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#### Article

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# Developed Coyote Optimization Algorithm and its application to optimal parameters estimation of PEMFC model

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#### ABSTRACT

In this paper, a new approach has been introduced for optimal parameter estimation of a proton exchange membrane fuel cell (PEMFC) model. The main purpose is to minimize the total error between the empirical data and the proposed method by optimal parameter selection of the model. The methodology is based on using a newly introduced developed version of the Coyote Optimization Algorithm (DCOA) for determining the value of the unknown parameters in the model. Two different PEMFC models including 2 kW Nexa FC and 6kW NedSstack PS6 FC are adopted for validation and the results are compared with the empirical data and some well-known methods including conventional COA, Seagull Optimization Algorithm, and (N +  $\lambda$ ) - ES algorithm to show the proposed method's superiority toward the literature methods. The final results declared a satisfying agreement between the proposed DCOA and the empirical data. The results also declared the excellence of the presented method toward the other compared methods.

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#### 1. Introduction

One of the most important challenges facing humankind is to find new and efficient ways of converting fuels into usable energy (Zhang et al., 2016). A fuel cell is a new technology for high-quality energy production through direct mixing between fuel and oxidizer without causing environmental and noise pollution (Xia et al., 2016). One of the new technologies in electricity production based on the direct conversion of chemical energy into electricity is to use fuel cells. Among different types of fuel cells, proton-exchange membrane fuel cell (PEMFC) is the most popular one which is used in different applications (Lin et al., 2014). Since PEMFC has outstanding characteristics like a solid electrolyte, higher efficiency, clean energy generation, short startup time without noise, and variability, it can be a good alternative for transportation applications. In addition to transportation applications, the use of such fuel cells in portable devices such as laptops, cell phones, and walkers is rapidly increasing. Of course, to be commercially viable, its price should be going down and also its lifetime should be optimized. The computational model for the PEMFC is a mathematical representation of the physical phenomena as well as the electrochemical processes governing the performance of the fuel cell. This model consists

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of a differential equation system with boundary conditions that describe the transition processes. It also includes the equations to shows how the equations of transmission relate to each other. To proper modeling of a PEMFC, the equations that describe the physical and electrochemical properties of the materials should be taken into consideration. After preparing the mathematical model equations, the equations system is numerically solved. The computational models of the polymer membrane fuel cell are used for two purposes. First, these models facilitate the learning of more complex physical phenomena that govern fuel cell performance and secondly due to the nature of the fuel cell, some of the physical phenomena are obtained in their natural location and are determined by a mathematical model of this information (Cao et al., 2019b). Computational models are also used as tools for designing the fuel cell (Gholamreza and Ghadimi, 2018). As a possible example, the modeling may be used to conduct a parametric study on the fuel cell design to evaluate its performance. Based on the purpose of design, models can be designed simple or complex (Fei et al., 2019).

Yang et al. (2018) analyzed the reliability and the efficiency of a self-designed PEMFC stack with 5 single cells. The research analyzed the impact of dummy load usage on degradation efficiency during the shut-down process over determining polarization profiles and electrochemical impedance spectroscopy (EIS) after various start-up and shut-down (SU/SD) cycles. Final results showed that the presence of dummy load lessens efficiency degradation

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**Research** paper





Nomenclature	
А	Membrane activity
В	Parametric coefficient
С	saturation in the interface of cathode
	catalytic (mol/cm <sup>3</sup> )
D	coefficient of the effective diffusion for
_	the reacting
E	Nernst Potential (v)
$E_0^{\circ}$	standard reference potential
F	Faraday constant
1	The cell stack current (A)
l D	Pasistance (Q)
К Т	Temperature (%C)
l V	Voltago (v)
v	Voltage (v)
Greek letters	
λ	adjustable parameter
η	Efficiency
ξ	Pseudo-experimental parametric coeffi- cients
arphi	tunable parameter
Subscripts	
А	Anode
Act	Activation
С	Cathode
CONC	Concentration
CO <sub>2</sub>	oxygen concentration at the
	cathode/gas interface (mol.cm <sup>-3</sup> )
CH <sub>2</sub>	Hydrogen concentration at the anode
	membrane /gas interface (mol.cm <sup>-3</sup> )
H <sub>2</sub>	Hydrogen
H <sub>2</sub> U	water
niem	Ovugen
O <sub>2</sub>	Obmic
DEM	Omme Proton-eychange membrane fuel cell
1 L1VI	roton-exchange memorane rder ten

and improves the reliability of the PEMFC stack. The results also showed that SU/SD process has a significant effect on a single cell, but not on uniformity of stack.

Zhong et al. (2020) analyzed the durability of a low temperature 5-cells PEMFC stack. During testing the polarization profile, the consistency of the output efficiency degradation for the cells was showed. The results showed that the cell No.1 has the worst degradation in reliability after Freezing/Thaw cycles. 3D imaging showed the membrane cracks in situ. The results also showed higher growing for the crack located within the membrane toward the delamination.

There are several studies about the numerical modeling of the fuel cells (Alpaydin et al., 2019). Some of them are aimed to investigate a specific phenomenon such as water management (Bae et al., 2020) and buoyancy (Huang et al., 2020), and some other models are at large targets (as far as possible) to explore all mechanisms within the fuel cells (Zhang and Jiao, 2018). For example, Ebrahimi et al. Yang et al. (2017) proposed a method for modeling PEMFC by optimal distribution of the catalyst over the fuel cell channel. The modeling was based on a genetic algorithm (GA) and computational fluid dynamic (CFD). The method comprised some

polynomial functions with unknown coefficients that were found optimally based on GA. The results showed that catalyst loading distribution has a principal impact on the PEMFC efficiency such that based on their founding, it can increase the performance by about 14%.

Yu et al. Gollou and Ghadimi (2017) introduced another identification method for the PEMFC parameters based on artificial neural networks. In that work, an optimized Elman neural network was investigated for the proper selection of the neural network. The optimization methodology was applied by using a new hybrid meta-heuristic based on two algorithms, fluid Search Optimization (FSO) algorithms and world cup optimization (WCO). The method was analyzed based on four different conditions and the efficiency was analyzed and compared with some other methods to show the method capability.

Fathy and Rezk (2018) proposed a new optimization algorithm for optimal identifying of PEMFC parameters under determined conditions. The optimization process is based on applying a multiverse optimizer (MVO) to seven parameters to achieve the polarization curves. The results of the method were then compared by several methods reported by the literature to show the method's efficiency.

In 2019, Yang et al. (2019) analyzed the connection among a transient PEMFC and its associated accessories such as hydrogen pump, humidifier, radiator, and air compressor. All the accessories were verified based on empirical data. Final results showed that by increasing the humidifier temperature, membrane dehydration efficiency is decreased and reducing the air stoichiometry develops the total water utilization.

Cao et al. (2019a) proposed empirical modeling of a PEMFC using a developed model of the seagull optimization algorithm. The study worked on optimal designing and simulating the PEMFC. To do so, the optimization algorithm is used to properly select the model parameters. The results were investigated based on two empirical examples and the achievements were compared with several algorithms reported from the literature to declare the algorithm's excellence toward the compared methods.

In addition, several numbers of optimization methods have been proposed for model identification of the PEMFC, for example, hybrid Teaching Learning-Differential Evolution algorithm (Turgut and Coban, 2016), Gray Wolf Optimizer (Ali et al., 2017), Genetic Algorithm (Ariza et al., 2018), Salp Swarm Optimizer (El-Fergany, 2018), Cuckoo Search Algorithm (Zhu and Wang, 2019), hybrid vortex search algorithm and differential evolution (Zhu and Wang, 2019), Pollination Algorithm (Priya and Rajasekar, 2019), and RNA genetic algorithm (Wang et al., 2020), Seagull Optimization Algorithm (SOA (Cao et al., 2019a)), (N +  $\lambda$ ) –ES algorithm (Restrepo et al., 2014), Emperor Penguin Optimizer (EPO) (Dhiman and Kumar, 2018), and Deer Hunting Optimization Algorithm (DHOA) (Brammya et al., 2019).

In 2018, Pierezan and Coelho (2018) presented a new metaheuristic technique inspired by coyotes living behavior. A literature review shows that the Cayote Optimization Algorithm makes a good balance between exploitation and exploration. Besides, its ability to keeping higher diversity helps it to obtain the optimal cost. These characteristics lead us to work on a developed version of this algorithm for empirical modeling of a PEMFC based on parameter identification. The main novelty of this paper is given below:

- 1. The new technique proposed for optimal selection of PEMFC parameters.
- 2. The method is based on a new model of the Coyote Optimization Algorithm.
- 3. Two case studies including Nexa FC and NedSstack PS6 FCs are adopted for model verification.



Fig. 1. A typical schematic of a PEMFC (Yin and Razmjooy, 2020).

4. The results are compared with the empirical data and four states of art algorithms.

The remained part of the paper is as follows: in Section 2, the mathematical model of the proton exchange membrane fuel cell is explained in brief. Section 3 presents the materials and the method of using a new optimization algorithm to solve the problem. Section 4 explains simulation results and the paper is concluded in Section 5.

#### 2. PEMFC model description

In this section, the equivalent circuit-based model of the Temasek's 1kW PEMFC has been determined. The main conception of this subject is based on Larminie's model (Larminie et al., 2003). In the following, a brief description of the structure of a PEMFC is first explained. The PEMFC stack includes two electrodes (anode and cathode) and one electrolyte between these two electrodes and the membrane to separate the two cell parts. At the anode pole, hydrogen reacts with a catalyst to form a positive charge ion and a negatively charged electron. The proton passes through the electrolyte environment while the electron moves through the circuit and generates a current. At the cathode pole, oxygen reacts with ions and electrons, producing water and heat. Each cell can generate about 0.7 volts of electric drive power, which is enough to light a small lamp. If these cells are in series, they will be able to generate power at several megawatts. The electrochemical reactions of the PEMFC based on the oxygencontaining cathode gas and hydrogen-containing anode gas have been given below:

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

Cathode:  $4H^+ + O_2 + 4e^- \rightarrow 2H_2O$  (2)

$$Overall: 2H_2 + O_2 \rightarrow 2H_2O \tag{3}$$

Fig. 1 shows a typical schematic of a PEMFC (Yin and Razmjooy, 2020).

As already noted, the model description of the PEMFC is so significant to illustrate the parameter complexity for the PEMFC. The electrical circuit equivalent of a PEMFC is shown in Fig. 1 that contains all the stack losses such as the ohmic resistance voltage drop, activation loss, the electrodes double layer charging effect, and the concentration overpotential. By considering Fig. 2, the output voltage can be formulated as follows:

$$V_{OUT} = E - V_a - V_c - V_{ohm} \tag{4}$$



Fig. 2. The electrical circuit equivalent of a PEMFC (Restrepo et al., 2014).

where, *E* describes the Nernst (reversible) potential and is achieved by the following Melika et al. (2018):

$$E = E_0^0 - k_E T^c - \lambda_e I(s) \frac{\tau_e s}{\tau_e s + 1} + \frac{RT}{2F} \left( p H_2 \sqrt{P_{0_2}} \right)$$
(5)

where,  $\tau_e$  describes the constant time delay of the FC output voltage due to fuel and oxidant delays during load transients, R describes the ideal gas constant (8.3143 J/(mol K)),  $T^c$  represents the fuel cell temperature (°C),  $E_0^0$  describes the standard reference potential, *F* determines the Faraday constant (96.487 kC/mol),  $\lambda_e$  describes a constant factor ( $\Omega$ ),  $k_E$  defines experimental constant (V/K), and  $P_{O_2}$  and  $pH_2$  describe the oxygen and hydrogen partial pressures (Pa).

Based on Lazarou et al. (2009),  $E_0^0$  is assumed as 1.229 V. An assumption from different literature studies defines that to define the fuel cell stack, all of the parameters for the cells should be collected with together. In contrast, there is some other literature that illustrated determinative differences between the membrane–electrode connection voltage levels of identical fuel cells at the same conditions (Shakhshir et al., 2020). This makes  $E_0^0$  as one of the parameters which should be achieved optimally. The value of the constants  $\lambda_e$  and  $\tau_e$  were obtained 3.3  $\Omega$  and 80 s, respectively for the model PEM SR-12 FC (Shakhshir et al., 2020). In this study, the value of the  $\lambda_e$  and  $\tau_e$  are also considered for optimal estimation. In addition, the activation loss is another part with some unknown parameters. The activation loss is a speed reducer of the reactions on the electrode's surface. The following equation shows the mathematically model of the activation loss:



Table 1

 The thicknesses for some different models of Nafion membranes

 (Corrêa et al., 2004).

 Parameter
 Thickness

51 µm
127 μm
178 µm
254 µm
89 µm

Therein,  $\xi_i$  describes pseudo-experimental parametric coefficients, *I* defines the fuel cell stack current and CO<sub>2</sub> describes the oxygen concentration at the cathode/gas interface (mol.cm<sup>-3</sup>) that is formulated as follows:

$$CO_2 = \frac{p_{O_2}}{50.8 \times 10^7 \times e^{\left(\frac{-498}{T}\right)}}$$
(7)

In the following, comprehensive limitation of the  $\xi_i$  parameters have been given Restrepo et al. (2014).

$$\xi_1 = -0.95 \pm 0.004 \tag{8}$$

$$\xi_2 = 0.003 + 0.0002 \ln (A) + 43 \times 10^{-6} \ln (C_{H_2})$$
(9)

 $\xi_3 = (7.6 \pm 0.2) \times 10^{-5} \tag{10}$ 

$$\boldsymbol{\xi_4} = -\left(1.93 \pm 0.05\right) \times 10^{-4} \tag{11}$$

And **CH**<sub>2</sub> is the Hydrogen concentration at the anode membrane /gas interface (**mol.cm**<sup>-3</sup>) that is formulated as follows:

$$CH_2 = \frac{p_{H_2}}{10.9 \times 10^7 \times e^{\left(\frac{77}{T}\right)}}$$
(12)

The ohmic resistance is another term of the model that models the PEM resistance for protons transferring and the electrode resistance and the collector plate for electrons transferring. The ohmic loss of the PEMFC is considered as follows Khan et al. (2019):

$$\boldsymbol{R}_{ohm} = \boldsymbol{R}_{mem} + \boldsymbol{R}_t \tag{13}$$

where,  $R_t = 300 \ \mu\Omega$  determines the equivalent resistance for the transferred protons across the membrane, and  $R_{mem}$  describes the membrane resistance ( $\Omega$ ) and is formulated as follows Khan et al. (2019):

$$R_{mem} = 181.6 \times \frac{l}{A} \times \frac{1 + 0.03 \times \frac{l}{A} + 0.062 \times \left(\frac{T}{303}\right)^2 \times \left(\frac{l}{A}\right)^{2.5}}{\left(\varphi - 0.634 - \frac{3l}{A}\right) \times e^{\left(4.18 \times \frac{T^c - 30}{T^c}\right)}}$$
(14)

where, *l* defines the thickness of the PEM ( $\mu$ m),  $\varphi < 23$  (San Martin et al., 2010) describes a tunable parameter which depends on the anode gas stoichiometric ratio, the membrane age, and the relative humidity.

Due to the wide application of the Nafion membranes in the PEMFCs, this type is considered here for the analysis. Table 1 illustrates the thicknesses for some different models of Nafion membranes (Corrêa et al., 2004):

Several works considered Nafion 112 for the simulation (Corrêa et al., 2004). Due to the uncertainties in different fuel cells with the same kind, parameters  $\varphi$  and *l* should be estimated in the best way. Furthermore, the losses of mass transport reduce the reactant's concentration on the electrodes' surface. The formulation for the concentration losses ( $R_{CONC}$ ) are as follows Spiegel (2011).

$$R_{\text{CONC}} = \frac{B}{I} \times \ln\left(\frac{I_{mr}}{I_{mr} - I}\right)$$
(15)

where, *B* describes the parametric coefficient that depends on the operation state of the cell that is achieved empirically. Therefore, this parameter is also considered as another parameter for estimation. Based on the PEMFC model, there is also a capacitor that models the double-layer charging effect between the membrane and porous cathode. The voltage for this capacitor is achieved as follows:

$$V_{\rm C} = \left(I - C\frac{dV_{\rm c}}{dt}\right) \times \left(R_{\rm CONC} + R_{\rm ACT}\right) \tag{16}$$

Due to the porous behavior of the PEMFC, the capacitance value has always uncertainties. So, this parameter is also considered as another parameter for optimal estimation of the system.

Finally,  $I_{mr}$  determines the current limitation that shows the maximum rate that can be provided to an electrode and is formulated as follows Spiegel (2011).

$$I_{mr} = N_r \times D \times F \times C_b \times \tau^{-1}$$
<sup>(17)</sup>

where,  $N_r$  describes the number of electrons employed for the reaction, *D* represents the coefficient of the effective diffusion for the reacting,  $C_b$  describes the bulk concentration that indicates the concentration at the bulk solution away from the electrode surface, and  $\tau$  determines the diffusion layer thickness.

#### 3. Materials and methods

To estimate the explained parameters in the previous section, the predicted parameters should be confirmed based on actual outputs. In this study, a new bio-inspired optimization algorithm is employed for this investigation. The optimization process is based on a developed model of the Coyote Optimization Algorithm. In the following, the method of optimal estimation is explained in detail.

#### 3.1. Objective function

By considering the empirical data from the studied PEMFC, the estimation of the fuel cell is rather a simple task. The main purpose here is to achieve the parameter values of the fuel cell such that error value between the actual and the obtained data for the output voltage of the PEMFC stack gets minimized. The model is simulated based on the MATLAB platform and based on the electrical circuit equivalent that is given in Fig. 2. Fig. 3 shows the load current profile for simulation.

The adopted error function here is the integral of the absolute value of the voltage error (IAE). The formulation of this objective function is given below:

$$\min \sum_{j=1}^{n} \left| V_{exp,j} - V_{est,j} \right| \tag{18}$$

Subject to the constraints introduced in Table 2. where, *n* describes the number of experimental data that is used for training, and  $V_{est,j}$  and  $V_{exp,j}$  represent the estimated and the experimental voltages of the PEMFC, respectively.

Since the model constraints are not defined by a set of algebraic equations, classic optimization techniques like gradient method fail to obtain a global minimum for this purpose. Therefore, in this study, a new improved technique based on metaheuristics conception has been adopted.



Fig. 3. The empirical adopted current profile for training the PEMFC model for (A) 2 kW Nexa and (B) NedSstack PS6.

#### 3.2. Coyote optimization algorithm

Nature-inspired meta-heuristics are some kinds of optimization techniques that mimic nature for solving the optimization problems. Although many research efforts have focused on this area over the past decade, science is still young and the results are amazing which expand the scope and feasibility of nature-inspired algorithms and increase the exploration of them in different areas such as computer science (Razmjooy et al., 2016, 2018), engineering (Hua et al., 2018; Paria et al., 2019; Homavoun et al., 2018; Hamid Asadi et al., 2018), computing and industry (Fei et al., 2019; Gollou and Ghadimi, 2017; Cao et al., 2019a; Milad et al., 2016; Firouz and Ghadimi, 2016). There are different types of nature-inspired algorithms that mimic different phenomena from natural reactions (Mahdiyeh et al., 2019; Mohammadhossein et al., 2019; Mousavi and Soleymani, 2014) to social behavior (Aliniva and Mirroshandel, 2019; Atashpaz-Gargari and Lucas, 2007; Razmjooy et al., 2017) and human competitions (Razmjooy et al., 2016, 2018; Bandaghiri et al., 2016) such as Variance Reduction of Gaussian Distribution (VRGD) (Namadchian et al., 2016), World Cup Optimization (Razmjooy et al., 2016), Quantum Invasive Weed Optimization (QIWO) algorithm (Razmjooy and Ramezani, 2014), Deer Hunting Optimization Algorithm (DHOA) (Brammya et al., 2019), Emperor Penguin Optimizer (EPO) (Dhiman and Kumar, 2018), and Coyote Optimization Algorithm (COA) (Pierezan and Coelho, 2018). Coyote Optimization Algorithm (COA) is a newly introduced meta-heuristic algorithm that is introduced by Pierezan and Coelho (Pierezan and Coelho, 2018). The algorithm is based on the adaptation behavior of the coyote by the environment and also the coyote's experiences exchanging. COA has an interesting technique to get a balance between exploration and exploitation.

The algorithm starts with  $N_P$  number of populations and  $N_c$  number of coyotes as the candidate solutions. The COA models the social behavior of coyote as the cost function. In this regard, the social behavior for coyote is as follows:

$$SOC_{c}^{p,t} = x = [x_1, x_2, \dots, x_D]$$
 (19)

where, c describes the number and p describes the group and t stands for the time of the simulation for the design variables.

At first, some random cayotes have been generated as the solution candidates in the search space. The following equation illustrates this process modeling:

$$SOC_{c,i}^{p,t} = LB_j + \eta \times (Ur_j - Lr_j)$$
<sup>(20)</sup>

where,  $\eta \in [0, 1]$  determines is a random value, and  $Lr_j$  and  $Ur_j$  describe the lower and the upper ranges of the *j*th variable in the search space.

The cost function of each coyote can be considered by the following:

$$obj_{c}^{p,t} = f\left(SOC_{c\,i}^{p,t}\right) \tag{21}$$

The algorithm updates the groups location randomly. Besides, the candidates update their position by leaving their groups to another one. The following equation determines the leaving process based on the probability formulation:

$$P_l = 0.05 \times N_c^2 \tag{22}$$

Such that by considering  $Nc \leq \sqrt{200}$ ,  $P_l$  has values greater than 1. The number of each coyote in the groups is limited to 14 for improving the algorithm diversity, i.e. cultural exchange among the cayotes.

The best solution of each iteration is considered as the alpha coyote and achieved by the following equation:

$$\alpha^{p,t} = \operatorname{soc}_{c}^{p,t} \operatorname{for} \min obj_{c}^{p,t}$$
(23)

The common properties of the coyotes for the culture transformation is as follows:

$$cul_{j}^{p,t} = \begin{cases} R_{\frac{N_{c}+1}{2},j}^{p,t}, N_{c} \text{ is odd number} \\ \frac{1}{2} \left( R_{\frac{N_{c}}{2},j}^{p,t} + R_{\frac{N_{c}}{2}+1,j}^{p,t} \right) O.W. \end{cases}$$
(24)

where,  $R^{p,t}$  determines the coyotes, social condition ranking for group number p at time t for the variable j.

The COA also considers the life cycle of the coyotes which is a combination of environmental factors and social behavior of the parent coyotes. The life cycle is modeled in the following:

$$Ble_{j}^{p,t} = \begin{cases} soc_{r_{1},j}^{p,t}, r_{j} < pr_{s} \text{ or } j = j_{1} \\ soc_{r_{2},j}^{p,t}, r_{j} \ge pr_{s} + pr_{a} \text{ or } j = j_{2} \\ \sigma_{j}, 0.W. \end{cases}$$
(25)

where,  $r_j \in [0, 1]$  describes a random value and  $r_2$  determines a random coyote in the group p,  $\sigma_j$  describes a random value within the design variable limit,  $j_1$  and  $j_2$  determine random design variables, and  $pr_a$  and  $pr_s$  represent the association and scatter probabilities, respectively that declare the coyote's cultural diversity from the group. The mathematical model for  $pr_a$  and  $pr_s$  is as follows:

$$pr_s = \frac{1}{d} \tag{26}$$

$$Pr_a = \frac{1}{2} (1 - pr_s)$$
 (27)

where, *d* determines the dimension for variables.

The pseudo-code of the balancing process for the life cycle is given below:

Determine *i* and  $\omega$ if *i* = 1 *Ble* lives and coyote in  $\omega$  dies else if *i* > 1 *Ble* lives and oldest coyote in  $\omega$  dies else *Ble* dies End if

where, *i* describes the number of coyotes in the groups,  $\omega$  determines the worst results of the coyotes, and the chance of dying is for *Ble* is considered 10%. The cultural transition among the groups is defined by two factors including  $\delta_1$  and  $\delta_2$  as follows:

$$\delta_1 = \alpha^{p,t} - \operatorname{soc}_{cr1}^{p,t} \tag{28}$$

 $\delta_1 = \alpha^{p,r} - \operatorname{soc}_{cr1}^{p,t}$   $\delta_2 = cul^{p,t} - \operatorname{soc}_{cr2}^{p,t}$ (28)
(29)

where,  $\delta_1$  represents the culture differences between the leader (alpha) and the selected coyote (*cr*1) and  $\delta_2$  describes the culture difference between group culture trending and the selected coyote (*cr*2).

For updating the social behavior based on the leader and the group impact, the following equation has been employed:

$$nsoc_c^{p,t} = soc_c^{p,t} + r_1 \times \delta_1 + r_2 \times \delta_2$$
(30)

where  $r_1$  and  $r_2$  are random numbers between 0 and 1.

By considering the updating equations, the new cost is finally obtained by the following equation:

$$nobj_{c}^{p,t} = f(nsoc_{c}^{p,t})$$
(31)  
$$soc_{c}^{p,t+1} = \begin{cases} nsoc_{c}^{p,t}, \ nobj_{c}^{p,t} < obj_{c}^{p,t} \\ soc_{c}^{p,t}, & O.W. \end{cases}$$
(32)

An important part of these techniques is their ability for escaping from the local optimum point.

#### 3.3. Developed coyote optimization algorithm

As it is clear from the aforementioned explanations, once the population has been selected randomly in each generation, premature convergence may be created that enhances the running time. To resolve this problem, different techniques have been introduced. One of the widely used mechanisms to develop metaheuristics efficiency is the Lévy flight (LF) mechanism (Ingle and Jatoth, 2019). The LF mechanism is modeled based on random walk behavior for managing the local search position as follows:

$$Lf(w) \approx w^{-1-\tau} \tag{33}$$

$$w = A/|B|^{1/\tau} \tag{34}$$

$$\sigma^{2} = \left\{ \frac{\sin(\pi \tau/2)}{2^{(1+\tau)/2}} \times \frac{\Gamma(1+\tau)}{\tau \Gamma((1+\tau)/2)} \right\}^{\frac{2}{\tau}}$$
(35)

where,  $\tau = 1.5$  describes the *Lf* mechanism (Li et al., 2018), *w* represents the step size,  $\Gamma$  (.) Describes the Gamma function,  $A \sim N(0, \sigma^2)$  and  $B \sim N(0, \sigma^2)$ .

The updating formulation of the algorithm based on Lf is given below:

$$\operatorname{soc}_{c,new}^{p,t+1} = \begin{cases} \operatorname{soc}_{c}^{p,t+1} + Lf(\sigma) \times f\left(\operatorname{soc}_{c}^{p,t+1}\right), \, \operatorname{rand} > 0.5\\ \operatorname{soc}_{c}^{p,t+1} - Lf(\sigma) \times f\left(\operatorname{soc}_{c}^{p,t+1}\right), \, \operatorname{rand} \le 0.5 \end{cases}$$
(36)

where,  $f\left(soc_{c,worst}^{p,t+1}\right)$ , and  $f\left(soc_{c,best}^{p,t+1}\right)$  determine the cost values for the worst and best solutions for social behavior, respectively.

The next term for algorithm improvement is to use the Chaos mechanism. A comprehensive formulation of the chaos mechanism is based on the following equation:

$$CM_{i+1}^{j} = f\left(CM_{i}^{j}\right), j = 1, 2, \dots, D$$
 (37)

where, *D* determines the dimension for the map and  $f\left(CM_{i}^{j}\right)$  describes the generator function (Rim et al., 2018).

This study employs a sinusoidal chaotic map to develop the COA by resolving the premature convergence problem. In other words, the chaos mechanism is employed for resolving the local optimum problem that makes a wrong solution with premature convergence. This problem is solved by employing pseudorandom values (Rim et al., 2018; Yang et al., 2007). This term is applied to three parameters of the algorithm ( $\eta$ ,  $r_1$ ,  $r_2$ ). The formulation of this modeling is as follows:

$$\eta_{k+1}^{new} = a \left(\eta_k^{new}\right)^2 \sin\left(\pi \eta_k^{new}\right), \tag{38}$$

$$r_{1,k+1}^{new} = a \left( r_{1,k}^{new} \right)^2 \sin \left( \pi r_{1,k}^{new} \right), \tag{39}$$

$$r_{2,k+1}^{new} = a \left( r_{2,k}^{new} \right)^2 \sin \left( \pi r_{2,k}^{new} \right), \tag{40}$$

$$\left(\eta_0^{new}, r_{1,0}^{new}, r_{2,0}^{new}\right) \in [0, 1], a \in (0, 4]$$
(41)

where, k determines the number of the iterations.

Fig. 4 indicates the flowchart diagram of the DCOA algorithm.

#### 3.4. Algorithm verification

To verify the algorithm capability in terms of precision and accuracy, it is applied to some standard benchmark functions. Afterward, the results of the presented DCOA are compared with some new and popular bio-inspired algorithms including DHOA (Brammya et al., 2019), EPO (Dhiman and Kumar, 2018), and the standard COA (Pierezan and Coelho, 2018) to show its advantages toward the other algorithms and the conventional COA. Table 3 illustrate the details of the adopted benchmarks for verification.

The population size of the algorithms is considered 100 and the stopping criteria will be reached when the maximum number of evaluated functions have been implemented. Table 4 illustrates the results of the verification based on three measures including *Median* which determines the median value for the objective function, *std* which determines the standard deviation, and also *maximum* and *minimum* which represent the maximum and the minimum values of the objective function, respectively in all the validated algorithms.



Fig. 4. The flowchart diagram of the proposed DCOA.

# Table 3 The utilized functions for the verification.

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

#### Table 4

The comparison results of the cost functions for the validation of the algorithm.

		DHOA (Brammya et al., 2019)	EPO (Dhiman and Kumar, 2018)	COA (Pierezan and Coelho, 2018)	DCOA
<i>F</i> <sub>1</sub>	Maximum	-9.53	-10.19	10.28	-11.37
	Minimum	-18.51	-18.52	18.55	-18.55
	Median	-15.52	-15.96	16.98	-16.42
	std	3.32	2.81	3.15	2.13
F <sub>2</sub>	Maximum	0.5217	0.513	0.502	0.500
	Minimum	0.500	0.500	0.500	0.500
	Median	0.513	0.507	0.501	0.500
	std	0.012	0.006	0.002	0.000
F <sub>3</sub>	Maximum	0.075	0.152	-0.244	-0.115
	Minimum	0.225	0.250	-0.245	-0.25
	Median	0.108	0.246	-0.244	-0.19
	std	0.135	0.412	0.015	0.013
<i>F</i> <sub>4</sub>	Maximum	15.83	33.27	5.162	1.165
	Minimum	3.142	0.000	0.000	0.000
	Median	5.375	12.06	0.053	0.031
	std	3.160	7.00	0.102	0.083

Fig. 5 presents a graphical conception of the algorithms results on the validated test functions. As can be observed, the presented DCOA has the highest accuracy among the other algorithms. in addition, the proposed method reaches faster to the optimum values in all analyzed test functions.

Table 4 also shows that the minimum values for standard deviation belong to the proposed DCOA which shows its higher precision among the other compared algorithms. Therefore, based on the above verification, it can be confirmed that the proposed DCOA has a proper balance between accuracy and precision that can help to achieve the desired solution for optimization purposes.

#### 4. Simulation results

The presented method has been implemented to two case studies including 2 kW Nexa PEMFC and 6kW NedSstack PS6 PEMFC for better validation.

#### 4.1. 2 kW Nexa PEMFC

The proposed DCOA has been simulated in MATLAB R2017b. The selected parameters for the DCOA to obtain the best feasible estimation for the PEMFC are:  $N_P = 50$ ,  $N_c = 10$  with 70 iterations. The optimum value for the objective function, IAE is 16 that is obtained after 70 iterations. The optimal values for the PEMFC parameters based on the proposed DCOA, conventional



Fig. 5. The comparison results of cost value minimization for the algorithms.



Fig. 6. The minimum value for the ITAE achieved by different algorithms for the Nexa PEMFC.

COA (Pierezan and Coelho, 2018), Seagull Optimization Algorithm (SOA (Cao et al., 2019a)), and  $(N + \lambda)$  –ES algorithm (Restrepo et al., 2014) are illustrated in Table 5.

Fig. 6 shows the optimal results of the compared algorithms for the ITAE. As can be indicated, the presented DCOA has the minimum value for the objective function that shows its better efficiency among the other compared algorithms for the considered case study. For more clarification, the output voltage static characteristics of the empirical data have been compared with conventional COA (Pierezan and Coelho, 2018), Seagull Optimization Algorithm (SOA (Cao et al., 2019a)), and (N +  $\lambda$ ) –ES algorithm (Restrepo et al., 2014). Fig. 8 shows the voltage-to-current static characteristic that is evaluated as a mean value of voltage in Fig. 7 inside each step of the current profile shown in Fig. 3. The characteristic profile achieved by this static characteristic for the absolute value of the voltage error for parameters obtained from the COA, SOA, and (N +  $\lambda$ ) –ES algorithm is illustrated in Fig. 6.

As can be seen, the DCOA has the closest behavior to the experimental data that is a reason for its befit for the PEMFC modeling. Here, SOA and COA have an error like bias in higher voltage than experimental data and ES and especially DCOA give closer behavior to the experimental data.

#### 4.2. 6 kW NedSstack PS6 PEMFC

For more verification of the method capability, a 6 kW NedSstack PS6 PEMFC has been also analyzed. The details for the simulation of this case are obtained from N.F.C. Technology (0000), El Monem et al. (2014). A number of cells are assumed 65. The area of each cell is considered 240 cm<sup>2</sup>, the thickness is 178  $\mu$ m, the supply pressure is in the range 0.5 bar to 5 bar, the cell temperature is considered 343 K. The operating range of the output voltage is between 32 V and 60 V DC, and the

Optimal values for the PEMFC parameters based on different algorithms for the Nexa PEMFC.

Parameter Method					Unit
	DCOA	COA (Pierezan and Coelho, 2018)SOA (Cao et al., 2019a)ES (Restrepo et al., 2014)			
$E_{0}^{0}$	1.245	1.362	1.307	1.256	V
ξ1	-0.427	-0.430	-0.443	-0.435	-
ξ2	2.79e10-3	1.99e10-3	1.42e10-3	1.08e10-3	-
ξ3	$5.851\times10^{-5}$	$5.912\times10^{-5}$	$6.374\times10^{-5}$	$6.219  imes 10^{-5}$	-
ξ4	$-1.386 \times 10^{-4}$	$4 - 1.390  imes 10^{-4}$	$-1.389\times10^{-4}$	$-1.527  imes 10^{-4}$	-
Α	115.62	117.40	117.28	119.37	cm <sup>2</sup>
$\varphi$	14.28	13.52	14.19	13.62	-
$\lambda_e$	0.004	0.004	0.006	0.005	Ω
1	$48\times10^{-6}$	$50 \times 10^{-6}$	$52  imes 10^{-6}$	$52  imes 10^{-6}$	m
В	0.065	0.064	0.073	0.068	V
С	5.72	5.88	6.19	6.20	F



Fig. 7. Empirical and estimated PEMFC voltage data based on the load profile from Fig. 3A.



Fig. 8. Empirical and estimated PEMFC static V-I characteristic for the Nexa PEMFC.

operating range of the output current is between 0 and 225 A. Table 6 illustrates the optimal values for the NedSstack PEMFC parameters based on different algorithms. After applying DCOA to the model, the best-estimated solution for each algorithm has been given. The results achieved after 50 independent runs.

Fig. 9 shows the minimum value for the ITAE for different algorithms on the NedSstack PEMFC after 50 independent runs.

Fig. 10 indicates the empirical diagram of the PEMFC voltage data based on the load profile compared with conventional COA (Pierezan and Coelho, 2018), Seagull Optimization Algorithm (SOA (Cao et al., 2019a)), and  $(N + \lambda)$  –ES algorithm (Restrepo et al., 2014).

Fig. 11 shows the Empirical and estimated PEMFC static V-I characteristic for the NedStack PEMFC. It can be seen that the results give promising fitting between the experimental voltage model and the estimated data achieved by DCOA.

It can be seen that there is a small non-linear behavior located in the range 100 A-160A of the stack voltage simulated with the DCOA which is due to keep a proper trade-off between the accuracy and the computational cost for the algorithm, however,

Table 5

Optimal values for the NedSstack PEMFC parameters based on different algorithms.

Parameter Method					Unit
	DCOA	COA (Pierezan and Coelho, 2018	8) SOA (Cao et al., 2019	a) ES (Restrepo et al., 2014	4)
$E_{0}^{0}$	1.36	1.34	1.28	1.21	V
ξ1	-0.823	-0.980	1.402	1.615	-
ξ2	2.39-3	2.11e10-3	1.42e10-3	1.75e10-3	-
ξ3	$7.38\times10^{-5}$	$7.45 \times 10^{-5}$	$3.84\times10^{-5}$	$4.19\times10^{-5}$	-
$\xi_4$	$-9.48 \times 10^{-1}$	$^{4}-9.51 imes 10^{-4}$	$-9.48\times10^{-4}$	$-9.48\times10^{-4}$	-
Α	240	240	240	240	cm <sup>2</sup>
$\varphi$	16.37	15.96	13.28	13.15	-
$\lambda_e$	0.009	0.007	0.006	0.006	Ω
l	$178  imes 10^{-6}$	$178 \times 10^{-6}$	$178  imes 10^{-6}$	$178  imes 10^{-6}$	m
В	0.049	0.047	0.058	0.034	V
С	6.40	6.05	6.27	6.17	F



Fig. 9. The minimum value for the ITAE achieved by different algorithms for the NedSstack PEMFC.



Fig. 10. Empirical and estimated PEMFC voltage data based on the load profile from Fig. 3B.

by the selected values for the algorithm, it is still the best results among the other compared results.

Table 6

#### 5. Conclusions

In this paper, a new method for optimal parameter estimation of PEM fuel cells (PEMFCs) was proposed. The model parameters of the PEMFC were achieved optimally based on a newly introduced developed version of the Coyote Optimization Algorithm (DCOA). To do so, the circuit-based model of the PEMFC has been considered. Afterward, the unknown parameters were achieved based on the proposed DCOA method. Here, two different case studies including 2 kW Nexa PEMFC and 6kW NedSstack PS6 PEMFC were tested. Simulation results based on the MATLAB platform showed good compliance between the proposed DCOA and the empirical data. Furthermore, the results of the proposed method were compared with conventional COA (Pierezan and Coelho, 2018), Seagull Optimization Algorithm (SOA (Cao et al., 2019a)), and (N +  $\lambda$ ) –ES algorithm (Restrepo et al., 2014) to show the proposed method's superiority toward the literature methods. In future work, different uncertainties that maybe happened in the system model will be considered.

#### **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.



Fig. 11. Empirical and estimated PEMFC static V-I characteristic for the NedStack PEMFC.

#### **CRediT authorship contribution statement**

**Zhi Yuan:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Weiqing Wang:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Haiyun Wang:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Abdullah Yildizbasi:** Conceptualization, Data curation, Data curation, Writing - review & editing. - review & editing. - review & editing.

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