

Yuan, Zhi; Wang, Weiqing; Wang, Haiyun; Ashourian, Mohsen

## Article

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## Research paper

## Parameter identification of PEMFC based on Convolutional neural network optimized by balanced deer hunting optimization algorithm

Zhi Yuan<sup>a,\*</sup>, Weiqing Wang<sup>a</sup>, Haiyun Wang<sup>a</sup>, Mohsen Ashourian<sup>b</sup><sup>a</sup> Engineering Research Center of Renewable Energy Power Generation and Grid-connected Control, Ministry of Education, Xinjiang University, Urumqi, Xinjiang, 830047, China<sup>b</sup> Department of Electrical Engineering, Majlesi branch, Islamic Azad University, Isfahan, Iran

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## ABSTRACT

This paper proposes a new optimal method for the parameter identification of a proton exchange membrane fuel cell (PEMFC) for increasing the model accuracy. In this research, a new improved version based on deer hunting optimization algorithm (DHOA) is applied to the Convolutional neural network for the PEMFC parameters identification purpose. Indeed, the method is implemented to develop the method performance for estimating the PEMFC model parameters. The method is then validated based on 4 operational conditions. Experimental results declared that utilizing the proposed method gives a prediction with higher accuracy for the parameters of the PEMFC model.

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## 1. Introduction

In recent years, more than ever, our world is threatened with a strong dependence on fossil fuels, especially oil and coal. Air pollution, environmental degradation, and climate changes are the result of this dependence. According to NASA's Goddard Space Flight Center, the amount of carbon dioxide in the air has been at its highest value for the past 7000 years which is 1 ppm. Alongside these problems, glacial melt and rising sea levels are other climate change problems (Shaw et al., 2018). That is why it is important to supply energy from renewable sources. Renewable energy sources are clean and cause the least damage to the environment. At the same time, these resources are endless and will be usable for many years and generations to come (Askari and Ameri, 2012; Avdis et al., 2018; Bartolucci et al., 2019). Among different types of renewable and clean energies, hydrogen is one of the new popular sources that have unique advantages toward the others, such as its very low pollution, its reversibility during the production cycle, and its low effect on the greenhouse effect. Besides, since hydrogen gas in itself is not abundant, but it is available in various other forms, such that the other sources can be used to obtain hydrogen through reformation and other relevant techniques. The best method for using hydrogen energy is to adopt it as a fuel for the fuel cells. Fuel cells are a type of energy converter that converts chemical energy directly into electrical energy. They act like batteries, but unlike batteries, they

do not run out of fuel and do not require recharging. Fuel cells convert the chemical potential of hydrogen into electrical energy and its by-product is water and heat (Mahdiyeh et al., 2019; Ijaodola et al., 2019).

In the meantime, proton-exchange membrane fuel cell (PEMFC) is known as a popular model of fuel cells. PEMFC with a suitable power density of 1400 W/L is a good alternative to internal combustion engines in the transmission system. The fuel cell itself is divided into hydrogen and methanol fuel cells. Hydrogen is currently used for heavier and higher power systems such as cars and buses and methanol for portable and portable systems such as mobile and laptop. PEMFCs are the most efficient energy generation among different types of fuel cells. They also operate fast with no contamination and low operational temperature in the range 60 °C–80 °C (Zhou and Dhupia, 2020). Therefore, studying these kinds of fuel cells can be helpful. In recent years, researchers are studying different techniques for improving the PEMFC's efficiency. Several researches have been performed to the fuel cell applications, like dynamic modeling of the fuel cell, extracting empirical data from the experimental results of the fuel cell, and steady-state stability of the fuel cell (Sun et al., 2015; Ge et al., 2018; El-Hay et al., 2019).

In this study, an optimal technique is addressed to develop the performance of a PEMFC. To do so, a modified deep neural network is introduced and utilized for the system parameters identification. The adopted technique is a new improved version of the deer hunting optimization algorithm that is recently introduced and has better convergence speed characteristics than the original type.

Finally, as aforementioned, the proposed optimal network is employed for nonlinear modeling of a PEMFC system.

\* Corresponding author.

E-mail address: [yz19xju@163.com](mailto:yz19xju@163.com) (Z. Yuan).

## 2. Literature review

Several works have been performed for modeling of the PEMFCs. For instance, in 2000, [Baschuk and Li \(2000\)](#) introduced a mathematical model for studying a PEMFC system's operation and efficiency. The model considered electrochemical and physical processes occurring in the system. The model results were compared with some different methods and demonstrated its superiority toward the other models.

In 2005, [Ramousse et al. \(2005\)](#) proposed a model by considering the gas diffusion in the water diffusion, electro-osmotic transport, and the porous electrodes through the polymeric membrane. The model was built by synthesizing independent determination of mass and heat transfers in the cell with a third definition of coupled charge and mass transfers in the electrodes.

In 2010, [Asl et al. \(2010\)](#) presented a model for PEMFC based on voltage–load current features. Two mathematical modelings were developed for computing the steady-state electrochemical model and dynamic voltage–current (V–I) characteristics of PEMFCs. The humidity of the membrane in steady-state conditions has been considered by mathematical and theoretical equations. The results showed good confirmation for the algorithm with other simulation and experimental results.

In 2011, [Steiner et al. \(2011\)](#) presented a method for the fault detection of a PEMFC based on the Elman Neural Network. Two residuals are considered based on the comparison between the parameters evaluated by a neural network and the practical operation of the fuel cell in the normal condition. The residuals are then used for the classification and the detection of fuel cell's states-of-health between normal operation and flooding (or drying out).

In 2014, [Papadopoulos et al. \(2014\)](#) presented two dynamical models based on the electrical equivalent and the semi-empirical formulas for PEMFC. Furthermore, they developed a model based on a transfer function following the semi-empirical equations.

In 2017, [Kumar et al. \(2018\)](#) presented a model for PEMFC based on autoregressive with exogenous input (ARX) and autoregressive moving average with exogenous input (ARMAX) validation. PI and PID controllers were then adopted to achieve the desired load current.

However, the described models were useful to design and for performance analysis of the fuel cells, there are some problems for them. Several models were presented based on accurate modeling of the fuel cells which consider different physical concepts for these models, such as momentum's conservation, thermodynamics, mass, power, and energy to achieve a proper thermal model. This conception makes the system model complicated. Besides, there are always some phenomena that are unknown and cannot be measured in the model, such as unknown disturbances and parameter uncertainties. In recent years, because of the potential of the neural networks for solving complicated and nonlinear dynamic models, they become an efficient tool to solve nonlinear systems ([Tao et al., 2005](#); [Hatti and Tioursi, 2009](#); [Rezazadeh et al., 2010](#)). There are different works about using neural networks for system identification ([Grondin-Perez et al., 2014](#); [Maleki and Maleki, 2015](#); [Jianmin et al., 2014](#)). In 2016, [Abbaspour et al. \(2016\)](#) introduced a robust control for PEMFC based on a neural network.

Due to the deviations between the partial pressure of hydrogen and oxygen in PEMFCs that lead to serious membrane damage, the study used a robust and adaptive control to stabilize the partial pressure to lengthen their lifetime. The neural network was utilized to provide PEMFC nonlinearities in the problem.

A big problem in the neural networks is their shortcoming in searching the global minimum of the network error, that is, the main drawback of the classic neural networks based on

gradient descent is to escape from the local minimum. Recently, several methods have been introduced for solving this problem. For instance, [Razmjoooy and Ramezani \(0000\)](#) presented an improved model of the neural network for optimal system identification. In that study, a new hybrid WNN is adopted based on the gravitational search algorithm for the identification.

[Jun et al. \(2020\)](#) proposed an applicable method for parameter estimation of the PEMFC. The method was based on a modified Elman neural network using a combined metaheuristic algorithm where the suggested metaheuristic algorithm was based on a combination of the World Cup Optimization (WCO) and the Fluid Search Optimization (FSO) algorithms. The method was finally verified under different operational conditions to show the method efficiency.

There are also several types of research works that have been performed over the modeling of PEMFC ([Bao and Bessler, 2015](#); [Solsona et al., 2017](#)). From the literature, it is obvious that using optimization algorithms can develop the performance of the neural networks by moving toward the global minimum error ([Razmjoooy et al., 2016](#); [Gholamreza and Ghadimi, 2018](#); [Dongmin and Ghadimi, 2019](#)). By considering the aforesaid explanations, in this study, a new improved optimization method is presented for optimizing the performance of a deep neural network for nonlinear modeling of a PEMFC.

## 3. Convolutional neural networks

Artificial neural networks are inspired by the connections of the neurons in the human brain to solve different complicated problems. Several types of neural networks have been introduced ([Yang et al., 2017](#); [Rahimi and Ghadimi, 2017](#); [Farzaneh et al., 2019](#)). In recent years, utilizing the deep learning in the neural networks (i.e. deep neural networks), because of their high efficiency is exponentially increasing ([Firouz et al., 2016](#)). Convolutional Neural Network (CNN) is a kind of these networks. The main source of CNN is inspired by the main structure of the visual ability in the animals.

In this network, the membranous neurons respond to motive in bounded areas called the *receptive field*. The receptive field for the neurons partially overlaps until the visual field is tiled. Convolution operators can be adopted for modeling the reply to the motive in single neurons. An important part of CNN belongs to the Convolutional neuron layers. There is no limitation about the equality in the number of the input and the output matrices. The principal purpose of the learning step is to achieve some kernel to be utilized in system identification.

In this research, a backpropagation algorithm has been adopted for the optimal selection of the network connection weights. In this layer, the sliding window is employed for the convolution. A vector is then created by the sliding window and the dot product of the weights and the inputs are added up. Rectified Linear Unit (ReLU) with a function  $f(x) = \max(x, 0)$  is adopted as the activation function for the neurons ([Melika et al., 2018](#)).

This process has been implemented in the PEMFC model. Max pooling is also adopted for more scale reduction of the output. In this study, the highest value is selected for the subsequent layer of the sliding grid. Based on the aforementioned cases in the introduction, after initializing the CNN, a proper method is required for minimizing error value between the achieved values compared with the desired value. This process is usually applied by the backpropagation (BP) algorithm. Based on the BP algorithm, after calculating the error between the training pairs, it is adopted for adjusting the neurons weights based on the desired output ([Farzaneh et al., 2019](#); [Hua et al., 2018](#)). The technique for minimizing the error in BPs is gradient descent. This method minimizes the cross-entropy loss as the fitness function for achieving

the minimum error value (Paria et al., 2019). Consider  $\delta^{l+1}$  as the error term for the  $(l + 1)$  st layer in the network with a cost function  $F(W, b; x, y)$  where  $(W, b)$  define the parameters and  $(x, y)$  signifies the training data and label pairs. If the  $l$ th layer is densely connected to the  $(l + 1)$  st layer, then the error for the  $l$ st layer is achieved as follows:

$$\delta^l = ((W^l)^T \delta^{l+1}) \times f'(z^l) \quad (1)$$

where the gradients are,

$$\nabla_{W^l} F(W, b; x, y) = \delta^{l+1} \times (a^l)^T \quad (2)$$

$$\nabla_{b^l} F(W, b; x, y) = \delta^{l+1} \quad (3)$$

where,  $a^l$  signifies the input to the  $l$ th layer and  $a^1$  is the input data. If the  $l$ st layer is a subsampling and convolutional layer, the error is achieved as follows:

$$\delta^l = U \left( (W_k^l)^T \delta_k^{l+1} \right) \times f'(z_k^l) \quad (4)$$

where,  $k$  signifies the filter number,  $f'(z_k^l)$  is the derivative of the activation function, and the operation  $U$  spread the error over the pooling layer by evaluating the error of the entered units to the pooling layer.

Finally, for evaluating the gradient error, the border handling convolution operation flip the error matrix  $\delta_k^l$  the same way we flip the filters in the convolutional layer.

$$\nabla_{W_k^l} F(W, b; x, y) = \sum_{i=1}^m (a_i^l) \times \text{rot}90(\delta_k^{l+1}, 2) \quad (5)$$

$$\nabla_{b_k^l} F(W, b; x, y) = \sum_{a,b} (\delta_k^{l+1})_{a,b} \quad (6)$$

where,  $m$  is the number of samples.

However, CNN has been considered as a strong model identifier, designing an optimal structure for its layout is a principal problem; because most of the layouts are designed experimentally.

Recently, several research works have been introduced to modify them based on meta-heuristic algorithms (Homayoun et al., 2018; Bengio et al., 2007).

#### 4. Deer Hunting Optimization Algorithm (DHOA)

Optimization is a mechanism for achieving the optimum value of a given problem based on the system dynamic and its constraints. Sometimes using classic optimization algorithms fails in finding the best solution or needs a significant amount of time to solve it. Recently, using Meta-heuristics as a kind of new and fast techniques have been introduced for solving different NP-hard problems. These problems are inspired by different phenomena such as physics, nature, and human social reactions.

In some cases, these algorithms are also improved to achieve a better optimal solution in the global optimum point.

Some examples of these algorithms are the Genetic algorithm (Aghdam et al., 2011; Mohammadossein et al., 2019; Holland, 1992; Mirjalili, 2019; Mousavi and Soleymani, 2014), particle swarm optimization (Razmjoooy and Ramezani, 0000; Moallem and Razmjoooy, 2012), world cup optimization algorithm (Razmjoooy et al., 2016), and Variance Reduction of Gaussian Distribution (Dongmin and Ghadimi, 2019) which have been designed for solving different complicated problems.

In the present year, Brammya et al. presented a new meta-heuristic algorithm based on hunting the deer (Brammya et al., 2019). Deer has special features that make the hunting process difficult for the predators. The visual sense is a prominent feature in a deer. This sense is five times stronger than the human visual

sense. Another feature is its olfactory sense. The olfactory sense is sixty times stronger than humans.

Once a deer senses danger, it alerts other deer by sniffing loudly and treading heavily. Another specific feature of a deer is its ability in the detection of ultra-high-frequency sounds. In the following, the method of deer hunting is illustrated in detail.

– initialization

Like any meta-heuristic algorithm, deer hunting optimization starts with a set of the random population called hunters. This initializing can be determined as follows:

$$X = [y_1, y_2, \dots, y_m], \quad 1 < i \leq m \quad (7)$$

where,  $m$  describes the number of hunters population (solutions) and  $X$  is the total population.

– Initializing the Parameters

In the second step, the deer's position angle (position angle) and wind angle as the main parameters of the algorithm should be initialized. Because the search space is assumed as a circle, the wind angle is formulated in the circumference of a circle.

$$\theta_i = 2\pi\lambda \quad (8)$$

where,  $\lambda$  describes a random value between 0 and 1 and  $i$  is at the present iteration. In addition, the position angle of the deer is modeled as follows:

$$\phi_i = \pi + \theta \quad (9)$$

where,  $\theta$  represents the wind angle.

– Position propagation

Finding the best solution to the algorithm at the first iteration is almost impossible. However, after evaluating the value of the cost function based on the randomly generated values, the best value is assumed as the candidate optimum solution value.

In this part, two parameters are considered; the first one is the leader position ( $X^L$ ) that describes the first best position of the hunter and the second parameter is the successor position ( $X^S$ ) that is the succeeding hunter position.

(a) Propagation based on the leader's position:

By applying the first iteration for achieving the best positions, all the population attempts to obtain the best position by updating the position of them. Therefore, encircling behavior can be formulated as follows:

$$X_{i+1} = X^L - Y \times S_w \times |L \times X^L - X_i| \quad (10)$$

where,  $X_i$  and  $X_{i+1}$  describe the current and the next positions,  $S_w$  describes a random value based on the wind speed in the range  $[0, 2]$ , and  $L$  and  $Y$  illustrate the coefficient vectors which can be formulated as follows:

$$Y = 0.25 \times \log \left( I + \frac{1}{I_{max}} \right) \beta \quad (11)$$

$$L = 2 \times \tau \quad (12)$$

where,  $I_{max}$  describes the maximum iteration,  $\beta$  and is a random parameter in the range  $-1$  and  $1$ , and  $\tau$  is a random value in the range  $[0, 1]$ .

Fig. 1 shows the position updating, where  $(X, Z)$  describes the initial position of the hunter which can be updated based on the prey position. The position updating will be continuing once the best position ( $X^*, Z^*$ ) is achieved based on  $L$  and  $Y$ .

Hunters move to the direction where the leader is positioned. If the leader has an unsuccessful movement, the hunter will remain in the prior position.

Position update follows Eq. (8) only when  $S_w < 1$ , i.e. the hunters can randomly move in any direction without respect to

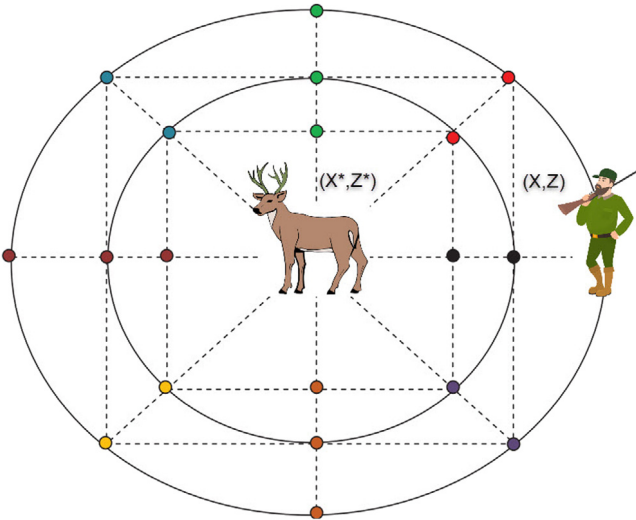


Fig. 1. Updating the best position  $X^*$ .

the position angle. So, based on Eqs. (7) and (8), the hunters can update their position in any random location within the space.

(b) Propagation based on the position angle

With considering the position angle in the update rule, we can develop the solution space. The evaluating of the angle is important for assigning the position of the hunter such that prey is uninformed of the attack which makes the hunting process successful. The angle of visualization for the prey (deer) is formulated as follows:

$$a_i = \frac{1}{8} \times \pi \times \lambda \quad (13)$$

By considering the difference between the prey visual angle and the wind angle, we can evaluate a parameter that helps for updating the position angle.

$$d_i = \theta_i - a_i \quad (14)$$

where,  $\theta$  represents the wind angle.

Afterward, for updating the position angle,

$$\phi_{i+1} = \phi_i + d_i \quad (15)$$

And finally, by using the achieved position angle, the new position is achieved by the following equation,

$$X_{i+1} = X^L - S_w \times |\cos(\phi_{i+1}) \times X^L - X_i| \quad (16)$$

Since the hunter is out of the visual angle of the deer, the hunter is not in the view of it.

(c) Propagation based on the position of the successor

For applying the exploration term to the encircling behavior, the vector  $L$  can be adjusted. Based on assuming an initial random search, the value of the vector  $L$  is not considered more than 1.

Hence, the successor position is utilized for updating instead of the first achieved best solution. This process makes a global search for the algorithm as the following equation:

$$X_{i+1} = X^S - Y \times S_w \times |L \times X^L - X_i| \quad (17)$$

where,  $X^S$  describes the successor position of the hunters from the current population.

In each iteration, the algorithm updates the position of the hunters by considering the best solution. The best solution has been selected when  $|L| \geq 1$ . Once  $|L| < 1$ , a hunter will be chosen randomly.

This procedure gives a switch called  $L$  which can change the algorithm between exploitation and exploration phases.

A disadvantage of the original DHOA is it is the problem of premature convergence. In the next part, a new mechanism is proposed for removing this shortcoming.

– The balanced DHOA

In this part, Lévy flight (LF) is adopted to develop the DHOA. Lévy flight is a mechanism for resolving the problem of premature convergence drawback.

Lévy flight generate a random walk mechanism for suitable controlling of the local search (Choi and Lee, 1998) as follows:

$$\text{Le}(w) \approx w^{-1-\xi} \quad (18)$$

$$w = \frac{A}{|B|^{1/\xi}} \quad (19)$$

$$\sigma^2 = \left\{ \frac{\Gamma(1+\xi)}{\xi \Gamma((1+\xi)/2)} \frac{\sin(\pi\xi/2)}{2^{(1+\xi)/2}} \right\}^{\frac{2}{\xi}} \quad (20)$$

where,  $0 < \tau \leq 2$ ,  $A \sim N(0, \sigma^2)$  and  $B \sim N(0, \sigma^2)$ ,  $\Gamma(\cdot)$  describes the Gamma function,  $w$  represents the step size,  $\xi$  represents Lévy index,  $A/B \sim N(0, \sigma^2)$  means that the samples generated from a Gaussian distribution in which mean are zero and variance is  $\sigma^2$ , respectively.

In this study,  $\xi = 3/2$  (Li et al., 2018).

Based on the Lévy flight mechanism, the new improved position for the hunters is:

$$X_{i+1}^l = X_{i+1} + (X^* - AD) \times \text{Le}(\delta) \quad (21)$$

where,  $X_{i+1}^l$  represents the new position of search agent  $X_{i+1}$  and,

$$A = a(2 \times r - 1) \quad (22)$$

$$D = CX'(t) - X(t) \quad (23)$$

where,  $a$  is in the range 0 and 2,  $r$  is a random value in the interval  $[0, 1]$ , and  $X'(t)$  describes a random position vector selected from the present population.

To guarantee the best solution candidates, fitter agents are kept:

$$\vec{D}_{el} = \begin{cases} X_{i+1}^l & F(X_{i+1}^l) > F(X_{i+1}) \\ X_{i+1} & \text{otherwise} \end{cases} \quad (24)$$

The flowchart of the balanced DHOA (BDHOA) is given in Fig. 2.

## 5. Validation of the BDHOA

In this section, a comparative study has been implemented between the proposed method and some different popular and new algorithms for performance analysis of the proposed BDHOA. To do so, four standard benchmarks have been validated on the presented BDHOA, particle swarm optimization algorithm (PSO) (Bansal, 2019), genetic algorithm (GA) (Holland, 1992), standard whale optimization algorithm (WOA) (Mirjalili and Lewis, 2016), and world cup optimization (WCO) algorithm (Razmjooy et al., 2016). The algorithm has also been compared with the original DHOA for illustrating the improved system's capability.

The simulations have been implemented in MATLAB R2016b with a laptop configuration of 2.50 GHz CPU and 16.0 GB RAM. Table 1 illustrates the utilized benchmarks with  $D$  dimensions and  $x$  as the parameter that should be optimally selected.

The results of the comparison based on mean deviation (MD) and the standard deviation (SD) values are illustrated in Table 2.

As can be reported from Table 2, the proposed BDHOA has the smallest mean deviation value compared with the other algorithms. The mean deviation (MD) is a measure that determines

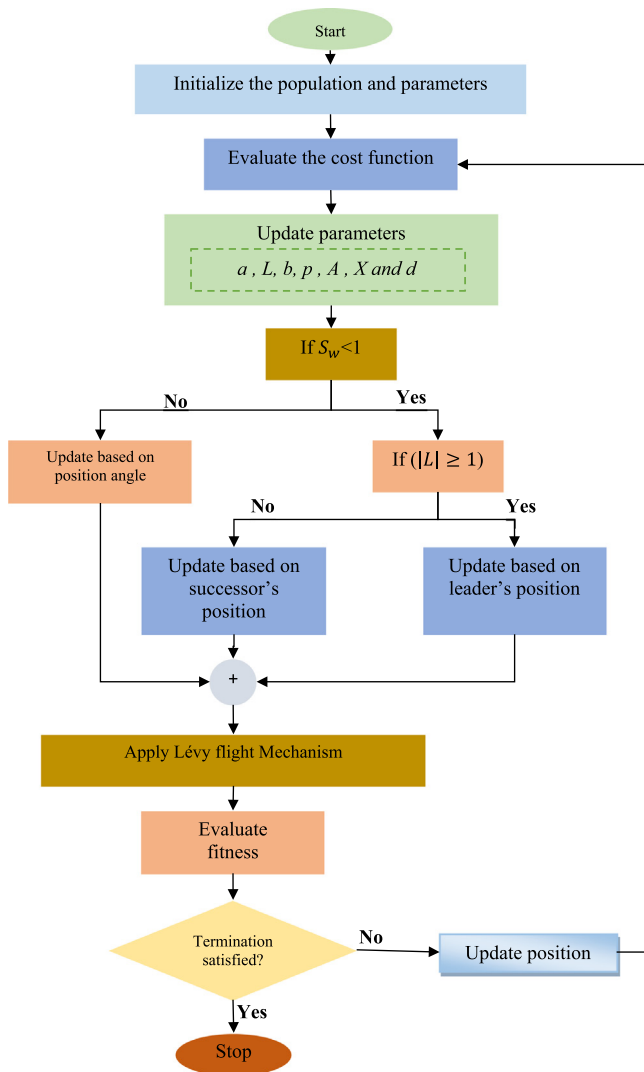


Fig. 2. The Flowchart diagram of the improved BDHOA.

how much the observations in the data set deviates from the mean value of the observations in the data set. Therefore, the minimum value of MD in BDHOA shows its higher accuracy compared with others. On the other hand, it can be observed that the minimum value of standard deviation (Std) also has been achieved by the suggested BDHOA. The Std is a measure to show how spread out the numbers are. Therefore, the minimum value of std by the suggested BDHOA shows its higher robustness toward the other compared algorithms.

## 6. Validation of the method by PEMFC

A PEMFC is a conversion system that employs and converts hydrogen and the oxygen in the air to generate energy. PEMFC includes a thin polymer membrane as the electrolyte for supplying a catalytic environment to develop the necessary reactions on both sides of the electrodes.

A PEMC releases the chemical energy released by the electrochemical reaction of hydrogen and oxygen into electrical energy, in contrast to the process of direct combustion of hydrogen and oxygen gases that produce thermal energy. Hydrogen gas enters the fuel cell from the anode side. In the anode and the vicinity of the catalyst, it becomes a proton and an electron. The proton penetrates the cathode through the electrolytic membrane.

The electrons also travel through the outer charge circuit to the cathode, generating an electric current from the fuel cell. Meanwhile, a stream of oxygen enters the fuel cell from the cathode and is formed on the same side by combining with the protons transferred from the anode and the electrons entering through the outer circuit during a chemical reaction of water molecules. A general structure of a PEMFC is shown in Fig. 3.

For validation of the total system efficiency, it is applied to a 250 watts PEMFC in 4 different operational conditions including 3/5 bar with 353.15 K, 1.1 bar with 343.15 K, 2.5/3 bar with 343.15 K, and 1.1/1.5 bar with 343.15 K.

The empirical data for validating the voltage efficiency is extracted from the model in Zhang and Wang (2013). From the four aforementioned operational conditions, 224 pairs of inputs and outputs have been selected, where, 157 of pairs (about 70%) of the data is adopted for training of the proposed optimized CNN, 22 pairs (10%) for validating, and 45 pairs (20%) are utilized for testing the data. This kind of splitting the data between training, validation, and testing is based on k-fold and due to the small size of data (Zhang et al., 2014). Furthermore, a set of 60 pairs with different operational conditions is employed from Mo et al. (2006) for analyzing the diagrams and for validating the forecasting precision by the proposed optimized CNN. To precise validating of the data, it is first normalized to the range [0, 1] before training as follows:

$$x_j = \frac{x_j - x_{j\_min}}{x_{j\_max} - x_{j\_min}} \quad (25)$$

where,  $x_j$  represents the  $j$ th basic data,  $x_{j\_min}$  and  $x_{j\_max}$  describe the lower and upper limitations of the main information in the defined dataset, respectively.

## 7. Modified CNN based on BDHOA

In this section, a new improved Convolutional neural network is presented by the justification of the weights for the hyper-parameters. The main purpose of the optimized neural network here is to design a proper system for the PEMFC system identification. Candidate solutions in the proposed optimized identifier are a sequence of integers.

Here, the output voltage forecasting of the PEMFC based on the optimized CNN model is studied to analyze the voltage values at present and the past. A general form of the identification system is shown in Fig. 4.

To achieve an optimal structure for the CNN, the minimum distance between the desired and the measured values are required for training the CNN (based on the proposed BDHOA), i.e. training the network by minimizing the sum of squared error between the obtained voltage from the network (*Output*) and the empirical output voltage of the PEMFC is as follows:

$$\min \varepsilon = \min \left\{ \sum_{j=1}^M (Z - Z^*)^2 \right\} \quad (26)$$

where,  $M$  represents the quantity of the samples for the experimental data, and  $Z$  and  $Z^*$  are the achieved voltage from the network and the output voltage obtained by the experiment from the PEMFC.

The mentioned error function above should be minimized by the proposed BDHOA algorithm to design an optimal network. The initializing of CNN is based on the training dataset. The presented improved algorithm is then used for optimizing the hidden nodes. Fig. 5 shows the training error profile for the PEMFC parameter identification using the proposed method.

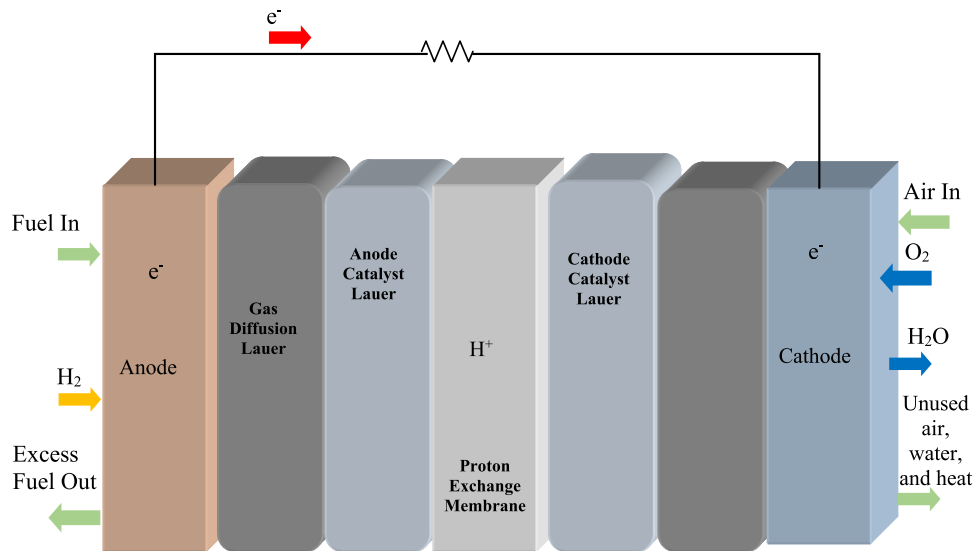
The training error profile results for 4 different conditions are simulated and shown in Figs. 6–9 where the values of  $P_{H_2}/P_{O_2}$  are indicated under different temperatures.

**Table 1**  
The utilized benchmarks for the performance analysis.

Benchmark	Formula	Constraint	Dimension
Rastrigin	$F_1(x) = 10 \times D + \sum_{i=1}^D (x_i^2 - 10 \times \cos(2\pi x_i))$	$[-512, 512]$	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	$F_3(x) = 20 + \exp(1) - 20 \times \exp\left(-0.2 \sqrt{0.5 \sum_{i=1}^D x_i^2}\right) - \exp\left(0.5 \sum_{i=1}^D \cos(2\pi x_i)\right)$	$[-10, 10]$	30–50
Sphere	$F_4(x) = \sum_{i=1}^D x_i^2$	$[-512, 512]$	30–50

**Table 2**  
The performance analysis of the compared methods by 30 dimensions.

Benchmark	BDHOA	DHOA	GA (Holland, 1992)	PSO (Bansal, 2019)	WCO (Razmjoooy et al., 2016)	WOA (Mirjalili and Lewis, 2016)
$f_1$	MD 0.00	3.16	70.61	74.24	2.19	2.58
	Std $7.14e-5$	2.58	1.66	8.96	4.35	2.14
$f_2$	MD 7.35	9.51	35.41	200.1	13.16	8.47
	Std 1.86	2.24	27.15	59.00	4.62	1.73
$f_3$	MD 0.00	$5.19e-15$	$3.19e-2$	8.26	$3.14e-3$	$3.17e-16$
	Std $8.29e-10$	$2.14e-7$	$2.14e-2$	1.19	$1.12e-3$	0.00
$f_4$	MD 0.00	$1.28e-10$	$1.15e-4$	$8.27e-4$	$6.19e-9$	$9.65e-11$
	Std $5.61e-22$	$15.27e-17$	$3.14e-5$	$5.12e-4$	$3.28e-9$	$9.83e-17$



**Fig. 3.** A schematic of the model of a PEMFC.

From the above figures, it is obvious that firstly, the training error for different partial pressure is different and secondly, the training error for the presented method is low that gives satisfying results for the presented method for the PEMFC parameter identification. Fig. 10 shows the polarization profile for the 4 explained operational conditions are shown to prove the identification accuracy of the improved CNN model. It is also important to note that the training error profile of the PEMFC identification

for 3/5 bar, 353.15 K has the highest error that shows that higher pressure and temperature results higher estimation error.

Besides, Fig. 10 shows the polarization profiles of the operational conditions to validate the model accuracy of the network. Here, the voltage curves are achieved according to current, that is estimated by the network. The achievements showed that the experimental and estimated values give almost identical results.

From Fig. 10, it is observed that the predicted voltage value versus current based on the proposed optimized Convolutional

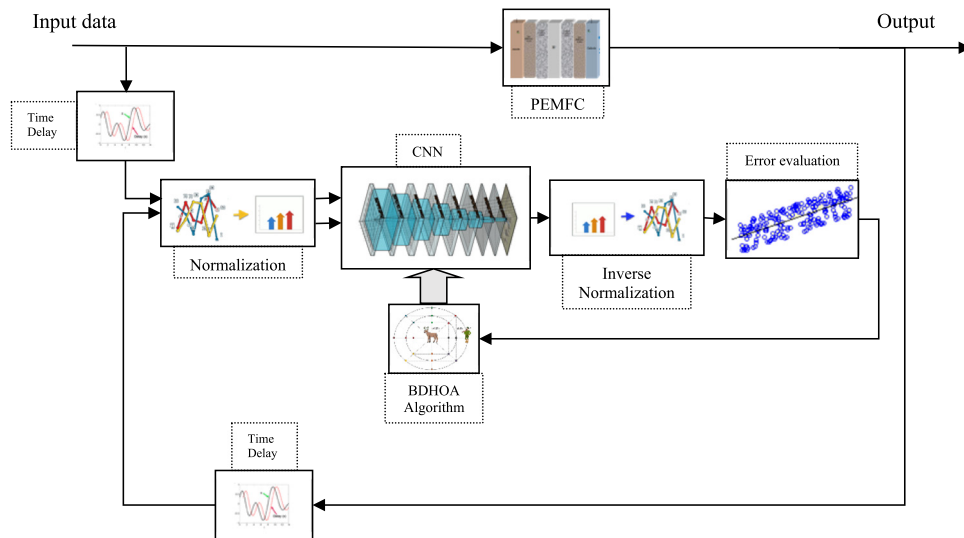


Fig. 4. The general form of the proposed system.

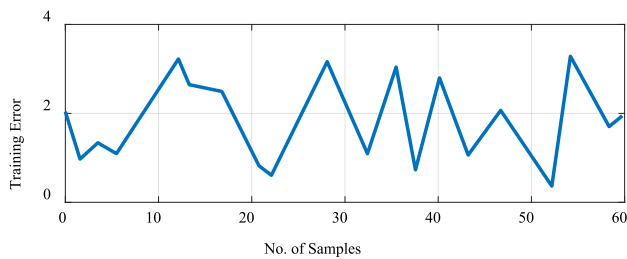


Fig. 5. The training error profile of the sample data for PEMFC parameter identification.

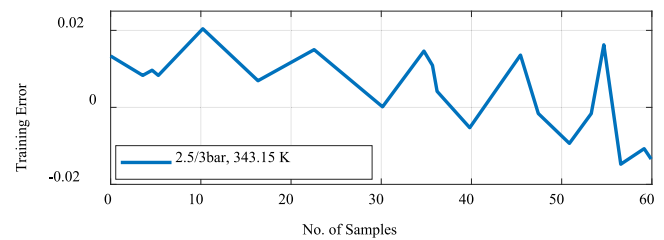


Fig. 8. The training error profile of the PEMFC identification for 2.5/3 bar, 343.15 K.

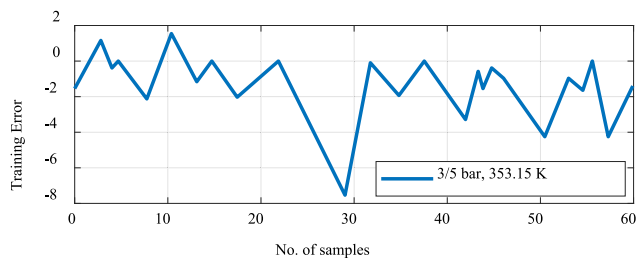


Fig. 6. The training error profile of the PEMFC identification for 3/5 bar, 353.15 K.

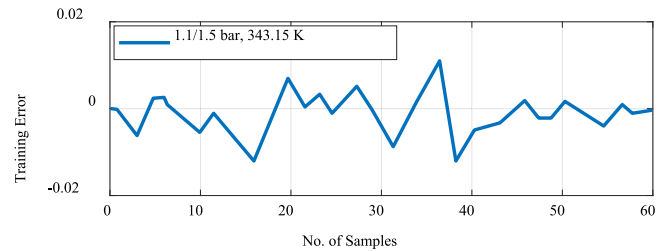


Fig. 9. The training error profile of the PEMFC identification for 1.1/1.5 bar, 343.15 K.

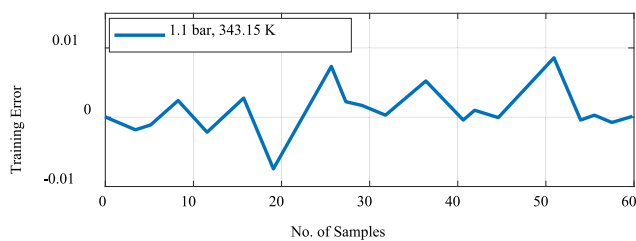


Fig. 7. The training error profile of the PEMFC identification for 1.1 bar, 343.15 K.

neural network is fitted to the empirical data which shows the proposed method's efficiency in reaching a good agreement between the actual voltage and the estimated voltage.

### 8. Conclusions

A fuel cell is a system for direct generating power by converting the chemical energy into electricity. Hydrogen gas is employed as an ideal fuel in fuel cells due to its high reactivity, abundance, and environmental pollution. This research studies on a proton exchange membrane fuel cell (PEMFC). The main purpose here is to optimal designing of a PEMFC model with high precision. To achieve this aim, a new improved optimization technique based on the deer hunting optimization algorithm (DHOA) is proposed. The performance analysis and comparison with some other algorithms showed that using the new improved version increases the algorithm convergence speed. After designing the proposed algorithm, it is adopted for optimizing the weights of a Convolutional neural network (CNN) for the identification of PEMFC parameters. The designed model is then validated by four different operational conditions and the final results showed the performance of the presented optimal CNN network for modeling the nonlinear PEMFC.



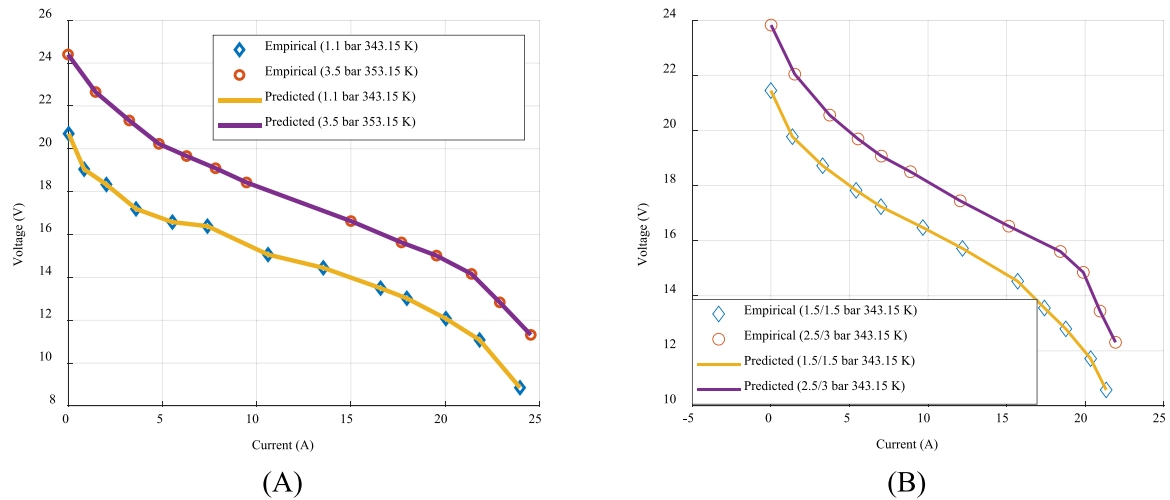


Fig. 10. The polarization diagram of the empirical and the predicted data for the operational conditions.

### 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. **Mohsen Ashourian:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing.

### Declaration of competing interest

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

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