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Parameter identification of solid oxide fuel cells with ranking teaching-learning based algorithm

Guojiang Xiong[a,*], Jing Zhang[a], Dongyuan Shi[b], Yu He[a]

[a] Guizhou Key Laboratory of Intelligent Technology in Power System, College of Electrical Engineering, Guizhou University, Guiyang 550025, China
[b] State Key Laboratory of Advanced Electromagnetic Engineering and Technology, Huazhong University of Science and Technology, Wuhan 430074, China

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ABSTRACT

The performance of a solid oxide fuel cell (SOFC) is tightly related to relevant parameters associated with the internal multi-physicochemical processes. Accurate identification of these parameters is considerably important for modelling the voltage versus current (*V-I*) characteristic of SOFCs. In this paper, an improved teaching-learning based algorithm (TLBO) referred to as RTLBO is proposed to identify the exact values for these parameters. The parameter identification of SOFCs is transformed into a minimization optimization problem. The mean square error (MSE) between the measured output voltage and the calculated output voltage is used as the objective function. TLBO has been shown to be competitive with other population-based algorithms. However, its convergence rate is relatively slow especially for complex optimization problems. Inspired by the ranking mechanism in the actual scenarios of teaching-learning process, a ranking based learner selection method is proposed and integrated into both the teacher and learner phases of RTLBO. In RTLBO, poor learners are more likely to be eliminated from the current class in the ranking based teacher phase and good learners are more likely to be chosen to interact with others in the ranking based learner phase, which hence can improve the overall performance of the class quickly. The experimental results on a 5-kW SOFC stack comprehensively demonstrate that RTLBO is able to achieve a better trade-off between the exploration and exploitation compared with twelve advanced TLBO variants and eight popular advanced non-TLBO based methods. In addition, the sensitivity of RTLBO to variations of population size is empirically investigated.

1. Introduction

A solid oxide fuel cell (SOFC) is one of the most attractive technologies for converting the chemical energy fuels to electricity through electrochemical reactions [1–4]. SOFCs have many advantages such as high electrical efficiency, low emission, and fuel flexibility, which make them obtain a wide range of applications especially in the combined generation of electric power and heat [5–15].

To further improve the performance of a SOFC, many efforts such as utilizing various materials and developing different models have been made. Nevertheless, no matter what the material or model type, accurately measuring the various voltage losses or drops of the fuel cell is the key and also the challenge to fully enjoy the performance improvement. Voltage drops of a SOFC are tightly related to relevant parameters associated with the internal multi-physicochemical processes and it appears that to realize further improvements in fuel cell performance may require accurate identification of these parameters [16,17].

Identification of relevant parameters of a SOFC model seems to be a tough problem due to that the SOFC is a complex multivariable strongly coupled system. In order to obtain accurate values for these parameters, many approaches have been proposed. Among them, the utilization of meta-heuristics has emerged as a viable and promising option due to their robustness, simplicity, ease of implementation, and derivative-free feature, etc. For examples, Jiang et al. [18] developed a breed particle swarm optimization for parameter identification of a high-fidelity control-oriented dynamic model for a steam reformer. Yang et al. [19] proposed an improved genetic algorithm which consists of speed cycle, fine adjustment, and renascence to optimize parameters for a tubular SOFC stack. Jiang et al. [20] employed a cooperative coevolution strategy to decompose the objective function of parameter identification of SOFCs into four relative simple subfunctions first, and then utilized a hybrid learning based barebone particle swarm optimization to solve each subfunction. Gong et al. [21] presented an improved

* Corresponding author at: Room #401, College of Electrical Engineering, Guizhou University, Jiaxiu South Road, Huaxi District, Postcode: 550025, Guiyang City, Guizhou Province, China.
E-mail address: gjxiongee@foxmail.com (G. Xiong).

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Jingqiao adaptive differential evolution algorithm, in which three strategies, i.e., parameter adaptation, ranking-based vector selection, and crossover rate repairing technique are combined to enhance the algorithm performance. El-Hay et al. [22] implemented a satin bowerbird optimizer to both the steady-state and dynamic models of SOFCs. Besides application in SOFCs, meta-heuristics have also gained a significant attention in solving parameter identification problems of other fuel cells. For instances, Ding et al. [23] applied a cuckoo search algorithm for area-specific resistance of direct methanol fuel cells. El-Fergany [24] utilized a salp swarm optimizer for polymer exchange membrane fuel cells. Askarzadeh and Coelho [25] combined backtracking search algorithm with Burger's chaotic map for proton exchange membrane fuel cells. Niu et al. [26] proposed a biogeography-based optimization algorithm with mutation strategies for proton exchange membrane fuel cells.

Compared with the aforementioned meta-heuristics, teaching-learning based optimization (TLBO) [27,28] is another simple yet powerful meta-heuristic. It is inspired by the philosophy of classical teaching-learning process. TLBO consists of two phases, i.e., the teacher phase and learner phase. In TLBO, population individuals or learners acquire their knowledge through learning from the teacher and interacting with other peer learners. It is simple and parameterless except the population size. Due to its versatility, TLBO has been successfully applied to a variety of real-world optimization problems. However, to the best of our knowledge, the use of TLBO for the parameter identification problem of SOFCs has not been reported so far. Both reasons motivate us to study the feasibility and validity of TLBO in this optimization problem. Although TLBO has already proven a worthy optimization method compared with other popular meta-heuristics such as GA, PSO, and DE, similar to other algorithms, it also faces up to poor convergence [29,30]. The main reason is that the specific mechanisms used in the basic TLBO do not accurately reflect the actual scenarios of the classical teaching-learning process [31]. In practice, the teaching-learning process has diverse forms and it is impossible to completely model them in an algorithm. The only thing we can do is decreasing the deviation between the modeling and the actual scenarios as much as possible. In this work, inspired by the ranking mechanism in the actual scenarios of teaching-learning process, we propose a ranking based learner selection method and integrate it into both the teacher and learner phases of TLBO to accelerate its convergence rate. The developed TLBO variant is referred to as RTLBO for short.

The main contributions of this work are as follows:

(1) RTLBO is proposed to effectively solve the parameter identification problem of SOFC models. In RTLBO, a ranking based teacher phase and a ranking based learner phase are developed. In the former phase, those relatively poor learners are more likely to be eliminated from the current class by better learners from other classes. In the latter phase, each learner is more likely to interact with relatively good learners.
(2) RTLBO is applied to a 5-kW SOFC stack. Its performance is thoroughly verified under different temperatures and pressures. In addition, the sensitivity of RTLBO to variations of population size is empirically investigated.
(3) The superiority of RTLBO is comprehensively validated through comparing with twelve advanced TLBO variants and eight popular advanced non-TLBO based methods from multiple performance perspectives. The experimental results demonstrate that RTLBO is able to yield a proper equilibrium between the exploration and exploitation.

The remainder of this paper is organized as follows. Section 2 briefly introduces the SOFC model and the mathematical formulation of parameter identification problem. Section 3 presents the basic TLBO. The proposed RTLBO is elaborated in Section 4. In Section 5, experimental results and comparisons are provided. Finally, Section 6 is devoted to conclusions and future work.

2. Problem formulation

2.1. Mathematical model of SOFC

The output voltage V_{cell} of a SOFC can be expressed as follows [17,32–34]:

$$V_{cell} = E_{oc} - V_{act} - V_{conc} - V_{ohm} \tag{1}$$

where E_{oc} is the open circuit voltage, $V_{act}$is the activation voltage drop, V_{conc} is the concentration voltage drop, and V_{ohm} is the ohmic voltage drop.

The open circuit voltage E_{oc} is typically assumed to be equivalent to the Nernst reversible voltage E as follows [33,34]:

$$E_{oc} \approx E = E_0 + \frac{RT}{2F}\ln\left[\frac{P_{H_2}P_{O_2}^{0.5}}{P_{H_2O}}\right] \tag{2}$$

where E_0 is the standard potential, $R = 8.314$ kJ $(\text{kmol}\cdot\text{K})^{-1}$ is the universal gas constant, $F = 96486$ C mol^{-1} is the Faraday constant, T is the operating temperature of the fuel cell in Kelvin, P_{H_2} is the hydrogen partial pressure, P_{O_2} is the oxygen partial pressure, and P_{H_2O} is the water partial pressure.

The activation voltage drop V_{act} is caused by the energy barrier that the reactants must overcome before the chemical reaction occurs. In general, the well-known Butler-Volmer equation is used to calculate V_{act} as follows [35–38]:

$$V_{act} = A\sinh^{-1}\left(\frac{I_{load}}{2I_{0,a}}\right) + A\sinh^{-1}\left(\frac{I_{load}}{2I_{0,c}}\right) \tag{3}$$

where I_{load} is the load current density, $I_{0,a}$ and $I_{0,c}$ are the anode and cathode exchange current densities, respectively, in mA cm^{-2}, A is the slope of Tafel line.

The concentration voltage drop V_{conc} is caused by the mass transfer processes from the channels to the reaction sites in the porous electrodes. It does not give rise to excessive voltage loss until the current density approaches the limiting current. It can be expressed as follows [33–36,38,39]:

$$V_{conc} = B\ln\left(1 - \frac{I_{load}}{I_L}\right) \tag{4}$$

where B is a constant that depends on the fuel cell and its operating state, and I_L is the limiting current density in A cm^{-2}.

The ohmic voltage drop V_{ohm} is caused by the resistance to the flow of ions in the electrolyte and resistance to flow of electrons through the electrode materials. It obeys Ohm's law and can be calculated as follows [35]:

$$V_{ohm} = I_{load}R_{ohm} \tag{5}$$

where R_{ohm} is the ionic resistance.

Substituting Eqs. (3), (4) and (5) back into Eq. (1), we can obtain

$$V_{cell} = E_{oc} - V_{act} - V_{conc} - V_{ohm} = E_{oc} - A\sinh^{-1}\left(\frac{I_{load}}{2I_{0,a}}\right) + A\sinh^{-1}\left(\frac{I_{load}}{2I_{0,c}}\right) - B\ln\left(1 - \frac{I_{load}}{I_L}\right) - I_{load}R_{ohm} \tag{6}$$

For modeling an aggregated fuel cell stack consisting of N_{cell} cells, the total output voltage V_{out} can be calculated as follows [40]:

$$V_{out} = N_{cell}V_{cell} \tag{7}$$

It can be seen from Eqs. (6) and (7) that, in this model, the unknown parameters are E_{oc}, A, $I_{0,a}$, $I_{0,c}$, B, I_L and R_{ohm}. The major difficulty is the lack of information about the precise value of these parameters under different operating conditions.