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Parameter identification for proton exchange membrane fuel cell model using particle swarm optimization

Meiying Ye[a,*], *Xiaodong Wang*[b], *Yousheng Xu*[a]

[a]*Department of Physics, Zhejiang Normal University, No. 299, Beishan Lu Road, Jinhua, Zhejiang 321004, People's Republic of China*
[b]*Department of Electronic Engineering, Zhejiang Normal University, Jinhua 321004, People's Republic of China*

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ABSTRACT

The accurate mathematical model is an extremely useful tool for simulation and design analysis of fuel cell power systems. Particle swarm optimization (PSO) is a recently invented high-performance algorithm. In this work, a PSO-based parameter identification technique of proton exchange membrane (PEM) fuel cell models was proposed in terms of the voltage–current characteristics. Using the simulated and experimental voltage–current data, the validity of the proposed method has been confirmed. The results indicate that the PSO is an effective technique for identifying the parameters of PEM fuel cell models even in the presence of measuring noise. Moreover, the proposed method does not particularly necessitate initial guesses as close as possible to the solutions, required only is a broad range specified for each of the parameters. Therefore, the PSO method outperforms the GA and traditional optimization methods.

1. Introduction

An efficient and clean generation of electrical energy has become a necessity due to a worldwide increase in air pollution and power demand. With low emissions and very high conversion efficiencies, fuel cells are the best candidate to become the primary source of power in the future. So worldwide attention has been focused on their development [1], especially in transportation industry domain. The fuel cell vehicle, for example, is acclaimed as the vehicle of the future that almost all manufacturers have made a developmental priority. Among various kinds of fuel cells, the proton exchange membrane (PEM) fuel cell, with its low operating temperature, high power density, high efficiency, fast startup, quick response and zero emission, is the most suitable for vehicles [2]. Nowadays, the PEM fuel cells are the subject of priority research in many countries [3].

Mathematical modeling is a crucial element in the development of fuel cell technology [4]. Fuel cell modeling has received much attention over the last decade in an attempt to better understand the phenomena occurring within the cell [5]. So far, many modeling methods for the PEM fuel cell have been developed in the previous literature [2,6–31]. In spite of advances in PEM fuel cell modeling, the PEM fuel cell system is a complex nonlinear, multi-variable system that is hard to model by conventional methods [2,12]. In order to improve the accuracy of the models and make the models reflect the actual PEM fuel cell performance better, it is necessary to identify the parameters of the models using optimization techniques.

In recent years, the evolutionary computation technique based on genetic algorithm (GA) or its variation has attracted much attention in the investigation of fuel cell systems [32–39]. For example, the GA was proposed for improving the accuracy of the fuel cell model parameter identification

* *Corresponding author*. Tel.: +86 579 82298904; fax: +86 579 82298188.
E-mail address: ymy@zjnu.cn (M. Ye).
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[36,38]. Nevertheless, there are still some deficiencies in GA performance [40,41]. The degradation in efficiency is apparent in applications with highly epistatic objective functions, i.e. where the parameters being optimized are highly correlated. In this case, the crossover and mutation operations cannot ensure better fitness of offspring because chromosomes in the population have similar structures and their average fitness is high toward the end of the evolutionary process.

As an alternative to GA, particle swarm optimization (PSO) [42] is a recently invented high-performance algorithm. Its development is based on observations of the social behavior of animals such as bird flocking, fish schooling, and swarm theory. PSO is initialized with a population of random solutions. Each individual is assigned with a randomized velocity according to its own and its companions' flying experiences. The individuals, called particles, are then flown through hyperspace. Compared with GA, the PSO has some attractive characteristics. Firstly, PSO has memory, that is, the knowledge of good solutions is retained by all particles, whereas in GA, the previous knowledge of the problem is destroyed once the population changes. Secondly, PSO has constructive cooperation between particles, that is, particles in the swarm share their information [43]. Due to the simple concept, easy implementation, robustness to control variables, and computational efficiency, when compared with other heuristic optimization techniques, nowadays PSO has gained much attention and wide applications in different fields.

The focus of this work is to identify fuel cell model parameters using the PSO method through fitting the mathematical model to actual experimental data.

2. PEM fuel cell model

The PEM fuel cells consist of three major components—an anode, typically featuring a platinum or platinum-containing catalyst, a thin, solid polymeric sheet which acts as electrolyte, and a cathode, also platinum-catalyzed. The various reactions for a PEM fuel cell fed with a hydrogen-containing anode gas and an oxygen-containing cathode gas are

$$\text{Anode}: H_2 \rightarrow 2H^+ + 2e^-$$

$$\text{Cathode}: 2H^+ + \frac{1}{2}O_2 + 2e^- \rightarrow H_2O$$

$$\text{Overall}: H_2 + \frac{1}{2}O_2 \rightarrow H_2O$$

The products of this process are dc electricity, liquid water and heat.

In current investigation, a fuel cell model described in the literature [37,44] is taken into account, whose basic expression for the voltage for a PEM fuel cell can be given by:

$$V = E_o - \eta_{ohm} - \eta_{act} - \eta_{con} \quad (1)$$

where V is the voltage, η_{ohm}, η_{act}, η_{con} the voltage drops occurring when the load draws a current from the fuel cell, and E_o the open circuit voltage. The theoretical open circuit voltage E_o for a hydrogen–oxygen fuel cell is about 1.2 V. Practically, the operating voltage is less than this value due to a number of irreversibilities [37]. All quantities about E_o, η_{ohm}, η_{act}, η_{con} in Eq. (1) are in units of volts. The voltage drops η_{ohm}, η_{act}, η_{con} will now be separately discussed in the following text.

Firstly, the ohmic loss η_{ohm} is due to the electrolyte resistance to the flow of ions across it, and the resistance of the electrode material to the flow of electrons. The ohmic loss is linearly proportional to the current and is given by the following simple expression:

$$\eta_{ohm} = ri \quad (2)$$

where r is the area specific resistance of the fuel cell measured in $k\Omega\,cm^2$, and i the fuel cell current density in $mA\,cm^{-2}$.

Secondly, the activation over potential η_{act} is due to voltage lost in activating the chemical reactions to take place at the fuel cell electrodes. This over potential is important at low currents and can be expressed as:

$$\eta_{act} = A \ln\left(\frac{i}{i_o}\right) \quad (3)$$

where A is called Tafel slope and is measured in volts, and i_o the exchange current density in $mA\,cm^{-2}$.

Finally, the concentration loss η_{con} is related to the consumption of reactants by the fuel cell. As the reactants are used by the fuel cell, their concentration changes at the surface of the cell electrodes causing a drop in operating voltage. Concentration loss is related to the fuel cell current by the following equation:

$$\eta_{con} = -B \ln\left(1 - \frac{i}{i_L}\right) \quad (4)$$

where B is a concentration loss constant given in volts, and i_L the limiting current density at which the fuel is being used at the same rate as the maximum supply speed. The current density cannot surpass this limit because the fuel cannot be supplied at a larger rate. The i_L is measured in $mA\,cm^{-2}$.

There are other causes for the fuel cell voltage drop due to fuel crossover and internal currents. Reasons for this are the waste of fuel that passes directly through the electrolyte producing no electrons and electron conduction through the electrolyte and not passing through the electrodes. This will have an increasing effect on the current withdrawn from the cell by a value of in i_n. Therefore, by incorporating above i_n with Eqs. (1)–(4), the mathematical polarization curve model of the fuel cell can be written as:

$$V = E_o - r(i + i_n) - A \ln\left(\frac{i + i_n}{i_o}\right) + B \ln\left(1 - \frac{i + i_n}{i_L}\right) \quad (5)$$

From Eq. (5), it is seen that the PEM fuel cell parameter identification problem reduces to extraction of the six parameters (E_o, A, i_n, i_o, r and B) so that Eq. (5) may matches experimental data.

Note that many single cells can be assembled into a fuel cell stack system in order to provide the required amount of power. In this case, the voltage can be calculated by:

$$V_s = ZV \quad (6)$$

where Z is the number of fuel cells connected in series.

After the description of the PEM fuel cell model, the approach identified the model parameters will be detailed in the following sections.