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# A biogeography-based optimization algorithm with mutation strategies for model parameter estimation of solar and fuel cells

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

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#### ABSTRACT

Mathematical models are useful tools for simulation, evaluation, optimal operation and control of solar cells and proton exchange membrane fuel cells (PEMFCs). To identify the model parameters of these two type of cells efficiently, a biogeography-based optimization algorithm with mutation strategies (BBO-M) is proposed. The BBO-M uses the structure of biogeography-based optimization algorithm (BBO), and both the mutation motivated from the differential evolution (DE) algorithm and the chaos theory are incorporated into the BBO structure for improving the global searching capability of the algorithm. Numerical experiments have been conducted on ten benchmark functions with 50 dimensions, and the results show that BBO-M can produce solutions of high quality and has fast convergence rate. Then, the proposed BBO-M is applied to the model parameter estimation of the two type of cells. The experimental results clearly demonstrate the power of the proposed BBO-M in estimating model parameters of both solar and fuel cells. © 2014 Elsevier Ltd. All rights reserved.

#### 1. Introduction

The greenhouse emissions and fossil fuels shortage are the twin challenges facing the mankind, and the development of new clean energy technologies has been recognized as the key to tackle the problems. Solar cells and proton exchange membrane fuel cells (PEMFCs) have attracted considerable attention due to the features of their high power density, no pollution and low noise. As photoelectric converters, solar cells not only have no byproduct but also have the advantages of easy installation and little maintenance cost. Similarly, PEMFCs generate electricity by oxidizing hydrogen under relative low operating temperatures with non-polluting byproducts, and have been widely used in vehicle propulsion, small distributed generation and portable applications [1–4].

Modeling the operation of solar cells and PEMFCs has become a significant research topic in recent years in order to better explore and utilize their properties. Some models have been proposed to simulate the behaviors of both cells under different operating conditions [5–10], and most of them are less useful in practical applications due to the complexity and problem specific. In recent years, mathematical models with some unknown parameters are widely used in practice [11–13]. These parameters which reflect the actual performances (such as air pressure, fuel flow rate, cell temperature,

diffusion and recombination diode resistance) are primarily chosen based on experience, and these low-accurate empirical values inevitably affect effectiveness of the developed models in simulation, design, optimal operation and control. Therefore, it is indispensable to investigate the problems of parameter estimation problems of the solar cell and PEMFC models.

Some conventional deterministic optimization methods have been used to solve the parameter estimations [14–18]. However, these two kinds of cells are nonlinear, non-convex and strongly coupled systems and most of these conventional approaches require continuity, convexity and differentiability conditions, which make them hard to handle the parameter estimation problems mentioned above. With the development of computing technologies and artificial intelligence, many meta-heuristic optimization algorithms, which are of conceptual and computational simplicity, being excellent real-world problem solvers and robust to dynamic environments, capable of solving problems with no known solutions and with no need for analytic expression of the problems [19], have been applied to the parameter estimation problems of solar cell and PEM-FC. Genetic algorithm (GA) [20-23], simulated annealing (SA) [24,25], particle swarm optimization (PSO) [26-29], differential evolution (DE) [30,31] and artificial neural networks (ANNs) [32,33] have been proposed to improve the parameter accuracy for both cell models respectively. Besides, several other methods including bird mating optimizer (BMO) [34,35] and seeker optimization algorithm (SOA) [36] have also been used to solve







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$\begin{array}{cccc} V_{C} & \mbox{the output voltage (V)} & V_{con} & \mbox{concentration voltage loss (V)} \\ T & \mbox{temperature in Kelvin (K)} & P_{O_{2}} & \mbox{partial pressure of the oxygen (atm)} \\ P_{H_{2}} & \mbox{partial pressure of the hydrogen (atm)} \\ P_{H_{2}} & \mbox{partial pressure of water (atm)} \\ P_{H_{2}} & \mbox{partial pressure (atm)} \\ P_{H_{2}} & \mbox{partial pressure of water (atm)} \\ P_{H_{2}} & \mbox{partial pressure of water (atm)} \\ P_{H_{2}} & \mbox{partial pressure (atm)} \\ P_{H_{2}} & $	Nomenclature					
$q$ creating (C) $\rho_M$ membrane specific resistivity ( $\Omega$ /cm) $k$ Boltzmann constant (J/K) $l$ membrane thickness (cm) $k$ $\lambda$ parameter influenced by anode gasPEM fuel cell $b$ concentration loss constant (V) $E_{Nernst}$ reversible open circuit voltage (V) $I_{max}$ maximum current density ( $A/cm^2$ ) $V_{act}$ activation voltage loss (V) $N_s$ number of series PEM fuel cells $V_{ohmic}$ ohmic voltage loss (V) $A$ efficient active area of cell (cm <sup>2</sup> )		Nomenclatur $V_C$ T Solar cell $I_C$ $I_{ph}$ $I_{D1}, I_{D2}, I_D$ $I_{SD1}, I_{SD2}$ $I_{sh}$ $R_S$ $R_{SH}$ $n, n_1, n_2$	re the output voltage (V) temperature in Kelvin (K) output current (A) photo-induced current (A) diode current (A) saturation current (A) shunt resistor current (A) series resistance (Ω) shunt resistance (Ω) diode ideality constants electronic charge (C)	$V_{con} \\ P_{O_2} \\ P_{H_2} \\ P_{at_2}^{H_2} \\ P_a \\ P_c \\ RH_a \\ RH_c \\ i \\ \xi_1, \xi_2, \xi_3, \xi_4 \\ C_{O_2} \\ R_M \\ R_C$	concentration voltage loss (V) partial pressure of the oxygen (atm) partial pressure of the hydrogen (atm) saturation pressure of water (atm) inlet anode pressure (atm) inlet cathode pressure (atm) relative humidity in anode relative humidity in cathode experimental current (A) parametric coefficient of cell oxygen concentration (mol/cm <sup>3</sup> ) membrane resistance ( $\Omega$ ) contact resistance ( $\Omega$ )	
PEM fuel cellbconcentration loss constant (V) $E_{Nernst}$ reversible open circuit voltage (V) $I_{max}$ maximum current density (A/cm²) $V_{act}$ activation voltage loss (V) $N_s$ number of series PEM fuel cells $V_{ohmic}$ ohmic voltage loss (V)Aefficient active area of cell (cm²)		q k	electronic charge (C) Boltzmann constant (J/K)	$\rho_M$	membrane specific resistivity ( $\Omega$ /cm) membrane thickness (cm) parameter influenced by anode gas	
$E_{Nernst}$ reversible open circuit voltage (V) $I_{max}$ maximum current density (A/cm <sup>2</sup> ) $V_{act}$ activation voltage loss (V) $N_s$ number of series PEM fuel cells $V_{ohmic}$ ohmic voltage loss (V)Aefficient active area of cell (cm <sup>2</sup> )		PEM fuel cell		b	concentration loss constant (V)	
$V_{act}$ activation voltage loss (V) $N_s$ number of series PEM fuel cells $V_{ohmic}$ ohmic voltage loss (V) $A$ efficient active area of cell (cm <sup>2</sup> )		E <sub>Nernst</sub>	reversible open circuit voltage (V)	I <sub>max</sub>	maximum current density (A/cm <sup>2</sup> )	
		V <sub>act</sub> V <sub>ohmic</sub>	activation voltage loss (V) ohmic voltage loss (V)	N <sub>s</sub> A	number of series PEM fuel cells efficient active area of cell (cm <sup>2</sup> )	

the PEMFC model parameter estimation problem. In addition, the solar cell modeling problem was addressed by pattern search (PS) [37] and artificial bee swarm optimization algorithm (ABSO) [38]. Although these methods have achieved good performance, they are only used for single cell parameter estimation and potentially do not fit other cell problems, and parameter estimation is a challenging problem which requires the obtained physical parameters match well with reality. It is necessary to find a new approach to solve both solar cell and PEMFC problems more efficiently.

Biogeography-based optimization (BBO) proposed by Dan Simon in 2008 [39] is a stochastic global search technique which attempts to imitate the phenomenon of the theory of island biogeography, and it has two operators namely migration and mutation. Although the BBO has been applied to a number of real world optimization problems such as chemical industry [42], power systems [43], control systems [44] and scheduling problems [45], to the best of our knowledge, no studies have been reported so far on applying the BBO method to the parameter estimation problems of fuel and solar cells. In this paper, the BBO algorithm with two mutation strategies (BBO-M) is proposed to identify the optimal estimation parameters of both solar cell and PEMFC models. Considering about some drawbacks of conventional BBO [46], two improvements are designed to combine with BBO. In order to enhance the exploitation, the mutation strategy from differential evolution (DE) is introduced into the migration of BBO in this paper. Meanwhile, to avoid premature convergence, chaos theory [47] is also employed in BBO to adjust the solution in the mutation stage. To demonstrate the performance of the BBO-M method, it is compared with conventional BBO and four popular methods, including DE [48], GHS [49], PSO-w [50], GA toolbox [51] on ten numerical benchmark functions. Furthermore, BBO-M is also employed to estimate the parameters of both solar cell and PEMFC problems and compared with the reported results in the literatures. According to the results obtained, the BBO-M shows a superior performance and the potential in solving real-life problems.

## 2. Electrochemical models for the solar cell and fuel cell

## 2.1. Solar cell models

A solar cell is a conversion device that converts the light energy to electrical energy directly and continuously. Among various types of solar cell models, only two are widely used. The first one is the double diode model which incorporates an additional and separate current diode with its own exponential voltage dependence [11]. The second model, commonly known as the single diode model, assumes that one lumped diode mechanism is enough to describe the characteristic of the solar cell [12]. In the following subsections these two models will be given.

## 2.1.1. Double diode model

The double diode model is shown in Fig. 1, which conforms quite closely to the Shockley theory [52]. When exposed to the light, the solar cell will absorb the photons and create an electron-hole pair in the case that the energy of the photons is higher than the band gap energy of the semiconductor, and the output current of the model can be calculated as follows:

$$I_{\rm C} = I_{\rm ph} - I_{\rm D1} - I_{\rm D2} - I_{\rm sh} \tag{1}$$

where  $I_C$  denotes the output current,  $I_{ph}$  is the photo-induced current,  $I_{D1}$ ,  $I_{D2}$  are the first and second diode currents, and  $I_{sh}$  denotes the shunt resistor current. The two diodes currents  $I_{D1}$  and  $I_{D2}$  are formulated respectively in Eqs. (1) and (2), and the shunt resistor current  $I_{sh}$  is illustrated in Eq. (4):

$$I_{D1} = I_{SD1} \left[ \exp\left(\frac{q(V_C + I_C R_S)}{n_1 kT}\right) - 1 \right]$$
(2)

$$I_{D2} = I_{SD2} \left[ \exp\left(\frac{q(V_C + I_C R_S)}{n_2 kT}\right) - 1 \right]$$
(3)

$$I_{sh} = \frac{V_C + I_C R_S}{R_{sh}} \tag{4}$$



Fig. 1. The double diode model of the solar cell.

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