Energy Conversion and Management 174 (2018) 913–921

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

Fast and accurate parameter extraction for different types of fuel cells with decomposition and nature-inspired optimization method

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A B S T R A C T

Fast and accurate parameter extraction of fuel cells is crucial to the control and performance analysis of fuel cell power systems. Unfortunately, due to the multi-variable and nonlinear features of fuel cell models, it is a difficult task to identify the parameters of the models. In this paper, we propose a decomposition technique, where the unknown parameters are divided into two groups: nonlinear and linear. The optimization techniques only need to optimize the nonlinear parameters, and then the linear parameters are determined based on the nonlinear ones. With the help of the decomposition technique, a generalized framework by using the nature-inspired optimization method is proposed to try to fast and accurately extract the parameters for different types of fuel cells. To test the performances of our approach, two widely used types of fuel cells are studied, i.e., proton exchange membrane fuel cell and solid oxide fuel cell. Extensive simulation tests with thirty-two instances are carried out for comparing our approach with existing approaches. The comparison demonstrates the efficiency of the decomposition technique. Moreover, the results show that our approach can not only significantly reduce the computational resources, but also yields high quality solutions.

A R T I C L E I N F O

Keywords:
Fuel cells
Parameter extraction
Decomposition technique
Nature-inspired optimization method

1. Introduction

A fuel cell (FC) is an electrochemical device that directly converts the chemical energy of fuels (usually a gas rich in hydrogen) to electricity [1,2]. Due to its noise-free, clean, sustainable, and reliable advantages, the power generated by FCs obtains increasing attention all over the world recently [3–5]. According to the type of electrolyte materials, there are several different types of FCs, such as alkaline FC, proton exchange membrane FC (PEMFC), solid oxide FC (SOFC), and direct methanol FC [6,7]. Among various types of FCs, PEMFC and SOFC are widely used and developed [8,9].

For the control, design, and performance analysis of PEMFC and SOFC, a variety of models have been developed during the last few decades, such as models for PEMFC [10–14], and models for SOFC [15–19]. Regarding different models of PEMFC and SOFC, there are several unknown parameters of the models that significantly affect the model results [20–22]. Therefore, to predict the dynamic behavior of FC power systems, these parameters need to be precisely extracted. However, because of the multi-variable, nonlinear, and strongly coupled features of the models, it is a challenging task to extract them by traditional approaches [23–25].

In recent years, the use of nature-inspired optimization methods for parameter extraction of FC models has become popular [5], such as genetic algorithms [26,25], particle swarm optimization [27,24,28,29], harmony search [30,31], and differential evolution (DE) [32–34]. Most recently, some newly proposed swarm intelligence algorithms are also used to extract the parameters of FC models, *e.g.*, grey wolf optimizer [35], multi-verse optimizer [36], salp swarm optimizer [37], and so on. The advantages of the nature-inspired optimization methods are the insensitivity to the initial guess, flexibility, global search ability, etc. However, one disadvantage of these methods is that they require significant computational resources when extracting parameters from FC models. For example, the maximum number of function evaluations[1] (Max_NFEs) in [28] is 100,000; in [25], 90,000; in [36], 100,000; and

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[1] In this work, the number of function evaluations means the number of function calls of the objective function.

https://doi.org/10.1016/j.enconman.2018.08.082
Received 29 May 2018; Received in revised form 21 August 2018; Accepted 22 August 2018

in [33], 15,000.

To fast and accurately extract the parameters of FC models, firstly a decomposition technique is proposed, where the parameters of FC models are decomposed into the nonlinear group and linear group. Then, based on the decomposition technique, we develop a generalized framework for parameter extraction via a nature-inspired optimization method in order to obtain the nonlinear parameters. The nonlinear parameters are obtained by the nature-inspired optimization method. Then, the linear parameters are determined by the algebraic method and the corresponding nonlinear parameters. Benefit from the proposed decomposition technique, the search space can be reduced. Therefore, it can save the computational resources of the nature-inspired optimization method and thus accelerate the parameter extraction process greatly. Our proposed approach is extensively evaluated with 7 representative nature-inspired optimization methods and 32 instances of PEMFC and SOFC models. The results show that our approach can obtain high quality solutions only with Max_NFEs = 500.

The rest of the paper is organized as follows. In Section 2, the problem statement is described. Section 3 explains our proposed approach in detail. The results and analysis are given in Section 4. Finally, in Section 5, we conclude this paper and point out some future work.

2. PEMFC and SOFC models

In this section, the mathematical formulations of both the PEMFC and SOFC stack models are described. Then, the objective function for parameter extraction of the PEMFC and SOFC models is given.

2.1. Mathematical formulation of PEMFC stack model

In this work, the PEMFC stack model in [38] is used, which was also studied in [39–41]. If the internal current is considered, the model can be formulated as follows:

$$\begin{aligned} V &= N_{\text{cell}} \cdot V_{\text{cell}} \\ &= N_{\text{cell}} \cdot \{E_o - A \cdot \ln(i + i_n) \\ &\quad - R \cdot (i + i_n) - m \cdot \exp[n \cdot (i + i_n)]\}, \end{aligned} \tag{1}$$

where V is the voltage (in V) of the stack formed by N_{cell} cells connected in series; V_{cell} is the cell voltage (in V); E_o is the open circuit voltage (in V); A is the Tafel's parameter (in V); i is the current density (in A/cm^2); i_n is the internal current density (in A/cm^2); R is the resistance (in Ω), and m and n are the diffusion's parameters (in V and A^{-1}). In this model, there are six parameters (*i.e.*, E_o, A, R, m, n, and i_n) that must be extracted.

2.2. Mathematical formulation of SOFC stack model

In this work, the SOFC stack model [33] is as follows:

$$\begin{aligned} V &= N_{\text{cell}} \cdot V_{\text{cell}} \\ &= N_{\text{cell}} \cdot \left[E_o - i \cdot R - A \cdot \sinh^{-1}\left(\frac{i}{2i_{0,a}}\right) \right. \\ &\quad \left. - A \cdot \sinh^{-1}\left(\frac{i}{2i_{0,c}}\right) + B \cdot \ln\left(1 - \frac{i}{i_l}\right) \right], \end{aligned} \tag{2}$$

where $i_{0,a}$ and $i_{0,c}$ are respectively the anode and cathode exchange current density (in A/cm^2); B is a constant that depends on the fuel cell and its operating state (in V), and i_l is the limiting current density (in A/cm^2). In this model, the parameters that must be extracted are E_o, A, R, B, $i_{0,a}$, $i_{0,c}$, and i_l.

2.3. Objective function

In order to extract the parameters of the PEMFC and SOFC models in Eqs. (1) and (2) based on the measured data, the parameter extraction problem is usually formulated into an optimization problem. In this work, the mean square error is used as the objective function for both the PEMFC and SOFC models [27,25,30]:

$$\begin{aligned} \min \quad f(\mathbf{x}, i_k) &= \frac{1}{N_{\text{data}}} \sum_{k=1}^{K} (V_k^{\text{m}} - V_k^{\text{s}})^2 \\ &= \frac{N_{\text{cell}}^2}{K} \sum_{k=1}^{K} (V_{\text{cell},k}^{\text{m}} - V_{\text{cell},k}^{\text{s}})^2, \end{aligned} \tag{3}$$

where $\mathbf{x}$ is the parameter vector[2]; for the PEMFC model, $\mathbf{x} = [E_o, A, R, m, n, i_n]^{\text{T}}$; and for the SOFC model, $\mathbf{x} = [E_o, A, R, B, i_{0,a}, i_{0,b}, i_l]^{\text{T}}$. Additionally, K is the number of the measured data; i_k is the k^{th} current density of the measured data; V_k^{m} is the k^{th} voltage of the measured data, and V_k^{s} is the k^{th} voltage of the simulated data. The objective of the parameter extraction problem is to minimize the error between the simulated data and the measured data. Note that for the SOFC model, the following constraint must be satisfied:

$$i_k < i_l, \tag{4}$$

where i_k is the k^{th} current density of the measured data.

3. Parameter extraction based on decomposition and nature-inspired optimization

In this section, we explain our approach in detail, including the motivations of this work, the decomposition technique for search space reduction, and the framework based on the nature-inspired optimization method and the proposed decomposition technique for parameter extraction of FC models.

3.1. Motivations

Although nature-inspired optimization methods have been widely used to extract parameters for the PEMFC and SOFC models, they cannot extract the parameters fast. The reason is that all unknown parameters need to be obtained by the optimization methods, in this way, the search space is very large. As a result, the optimization methods have to cost too many computational resources to minimize the error between the simulated data and the measured data.

In Eqs. (1) and (2), we observe that the parameters that must be extracted can be classified into two groups: *i.e.*, linear and nonlinear. For PEMFC, the linear parameters are E_o, A, R, and m; and the nonlinear ones are n and i_n. For SOFC, the linear parameters are E_o, A, R, and B; and the nonlinear ones are $i_{0,a}$, $i_{0,c}$, and i_l. By using the measured data, the linear parameters are determined by the nonlinear ones.

Based on the above observations, in order to reduce the computational resources, we propose a decomposition approach, where the optimization method only needs to obtain the nonlinear parameters. The linear parameters can be further determined by the obtained nonlinear parameters.

3.2. Decomposition of search space

For the sake of simple description, in this subsection, the term $\frac{N_{\text{cell}}^2}{K}$ in Eq. (3) is omitted. Therefore, the objective function can be reformulated as

$$\begin{aligned} \min \quad f(\mathbf{x}, i_k) &= \sum_{k=1}^{K} (V_{\text{cell},k}^{\text{m}} - V_{\text{cell},k}^{\text{s}})^2 \\ &= (\mathbf{V}_{\text{cell}}^{\text{m}} - \mathbf{V}_{\text{cell}}^{\text{s}})^{\text{T}} (\mathbf{V}_{\text{cell}}^{\text{m}} - \mathbf{V}_{\text{cell}}^{\text{s}}), \end{aligned} \tag{5}$$

subject to

[2] Hereinafter, vectors are assumed to be the column vectors unless otherwise noted.