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Article

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Research paper

PEM fuel cells model parameter identification based on a new improved fluid search optimization algorithm



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ABSTRACT

Model-identification and parameter extraction of the proton exchange membrane fuel cell (PEMFC) is a well-defined procedure for improving the PEMFC efficiency for designing and control purposes. This paper presents a new version of the improved fluid search optimization algorithm for optimal parameter identification of the undetermined parameters of the PEMFCs. The total of square deviations between the experimentally measured values and the optimal achieved values from the algorithm is considered the cost function. Two empirical PEMFC models including BCS 500-W and NedStack PS6 are employed and analyzed to present the capability of the proposed procedure under different conditions. Simulation results are compared with different optimizers under the same conditions to demonstrate the system efficiency. The final results showed that the proposed chaos-based fluid search optimization algorithm is successfully used to extract the parameters of a PEMFC model precisely.

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1. Introduction

Many countries rely heavily on coal, oil and natural gas to provide their energy, but dependence on fossil fuels is a big problem (Liu et al., 2020; Ahadi et al., 2015; Ye et al., 2020). The main issue is that the amount of fossil fuels is limited and will eventually end or when the extraction of the remaining remains very costly.

Also, fossil fuels cause pollution of air, water, and soil and produce greenhouse gases that cause global warming. A clean and green alternative energy source for fossil fuels is renewable energy sources.

Renewable energy is the energy that comes from renewable or recyclable sources and can be replaced by natural resources. Renewable energy sources have a much less environmental impact than fossil fuels. That is why renewable energy sources are very important. They bring humans to a world with less pollution.

Fuel cells have a huge potential as a future source of renewable energy because of their many advantages such as increased energy conversion and greater environmental compatibility and rapid advances in their technology.

Hydrogen is recovered from hydrocarbon as a fuel for energy sources by fuel cells. Nowadays, due to the expansion of wind and solar energy sources in different countries and having high

and low energy costs, when it is not needed, the possibility of hydrogen extraction from the process of electrolysis of water has been economical, i.e. fuel cells are power generation components that have the capability of direct converting of the chemical power into the heating and the electricity power.

Fuel cells, because of the ability to be portable, are widely used in mobile and portable applications such as UAVs and electric vehicles (Karimi et al., 2012; Ijaodola et al., 2019).

Several types of fuel cells are classified in terms of the type of electrolyte (Mekhilef et al., 2012). Among different types of fuel cells, polymer electrolyte membrane (PEM) has provided a satisfying energy alternative and is turned into one of the popular ones.

Furthermore, PEMFC needs less time for startup due to its low operating temperature and high power density.

The efficiency of typical PEMFCs is between 30% and 60%; this value depends on their loading condition. PEMFCs have also an operating temperature between 30 °C and 100 °C.

Since PEMFCs generate unregulated DC voltage, they require a precise model to take into account their efficiency for the design, control, and dynamic and steady-state simulation. In the literature, several models have been given based on the thermodynamic and chemical aspects (Luo et al., 2015; Razmjoooy et al., 2018a). Fig. 1 shows the PEMFC energy production process.

There are also different characteristics in the system like its steady-state stability, the dynamic models of the system and empirical data from the experiments that can be utilized for

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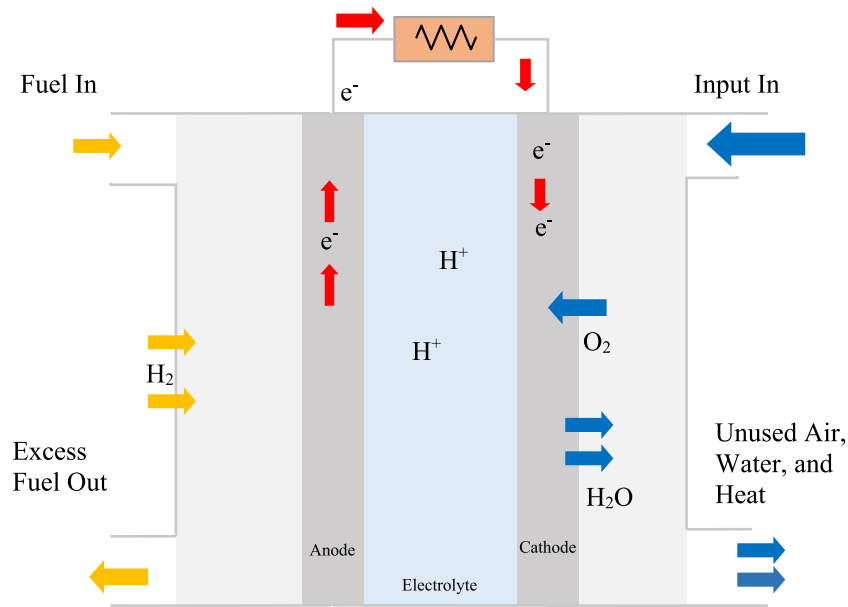


Fig. 1. The PEMFC energy production process.

modeling (Sun et al., 2015; Ge et al., 2018; Aghajani and Ghadimi, 2018).

In 1991, a steady-state, one-dimensional model was proposed for the PEMFC by Springer et al. (Liu et al., 2017). A steady-state and isothermal model is studied for the PEMFC.

In 2010, a state-space identification model was presented for energy management in HEVs by Caux et al. (Gollou and Ghadimi, 2017). The control process of the fuel cell's temperature and gas flows was also considered.

In 2014, two dynamical models based on the semi-empirical formulas and the electrical equivalent were proposed for PEMFC by Panagiotis et al. (Mirzapour et al., 2019). Besides, an improved model based on a transfer function by considering semi-empirical equations was proposed. The main purpose was to design a parametric analysis for model ability.

In 2017, an empirically validated model for a low-temperature PEMFC was proposed by considering the humidifier in the model by Solsona et al. (Hosseini Firouz and Ghadimi, 2016). The control method was a control-oriented model of a Nafion® membrane. The final results were compared with the empirical results.

In 2017, Kumar et al. presented a real-time model for PEMFC and then they analyzed the modality of the method by different validation like ARX and ARMAX (Hamian et al., 2018). MATLAB toolbox was utilized for system identification. PI and PID controllers were also utilized for obtaining the desired load current.

Furthermore, different research works have been performed over the modeling of PEMFC (Hosseini Firouz and Ghadimi, 2016; Leng et al., 2018).

Although the aforesaid classic models are efficient for designing and for analyzing the fuel cells performance, there are some limitations to these methods.

Classic methods are based on the precise modeling and solving these models by considering the physical concepts of the fuel cells like thermodynamics, power, momentum's conservation, and mass to obtain a precise thermal model for anything that happens in them. Although this procedure is ideal, it makes the identification process more complicated.

Some features in the system nature cannot be measured in the model. This reason makes these models improper for modeling the fuel cells, especially in real-time applications.

In the meantime, for improving the model's precision to reach into a so close performance model of the actual PEMFC, it is important to obtain the best parameter values of the system model.

Recently, the applications of meta-heuristics in optimization have been extensively increasing. Different types of meta-heuristics have been inspired by nature, physics, and humans' social reactions (Akbari et al., 2019; Ebrahimian et al., 2018; Khodaei et al., 2018; Bagal et al., 2018).

Several research works have been proposed for using the meta-heuristic methods for parameter identification in the PEMFCs. For instance, using differential evolution algorithm (Sun et al., 2015), particle swarm optimization (Gheydi et al., 2016), Multi-verse optimizer (Firouz and Ghadimi, 2016), Genetic algorithm (Eslami et al., 2019), dragonfly algorithm (Saeedi et al., 2019), etc.

From the literature review, it is clear that using the optimization algorithms gives better results for the identification of the PEMFC. The main idea behind this is that they can escape from the local minimum which leads them to obtain almost the global optimum (Khodaei et al., 2018; Bagal et al., 2018; Namadchian et al., 2016).

By considering the above methods and to their promising results in generating high-quality solutions, meta-heuristics have been extensively utilized in PEMFCs. However, there is still a lot of potential for improving identification efficiency.

The main purpose of the proposed method is to parameter identification of the PEMFCs using a new modified version of the fluid search optimization algorithm. The fitness function is the error between the obtained values and the empirical values measured for the voltage data.

Two experimental case studies are performed to show the efficiency of the proposed modified FSO through essential comparisons. Efficiency analysis of the measures is performed to endorse the capability of the proposed approach.

2. Materials and methods

2.1. Mathematical modeling of the PEMFC

Generally, the nominal value of the output voltage for a single PEMFC component by disregarding irreversibility losses and

entropy is between 0.9 to 1.23 V. Therefore, for using PEMFC in the practical applications, several numbers of them should be combined in series.

In PEMFCs, the current–voltage polarization curve drops rapidly because of the activation voltage, and then the curve drops slowly because of the Ohmic resistive voltage falling (Mo et al., 2006). In the following, diffusion over-potential makes the voltage value to drop it again at high loading conditions (Corrêa et al., 2004; Aouali et al., 2017).

The mathematical equation of total output voltage for the PEMFC stack is given below (Mo et al., 2006):

$$V_t = N_{cell} (V_{oc} - v_{act} - v_o - v_c) \quad (1)$$

where, N_{cell} describes the number of connected cells in a stack, V_{oc} describes the voltage of the open circuit condition per cell, v_{act} describes the activation over-potential for each cell, v_o is the Ohmic voltage drop in the cells, and v_c describes the over-potential saturation in cells.

The mathematical formulation for achieving the voltage of the open circuit condition that is so-called reversible voltage for the incorporating temperatures less than 100 °C based on the following equation (Mo et al., 2006):

$$V_{oc} = 1.23 - 85 \times 10^{-5} (T_{PEM} - 298.15) + 4.31 \times 10^{-5} T_{PEM} \ln \times (P_{H_2} \sqrt{P_{O_2}}) \quad (2)$$

where (Mo et al., 2006),

$$P_{O_2} = R_{hc} \times P_{H_2O} \left[\frac{1}{\frac{R_{hc} \times P_{H_2O}}{P_c} \times e^{\frac{1.635 I_{PEM}/A}{T_{PEM} \times 1.334}}} - 1 \right] \quad (3)$$

$$P_{H_2} = \frac{R_{ha} \times P_{H_2O}}{2} \left[\frac{1}{\frac{R_{ha} \times P_{H_2O}}{P_a} e^{\frac{1.635 I_{PEM}/A}{T_{PEM} \times 1.334}}} - 1 \right] \quad (4)$$

$$P_{H_2O} = 29.5 \times 10^{-3} T_c - 91.81 \times 10^{-6} T_c^2 + 14.4 \times 10^{-8} T_c^3 - 2.18 \quad (5)$$

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

The reference temperature value in the operating variations is considered at 77 °F (25 °C).

In the following, the mathematical equations for the activation over-potential are given (Chen and Wang, 2019):

$$v_{act} = - [\beta_1 + \beta_2 T_{PEM} + \beta_3 T_{PEM} \ln(C_{O_2}) + \beta_4 T_{PEM} \ln(I_{PEM})] \quad (7)$$

where (Chen and Wang, 2019),

$$\beta_2 = 28.6 \times 10^{-4} + 21 \times 10^{-5} \ln(A) + 43 \times 10^{-6} \ln(C_{H_2}) \quad (8)$$

The other stated voltage drops/losses are given below (Yazdani and Jolai, 2016):

$$C_{O_2} = \frac{P_{O_2}}{50.8 \times 10^5} \times e^{\frac{498}{T_{PEM}}} \quad (9)$$

$$C_{H_2} = \frac{P_{H_2}}{10.9 \times 10^5} \times e^{-\frac{77}{T_{PEM}}} \quad (10)$$

$$v_o = I_{PEM} (R_m + R_c) \quad (11)$$

where (Yazdani and Jolai, 2016),

$$R_m = \frac{\rho_m l}{A} \quad (12)$$

$$\rho_m = \frac{181.6 \left[1 + 0.03 \left(\frac{I_{PEM}}{A} \right) + 0.062 \left(\frac{T_{PEM}}{303} \right)^2 \left(\frac{I_{PEM}}{A} \right)^{2.5} \right]}{\left[\lambda - 0.634 - 3 \left(\frac{I_{PEM}}{A} \right) \right] e^{4.18 \times \frac{T_{PEM} - 303}{I_{PEM}}} \quad (13)$$

$$v_c = -\beta \ln \left(\frac{J_{max} - J}{J_{max}} \right) \quad (14)$$

where, T_{PEM} describes the operating cell temperature (K), P_{O_2} , P_{H_2} , and P_{H_2O} are the partial pressure of the O_2 , H_2 , and H_2O , respectively. R_{hc} and R_{ha} are the vapor relative humidity at cathode and anode, respectively, A is the membrane surface (cm^2), I_{PEM} describes the operating current for the PEMFC, P_a and P_c describe the anode and cathode's inlet pressures, C_{H_2} and C_{O_2} are the concentration of the hydrogen and oxygen (mol/cm^3), R_m and R_c describe the membrane resistance and the resistance of the connections, l represent the membrane thickness, β_i are the experimental coefficients, ρ_m describes the membrane resistivity, λ is tunable parameter, β describes a parametric coefficient, J describes the real current density, and J_{max} represents the maximum value of J .

Based on the above equations, it can be concluded that six factors are required to be determined. These parameters are not determined by the manufacturer's datasheet.

Therefore, to guarantee promising modeling of PEMFCs for simulation and control purposes, we need to find precise values for these parameters. Generally, the model of the PEMFC has six undetermined parameters including β_1 , β_3 , β_4 , β , R_c , λ .

The aforementioned six parameters have been optimized to obtain optimal values by considering their constraints using the modified chaos fluid search optimization algorithm.

2.2. Describing the fitness function and the constraints

In this study, the total of the squared deviations (TSD) is selected as the main part of the fitness function for the PEMFC parameter identification. The main objective of this research is to estimate the aforementioned undetermined six parameters of the PEM fuel cells by obtaining proper fitting between the evaluated voltage stack and the measured voltage.

Here, a chaotic fluid search optimization algorithm is employed to minimize the fitness function by considering a reasonable computational complexity with higher convergence speed. The minimization fitness function for this purpose is achieved from the literature as below:

$$F_{SI} = \text{Min}(TSD) = \text{Min} \left\{ \sum_{i=1}^n [V_S(i) - V_m(i)]^2 \right\} \quad (15)$$

where; n describes the number of measured points, i is the iteration number, and V_m and V_S describe the measured voltage and the evaluated voltage stack of the PEMFC. Indeed, TSD indicates the error between the actual and approximated voltage data for the PEMFC. The practical inequality constraints for the F_{SI} are illustrated below:

$$\text{s.t.} \begin{cases} \beta_{i,\min} \leq \beta_i \leq \beta_{i,\max}, \forall i = 1, 3, 4 \\ \beta_{\min} \leq \beta \leq \beta_{\max} \\ \lambda_{\min} \leq \lambda \leq \lambda_{\max} \\ R_{c,\min} \leq R_c \leq R_{c,\max} \end{cases} \quad (16)$$

where, $\beta_{i,\min}$ and $\beta_{i,\max}$ describe the lower and the higher bounds for the experimental achievements, β_{\min} and β_{\max} are the lower and the higher bounds of the model parameters, λ_{\min} and λ_{\max} describe the lower and the higher bounds for the water content, $R_{c,\min}$ and $R_{c,\max}$ are the lower and the higher bounds of the resistance of the cell connections.

It is important to know that these constraints are employed for updating the population in the optimization algorithm and also as a penalty part for the algorithm.

2.3. Fluid search optimization algorithm

In recent years, there have been introduced several types of optimization algorithms due to increasing the number of optimization problems. Since recently the complexity of the optimization problems is extensively increasing, there needs to employ some more powerful techniques to solve them (Sun et al., 2004).

Meta-heuristics are a kind of optimization approach that can be utilized for solving any complicated optimization problem. This approach is a type of optimization technique that has been inspired by different phenomena like from the nature, animals or human social behaviors, etc. some of the meta-heuristic methods are like genetic algorithm (Davis, 1991; Ghadimi, 2012; Mousavi and Soleymani, 2014), Bayesian optimization algorithm (Pelikan et al., 1999), harmony search algorithm (Geem et al., 2001), artificial bee colony (Karaboga and Aslan, 2018; Karaboga and Basturk, 2007; Razzmjoooy and Khalilpour, 2015), particle swarm optimization algorithm (Ghadimi et al., 2013; Moallem and Razzmjoooy, 2012; Razzmjoooy and Ramezani, 0000), quantum-based algorithms (Khodaei et al., 2018; Sun et al., 2004; Han and Kim, 2002), world cup optimization algorithm (Bagal et al., 2018; Bandaghihi et al., 2016; Razzmjoooy et al., 2017, 2018b; Shahrezaee, 2017), shark smell optimization algorithm (Ebrahimian et al., 2018; Meng et al., 2020; Hussain et al., 2010; Rao et al., 2019), and fluid Search Optimization (Dong and Wang).

In 2019, Dong et al. present a new optimization algorithm called Fluid Search Optimization (FSO) algorithm which is inspired by Bernoulli's principle in fluid mechanics.

Bernoulli's principle is about how the speed of a fluid is related to the pressure of the fluid so that by increasing the speed of the fluid, the potential energy and the pressure of the fluid have been decreased.

Bernoulli equation is evaluated by the following formula.

$$p + \frac{1}{2}\rho v^2 = p_0 \quad (17)$$

where, p defines the pressure of a chosen point on a streamline, p_0 is the constant system pressure, v describes the speed of the fluid flow at the point, and ρ is the fluid density at all points in the fluid.

Based on Eq. (17), Dong and Wang presented perform some simulations. They first re-formulated the Eq. (7) as follows.

$$v = \sqrt{\frac{2(p_0 - p)}{\rho}} \quad (18)$$

Afterward, they considered the new position of the solution as a recursive formula as follows,

$$x_{new} = x_{old} + v \quad (19)$$

where, x_{new} and x_{old} describe the new and the former position of the infinitesimals.

The pressure for the fluid infinitesimals is then considered as the value for the objective function so that by increasing the pressure, the velocity of the fluid infinitesimal is decreased.

The optimization process in the fluid infinitesimal is related to the inverse process of the fluid flowing from the high pressure to the low pressure involuntary.

The convergence of the fluid infinitesimals in the process of fluid flowing has been reached if the highest-pressure point is found that can be considered to reach the optimum value. More explanation of the algorithm parameters is given in detail.

2.3.1. Infinitesimal pressure

By considering the position of n number of infinitesimals as $X = [x_1, x_2, \dots, x_n]$, such that the fitness function is y , and the best and the worst values of the optimization are y_{best} and y_{worst} , respectively.

The equation for the infinitesimal pressure p_i is given below:

$$\begin{aligned} p_i &= \frac{(y_{worst} - y_i)}{(y_{worst} - y_{best})}, \\ p_0 &= 1 \end{aligned} \quad (20)$$

where, p_i is a normalized value between 0 and 1 to prevent the impact of various objective functions on the algorithm.

2.3.2. Infinitesimal density

Infinitesimal density is the total number of neighbor infinitesimals in the cell of the present infinitesimal. The value for other infinitesimals in the D -dimension hypercube is considered m . So, the infinitesimals density is:

$$\rho = \frac{m}{l^D} \quad (21)$$

where, l describes the cell side length.

2.3.3. The velocity of the fluid infinitesimal

Since Eq. (18) defines the value of the velocity without direction, to consider the flow direction in the fluid infinitesimal, the vector summation of the pressure between the current and the other infinitesimals should be achieved.

To prevent the impact of the given weight due to the distance from the other infinitesimals, the distance is normalized.

Afterward, the normalized value of the pressure is added to achieve better convergence for the algorithm as follows:

$$\vec{p}_i = \sum_{\substack{j=1 \\ j \neq i}}^n \text{rand} \otimes p_j \frac{(X_j - X_i)}{|(X_j - X_i)|_2} + \text{rand} \otimes p_{best} \times 2 \times \frac{(X_{best} - X_i)}{|(X_{best} - X_i)|_2} \quad (22)$$

where, \vec{p}_i represent a vector value.

The new direction can be achieved by as follows:

$$D_n = \gamma \times D_l + \frac{\vec{p}_i}{|\vec{p}_i|_2} \quad (23)$$

where, D_n and D_l describe the new direction and the last direction, respectively, and γ defines the inertial factor.

However the FSO algorithm has good results based on the literature, it has a prominent shortcoming. In the FSO algorithm, the best solution in each iteration is important and all the other infinitesimals attempt to move based on the best vector summation of the pressure. Thus, sometimes the best solution may be stuck in the local optimum. This condition makes a misleading to the other individuals in following the best vector summation of the pressure that finally leads to premature convergence. In this study, a technique based on chaos theory is utilized for solving this problem.

2.4. Fluid search optimization algorithm based on chaos theory (CFSO)

2.4.1. The concept of the chaos theory

Chaos theory is about studying the random and unpredictable processes in considered systems. Some systems have complicated and nonlinear behavior that is derived from their chaotic nature.

The idea here is to study the highly sensitive dynamic systems which have been affected by any small changes.

By considering the aforementioned explanation, a large diversity can be made for the population in the FSO algorithm to improve the diversity in the algorithm. This part can improve the FSO algorithm capability from the point of the convergence

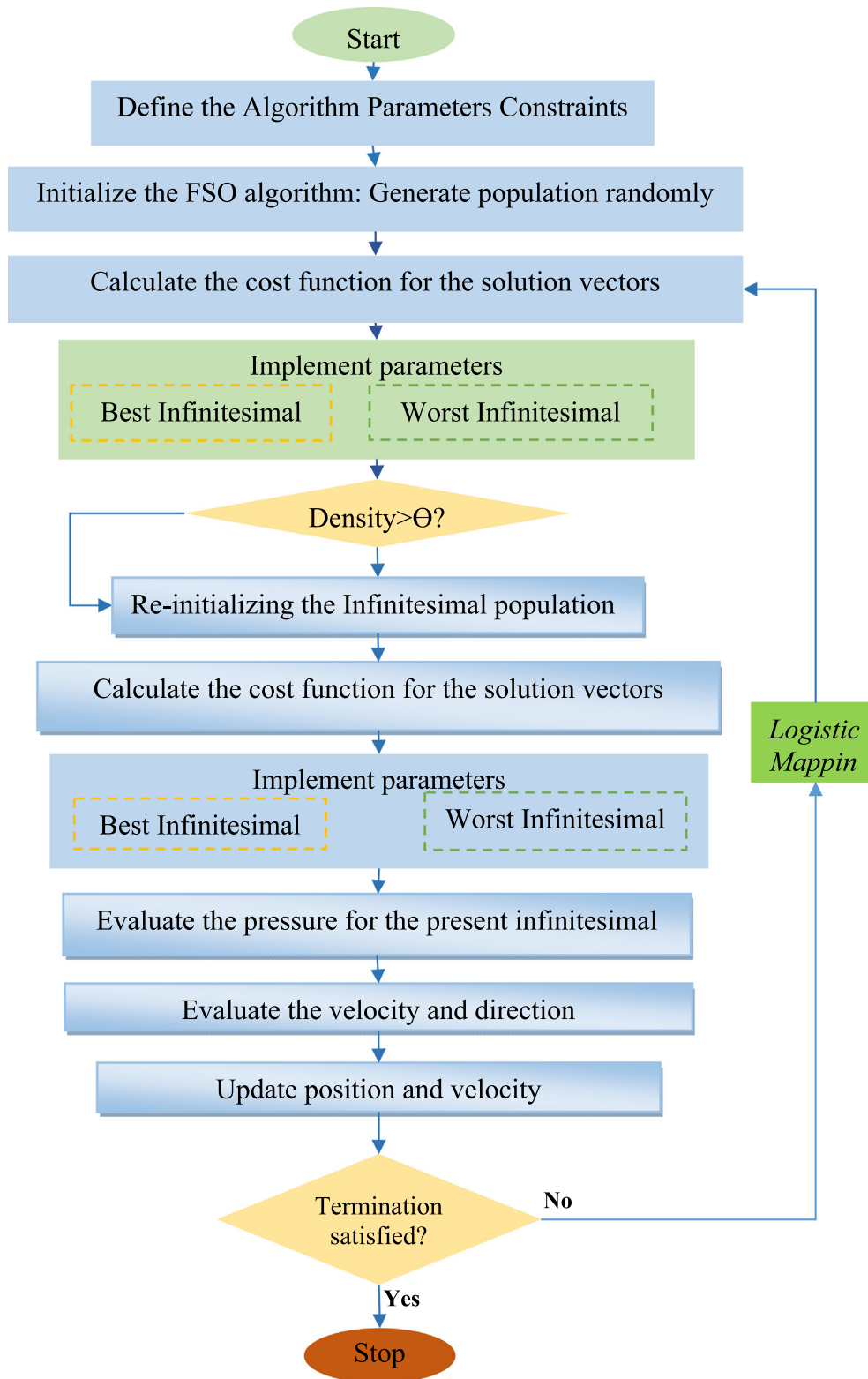


Fig. 2. The flowchart diagram of the proposed CFSO algorithm.

speed and also for escaping from falling into the local optimal point (Yang et al., 2007; Rim et al., 2018). A general definition for the chaos theory is formulated below:

$$CM_{i+1}^j = f(CM_i^j) \quad (24)$$

$j = 1, 2, \dots, k$

where, k is the map dimension, $f(CM_i^j)$ is the chaotic model generator function.

2.4.2. Improving the FSO algorithm based on the chaos theory

The proposed method is called Improved Chaotic World Cup Optimization (CFSO) algorithm. The main superiority of the presented work toward the original FSO algorithm is that can escape

from sticking in the local optimum point following by high speed in the convergence. In the presented CFSO algorithm, the parameter x_{Rand} is modeled based on the sinusoidal chaotic map as follows:

$$x_{Rand,k} = ap_k^2 \sin(\pi p_k) \quad (25)$$

$$p_0 \in [0, 1], a \in (0, 4)$$

where, k determines the number of iteration.

The improvement makes the spiral model handling selection easy for updating the teams ranking. Fig. 2 shows the flowchart diagram of the presented CFSO algorithm.

3. Validation of the modified FSO algorithm

For performance validation of the proposed method, four standard benchmarks have been analyzed. The results of the proposed CFSO algorithm are compared with some different state of the art algorithms including genetic algorithm (GA) (Akbari et al., 2019), world cup optimization algorithm (WCO) (Bagal et al., 2018), particle swarm optimization algorithm (PSO) (Bansal, 2019), and the original fluid search optimization algorithm (FSO) (Dong and Wang, 2018).

The simulations are performed based on MATLAB R2017b platform on a laptop computer with processor Intel® CoreTM i7-4720 HQ CPU@2.60 GHz with 16 GB RAM. Table 1 illustrates the benchmarks formulations which are employed for the performance analysis.

Table 2 illustrates the mean deviation (MD) and the standard deviation (SD) values of the compared methods for the analyzed benchmarks.

The results from Table 2 shows that in all four benchmarks, the proposed CFSO algorithm gives satisfying results toward the other methods, especially the original FSO algorithm.

4. Simulation results

Based on the computer configuration from the previous section, two practical case studies of typical commercial PEMFCs including BCS 500-W (Co, 0000) and NedStack PS6 (N. F. C. Technology, 0000) have been utilized for efficiency analysis of the proposed methodology (Priya et al., 2015; Ali et al., 2017; El-Fergany, 2017).

For better and fair analysis of the proposed methodology performance, some state of art works has been also employed to compare with the method by considering the same constraints from Mo et al. (2006). Empirical bounds for the six undetermined PEMFC model are given below:

$$\beta_{1,\min} = -1.2, \beta_{1,\max} = -0.80, \beta_{2,\min} = 1e-3,$$

$$\beta_{2,\max} = 5e-3,$$

$$\beta_{3,\min} = 3.5e-5, \beta_{3,\max} = 1e-4, \beta_{4,\min} = -3e-4,$$

$$\beta_{4,\max} = -8e-5,$$

$$\lambda_{\min} = 10, \lambda_{\max} = 24, R_{c,\min} = 8e-5, R_{c,\max} = 9.9e-4,$$

$$\beta_{\min} = 0.01, \beta_{\max} = 0.6$$

Relative humidity of vapors at both cathode and anode is considered 1.00.

At first, the designed algorithm based on chaos theory starts like other optimization algorithms with randomly initializing, but unlike them, from the second iteration, the new population will be a pseudo-random number based on the first iteration which helps to increase the convergence speed in the algorithm.

The method of identification is as follows:

- (1) Apply Initial CFSO algorithm
- (2) Find the TSD value based on the difference value from experimental data (Co, 0000; N. F. C. Technology, 0000) and the achieved value from the algorithm.

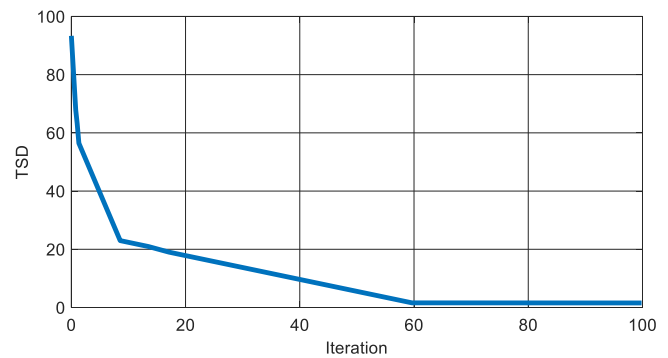


Fig. 3. The TSD convergence diagram of the proposed CFSO algorithm on the NedS stack.

- (3) Update algorithm based on its formulation
- (4) If the algorithm stopping criteria is reached, go to (5). Else, go to (1).
- (5) Return the solution

4.1. Case study 1: NedStack PS6

In this case study, a NedStack PS6 of 6 kW rated power fuel cell system has been analyzed for performance analysis of the CFSO algorithm. The main information for the simulation is collected from N. F. C. Technology (0000) and El Monem et al. (2014) such that $N_{\text{cells}} = 65$, $A = 240 \text{ cm}^2$, $l = 178 \mu\text{m}$, $T_{\text{PEM}} = 343 \text{ K}$, the operating ranges for the output voltage is Sun et al. (2004) and Ali et al. (2017) V dc, and for output current is [0,225] A dc, and supply pressure changes between 0.5 bar to 5 bar. By replacing these values to the mathematical model and combining the equations on the TSD error function, the only parameters that should be evaluated are $\beta_1, \beta_2, \beta_3, \beta_4, \lambda, R_c$, and β . These parameters are achieved optimally by considering the minimum value for the TSD error function. Table 3 shows the parameter values for the optimization algorithms in the studied system. The CFSO results here are compared with the FSO, GHO (El-Fergany, 2017), SSO (El-Fergany, 2018) which can be found in Tables 4 and 5.

After performing the CFSO to obtain the best solution for the six undetermined parameters, the final optimal values for the identified PEMFC model are given in Table 4 which shows the minimum value for the TSD overall 100 independent runs.

The convergence diagram of the proposed CFSO algorithm on the NedS stack PS6 of 6 kW is shown in Fig. 3.

The final optimal point after convergence is 2.176 which is the minimum TSD value among different compared methods. It is clear that after only 60 iterations, the TSD reached its minimum value that indicates very fast convergence characteristics.

Table 5 illustrates the Elapsed time for the state of art methods on the NedS stack PS6 of 6 kW. From the Table, it can be concluded that using the FSO algorithm gives the minimum time for the processing, but after applying the chaos procedure, i.e. CFSO, its convergence time decrease more.

The collected best results for I–V polarization characteristics of the NedStack estimated by the CFSO along with the empirical data, the absolute deviation of the voltages points and the TSD between the actual and approximated voltage data is shown in Fig. 4.

The results show a satisfying fitting between the empirical voltage model and the data achieved by the CFSO algorithm and show proper precision to finding the optimized values for the undetermined six parameters.

Table 1
The utilized benchmarks for efficiency analysis.

Benchmark	Formula	Constraints	Dimension
Rastrigin	$f_1(x) = 10D + \sum_{i=1}^D (x_i^2 - 10 \cos(2\pi x_i))$	[-512, 512]	30–50
Rosenbrock	$f_2(x) = \sum_{i=1}^{D-1} (100(x_i^2 - x_{i+1}) + (x_i - 1)^2)$	[-2.045, 2.045]	30–50
Ackley	$f_3(x) = -20 \exp\left(-0.2\sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2}\right) - \exp\left(\frac{1}{D} \sum_{i=1}^D \cos(2\pi x_i)\right) + 20 + e$	[-10, 10]	30–50
Sphere	$f_4(x) = \sum_{i=1}^D x_i^2$	[-512, 512]	30–50

Table 2
The results of the efficiency analysis by considering 30-dimensions.

Benchmark	CFSO	GA (Akbarly et al., 2019)	PSO (Bansal, 2019)	WCO (Bagal et al., 2018)	FSO (Dong and Wang, 2018)	
f_1	MD	0.00	70.61	74.24	2.19	3.42
	SD	0.00	1.66	8.96	4.35	3.27
f_2	MD	8.32	35.41	200.1	13.16	8.64
	SD	3.85	27.15	59.00	4.62	5.56
f_3	MD	0.00	3.19 e−2	8.26	3.14 e−3	4.46 e−16
	SD	0.00	2.14 e−2	1.19	1.12 e−3	0.00
f_4	MD	0.00	1.15 e−4	8.27 e−4	6.19 e−9	1.55 e−12
	SD	0.00	3.14 e−5	5.12 e−4	3.28 e−9	5.37 e−17

Table 3
Parameter selection of the optimization algorithms for the studied system.

Algorithm	Parameter	Value	Algorithm	Parameter	Value
GA	Crossover	0.8	FSO	Population size (N)	50
	Mutation	0.2		Maximum iteration (M)	100
GHO	L	1.0	CFSO	Maximum ratio of density (θ)	20%
	f	1.0		SSO	C ₁

Table 4
TSD validation for the NedStack PS6.

Parameter	Algorithm				
	CFSO	FSO	GA (El-Fergany, 2017)	GHO (El-Fergany, 2017)	SSO (El-Fergany, 2018)
β_1	−0.981	−0.931	−1.199	−1.120	−0.972
β_2	3.383 e−3	3.375 e−3	3.417 e−3	3.550 e−3	3.349 e−3
β_3	7.759 e−5	7.438 e−5	3.600 e−5	4.614 e−5	7.911 e−5
β_4	−9.540 e−5	−9.541 e−5	−9.540 e−5	−9.540 e−5	−9.543 e−5
λ	13.00	13.00	13.00	13.010	13.00
R_c	0.100	0.100	0.138	0.100	0.100
β	0.047	0.055	0.036	0.058	0.050
TSD	2.176	2.186	2.409	2.185	2.180

Table 5
The Elapsed time for the state of art methods on the NedS stack.

Algorithm	CFSO	FSO	GA (El-Fergany, 2017)	GHO (El-Fergany, 2017)	SSO (El-Fergany, 2018)
Elapsed time (s)	4.31	5.28	10.13	7.03	5.30

For more analyzing the method efficiency on the NedStack system under different conditions of partial pressures and the cell temperature, the I/V diagram is presented in Figs. 5 and 6.

Fig. 5 shows the variations on the partial pressures with 1/1 bar, 2/1.5 bar, and to 3/2 bar. It can be seen that by enhancing the supply pressures of the P_{H_2}/P_{O_2} , the stack output voltage is increased.

The variations on the constant cell temperatures with 323 K, 343 K, and 363 K are also shown in Fig. 6. Here, by enhancing the temperature, the stack output voltage is increased.

4.2. Test case 2

The second case study is the BCS PEMFC at a rated power of 500 W with a 30 A maximum current. This type is made by American Company BCS Technologies (Co, 0000).

More details for accurate simulation of this model can be found in Corrêa et al. (2004) such that $N_{cells} = 32$, $A = 64 \text{ cm}^2$, $l = 178 \text{ }\mu\text{m}$, $T_{PEM} = 333 \text{ K}$, the operating ranges for the partial pressures of H_2 and O_2 are 1 atm and 0.2075 atm, respectively.

Table 6 illustrates the results of the best optimal value for the voltage stack-based parameters on the proposed CFSSO compared with the FSO, GHO (El-Fergany, 2017), SSO (El-Fergany, 2018) on

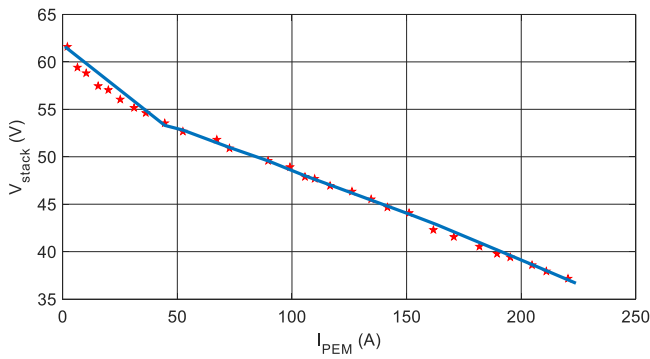


Fig. 4. The I-V diagram for the NedStack for the empirical curve (red-star) and model curve (blue-line).

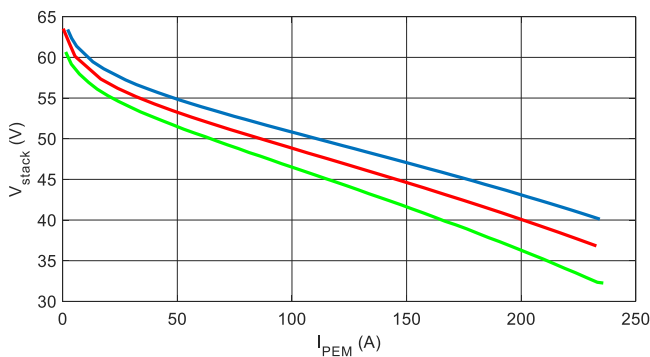


Fig. 5. The I/V diagram characteristics of NedStack for pressure variations for 3/2 bar (blue line), 2/1.5 bar (red line), 1/1 bar (green line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

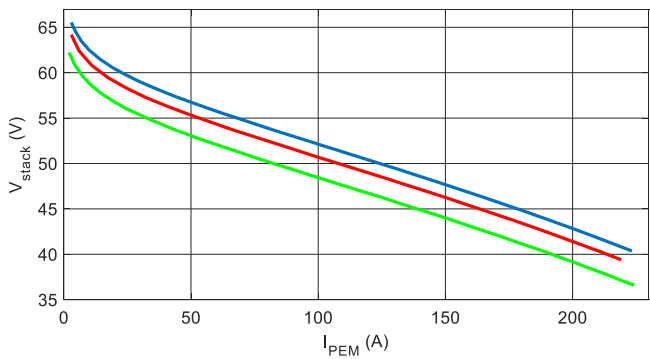


Fig. 6. The I/V diagram characteristics of NedStack for varying temperatures for 363K (blue line), 343 K (red line), 323 K (green line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

BCS PEMFC model for 100 independent runs.

$$\begin{aligned} \beta_{1,\min} &= -1.1997, \beta_{1,\max} = -0.8532, \beta_{3,\min} = 3.6e-5, \\ \beta_{3,\max} &= 9.8e-5, \beta_{4,\min} = -26e-5, \beta_{4,\max} = -9.54e-5, \\ \lambda_{\min} &= 13, \lambda_{\max} = 23, R_{c\min} = 0.1, R_{c\max} = 0.8, \\ \beta_{\min} &= 13.6e-3, \beta_{\max} = 0.5 \end{aligned}$$

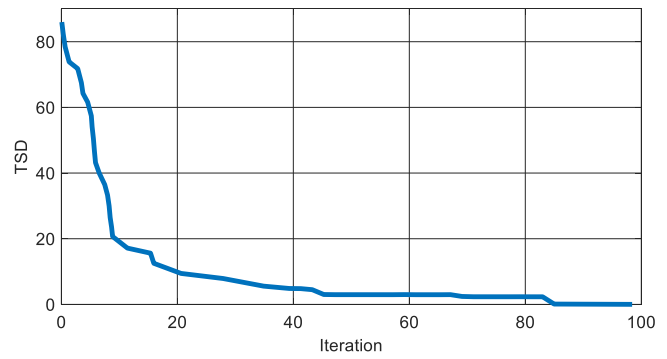


Fig. 7. The TSD convergence diagram of the proposed CFSO algorithm on the BCS PEMFC.

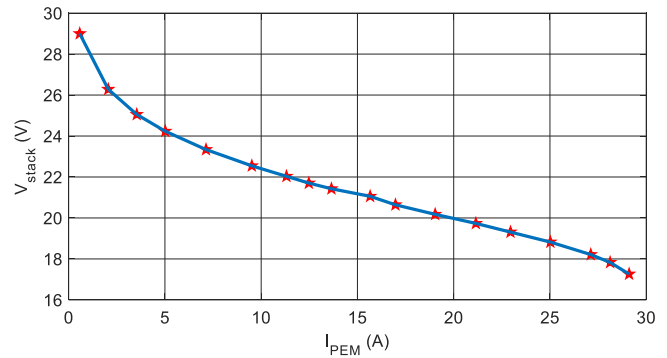


Fig. 8. The I-V diagram for the BCS PEMFC for the empirical curve (red-star) and model curve (blue-line).

Results show that using the proposed CFSO algorithm has better performance with minor TSD value toward the others in 100 independent runs.

Fig. 7 shows the TSD convergence diagram of the proposed CFSO algorithm on the BCS PEMFC. From the figure, it is clear that in this case study, like the before, the CFSO has the minimum TSD value.

The result shows the quick jumping of the algorithm into the minimum TSD after 5 iterations. Finally, the convergence in the algorithm is reached in iteration 85.

Final simulations showed that the presented CFSO algorithm has the best speed among the other methods again. This is illustrated in Table 7.

The collected best results for I-V polarization characteristics of the BCS PEMFC estimated by the CFSO along with the empirical data, the absolute deviation of the voltages points and the TSD between the actual and approximated voltage data is shown in Fig. 8.

Like case study 1, the results show a promising fitting between the empirical voltage model and the data achieved by the CFSO algorithm and show proper precision to finding the optimized values for the undetermined six parameters.

In the following, the I/V diagram characteristics of the BCS PEMFC for different temperatures and pressure are plotted.

Fig. 9 shows the variations on the partial pressures with 2.5/1.5 bar, 1.5/1 bar, and 1/0.21 bar.

It is obvious that by enhancing the supply pressures of the P_{H_2}/P_{O_2} , the output voltage of the stack is increased.

Finally, the variations on the constant cell temperatures with 373 K, 333 K, and 303 K are shown in Fig. 10 which shows that by enhancing the temperature, the stack output voltage is increased.

Table 6
TSD validation for the BCS PEMFC.

Parameter	Algorithm				
	CFSO	FSO	GA (El-Fergany, 2017)	GHO (El-Fergany, 2017)	SSO (El-Fergany, 2018)
β_1	-0.852	-0.8542	-1.023	-0.984	-0.853
β_2	4.810 e-3	4.811 e-3	4.811 e-3	2.811 e-3	4.811 e-3
β_3	9.412 e-5	8.943 e-5	8.200 e-5	5.341 e-5	9.433 e-5
β_4	-1.93 e-4	-1.93 e-4	-1.93 e-4	-1.358 e-4	-1.920 e-4
λ	23.000	23.000	23.000	19.428	23.000
R_c	0.312	0.312	0.315	0.746	0.350
β	0.016	0.018	0.017	0.012	0.016
TSD	0.011	0.012	0.015	8.341	0.012

Table 7
The Elapsed time for the state of art methods on the BCS PEMFC.

Algorithm	CFSO	FSO	GA (El-Fergany, 2017)	GHO (El-Fergany, 2017)	SSO (El-Fergany, 2018)
Elapsed time (s)	3.82	5.17	7.20	3.65	4.15

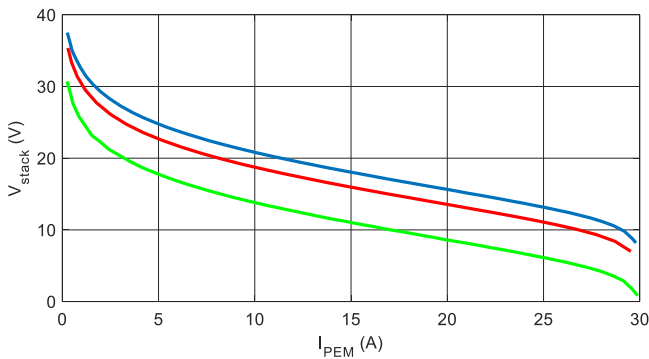


Fig. 9. The I/V diagram characteristics of BCS PEMFC for pressure variations for 2.5/1.5 bar (blue line), 1.5/1 bar (red line), 1/0.21 bar (green line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

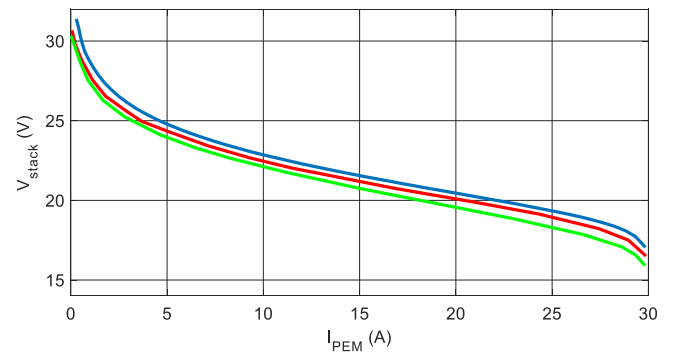


Fig. 10. The I/V diagram characteristics of BCS PEMFC for varying temperatures for 373 K (blue line), 333 K (red line), 303 K (green line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The modeling error of the analyzed models is shown in Fig. 11. As can be observed from the results, using the proposed method gives good results for the estimation of the PEMFC models.

5. Conclusions

In this study, a new procedure is presented for optimum parameter identification of the PEMFCs. The method is based on an optimization algorithm to guarantee the optimal values for

the system parameters. Here, an improved version of a new optimization algorithm called a fluid search optimization algorithm is proposed based on chaos theory. Results showed that using this theory speeds up the convergence of the algorithm. Two empirical PEMFC types are applied to analyze the performance of the presented algorithm for parameter identification. Simulations showed well-fitting results between the achieved values and the experimentally measured values for the voltage stack points. For more analysis, different conditions from the point of the partial pressures and the cell temperature are studied. The final

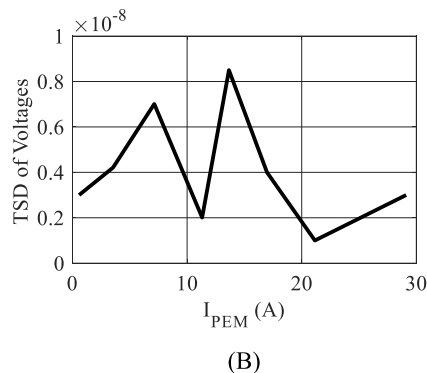
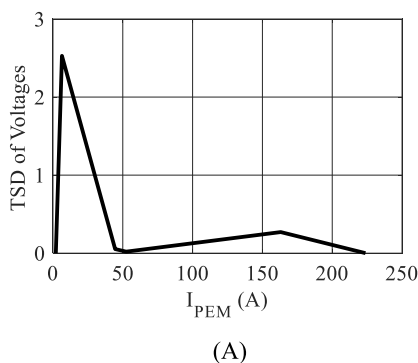


Fig. 11. The modeling error for (A) NedStack and (B) BCS PEMFC.

results prove the high capability and robustness of the proposed approach.

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.

CRediT authorship contribution statement

Yan Cao: Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Xiaoxi Kou:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Yujia Wu:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Kittisak Jermsittiparsert:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Abdullah Yildizbasi:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing.

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