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### Article

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# A new technique for optimal estimation of the circuit-based PEMFCs using developed Sunflower Optimization Algorithm

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#### ABSTRACT

This paper proposes a new methodology for the optimal selection of the parameters for proton exchange membrane fuel cell (PEMFC) models. The proposed method is to optimal parameter selection of the circuit-based model of the PEMFC model to minimize the sum of squared error (SSE) value between the estimated and the actual output voltage of the PEMFC stack. For minimizing the SSE, a newly developed model of the Sunflower Optimization Algorithm (DSFO) is proposed. Performance analysis is performed based on two practical models including NedSstack PS6 PEMFC and Horizon 500-W PEMFCs from the literature and the results have been compared with the empirical data and also some state of art methods including Seagull Optimization Algorithm (SOA), Multi-verse optimizer (MVO), and Shuffled Frog-Leaping Algorithm (SFLA). Final results indicate 2.18 and 0.014 SSE value for NedSstack PS6 PEMFC and Horizon 500-W open cathode PEMFC, respectively which are the minimum values compared with the other compared methods.

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#### 1. Introduction

Energy has been turned into a key driver of growth and development in the world, and energy consumption alongside the minimization of losses is an indicator for measuring the development of each country. For years, gasoline and diesel fuel have been the only sources of energy for transportation, electricity generation and meeting demand (Mohammadi and Ghadimi, 2015; Ahadi et al., 2015; Meng et al., 2020). Given the sharp increase in demand for fossil fuels in recent years and the nonrenewability of fossil fuels, the likelihood of a strong energy crisis and the search for new fuels and methods of energy production is of particular importance. In addition, the heavy pollution caused by fossil fuels in large cities has created disastrous conditions for consumers of these energy sources. This has led developed countries to undertake extensive research to find the right alternative to fossil fuels and to explore different options according to their conditions and resources. One of the most popular alternative options is Hydrogen, which, compared to fuels such as gasoline, diesel and natural gas (CNG and LPG), because of its simplified production technology, compliance with environmental standards and the prospect of an affordable price as one of the top fuels for energy supply (Hosseini Firouz and Ghadimi, 2016; Liu et al., 2020).

\* Corresponding author. *E-mail address:* yz19xju@163.com (Z. Yuan). Fuel cells are a type of energy converters that are adopted for converting the chemical fuel energy directly into electricity. Unlike batteries that cannot supply the required energy due to the limited amount of reactive material in the battery tank, after a while the fuel cells in the fuel cell are continuously pumped and the products are continuously discharged, so the fuel cell can work continuously. It is also highly efficient thanks to the direct conversion of energy. In the fuel cell, hydrogen gas is used as a fuel and is produced by its reaction with oxygen, in addition to electrical energy, water, and heat. In other words, in this conversion, the photoelectrolysis reaction occurs (Ye et al., 2020; Nejad et al., 2019).

Proton exchange membrane fuel cell (PEMFC) is a type of efficient fuel cell that is developed mainly in UAVs and aircraft to increase flight persistence while providing the capability of securing the low temperature of the polymer cell for air vehicles, stationary energy generation applications and also portable energy generation applications (El-Fergany, 2018, 2017). PEMFCs are growing today due to their quite performance, no noise, no moving components and no greenhouse gas emissions or emissions, and lower temperature and pressure ranges (Fawzi et al., 2019).

The optimal design of PEMFCs can decrease the total fix price and can increase its efficiency. The model should include electrochemical processes governing the performance of the fuel cell (Selem et al., 2020). All the models contain ordinary or

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partial differential equations to define the PEMFC characteristics. Modeling PEMFCs has two important advantages. First, it can be used to simplify the learning of mathematical modeling of complicated physical phenomena in the PEMFCs and second, optimal selection of the variant parameters of the model for improving its efficiency based on different conditions. Researchers worked on different numerical models to analyze the designed fuel cell before the manufacturing stage (Cao et al., 2019; Karimi et al., 2012; Fei et al., 2019; Yu et al., 2019; Chen et al., 2020). Recently, a big contribution of the PEMFC modeling is assigned based on the meta-heuristics. For example, Gray Wolf Optimizer (Ali et al., 2017), Genetic Algorithm (Ariza et al., 2018), RNA genetic algorithm (Wang et al., 2020), Teaching Learning-Differential Evolution algorithm (Turgut and Coban, 2016), Salp Swarm Optimizer (El-Fergany, 2018), Cuckoo Search Algorithm (Zhu and Wang, 2019), Pollination Algorithm (Priva and Rajasekar, 2019), and hybrid vortex search algorithm and differential evolution (Zhu and Wang, 2019). These researches analyze special phenomenon such as buoyancy (Huang et al., 2020), water management (Bae et al., 2020) and some others investigate large purposes as it was possible to consider significant behaviors of the fuel cells (Deng et al., 2020; Goshtasbi et al., 2020). For example, El-Fergany et al. (2019) proposed a different method to determine the indefinite parameters of a PEMFC. The optimization of the method was based on Whale Optimization Algorithm (WOA). the study considered seven unknown parameters that should be selected optimally based on the proposed method. The purpose of WOA was to minimize the cost function of some conditional constraints. The proposed method was applied to four several case studies and the results were compared with Genetic Algorithm (GA) as a popular method to show its superiority.

Isa et al. (2019) presented a comparative study on the optimal estimation of the PEMFC parameters based on two different meta-heuristics. Dragonfly Algorithm (DA) and Ant Lion Optimizer (ALO) were used in the analysis and the results were compared with each other in terms of efficiency. The results indicated that using ALO gives better results than the DA.

In addition to several advantages of the meta-heuristic algorithms for modeling of the PEMFCs, some hybrid and improved works have been also based on meta-heuristics to improve their shortcomings like their premature convergence, their accuracy, and their local optimization. for instance, Chen and Wang (2019) introduced another bio-inspired technique based on the Cuckoo Search (CS) algorithm to the optimal selection of the PEMFC model parameters. The method also utilized an explosion operator to develop the exploration of the algorithm. Numerical analysis of some case studies indicated that the presented CS algorithm gives better efficiency in terms of accuracy and convergence.

Cao et al. (2019) modeled PEMFC based on considering the experimental data and using a developed version of the Seagull Optimization Algorithm (SOA). The purpose was to present an optimal design to simulate the PEMFC by optimal selection of unknown parameters of the model. Simulation results were investigated based on two case studies to show the algorithm capability. The method was also compared with some different algorithms to show the superiority of the algorithm.

Xu et al. (2019) proposed a simple two-fold optimized method for PEMFC model parameter identification. The optimization method is a Nelder–Mead simplex algorithm based on the eagle strategy based on the JAYA algorithm for optimal estimating of the model unknown parameters. The method efficiency was investigated based on two experimental case studies with seven and nine unknown parameters. The results of the proposed method were compared with the standard JAYA algorithm and also 4 other newly reported bio-inspired algorithms to show its better performance. Aghajani and Ghadimi (2018) introduced another technique for the optimal selection of a PEMFC based on a Hybrid method of the Gray Wolf Optimizer (GWO) algorithm. The proposed GWO algorithm was hybridized by mutation and crossover operators to achieve better performance for the model. The proposed algorithm was first validated by some different bench functions to show its capability and then utilized for efficient determining of the PEMFC model.

Liu et al. (2017) proposed a method for modeling a PEMFC by considering the channel shape design. The study designed an optimal structure for the channel of the fuel cell based on a meta-heuristic wave-like structure. The method effect on the fuel cell has been analyzed over a 3D and non-isothermal model. Simulation results indicated that the efficiency of the design approach compared with fuel cells with a basic structure is better.

In 2019, Gomes et al. introduced a new algorithm based on the particular behavior of the sunflowers for searching the best orientation towards the sun. Literature review shows that the proposed algorithm despite being new gives good balancing between the exploitation and exploration in the optimization process. Besides, the algorithm has the ability to keeping higher diversity to get the optimal cost. The only problem of this algorithm is its premature convergence. These features attracted us to design a developed version of this algorithm for the purpose of PEMFC parameter identification. The main innovations of the presented study have been briefly given below:

- New Technique for Optimal Estimation of the PEM fuel cell (PEMFC) was proposed.
- The purpose was to the optimal selection of the parameters of the Circuit-based PEMFC model.
- The method was based on minimizing the sum of squared error (SSE) between the estimated and the actual output voltage.
- Newly developed model of the Sunflower Optimization Algorithm was proposed for optimization.
- The results were compared with empirical data and some state-of-the-art meta-heuristics.

#### 2. PEMFC model description

In the present section, the circuit-based modeling of a PEMFC stack has been explained. Carmine's model (Gollou and Ghadimi, 2017) is considered as the primary inspiration. Before modeling of the PEMFC, a detailed explanation about this stack should be considered.

By consider Fig. 1, a PEMFC stack contains three main parts including anode and cathode, and electrolyte. The electrolyte that is placed between the membrane and these two electrolytes (anode and the cathode) is utilized for separating them from each other. As can be seen from Fig. 1, in the anode side, a catalyst is adopted for reacting by the hydrogen to generate a negatively charged electron and a positive charge ion. The proton moves over the electrolyte so long as the electron passes over the circuit to produce the current. At the cathode side, ions and electrons react with oxygen and generate heat and water. The maximum voltage generated by a PEMFC cell is about 0.7 V that is enough to light a small lamp. Therefore, to use it for applications with more required voltage, it should be combined in series by some other cells. The main reaction of a PEMFC for the Anode pole is as follows:

$$H_2 \rightarrow 2H^+ + 2e^- \tag{1}$$

And its reaction for the Cathode pole is:

$$4H^{+} + O_{2} + 4e^{-} \rightarrow 2H_{2}O \tag{2}$$



Fig. 1. A typical structure of a PEMFC.



Fig. 2. The electrical circuit equivalent of a PEMFC.

Finally, the overall base reaction for the PEMFC is as follows:

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

As aforementioned, determining the model of a PEMFC is a big deal for the proper designing of this device. Because some parameters of the PEMFC do not give by the manufacturer, they should be obtained accurately for proper modeling.

Fig. 2 shows the electrical circuit equivalent of a PEMFC. By considering this figure, the output voltage of the PEMFC is achieved by the following:

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

where,  $V_a$  is the activation loss voltage,  $V_c$  is the concentration losses voltage,  $V_{\Omega}$  is the ohmic losses voltage, and *E* describes the Nernst (reversible) potential that is achieved as follows:

$$E = E_0^0 - \kappa T - \lambda_e I(s) \frac{\tau_e s}{\tau_e s + 1} + \frac{RT}{2F} \left( P_{\text{H}_2} \sqrt{P_{\text{O}_2}} \right)$$
(5)

where, *T* describes the fuel cell temperature, *F* represents the Faraday constant (96.487 kC/mol),  $E_0^0$  determines the standard reference potential,  $\lambda_e$  represents a constant factor ( $\Omega$ ),  $\kappa$  defines experimental constant (*V*/*K*), and  $P_{H_2}$  and  $P_{O_2}$  represent the hydrogen and the oxygen partial pressures (Pa).

The standard value for the standard reference potential is extracted from Mirzapour et al. (2019) ( $E_0^0 = 1.229$  V). Based on several researches that reported in the literature, they concluded that for defining of the fuel cell stack model, the overall parameters of the cells should be obtained together. In return, there are some other researches that described the specified differences between the membrane-electrode connection voltage levels of the identical fuel cells with the same conditions (Firouz et al.,

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The comprehensive limitation of the  $\beta_i$  parameters.

Parameter	Minimum value	Maximum value
$\beta_1$	-0.954	-0.946
$\beta_3$	$7.4  imes 10^{-5}$	$7.8  imes 10^{-5}$
$\beta_4$	$-1.98 imes10^{-4}$	$-1.88 imes10^{-4}$

2016). Based on the explanations, the optimal selection of the  $E_0^0$  has a high priority. So, this parameter is considered as one of the parameters that should be optimally achieved. Based on Firouz et al. (2016),  $\lambda_e = 3.3 \Omega$  and  $\tau_e = 80$  s. However, because the manufacturer achieves this value based on its own conditions that has a little uncertainty in different situations. Therefore, here, the value of the  $\lambda_e$  and  $\tau_e$  are also considered for optimal estimation.

In addition to the above parameters, the activation loss voltage includes different unknown parameters that should be properly selected. The mathematical model for the activation loss voltage is as follows:

$$V_a = \beta_1 + \beta_2 \times T + \beta_3 \times T \times \ln(\text{CO}_2) + \beta_4 \times T \times \ln(I)$$
(6)

where, *I* describe the PEMFC current,  $\beta_i$  represents the *i*th pseudoexperimental parametric coefficient, and CO<sub>2</sub> determines the oxygen concentration at the cathode/gas interface (mol cm<sup>-3</sup>) that is mathematically modeled as follows:

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

Table 1 illustrates the comprehensive limitation of the  $\beta_i$  parameters from Hamian et al. (2018).

And the value of the  $\beta_2$  is achieved as follows:

$$\beta_2 = 0.003 + 0.0002 \ln (A) + 43 \times 10^{-6} \ln (C_{\rm H_2})$$
(8)

where,  $CH_2$  describes the Hydrogen concentration at the anode membrane/gas interface (mol cm<sup>-3</sup>) and is achieved as follows:

$$CH_2 = \frac{P_{H_2} \times 10^{-7}}{10.9 \times e^{\binom{77}{T}}}$$
(9)

In addition to the above variants, the ohmic resistance is a term that models the PEM resistance for transferring the protons and the electrode and also the collector plate for transferring electrons. Based on Leng et al. (2018), the mathematical model for this term is as follows:

$$R_{ohm} = R_{mem} + R_t \tag{10}$$

where,  $R_t$  describes the equivalent resistance for the transferred protons over the membrane and is considered 300  $\mu\Omega$  and  $R_{mem}$  represents the membrane resistance ( $\Omega$ ) and is achieved as follows (Leng et al., 2018):

$$R_{mem} = 181.6 \times \frac{l}{A} \times \frac{1 + 0.03 \times \frac{l}{A} + 0.062 \times \left(\frac{T}{303}\right)^2 \times \left(\frac{l}{A}\right)^{2.5}}{\left(\varphi - 0.634 - \frac{3l}{A}\right) \times e^{\left(4.18 \times \frac{T^c - 30}{T^c}\right)}}$$
(11)

where, *l* represents the PEM fuel cell thickness ( $\mu$ m) and  $\varphi$  < 23 (Akbary et al., 2019) describes a regulative parameter that is affected by the relative humidity, the membrane age, and the anode gas stoichiometric ratio.

The mass transport losses decrease the reactant's concentration on the surface of electrodes. The mathematical model of concentration losses is as follows (Ebrahimian et al., 2018).

$$R_{\text{CONC}} = \frac{B}{I} \times \ln\left(\frac{I_l}{I_l - I}\right)$$
(12)

where, *B* represents a coefficient that is experimentally achieved based on the operation state of the cells.

This reason made us consider also this parameter as another parameter for parameter estimation.

By considering Fig. 1, it can be seen that the model has also a capacitor that simulates the double-layer charging effect between the membrane and porous cathode. The voltage of this capacitor based on the circuit is equal to:

$$V_C = \left(I - C\frac{dV_c}{dt}\right) \times \left(R_{CONC} + R_{ACT}\right)$$
(13)

The value of the capacitance has always some uncertainty that is made by the porous behavior of the PEMFC. Therefore, the capacitance is considered as another parameter that should be optimally estimated.

Finally,  $I_l$  stands for the current limitation and is achieved as follows (Ebrahimian et al., 2018).

$$I_l = N_r \times D \times F \times C_b \times \tau^{-1} \tag{14}$$

where, *D* describes the coefficient of the effective diffusion for reacting,  $N_r$  determines the number of employed electrons for the reaction,  $\tau$  is the diffusion layer thickness, and  $C_b$  represents the bulk concentration.

#### 3. Materials and methods

#### 3.1. Objective function

For simple and optimal parameters identification of the PEMFC model, we need to have some experimental data from the studied PEMFC. This research presents a new methodology for optimal identification of the unknown parameters and the parameters with uncertainties that are explained in the previous section. The method is based on minimizing the sum of squared error (SSE) value between the estimated data and the actual data for the output voltage of the PEMFC stack. The measure SSE is selected as the cost function because it is one of the widely used functions in the literature (Khodaei et al., 2018). Therefore, briefly, the main purpose of this research is to optimal parameters identification of a PEMFC by minimizing the following cost function:

Cost function = 
$$\sum_{i=1}^{N} (V_{m,FC}(i) - V_{e,FC}(i))^2$$
 (15)

where, *N* represents the sampling data number, and  $V_{m,FC}$  and  $V_{e,FC}$  determine the experimental and the estimated values for the output voltage of the PEMFC model.

Subject to the constraints given in Table 2,  $\beta_2$  can be achieved based on Eq. (8).

The model is simulated based on the MATLAB platform and based on the electrical circuit equivalent that is given in Fig. 2.

#### 3.2. Balanced sunflower optimization (BSFO) algorithm

Optimization is a process for tuning the inputs, the mathematical process, the features, or testing to obtain the optimum output (Bagal et al., 2018; Gheydi et al., 2016; Firouz and Ghadimi, 2016). The input contains a series of variables: the process or function known as the objective function, the fitness function, or cost function and the output that is the fitness or cost. There are several techniques to solve an optimization problem (Cao et al., 2019; Yu et al., 2019). Some of these methods are inspired by natural practices. All the methods begin with an initial set of variables and then move on until the maximum or the minimum absolute objective function is achieved. These algorithms attempt to combine the principles of heuristic methods to find a way to efficiently search for an answer space and are called metaheuristics. In short, meta-heuristic algorithms are global search strategies and offer steps and criteria that are very effective in avoiding local optimization (Eslami et al., 2019; Razmjooy and Ramezani, 2016).

A significant factor in these approaches is the dynamic balance between Intensification and diversification. Diversification stands for extensive search in the answer space, and Intensification means taking advantage of the experiences gained in the search process and focusing on the more prominent areas of the answer space. Therefore, by balancing these two strategies, on the one hand, the search leads to areas of better answering space and on the other hand, wastes no more time in the part of the solution space that was previously reviewed or included inferior solution. There are various types of meta-heuristic algorithms such as Emperor Penguin Optimizer (EPO) (Dhiman and Kumar, 2018), Variance Reduction of Gaussian Distribution (VRGD) (Gheydi et al., 2016), Owl Search Algorithm (OSA) (Jain et al., 2018), Butterfly Optimization Algorithm (BOA) (Arora and Singh, 2019), World Cup Optimization (WCO) algorithm (Bagal et al., 2018), Improved Cat Swarm Optimization (ICSO) algorithm (Kumar and Singh, 2018), Moth Search Algorithm (Wang, 2018), and sunflower optimization (SFO) algorithm (Gomes et al., 2019).

#### 3.2.1. Basic sunflower optimization (SFO) algorithm

The sunflower optimization (SFO) algorithm is one of the newest meta-heuristics that is introduced by Gomes et al. (2019). The algorithm is designed by considering the particular behavior of the sunflowers for searching the best orientation towards the sun. In the SFO algorithm, the pollination process has been simulated based on random generating of the seeds that are done by considering the minimum distance between the flower *i* and the flower i + 1. However, there are millions of pollen gametes in each natural flower, to obtain a fast solution in the optimization, the algorithm assumes only one generated pollen gamete for each sunflower with individual reproduction. In addition to the above feature, the algorithm simulates the sunflower inverse square law radiation which has an inversely proportional with the radiation intensity and the square of the distance, such that the radiation intensity value reduces directly by increasing the distance. The main objective of the algorithm is to minimize the distance between the plant and the sun to get sunlight and to stabilize them in its vicinity

In addition, the farther away the less heat is received. This behavior helps the algorithm to get better exploration to obtain the global solution (sun) as it is possible. The received heat (H) from the *i*th *the* plant is formulated below:

$$H_i = \frac{P_s}{4\pi d_i^2} \tag{16}$$

-

where, d describes the distance between a plant and the current best and P<sub>s</sub> represents the source power.

The mathematical model of the sunflowers direction into the sun is formulated as follows:

$$\overrightarrow{D}_{i} = \frac{Z^{*} - Z_{i}}{\|Z^{*} - Z_{i}\|}$$
(17)

where,  $Z^*$  and Z describe the best plantation and the current plantation, respectively.

The model of moving the sunflowers into the sun direction,  $S_i$  is as follows.

$$S_{i} = \omega \times ||Z_{i} + Z_{i-1}|| \times P_{i} (||Z_{i} + Z_{i-1}||)$$
(18)

where,  $\omega$  determines the inertial displacement of the plants, and  $P_i(||X_i + X_{i-1}||)$  represents the pollination probability.

The updating process for the algorithm is different for closer and farther candidates to the sun. For closer candidates, the algorithm movement contains smaller steps, while for other distant

1	dDI	e z												
T	he	range	of	all	the	parameters	which	should	be	considered	in	the	estimatio	n.
_														_

Parameter	Minimum range	Maximum range	Unit	Parameter	Minimum range	Maximum range	Unit
E <sub>0</sub> <sup>0</sup>	0.1	2	V	$\lambda_e$	0	0.01	Ω
$\beta_1$	-1.2	-0.85	-	$\beta_3$	$3.6 \times 10^{-5}$	$9.8  imes 10^{-5}$	-
$\beta_4$	$-26 \times 10^{-5}$	$-9.54 \times 10^{-5}$	-	1	51	89	m
Α	90	130	cm <sup>2</sup>	В	0.14	0.5	V
$\varphi$	10	23	-	С	0.1	10	F

candidates, the algorithm movement is done normally. The maximum step for the candidates is achieved based on the following equation:

$$S_{max} = \frac{\|Z_{max} - Z_{min}\|}{2 \times N_{\rm p}}$$
(19)

where,  $N_p$  describes the total number of plants, and  $Z_{max}$  and  $Z_{min}$  stand for the maximum and the minimum restrictions.

The mathematical formulation for updating the plantation is as follows:

$$\vec{Z}_{i+1} = \vec{Z}_i + S_i \times \overrightarrow{D_i}$$
<sup>(20)</sup>

The SFO algorithm starts with a set of random populations. Afterward, the best solution has been achieved by calculating the cost function and then updating the process has been applied to update the position of the plats toward the sunlight.

#### 3.2.2. Developed sunflower optimization (DSFO) algorithm

However SFO has different advantages (Gomes et al., 2019), it has a big drawback due to its premature convergence in some problems. This objection led us to design a newly developed version of SFO for the considered optimization problem. The first development is to use self-adaptive weighting to adjust the speed of the algorithm tendency to achieve the best solution. For updating the searching behavior of the plants, a random value has been considered based on the plantation terms. In this condition, to make a balance between exploration and exploitation in the algorithm, the exploration starts with a high divergence searching, while at final steps, it searches locally in the search space. This improvement is formulated as follows:

$$\vec{Z}_{i+1}^{new} = \begin{cases} \vec{Z}_{i+1} + \gamma \times S_i \times \overrightarrow{D_i} \times f\left(\vec{Z}_{i+1}\right), \ rand > 0.5\\ \vec{Z}_{i+1} - \gamma \times S_i \times \overrightarrow{D_i} \times f\left(\vec{Z}_{i+1}\right), \ rand \le 0.5 \end{cases}$$
(21)

where,

$$\gamma = \begin{cases} \left( \frac{f\left(\vec{Z}_{i+1}^{best}\right)}{f\left(\vec{Z}_{i+1}^{worst}\right)} \right)^2, & \text{if } f\left(\vec{Z}_{i+1}^{worst}\right) \neq 0 \\ 1, & \text{if } f\left(\vec{Z}_{i+1}^{worst}\right) = 0 \end{cases}$$
(22)

where,  $f\left(\vec{Z}_{i+1}^{worst}\right)$ , and  $f\left(\vec{Z}_{i+1}^{best}\right)$  represent the function cost values

for the worst and best solutions for plantation, respectively.

This improvement increases the exploration of the algorithm to reduce the difference between the best and the worst solutions. This study also uses the logistic map mechanism to more improving the system to escape from premature convergence (Rim et al., 2018). The logistic map is a chaos mechanism that is usually utilized for resolving the local optimum of the optimization problems. The logistic map performs based on employing pseudo-random values (Yang et al., 2007). By applying this mechanism on the total number of plants, the following updated equations have been made:

$$N_{p+1}^{new} = N_p^{new} + \beta_i \times N_p^{new}$$
(23)

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
$F2 = 0.5 + \frac{\sin 2\left(\sqrt{x^2 + y^2} - 0.5\right)}{1 + 0.1\left(x^2 + y^2\right)}$	0 < <i>x</i> , <i>y</i> < 2	0.5
$F3 = \left(x^2 + y^2\right)^{0.25} \times$	$[-\infty,\infty]$	-0.25
$\sin\left(30\left((x+0.5)^2+y^2\right)^{0.1}\right)+ x + y $		
$F4 = 90 + \sum_{i=1} (x_i^2 - 10\cos(2\pi x_i))$	[-5.12,5.12]	0

#### Table 4

Selected parameters for the presented DSFO algorithm.

Parameter	Value
Number of iterations	100
Number of sunflowers	120
The sun coefficient	0.6
The days for the algorithm	100

where,

$$\beta_{i+1} = 4 \times (\beta_i - \beta_i^2) \tag{24}$$

where,  $\beta_i$  describes the value for the *i*th chaotic iteration, and the initial value  $\beta_i$  describes a random value in the range 0 and 1.

Fig. 3 shows the flowchart diagrams of the proposed DSFO.

#### 3.3. Algorithm validation

To analyze the algorithm efficiency in terms of accuracy and precision, four popular benchmark functions have been employed and the results of the algorithm are compared with some new meta-heuristics consisting of Deer Hunting Optimization Algorithm (DHOA) (Brammya et al., 2019), Emperor Penguin Optimization (EPO) (Dhiman and Kumar, 2018), and the original SFO. More information about benchmarks has been given in Table 3.

 Table 4 indicates the selected parameters for the proposed

 DSFO algorithm that are achieved based on trials and errors.

In the following, by considering the above information, the methods including proposed DSFO, DHOA, EPO, and SFO have been verified. This validation is illustrated in Table 5. Based on Table 5, four different measures have been employed. The first measure is the Median that calculates the median value of the objective values. The next measure is *std* which has the duty for determining the standard deviation. Finally, *Minimum* and *Maximum* determine the minimum and the maximum values for the algorithms, respectively.

The median value and the standard deviation (std) of the algorithms have been illustrated based on 30 runs. As can be observed, the presented DSFO gives almost the best results except for standard deviation in some functions compared with DHOA and EPO (the first function) algorithm. But, after applying the proposed DSFO, it gives the best results compared with other algorithms. Fig. 4 shows the graphical results of the cost value minimization for the algorithms.



Fig. 3. The diagram flowchart of the proposed DSFO algorithm.

#### Table 5

The validation of the proposed algorithm toward the literature algorithms.

	Measure	DHOA (Brammya et al., 2019)	EPO (Dhiman and Kumar, 2018)	SFO (Pierezan and Coelho, 2018)	DSFO
$F_1$	Maximum	-9.53	-10.19	-10.11	-12.04
	Minimum	-18.51	-18.52	-18.47	-19.74
	Median	-15.52	-15.96	-15.58	-16.37
	std	3.32	2.81	2.91	1.96
F <sub>2</sub>	Maximum	0.5217	0.513	0.507	0.500
	Minimum	0.500	0.500	0.500	0.500
	Median	0.513	0.507	0.503	0.500
	std	0.012	0.006	0.005	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	0.251	0.025
F <sub>4</sub>	Maximum	15.83	33.27	7.57	1.165
	Minimum	3.142	0.000	0.000	0.000
	Median	5.375	12.06	0.179	0.073
	std	3.160	7.00	0.24	0.012

#### 4. Simulation results

In this section for validating the capability of the presented approach, two case studies have been simulated and analyzed. The simulation results also compared with some other metaheuristic-based PEMFC estimators to verify and to show the proposed method's excellence. The compared algorithms in this study are based on Seagull Optimization Algorithm (SOA) (Cao et al., 2019), Multi-verse optimizer (MVO) (Fathy and Rezk, 2018), and Shuffled Frog-Leaping Algorithm (SFLA) (Khodaei et al., 2018).

The population for all algorithms is considered 100 and the maximum iteration is considered 1000. The analysis of the presented method is performed by comparing the results with the experimental data that is extracted before. Table 6 illustrates the required parameters that are adopted for the algorithms, the values for these algorithms have been achieved based on trials and errors after several tests.

In the following, the study on the case studies has been explained.

#### 4.1. NedSstack PS6 PEMFC

The NedSstack PS6 is a PEMFC stack with 6 kW rated power. The operating data of this PEMFC is completely explained in El-Fergany (2018). For the NedSstack PS6, some necessary features are different from Table 2 that are illustrated in Table 7.

By considering the above characteristics as the constraints of the NedSstack PS6 and applying the DSFO algorithm on the system, the results indicate good achievements for the proposed



Fig. 4. The comparison results of cost value minimization for the algorithms.

Table	6			
Main	parameter	setting	for	tl

Main parameter setting for the algorithms.				
Algorithm	Parameter	value		
SOA (Cao et al., 2019)	Control parameter (A) $f_c$	[2, 0] 2		
SFLA (Khodaei et al., 2018)	Number of frogs (P) Number of memeplexes	200 20		
MVO (Fathy and Rezk, 2018)	WEP <sub>max</sub> WEP <sub>min</sub>	0.1 0.9		
DSFO	Pollination Days Sun	0.6 100 1		

#### Table 7

The necessary characteristics of the NedSstack PS6.

Parameter	Minimum range	Maximum range	Unit
Α	110	250	cm <sup>2</sup>
l	$1 \times 10^{-5}$	$1.5 \times 10^{-5}$	m

approach. For more details, pay attention to Table 8. Fig. 5 shows the sum square error for the compared algorithms. As can be observed from Fig. 5, the error value for all the algorithms is satisfying and among these algorithms, the proposed DSFO algorithm gives the best results with the minimum SSE.

The optimal selected parameters for NedSstack PS6 based on the algorithms are summarized in Table 8.

Fig. 6 shows the estimated voltage-current profile for the 5 kW NedSstack PEMFC based on DSFO.

Fig. 6 indicates that using the proposed DSFO algorithm gives a promising agreement by the experimental data with the minimum value for SSE between the estimated voltage and the actual voltage. To show the convergence ability of the proposed DSFO, the convergence profile of the algorithm is shown compared with other algorithms reported in the literature.



Fig. 5. SSE diagram of the NedSstack PS6 for the algorithms.



Fig. 6. The estimated V-I profile for the NedSstack PEMFC based on DSFO.

As can be observed from Fig. 7, the convergence speed in the DSFO algorithm is the fastest among the others and this advantage is considered alongside a good accuracy for the parameter solutions. Fig. 7 is achieved based on the mean value of 30 runs.

Table 8
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The o	ptimal	estimated	parameters	for	the	NedSstack	PS6	based	on	different	algorithms.

Parameter	Method						
	DSFO	SFLA (Khodaei et al., 2018)	SOA (Cao et al., 2019)	MVO (Mirjalili et al., 2016)			
$E_{0}^{0}$	1.32	1.32	1.28	1.26	V		
$\hat{\beta_1}$	-1.03	-0.75	-0.68	-0.62	-		
$eta_3 imes 10^{-5}$	7.84	7.96	6.48	6.27	-		
$eta_4 imes 10^{-5}$	-9.48	-9.48	-9.48	-9.48	-		
Α	210.58	200.73	230.27	202.41	cm <sup>2</sup>		
$\varphi$	15.93	14.85	14.36	1.227	-		
$\lambda_e$	0.01	0.01	0.01	0.01	Ω		
$l \times 10^{-5}$	1.2	1.4	0.8	0.9	m		
В	0.072	0.069	0.068	0.070	V		
С	5.17	5.23	4.82	5.19	F		



Fig. 7. The convergence profile of the algorithm for the NedSstack PS6 PEMFC stack.



Fig. 8. The overall structure of the test benchmark.

#### 4.2. 500-W horizon PEMFC

The Horizon Model is a PEMFC stack with 500 W rated power. The operating data of this PEMFC is completely explained in Saleh et al. (2016). The analyzed test benchmark has been shown in Fig. 8.

As can be observed from the figure, the 500-W Horizon PEMFC system contains an air-cooled self-humidification. Two axial fans have been used for the cooling and conditioning of the cathode in the PEMFC. Two inlet and outlet valves are also adopted for the anode arm of the stack and the inlet valve has been supplied by dry hydrogen with a flow rate of  $[0, 0.12]Ls^{-1}$ . The nitrogen and the condensed water evacuated from the outlet valve every 15 s for refilling the anode by fresh hydrogen. Table 9 illustrates

#### Table 9

Technical characteristics of the Horizon 500-W open cathode PEMFC (Saleh et al., 2016).

Init
tm
LPM
tm
m
V
С
С
$m^{-2}$
m <sup>2</sup>



Fig. 9. SSE diagram of the Horizon 500-W open cathode PEMFC for the algorithms.

the technical characteristics of the Horizon 500 W open cathode PEMFC (Saleh et al., 2016).

Fig. 9 shows the sum square error of the Horizon 500-W PEMFC for the compared algorithms. As can be observed, like the previous example, the error value for all the algorithms is promising and among these algorithms, the proposed DSFO algorithm gives the best results with the minimum SSE.

Table 10 indicates that the optimal parameters that are estimated based on the presented algorithm compared with other studied algorithms.

To show the convergence ability of the proposed DSFO in the Horizon 500-W open cathode, the convergence profile is shown in Fig. 10.

The voltage profile for the obtained parameters and the experimental data is shown in Fig. 11. It can be concluded that the estimated model based on DSFO can properly follow the reference output voltage of the PEMFC stack with a satisfying agreement.

As can be seen from the above results, the proposed method could provide the required precision for modeling the PEMFC

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Parameter	imeter Method					
	DSFO	SFLA (Khodaei et al., 2018)	SOA (Cao et al., 2019)	MVO (Mirjalili et al., 2016)		
$E_{0}^{0}$	1.28	1.26	1.15	1.12	V	
$\beta_1$	-0.84	-0.82	-0.82	-0.75	-	
$\beta_3  imes 10^{-5}$	8.47	7.85	8.21	8.36	-	
$eta_4 imes 10^{-5}$	-14.9	-14.7	-14.02	-14.8	-	
Α	52	50	56	51	cm <sup>2</sup>	
$\varphi$	14.92	13.91	14.57	14.38	-	
λε	0.02	0.02	0.02	0.02	Ω	
$l \times 10^{-5}$	0.86	1.05	0.83	0.80	m	
В	0.065	0.058	0.063	0.064	V	
С	4.92	4.18	5.03	4.62	F	



**Fig. 10.** The convergence profile of the algorithm for the Horizon 500-W PEMFC stack.



Fig. 11. The estimated voltage profile for the Horizon 500-W PEMFC stack based on DSFO.

system. The only gap of this study can be neglecting the system uncertainties for the modeling. To do so, we have to find a practical experimental data and solve it with a reliable method like interval analysis and affine analysis.

#### 5. Conclusion

This study presented a new approach for optimal estimation of the parameter in proton exchange membrane fuel cell (PEMFC). The estimation method was based on finding the optimal values for unknown parameters of a circuit-based model of PEMFC. To obtain these unknown parameters, a cost function based on the sum of squared error (SSE) value between the estimated and the actual output voltage of the PEMFC stack was introduced. To minimize the SSE, a newly developed model of the Sunflower Optimization Algorithm (DSFO) was introduced. For performance analysis of the presented technique, two practical models including NedSstack PS6 PEMFC and Horizon 500-W open cathode PEMFC from the literature were studied. The models were simulated based on MATLAB R2017b platform and the final results of the DSFO were compared with the basic Seagull Optimization Algorithm (SOA), Multi-verse optimizer (MVO), and Shuffled Frog-Leaping Algorithm (SFLA). Final results showed better efficiency of the presented method for both case studies in comparison with the other algorithms and its higher convergence in terms of convergence, accuracy, and precision, such that the SSE for NedSstack PS6 PEMFC and Horizon 500-W open cathode PEMFC based on the proposed method are 2.18 and 0.014 that are the minimum values compared with the other analyzed methods. In the future study, the PEMFC model will be modeled by considering its uncertainties to design a pseudo-optimal, but a reliable model for the system.

#### **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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