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## Accelerating parameter identification of proton exchange membrane fuel cell model with ranking-based differential evolution

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#### A R T I C L E I N F O

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#### ABSTRACT

Parameter identification of PEM (proton exchange membrane) fuel cell model is a very active area of research. Generally, it can be treated as a numerical optimization problem with complex nonlinear and multi-variable features. DE (differential evolution), which has been successfully used in various fields, is a simple yet efficient evolutionary algorithm for global numerical optimization. In this paper, with the objective of accelerating the process of parameter identification of PEM fuel cell models and reducing the necessary computational efforts, we firstly present a generic and simple ranking-based mutation operator for the DE algorithm. Then, the ranking-based mutation operator is incorporated into five highly-competitive DE variants to solve the PEM fuel cell model parameter identification problems. The main contributions of this work are the proposed ranking-based DE variants and their application to the parameter identification problems of PEM fuel cell models. Experiments have been conducted by using both the simulated voltage–current data and the data obtained from the literature to validate the performance of our approach. The results indicate that the ranking-based DE methods provide better results with respect to the solution quality, the convergence rate, and the success rate compared with their corresponding original DE methods. In addition, the voltage–current curves in all cases.

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#### 1. Introduction

Due to the high energy efficiency, superior durability, low emission, high scalability, good transient responses of the FC (fuel cell) technology, it has received a heightened research focus in recent years [1,2]. Among various types of fuel cells, the PEMFCs (proton exchange membrane fuel cells) have obtained an increasing interest for both mobile and stationary applications because of their high efficiency, low noise, no waste, low operating temperature, low pressure, etc [3]. Also, due to their advantages, they can be used to build hybrid energy generation systems, such as wind/ hydrogen hybrid systems to provide consistent sustainable energy supply [4].

Within different fields of research in PEMFC, the modeling of PEMFC has attracted considerable attention among researchers of different backgrounds, and different models of PEMFC are available in the literature [5–8]. Mo et al. [9] classified different PEMFC models into two approaches: i) mechanistic models and ii) models

based on empirical or semi-empirical equations. However, no matter what type of models, the parameters of models need to be identified in order to improve the accuracy of the models and make the models indicate the actual PEMFC performance better [9,10]. For example, the parameter settings of the hydrogen flow rate, air flow rate, inlet hydrogen pressure, membrane dehydration, catalyst layer flooding, mass transport, and fluid flow regimes affect the performance of PEMFC models significantly [11,12]. Identifying the parameters of PEMFC models can be treated as numerical optimization problems. However, since the PEMFC system is a complex nonlinear and multi-variable system, the parameter identification of PEMFC models is hard to be tractable by conventional methods. Therefore, it is essential to identify the parameters of PEMFC models using advanced optimization techniques.

In recent years, the use of heuristic optimization techniques for parameter identification of PEMFC models has received increasing interest, such as GAs (genetic algorithms) [9,13,14], simulated annealing [15,16], PSO (particle swarm optimization) [17,18], harmony search [3,19,20], seeker optimization algorithm [21], artificial immune system [22], P systems based optimization algorithm [23]. Most recently, differential evolution is also used to solve the parameter identification of PEMFC models [24]. However, in order to efficiently and fast solve the parameter identification problems

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in PEMFC models, it is necessary to investigate more efficient optimization techniques to reduce the necessary computational efforts to achieve an optimal design [25].

DE (differential evolution), proposed by Storn and Price [26], is a simple, efficient, and versatile numerical optimization algorithm. The advantages are its simple structure, ease of use, speed, and robustness. Due to these advantages, DE has been successfully applied in diverse fields, such as engineering design, digital filter design [27,28], optimal power flow [29], simulation of solarthermal refrigeration systems [30], hydrothermal generation scheduling [31,32], and so on. With the objective of accelerating the process of parameter identification of PEMFC models and reducing the necessary computational efforts, in this work, a generic and simple ranking-based mutation operator is presented for the DE algorithm. The ranking-based mutation operator does not increase the complexity of the original DE algorithm significantly, and it can be combined with most of advanced DE variants. Based on this consideration, it is incorporated into five highly-competitive DE variants, i.e., jDE [33], SaDE [34], JADE [35], CoDE [36], and DEGL [37]. The five ranking-based DE variants together with the five original DE variants are validated by using the simulated voltagecurrent data of PEMFC model and the data obtained from Ref. [9]. Numerical results indicate that the ranking-based DE methods provide better results with respect to the solution quality, the convergence rate, and the success rate compared with their corresponding original DE methods. In addition, the voltage-current characteristics obtained by our approach are in good agreement with the original voltage-current curves in all cases. Thus, the ranking-based DE approaches can be an efficient alternative for other complex parameter identification problems of FC models.

The rest of this paper is organized as follows. Section 2 briefly describes the PEMFC stack model used in this work and the objective function to be optimized. Next, in Section 3 we introduced the original DE algorithm in brief. In Section 4 our proposed ranking-based mutation operator is presented in detail, followed by the experiments and discussions in Section 5. Finally, Section 6 draws the conclusions from this work.

#### 2. Problem formulation

In this section, we first briefly introduce the PEMFC stack model used in this work. Then, the objective function to be optimized is specified.

#### 2.1. PEMFC stack model

In this work, the PEMFC stack model presented in Ref. [9] is used. For n cells connected in series to form a stack, the terminal voltage of the stack can be calculated by [38],

$$V_{\rm s} = n \cdot V_{\rm FC} \tag{1}$$

where  $V_{FC}$  is the output voltage of a single cell, which can be formulated as [7]

$$V_{\rm FC} = E_{\rm Nernst} - V_{\rm act} - V_{\rm ohm} - V_{\rm con} \tag{2}$$

 $E_{\text{Nernst}}$  is the thermodynamic potential defined by

$$E_{\text{Nernst}} = 1.229 - 0.85 \times 10^{-3} \cdot (T - 298.15) + 4.3085$$
$$\times 10^{-5} \cdot T \cdot \ln \left( P_{\text{H}_2}^* \sqrt{P_{\text{O}_2}^*} \right)$$
(3)

where *T* is the cell temperature (K),  $P_{H_2}^*$  and  $P_{O_2}^*$  are the hydrogen and oxygen partial pressures (atm), respectively. They are given by [5]

$$P_{H_2}^* = 0.5 \cdot RH_a \cdot P_{H_20}^{sat} \cdot \left(\frac{1}{\frac{RH_a \cdot P_{H_20}^{sat}}{P_a}} \exp\left(\frac{1.635(i_{cell}/A)}{T^{1.334}}\right) - 1\right)$$
(4)

$$P_{O_{2}}^{*} = RH_{c} \cdot P_{H_{2}O}^{sat} \cdot \left(\frac{1}{\frac{RH_{c} \cdot P_{H_{2}O}^{sat}}{P_{c}} exp\left(\frac{4.192(i_{cell}/A)}{T^{1.334}}\right)} - 1\right)$$
(5)

where  $RH_a$  and  $RH_c$  are the relative humidity of vapor in the anode and cathode,  $P_a$  and  $P_c$  are the anode and cathode inlet pressures (atm), respectively. A is the effective electrode area (cm<sup>2</sup>) and  $i_{cell}$  is the cell current (A).  $P_{H_{2O}}^{sat}$  is the saturation pressure of water vapor (atm), which is defined as a function of the temperature *T* as follows [9,24]

$$\log_{10}(P_{\rm H_2O}^{\rm sat}) = 2.95 \times 10^{-2} \cdot (T - 273.15) - 9.19$$
$$\times 10^{-5} \cdot (T - 273.15)^2 + 1.44$$
$$\times 10^{-7} \cdot (T - 273.15)^3 - 2.18 \tag{6}$$

According to Ref. [6], the activation overpotential  $V_{act}$ , including anode and cathode, can be expressed by the following formula

$$V_{\text{act}} = -\left[\xi_1 + \xi_2 \cdot T + \xi_3 \cdot T \cdot \ln\left(C^*_{O_2}\right) + \xi_4 \cdot T \cdot \ln(i_{\text{cell}})\right]$$
(7)

where  $\xi_1$ ,  $\xi_2$ ,  $\xi_3$ ,  $\xi_4$  are the parametric coefficients for each cell model, and  $C_{0_2}^*$  (mol/cm<sup>3</sup>) is the concentration of oxygen in the catalytic interface of the cathode, given by [7,9]

$$C_{O_2}^* = \frac{P_{O_2}^*}{5.08 \times 10^6 \cdot \exp(-498/T)}$$
(8)

The ohmic voltage drop  $V_{\text{ohm}}$  can be determined by the following expression [6]

$$V_{\rm ohm} = i_{\rm cell} \cdot (R_{\rm M} + R_{\rm C}) \tag{9}$$

where  $R_{\rm M}$  is the equivalent membrane resistance to proton conduction, and  $R_{\rm C}$  is the equivalent contact resistance to electron conduction.  $R_{\rm M}$  is defined by [9]

$$R_{\rm M} = \frac{\rho_{\rm M} \cdot \varrho}{A} \tag{10}$$

$$\rho_{\rm M} = \frac{181.6 \cdot \left[1 + 0.03 \cdot \left(\frac{i_{\rm cell}}{A}\right) + 0.062 \cdot \left(\frac{T}{303}\right) \cdot \left(\frac{i_{\rm cell}}{A}\right)^{2.5}\right]}{\left[\lambda - 0.634 - 3 \cdot \left(\frac{i_{\rm cell}}{A}\right)\right] \cdot \exp\left[4.18 \cdot \left(\frac{T - 303}{T}\right)\right]}$$
(11)

where  $\rho_{\rm M}$  is the membrane specific resistivity for the flow of hydrated protons ( $\Omega$  cm), and  $\ell$  is the thickness of the membrane (cm), which serves as the electrolyte of the cell. The parameter  $\lambda$  is an adjustable parameter with a possible range of Refs. [10,24].

The concentration overpotential  $V_{con}$  caused by the change in the concentration of the reactants at the surface of the electrodes as the fuel is calculated by [7]

$$V_{\rm con} = -B \cdot \ln\left(1 - \frac{J}{J_{max}}\right) \tag{12}$$

where B (V) is a parametric coefficient, which depends on the cell and its operation state. *J* is the actual current density of the cell (A/cm<sup>2</sup>), and  $J_{max}$  is the maximum value of *J*. Download English Version:

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