and widely used model of fuel cells is Solid Oxide Fuel Cell (SOFC) (Liu et al., 2020; Meng et al., 2020). The high operating temperature of this type of fuel cell

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has led to the use of various fuels such as natural gas in such a direct way. In addition, the heat generated in this type of fuel cell is of high quality and can be used in most thermal systems. The operating range of solid oxide combustion coils is about 700 °C to 1000 °C (Ramadhani et al., 2017). To design a proper SOFC system, we need to have a complete information about them. In other words, mathematical modeling of SOFCs is an important part of optimal designing of this component (Firouz and Ghadimi, 2016). Numerous methods have been presented for mathematical Modeling of fuel cells. For example, Tang et al. (2018) presented a technique for model parameters estimation of SOFCs using Extreme Learning Machine-Hammerstein (ELM-Hammerstein). By considering the Lipschitz criterion, the generalized ELM was performed to the model for parameter estimation of the model. Simulation results indicated that the technique give proper confirmation with empirical data.

Another technique for optimal parameter selection of an SOFC using metaheuristics is proposed by Wei and Stanford (2019). The idea minimizes the mean squared deviation error between the actual data and the estimated value by optimal selecting of the model undetermined parameters. The minimization process in the work was developed by a modified version of Binary Shark Smell Optimizer. The method was compared with some other works to indicated its efficient performance. Wu et al. (2019) introduced a multi-objective problem for the SOFC system. The main idea was to maximize the total performance of the SOFC and to minimize the system cost when air leakage fault happens. The authors used

a non-dominated sorting Particle Swarm optimization (PSO) algorithm for the optimization. The method was compared with some state of art methods to indicate its higher efficiency with minimum cost toward different methods.

in 2020, Wang et al. (2020) proposed an RNA-genetic algorithm to achieve optimal values for parameter identification of the SOFC. The study investigated a sensitivity analysis for the system and the algorithm efficiency was compared with some other methods. Simulation results indicated a proper agreement for the algorithm in modeling of the SOFC.

By considering the above literature, it is observed that there are numerous studies which have been proposed for parameters identification of an SOFC in both transient and steady-state scenarios. However, there are still lots of improvements that can be performed for developing the efficiency of the identification methodology. The main idea of this study is to present a reliable procedure for optimal parameters selection of the SOFC. The contributions of this study are briefly given below:

- New optimized design has been proposed for optimal selection of SOFC parameters.
- The method is developed based on a new model of Grass Fibrous Root Optimization Algorithm.
- The method is analyzed under various temperatures and pressures.
- The method results are compared with some different works from the literature
- Wilcoxon's statistical analysis and Friedman test are used for more analysis.

## 2. Mathematical model of Solid Oxide Fuel Cell

The mathematical model of a SOFC is briefly described in this section. Generally, the output voltage of a single SOFC cell is defined as follows:

$$V_{cell} = E_{Nernst} - V_{conc} - V_{\Omega} - V_{act} \quad (1)$$

where,  $E_{Nernst}$  defines the Nernst reversible voltage,  $V_{conc}$  describes the concentration loss voltage,  $V_{\Omega}$  represents the ohmic loss voltage, and  $V_{act}$  is the activation loss voltage.

Accordingly, the total output voltage for a SOFC stack including  $N_{cell}$  number of cells is defined by the following equation:

$$V_{stack} = N_{cell} \times V_{cell} = E_{Nernst} - E_{conc} - E_{\Omega} - E_{act} \quad (2)$$

where, the Nernst reversible voltage is obtained by the following equation (Meng et al., 2020):

$$E_{Nernst} = E_0 + \frac{R \times T}{4 \times F} \ln \left( \frac{P_{O_2} \times P_{H_2}^2}{P_{H_2O}^2} \right) \quad (3)$$

where,  $E_0$  defines the standard potential,  $T$  represents the SOFC operating temperature (K),  $P_{O_2}$ ,  $P_{H_2}$ , and  $P_{H_2O}$  define the partial pressure of oxygen, hydrogen, and water,  $R$  stands for the universal gas constant, and  $F$  describes the Faraday constant. Here,  $R = 8.314 \text{ kJ (k mol K)}^{-1}$ ,  $F = 96,486 \text{ Cmol}^{-1}$ . From Eq. (2),  $V_{act}$  is achieved as follows:

$$V_{act} = \frac{2 \times R \times T}{n_e \times F} \times \sinh^{-1} \left( \frac{I}{2 \times I_0} \right) \quad (4)$$

Accordingly, the ohmic loss voltage in the equation is achieved by the following formula.

$$V_{\Omega} = R_{\Omega} \times I \quad (5)$$

where,  $R_{\Omega}$  defines the ionic resistance that is decreased slowly by temperature increasing (Wang and Nehrir, 2007) and the current equation can be obtained based on the ButlereVolmer as follows (Chan et al., 2002):

$$I = I_0 \times \left[ \exp \left( \frac{\beta \times n_e \times F \times V_{act,cell}}{R \times T} \right) - \exp \left( \frac{(\beta - 1) \times n_e \times F \times V_{act,cell}}{R \times T} \right) \right] \quad (6)$$

where,  $I_0$  represents the exchange current density,  $\beta$  stands for transfer coefficient, and  $n_e$  describes the quantity value of the transferred mole electrons. Since  $\beta = 0.5$  (Gong et al., 2014), Eq. (6) is transferred to the following equation:

$$I = 2 \times I_0 \times \sinh \left( \frac{n_e \times F \times V_{act,cell}}{2 \times R \times T} \right) \quad (7)$$

Besides, the concentration voltage loss is achieved as follows:

$$V_{conc} = \frac{R \times T}{4 \times F} \times \left[ \ln \left( \frac{P_{H_2}^2 \times P_{O_2}}{P_{H_2O}^2} \right) - \ln \left( \frac{P_{H_2}^{*2} \times P_{O_2}^*}{P_{H_2O}^{*2}} \right) \right] \quad (8)$$

Finally, based on the ButlereVolmer (Chan et al., 2001; Larminie et al., 2003), the SOFC output voltage is defined as follows:

$$V_{stack} = E_0 - A \times \sinh^{-1} \left( \frac{I}{2 \times I_0^a} \right) - A \sinh^{-1} \left( \frac{I}{2 \times I_0^c} \right) - I \times R_{\Omega} + B \times \ln \left( \frac{I_L - I}{I_L} \right) \quad (9)$$

where,  $I_L$  stands for the current limitation density ( $\text{mA cm}^2$ ),  $A$  defines Tafel line slope,  $B$  defines a constant depends on the operating state of the fuel cell,  $R_{\Omega}$  describes the area-specific resistance ( $\text{k}\Omega \text{ cm}^2$ ),  $I_0^a$  and  $I_0^c$  describe the anode and the cathode exchange current density, respectively. The present study considers seven unknown parameters including  $E_0$ ,  $A$ ,  $B$ ,  $I_0^a$ ,  $I_0^c$ ,  $R_{\Omega}$ , and  $I_L$  of the SOFC model for designing an optimal model for it.

### 3. The objective function

To select optimal values for the undetermined parameters in SOFC model, the minimum value of the sum of squared error (SSE) between the output voltage and the experimental data has been considered that is formulated as follows:

$$\begin{aligned} \min SSE(x) &= \frac{1}{n} \sum_{i=1}^N (V_{out} - V_{est})^2 \tag{10} \\ &= \frac{1}{n} \sum_{i=1}^N \left( V_{out} - \left[ E_0 - A \times \sinh^{-1} \left( \frac{I}{2 \times I_0^a} \right) - A \sinh^{-1} \left( \frac{I}{2 \times I_0^c} \right) \right. \right. \\ &\quad \left. \left. - I \times R_\Omega + B \times \ln \left( \frac{I_L - L}{I_L} \right) \right] \right)^2 \end{aligned}$$

where,  $N$  describes the estimation data, and  $x = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\} = \{E_0, A, B, I_0^a, I_0^c, R_\Omega, I_L\}$  includes the optimization variables such that [Isa and Rahim \(2013\)](#):

$$\begin{aligned} L &\leq I_L \tag{11} \\ I_0^c &< I_0^a \\ \bar{x}_i &\leq x_i \leq \bar{x}_i \\ i &= 1, 2, \dots, n \end{aligned}$$

Eqs. (10) and (11) indicate the objective function and the constraints to achieve a good agreement between the experimental output voltage and the output voltage such that to achieve to this purpose, Eq. (10) should be minimized by optimal selection of the undetermined parameter ( $x$ ) under the constraint from Eq. (11). However, classic methods are the first option for achieving the minimum value of Eq. (10), they fail in solving complicated problems, or even stuck in the local optimum. Recently, the ability of the metaheuristics in solving different kinds of complicated optimization problems is exponentially increasing. which turned them as the first option to solve these types of problems ([Martens and Sutskever, 2011](#); [Bengio et al., 2007](#)). Since, in this study, a new modified version of metaheuristic method, called Converged Grass Fibrous Root Optimization Algorithm has been adopted for optimal selection of the SOFC parameters for optimal model estimation.

### 4. Converged Grass Fibrous Root Optimization Algorithm

In recent years, [Akkar and Mahdi \(2017a\)](#) proposed a new metaheuristic technique based on fibrous root system of the grass called Grass Fibrous Root Optimization Algorithm (GRA). The GRA is inspired by the grass plants regeneration, and their progress and fibrous root system. The grass plants have been regenerated by two mechanisms. The first one is based on the underground stems performed by sending out roots and shooting the rhizomes and the second procedure is based on the grown stems below the surface. The explained mechanisms continuously improve the secondary roots for replacing the vanished primary roots. The hair roots are produced by the secondary roots and are usually used for local and global searching of the mineral and the water resources. The aforementioned mechanisms of the grass plants make the main conception of the GRA. In this section, the Converged Grass Fibrous Root Optimization Algorithm (CGRA) will be presented in detail. Because CGRA is a modified model of GRA ([Akkar and Mahdi, 2017a](#)), the GRA is first briefly explained followed by the definition of the proposed CGRA.

#### 4.1. Mathematical model of GRA

The population (Pop) of GRA contains an initial swarm (grass swarm) that is generated randomly and uniformly in the solution

space. After initializing the algorithm in the seeding process ( $pop$ ), a new population ( $Pop_{New}$ ) is reproduced in the range  $[P_l, P_u]$  such that  $P_l$  and  $P_u$  define the lower and the upper ranges for the population. After initializing and evaluating the value of each grass swarm, the best value ( $G_{best}$ ) is achieved by the following equation:

$$G_{best} = \min (F (swarm)) \tag{12}$$

where,  $G_{best} \in R^d$  and  $d$  represents the dimension of the problem, and here  $F$  describes the mean square error (MSE) function between the estimated data and the experimental data from the SOFC model.

The new population ( $Pop_{New}$ ) also contains a number of grasses ( $Gr$ ) which is achieved by the  $G_{best}$  by stolons that are frequently deviated by the elementary grass ( $Gr_N$ ) with a step size less than  $Pop_{New}^H$  by the following equation:

$$Gr = \left\| \left( \frac{0.5 \times pop \times Avg (MSE)}{Avg (MSE) + \min (MSE)} \right) \right\| \tag{13}$$

where,  $min$  and  $Avg$  define the average value and the minimum value, respectively.

The new branch grasses deviated by the  $G_{best}$  and the survived best initial grasses have been achieved by the following equations:

$$Gr_N = ones (Gr, 1) \times G_{best} + 2 \times \max (Pop_{New}^H) \times (\sigma (Gr, 1) - 0.5) \times G_{best} \tag{14}$$

$$S_{de} = Gr_N + 2 \times \max (Pop_{New}^H) \times (\sigma (pop - Gr - 1, 1) - 0.5) \times Pop_{New}^H \tag{15}$$

where,  $\sigma$  points to a random value between 0 and 1,  $ones(\cdot)$  signify to the one's column vector, and  $Gr_N$  represents the  $(pop - Gr - 1)$  highest MSE initial population. Therefore, new population ( $Pop_{New}$ ) is achieved by the following equation:

$$Pop_{New} = [G_{best}; Gr_N; S_{de}] \tag{16}$$

The new population ( $Pop_{New}$ ) is obtained to provide the minimum valued MSE and is restricted in the range  $P_{New}^L$  and  $P_{New}^H$ . In this situation, once  $G_{best}$  gets better results than the preceding one, it is replaced with the best new grass as the new candidate, else, the absolute rate of decrease in MSE is achieved. Once the tolerance value ( $\epsilon$ ) gives low value, the global stack ( $stack_g$ ) is increased and after reaching to its maximum value, the next local search will start, i.e.

$$M = \min_{i=1, \dots, pop} (MSE) \tag{17}$$

$$best_{min} = \min_{j=1, \dots, iter} (M) \tag{18}$$

$$\left| \frac{\min_{i=1, \dots, pop} (MSE) - G_{best}}{\min_{i=1, \dots, pop} (MSE)} \right| \leq \epsilon \tag{19}$$

The updating process for the hair root location is achieved as follows:

$$m_{G_{best}} (1, i) = Avg (G_{best}) + G_{best} (1, i) + C_2 \times (\sigma - 0.5) \tag{20}$$

$$C = [C_1, C_2, \dots, C_{10}] \tag{21}$$

$$C_2 = C \times (1 + (\|\sigma \times 10\|)) \tag{22}$$

$$i = 1, 2, \dots, d, k = 1, 2, \dots, N \tag{23}$$

where,  $m_{G_{best}}$  represents the locally modified  $G_{best}$ ,  $C$  stands for the investigated step size vector equation,  $C_2$  is the random component of  $C$ , and  $N$  describes the number of secondary generated roots in the range 0 and  $d$ . In the event that the achieved  $m_{G_{best}}$  has a value less than the  $G_{best}$  value, the new  $G_{best}$  will be equal to  $m_{G_{best}}$ , else, the absolute rate of decreasing for MSE will be

**Table 1**  
The utilized test function in the paper.

Function	Equation	
$F_1(x)$	$\sum_{i=1}^{D-1} ((x_i - 1)^2 + 100(x_i^2 - x_{i+1}))$	[-2.045, 2.045]
$F_2(x)$	$\sum_{i=1}^D x_i^2$	[-512, 512]
$F_3(x)$	$10D + \sum_{i=1}^D (x_i^2 - 10\cos(2\pi x_i))$	[-512, 512]
$F_4(x)$	$-20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^D(x_i^2)}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^D(\cos(2\pi x_i))\right) + 20 + e$	[-10, 10]

**Table 2**  
The validation the proposed technique and the compared methods on utilized test functions.

Benchmark		CGRA	GRA (Akkar and Mahdi, 2017a)	DHO (Brammya et al., 2019)	BOA (Arora and Singh, 2019)	SOA (Dhiman and Kumar, 2019)	LOA (Yazdani and Jolai, 2016)
$F_1$	MV	0.00	0.00	3.66e-9	3.85e-4	2.14e-9	2.08e-4
	SD	0.00	0.00	6.29e-9	10.62e-4	6.38e-9	5.34e-5
$F_2$	MV	3.91	6.14	13.25	46.79	12.46	54.91
	SD	1.37	6.38	7.14	38.24	5.39	42.19
$F_3$	MV	0.00	3.42	6.29	56.17	9.94	28.37
	SD	0.00	2.76	4.40	17.29	5.08	9.43
$F_4$	MV	0.00	1.90e-16	7.16e-11	6.12	4.37e-3	6.31e-2
	SD	0.00	0.00	4.37e-3	4.25	6.23e-3	6.38e-2

obtained. Once the rate has a value less than  $\varepsilon$ , the local stack counter ( $stack_l$ ) has been increased by one, if  $stack_l$  results the maximum predefined value, the hair root loop will be stopped and a new secondary root loop has been started and at the final of each iteration, the stopping criteria ( $\varepsilon_{SC}$ ) has been checked.

4.2. Converged Grass Fibrous Root Optimization Algorithm (CGRA)

Although, the Grass Fibrous Root Optimization algorithm presents good results based on the literature (Akkar and Mahdi, 2017b, 2016), it has a significant shortcoming in reaching to a satisfied convergence. In this study, two modifications are presented to develop the algorithm performance and to resolve the explained consideration. In the first mechanism, Quasi-oppositional is adopted to develop the speed and the accuracy of the total algorithm. To have enough vision of the Quasi-oppositional, oppositional-based learning should be first defined. The oppositional-based is a mechanism to compare each individual in the population with its opposite value to select the better one as more proper candidate (Tizhoosh, 2005; Çelik, 2020). For using this mechanism, let us consider the swarms by defining them with  $P$  in the range  $[P_l, P_u]$  that are placed in a D-dementia search space. The opposite candidate for a considered  $P_i$  is defined as follows:

$$\check{P}_i = P_l + P_u - P_i \tag{24}$$

$$i = 1, 2, \dots, D \tag{25}$$

Accordingly, the quasi-opposite number of a considered  $P_i$  is defined as follows:

$$\dot{P}_i = rand\left(\frac{\alpha_i + \beta_i}{2}, \check{P}_i\right) \tag{26}$$

The second mechanism for improving the algorithm efficiency is to use the chaotic conception. The chaotic mechanism generates unpredictable behaviors in any system. Some systems have so complicated behavior which is originated based on their chaotic nature. This leads the researches to work on a field of science,

called chaos theory. This theory can be also used for the population diversity increasing and escaping from the local optimum (Yang et al., 2007; Rim et al., 2018). This study employed the logistic map as a well-defined model of chaotic functions for the algorithm modification. The logistic map is defined as follows:

$$\delta_{o,n}^{q+1} = 4\delta_{o,n}^q(1 - \delta_{o,n}^q) \tag{27}$$

where,  $o$  stands for the number of system generators,  $n$  represents the population number,  $q$  describes the number of iterations,  $\delta_n$  represents the value of the chaotic mechanism at iteration  $n$  in the range  $[0, 1]$  (Yang et al., 2007; Rim et al., 2018). Therefore, by considering the above assumption, the modified new branch grasses deviated by the  $G_{best}$  and the modified survived best initial grasses are obtained based on the following equations:

$$S_{de}^m = Gr_N + 2 \times \max(Pop_{New}^H) \times (\delta_{o,n}^q(pop-Gr - 1, 1) - 0.5) \times Pop_{New}^H \tag{28}$$

$$Gr_N^m = ones(Gr, 1) \times G_{best} + 2 \times \max(Pop_{New}^H) \times (\delta_{o,n}^q(Gr, 1) - 0.5) \times G_{best} \tag{29}$$

4.3. The performance verification of the proposed algorithm

To determine the capability of the CGRA and validate its efficiency toward other methods, it has been applied to some different benchmark functions and the results are compared with other well-known metaheuristics to show its prominence. For the comparison, the following algorithms have been employed: Deer Hunting Optimization (DHO) Algorithm (Brammya et al., 2019), Seagull Optimization Algorithm (SOA) (Dhiman and Kumar, 2019), Lion Optimization Algorithm (LOA) (Yazdani and Jolai, 2016), Butterfly optimization algorithm (BOA) (Arora and Singh, 2019), and basic Grass Fibrous Root Optimization Algorithm (GRA) (Akkar and Mahdi, 2017a). The utilized test functions in the present research have been given in the Table 1:

The validation results of the presented technique and the compared methods on utilized test functions have been given in Table 2.



**Table 3**  
The lower and the upper limitations for the unknown parameters.

Parameter	Range	Unit	Parameter	Range	Unit
$E_{oc}$	[0, 1.2]	V	$B$	[0, 1]	V
$A$	[0, 1]	V	$I_L$	[0, 10,000]	mA cm <sup>-2</sup>
$I_{0,a}$	[0, 100]	mA cm <sup>-2</sup>	$R_{ohm}$	[0,1]	KΩ cm <sup>-2</sup>
$I_{0,c}$	[0, 100]	mA cm <sup>-2</sup>			

As can be observed from Table 2, the mean value (MV) and the standard deviation value (SD) in the presented algorithm for all of the functions is the least. The small value of MV shows the proposed CGRA has the highest accuracy toward the compared algorithms for the adopted test functions. Besides, the small value of SD shows that the presented method has the highest robustness than the others.

## 5. Simulation results

To calculate the efficiency of the proposed CGRA for optimal estimation of the SOFC unknown parameters, the experimental data of the SOFC with 96 cells are considered and extracted from Wang and Nehrir (2007) and the performance has been studied based on the voltage vs. current profile using MATLAB 2017b software. Table 3 illustrates the lower and the upper ranges for the unknown parameters.

Based on Zhang and Wang (2013) and Sun et al. (2015), the stopping criteria is considered for the maximum number of iteration by the value of 50,000 and number of grass swarm is set to be 60.

### 5.1. Analysis based on different temperatures

This subsection considers different temperature operating condition for the SOFC. Here, the simulation is applied to the model by considering various temperatures such that at every operational condition 120 data point has been generated. The data are measured under different temperatures including: 563.85 °C, 649.85 °C, 699.85 °C, 749.85 °C, and 799.85 °C at constant pressure, 3 atm. The results of sum of squared error between the achieved model and the experimental data under different temperatures are illustrated in Table 4. The method in Table also indicates a comparison between the suggested CGRA and some different state of art techniques including RNA-GA (Wang et al., 2020), ISI (El-Hay et al., 2019), BSSO (Wei and Stanford, 2019), SBO (El-Hay et al., 2018), ISA (El-Hay et al., 2019), and basic GRA (Akkar and Mahdi, 2017a).

Table 4 indicates that the suggested CGRA method has the minimum value of the SSE compared with other analyzed methods. Also, it is observed that the proposed CGRA method has the lowest standard deviation values compared with other methods. Table 5 indicates the optimal values for the unknown parameters based on the CRGA method at pressure 3 atm and under different temperatures.

**Table 4**  
The results of SSE between the achieved model and the experimental data under different temperatures.

Algorithms	563.85 °C	649.85 °C	699.85 °C	749.85 °C	799.85 °C
RNA-GA (Wang et al., 2020)	3.31E-2 (2.12E-2)	4.17E-2 (1.69E-2)	1.78E-2 (4.28E-2)	6.81E-1 (3.91E-1)	1.47 (8.98E-1)
ISI (El-Hay et al., 2019)	1.98E-2 (1.57E-2)	1.97E-2 (2.71E-2)	5.32E-2 (5.79E-2)	1.58E-1 (4.37E-1)	3.54 (7.59E-1)
BSSO (Wei and Stanford, 2019)	4.59E-3 (9.97E-3)	9.52E-3 (8.96E-3)	2.28E-2 (6.45E-2)	6.27E-2 (3.34E-1)	7.34E-2 (8.78E-2)
SBO (El-Hay et al., 2018)	2.84E-3 (5.39E-2)	2.04E-3 (4.47E-2)	1.45E-2 (3.60E-2)	1.38E-1 (3.31E-1)	2.83E-2 (7.24E-1)
ISA (El-Hay et al., 2019)	3.28E-2 (9.97E-2)	2.43E-2 (2.83E-2)	3.08E-2 (5.18E-2)	4.83E-2 (1.67E-1)	6.88E-2 (7.39E-2)
GRA (Akkar and Mahdi, 2017a)	1.59E-2 (1.89E-2)	2.26E-2 (1.89E-2)	7.36E-2 (9.94E-2)	1.29E-1 (3.31E-1)	5.34E-1 (9.35E-1)
CGRA	6.32E-4 (6.78E-4)	1.18E-3 (1.92E-3)	3.94E-3 (4.38E-3)	2.95E-3 (6.41E-3)	1.73E-3 (2.22E-4)

**Table 5**  
Optimal evaluated values for the unknown parameters at pressure 3 atm and under different temperatures.

Variables	563.85 °C	649.85 °C	699.85 °C	749.85 °C	799.85 °C
$E_{oc}$ (V)	1.213	1.150	1.135	1.198	1.138
$A$ (V)	0.094	0.084	0.052	0.046	0.039
$I_{0,a}$ (mA cm <sup>-2</sup> )	14.197	18.216	18.965	24.374	28.845
$I_{0,c}$ (mA cm <sup>-2</sup> )	5.322	7.005	7.147	7.264	7.832
$B$ (V)	0.051	0.068	0.062	0.064	0.075
$I_L$ (mA cm <sup>-2</sup> )	147.315	158.41	158.44	159.36	160.253
$R_{ohm}$ (KΩ cm <sup>-2</sup> )	0.112	0.013	0.0081	0.0012	0.0009
SSE	1.67E-4	1.84E-4	9.42E-4	1.87E-3	1.62E-3

It is important to note that the impact of temperature variations on the unknown parameters indicate that although by increasing the temperature value, the anode and cathode exchange current densities have been increased, the open circuit voltage has been decreased. Figs. 1 and 2 shows the polarization curve and the output power vs. current curve for modeled and the experimental data comparison for various operating temperatures and constant pressure of 3 atm.

Besides, the error profile for the voltage and the power of the data for different temperature values are shown in Figs. 3, 4.

As can be observed from Figs. 1–4, there is a good confirmation between the empirical data and the optimal model based on CGRA method. From Figs. 3 and 4 show that the error range for the output voltage under various temperatures are less than 0.16 V and the error range for the power under various temperatures are less than 0.0073 kW. From the results, it can be observed that lower temperatures give smaller errors. In other words, using the proposed method for the lower temperatures give better results.

### 5.2. Analysis based on different temperatures

This subsection considers different pressure operating condition for the SOFC. The data have been measured under different pressure including: 1 atm, 2 atm, 3 atm, 4 atm, and 5 atm at constant temperature, 799.85 °C. Table 6 illustrates the results of SSE between the achieved model and the experimental data under different pressures and Table 7 indicates optimal evaluated values for the unknown parameters at temperature 799.85 °C and under different pressures.

As can be observed from the results of Table 6, the minimum value of both SSE and standard deviation values is reached by the proposed CGRA method which shows the methods precision and robustness toward the other compared methods. The results obtained in Table 7 illustrates that by increasing the pressure values, the open circuit voltage has been enhanced. Besides, the anode and cathode exchange current densities similar to limiting current density change in a small limitation. It is important to note that the variables  $A$ ,  $B$ , and  $R_{ohm}$  are almost constant different pressures values. Figs. 5 and 6 shows the polarization curve and the output power vs. current curve for modeled and the

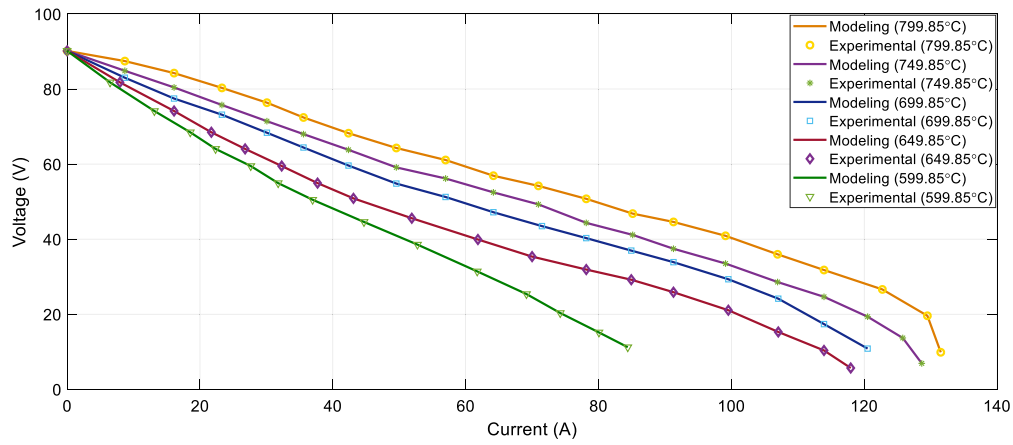


Fig. 1. The polarization curve for modeled and the experimental data comparison for various operating temperatures and constant pressure of 3 atm.

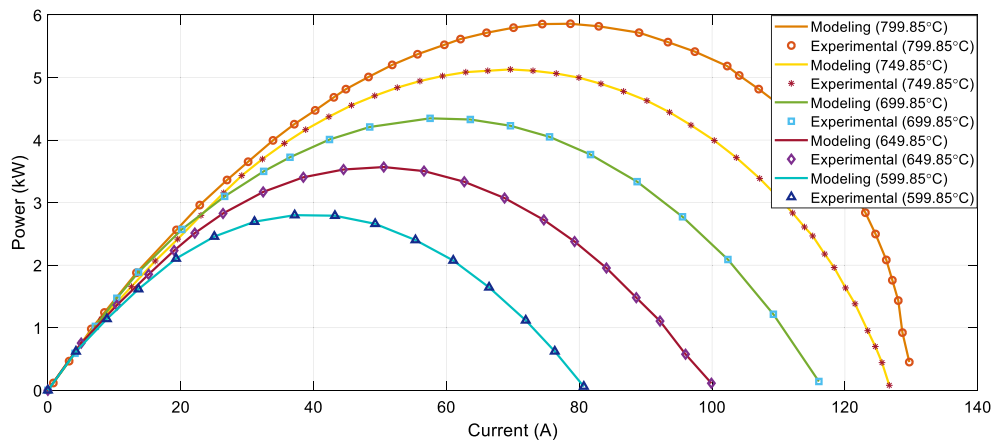


Fig. 2. The output power vs. current curve for modeled and the experimental data comparison for various operating temperatures and constant pressure of 3 atm.

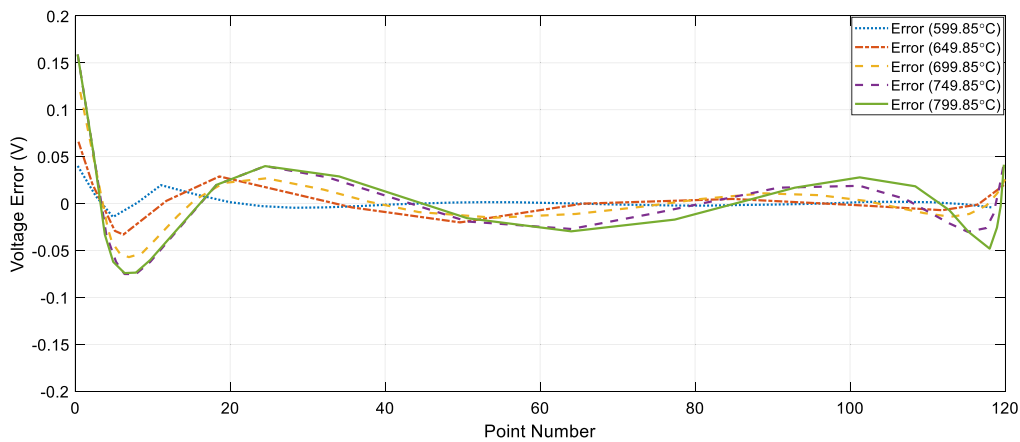


Fig. 3. Polarization curve error for modeled and the experimental data comparison for various operating temperatures and constant pressure of 3 atm.

Table 6

The results of SSE between the achieved model and the experimental data under different pressures.

Algorithms	1 atm	2 atm	3 atm	4 atm	5 atm
RNA-GA (Wang et al., 2020)	1.77 (9.31E - 1)	1.64 (8.42E - 1)	1.43 (6.16E - 1)	1.67 (8.94E - 1)	1.58 (8.67E - 1)
ISI (El-Hay et al., 2019)	1.47 (4.71E - 1)	4.13 (6.31E - 1)	3.48 (7.41E - 1)	3.50 (9.39E - 1)	3.50 (6.23E - 1)
BSSO (Wei and Stanford, 2019)	8.48E - 2 (10.12E - 2)	9.18E - 2 (10.04E - 2)	7.45E - 2 (8.71E - 2)	6.28E - 2 (9.34E - 2)	4.68E - 2 (7.34E - 2)
GRA (Akkar and Mahdi, 2017a)	6.59E - 1 (8.11E - 1)	8.86E - 1 (5.32E - 1)	5.64E - 1 (9.36E - 1)	5.95E - 1 (9.63E - 1)	7.44E - 1 (7.22E - 1)
CGRA	1.49E - 3 (5.23E - 5)	1.64E - 3 (1.92E - 4)	1.67E - 3 (2.27E - 2)	1.54E - 3 (1.87E - 5)	1.44E - 3 (1.98E - 5)

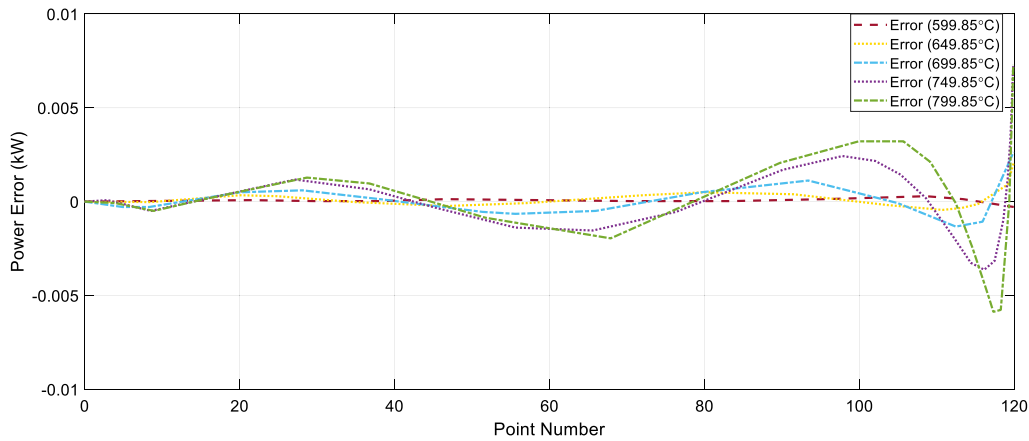


Fig. 4. Power current error for modeled and the experimental data comparison for various operating temperatures and constant pressure of 3 atm.

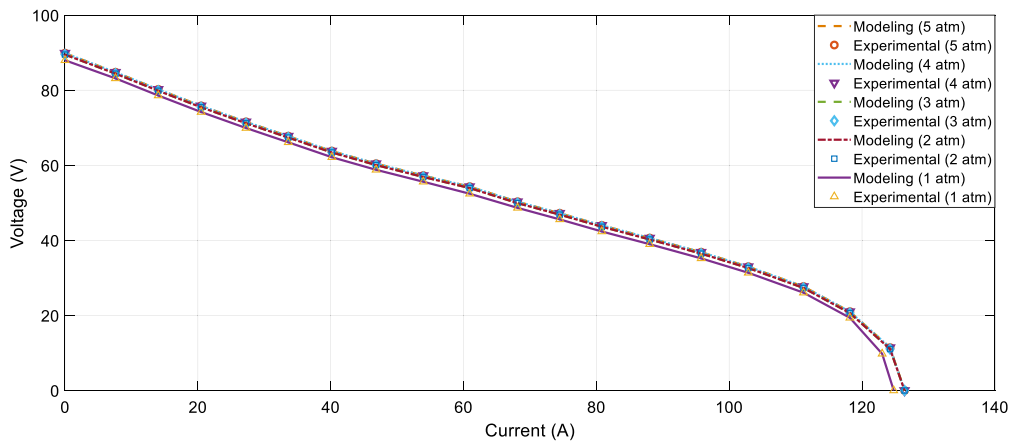


Fig. 5. The polarization curve for modeled and the experimental data comparison for various operating pressures and constant temperature of 799.85 °C.

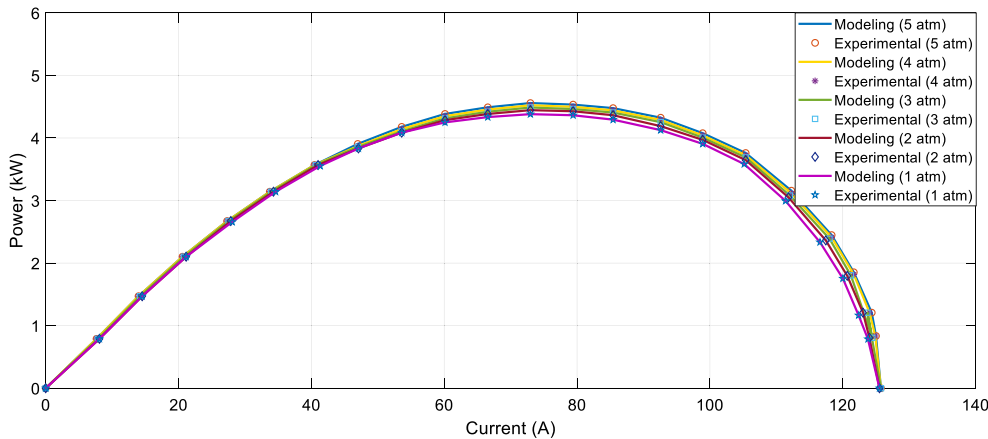


Fig. 6. The output power vs. current curve for modeled and the experimental data comparison for various operating pressures and constant temperatures of 799.85 °C.

experimental data comparison for various operating pressures and constant temperature of 799.85 °C for the proposed CGRA method.

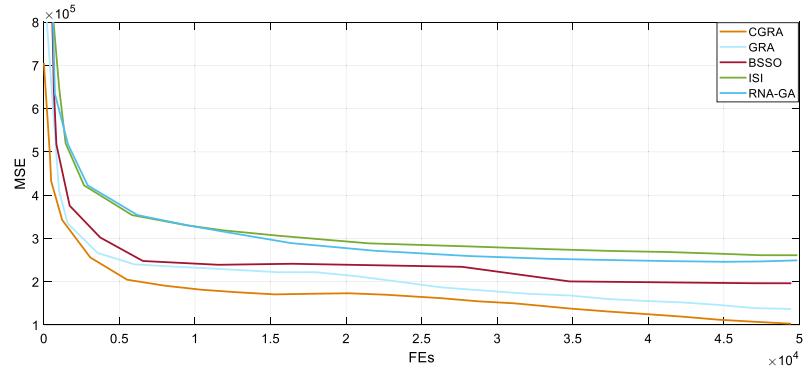
Also, the error profile for the voltage and the power of the data for different pressure values are shown in Figs. 5, 6.

As can be observed from Figs. 5, 6 and the comparison between the empirical data and the proposed model for voltage and power errors under different pressures and temperatures, the robustness of the model in different pressures is higher than the model with different temperatures.

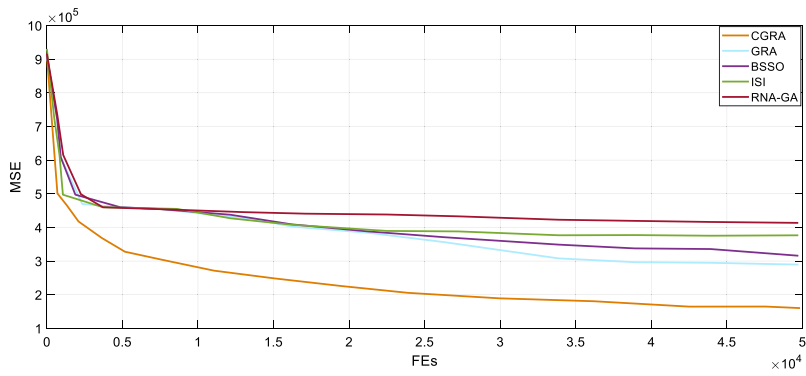
### 5.3. More analysis of the system

For more analysis of the system in terms of convergence efficiency, the convergence profiles for some different operation conditions are plotted in Fig. 7. From Fig. 7, it is observed that the speed of convergence for the proposed CGRA method has better condition toward the other compared methods for all operational conditions with different values of pressures and temperatures. This shows that the proposed method gives better balance between exploitation and exploration.

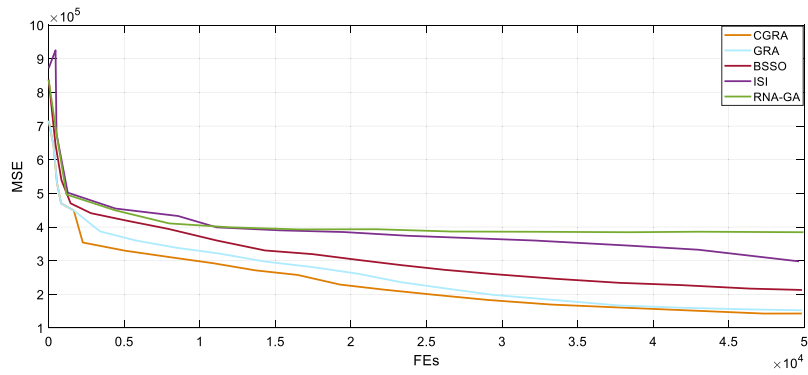




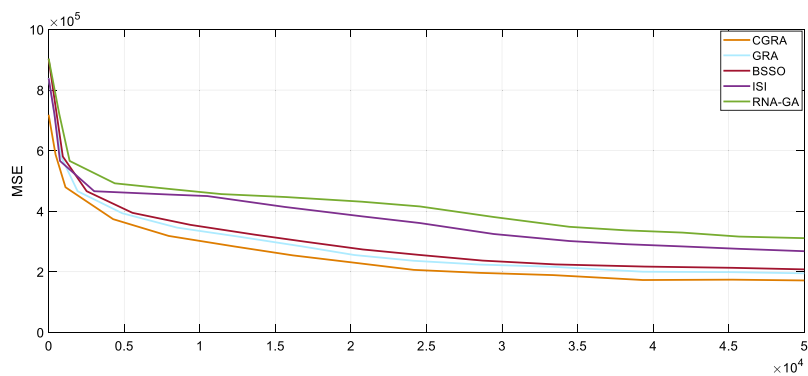
(A)



(B)



(C)



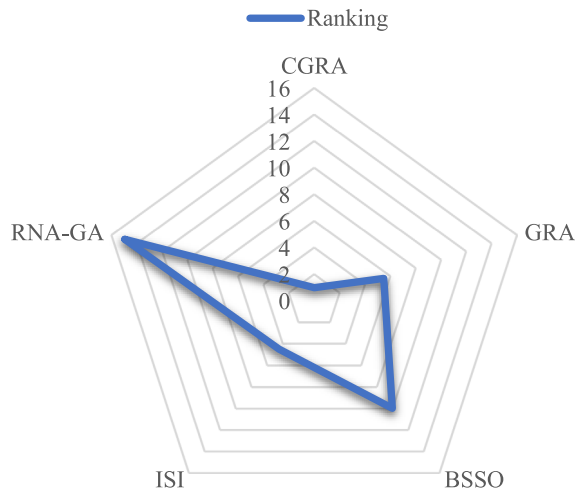
(D)

**Fig. 7.** The convergence profile under various operational pressures and temperatures for (A) (649.85 °C, 3atm), (B) (799.85 °C, 3 atm), (C) (749.85 °C, 1 atm), and (D) (799.85 °C, 5 atm).

**Table 7**

Optimal evaluated values for the unknown parameters at temperature 799.85 °C and under different pressures.

Variables	1 atm	2 atm	3 atm	4 atm	5 atm
$E_{oc}$ (V)	1.124	1.168	1.185	1.192	1.203
$A$ (V)	0.043	0.043	0.043	0.043	0.043
$I_{o,a}$ (mA cm <sup>-2</sup> )	28.42	28.59	28.48	28.41	28.34
$I_{o,c}$ (mA cm <sup>-2</sup> )	7.237	7.184	7.245	7.242	7.234
$B$ (V)	0.085	0.087	0.087	0.087	0.087
$I_L$ (mA cm <sup>-2</sup> )	161.11	161.24	161.35	161.28	161.25
$R_{ohm}$ (KΩ cm <sup>-2</sup> )	0.016	0.016	0.016	0.016	0.016
SSE	1.68E-3	1.84E-3	9.42E-3	1.87E-3	1.62E-3



**Fig. 8.** The results of Friedman test for the analyzed methods.

In the following, the Wilcoxon's statistical analysis has been utilized for evaluating the performance of the suggested CGRA and the compared methods under identical operational conditions. Tables 3 and 5 indicate this test. As it is observed, the best results are established by the suggested CGRA at higher than 97% probability level for all the operational condition for 30 independent runs. The Friedman test has been also performed for ranking the analyzed methods under the established operational conditions. The results of this test are shown in Fig. 8. The results for both tests indicate the suggested methods prominence toward the other compared methods.

## 6. Conclusions

This paper presented a new optimized technique for optimal parameters estimation of a Solid Oxide Fuel Cell (SOFC). The model was designed based on the voltage vs. current profile of the SOFC. The main purpose was to minimize the sum of squared error (SSE) between the experimental data and the achieved data as an objective function. For minimizing the objective function, a new metaheuristic called Converged Grass Fibrous Root Optimization Algorithm (CGRA) was introduced. For analyzing the performance of the proposed model, it was validated in different conditions with various temperature and pressure values. The convergence speed and statistical analysis were also applied to the model and the results were compared with some state of art methods including RNA-GA, ISI, BSSO, and the basic GRA (Wang et al., 2020) from the literature. The results for the CGRA showed that the SSE results for 3 atm constant pressure and 563.85 °C, 649.85 °C, 699.85 °C, 749.85 °C, and 799.85 °C are 1.67E-4,

1.84E-4, 9.42E-4, 1.87E-3, and 1.62E-3, respectively and for 799.85 °C constant temperature with 1 atm, 2 atm, 3 atm, 4 atm, and 5 atm, are 1.68E-3, 1.84E-3, 9.42E-3, 1.87E-3, and 1.62E-3, respectively that are the minimum values among the other analyzed methods. Simulation results showed well confirmation between the empirical results and the model designed based on the proposed CGRA. The results also showed the proposed method has better efficiency with the highest robustness compared with other analyzed methods. The future work for this study may be working on the Application of the suggested algorithm on different kinds of fuel cells such as polymer electrolyte membrane fuel cells.

## CRediT authorship contribution statement

**Hong Shi:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Jing Li:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Nicholas Zafetti:** 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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- Research and Practice of Cross-disciplinary Education and Teaching Reform Based on "Big Data +" (hxyjg1901).

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