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Short communication

A hybrid multi-variable experimental model for a PEMFC

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Abstract

A hybrid model composed of a least square support vector machine (LS-SVM) model and a pressure-incremental model is developed to dispose operation conditions of current, temperature, cathode and anode gas pressures, which have major impacts on a proton exchange membrane fuel cell's (PEMFC) performance. The LS-SVM model is built to incorporate current and temperature and a particle swarm optimization (PSO) algorithm is used to improve its performance. The optimized LS-SVM model fits the experimental data well, with a mean squared error of 0.0002 and a squared correlation coefficient of 99.98%. While a pressure-incremental model with only one empirical coefficient is constructed to for anode and cathode pressures with satisfactory results. Combining these two models together makes a powerful hybrid multi-variable model that can predict a PEMFC's voltage under any current, temperature, cathode and anode gas pressure. This black-box hybrid PEMFC model could be a competitive solution for system level designs such as simulation, real-time control, online optimization and so on.

Keywords: Proton exchange membrane fuel cell (PEMFC); Pressure-incremental; Hybrid model; Particle swarm optimization (PSO); Least square support vector machine (LS-SVM)

1. Introduction

As a clean energy conversion technology, proton exchange membrane fuel cells (PEMFC) receive more attention because of their low operating temperature, high power density, quick start-up capability and long lifetime. PEMFC is an interesting technology for the next generation of vehicles, portable units and so on [1]. A convenient PEMFC model can help greatly to control, simulate, and diagnose its behavior.

The PEMFC system is a nonlinear, multi-variable electrochemical system that is hard to model. A large number of publications on fuel cell modeling [2] target the complicated internal phenomena at the molecular level. Among them, two-dimensional and more complex three-dimensional, two-phase and non-isothermal models have been presented [3–5], these had very complicated expressions with some key physical parameters that were even immeasurable. These mechanistic models usually focused on the electrochemistry, thermodynamics and fluid mechanics. Typically, they were centered on the membrane–electrode assembly (MEA), which could help analyze, design and optimize cell components in the laboratory context. However, generally they were not suitable for system level research [6–9].

An empirical modeling approach is more practical in some applications. Researchers can deduce a PEMFC stack's voltage responses without knowing the fuel cell's complicated internal characteristics. An active empirical modeling methodology in recent years is based on machine learning theories, such as artificial neural networks [10–14] and support vector machines (SVM) [15,16]. By mapping the fuel cell voltage as a function of various operational conditions, these black-box models agree well with experimental data. A common requirement in using these modeling approaches is that sufficiently representative data should be supplied in the training set to build a multi-variable empirical model. However, the numbers of the training data needed will increase dramatically when the numbers of input variables are increased, and these data may not be available. For example, in our previous work [15], 100 experimental data points were used to build a two-variable PEMFC voltage model, but the number of experimental data points used by Li et al. [16] had achieved 1000 to build a five-variable PEMFC temperature model. Therefore, although current density, temperature, cathode and anode gas pressures are the most important controllable variables for a PEMFC's performance, few of those

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models proposed can deal with all of them simultaneously. One important reason is simply the absence of sufficient empirical data describing a broad range of operating conditions.

Herein, a hybrid modeling approach is proposed. In this way, only limited numbers of empirical data are needed to build a model which can deal with current density, temperature, cathode and anode gas pressures simultaneously. This model consists of two parts: one is an empirical LS-SVM model that concerns current density and temperature. Li et al. [16] built a dynamic temperature model of a PEMFC by LS-SVM, incorporating temperature, cooling water speed, hydrogen speed, air speed and output power. As a least square version of SVM, LS-SVM inherits the superior generalization performance of SVM. Although its precision is slightly lower than SVM, LS-SVM significantly reduces computation time.

The key to obtaining a highly accurate SVM or LS-SVM model is to choose a proper set of hyper-parameters, but no effective guide lines have been put forward; some recommendations on how to determine them are quite contradictory and confusing. A trial method is used in [15,16], which greatly relies on the user's experience. Therefore, particle swarm optimization (PSO) [17] is adopted in this paper to automatically determine the best set of hyper-parameters.

The other part of the hybrid model is a pressure-incremental model taking account of both the cathode and anode gas pressures. This model is developed based on the work of Amphlett et al. [18] and Mann et al. [19]. After a slightly simplification, the number of empirical coefficients was greatly reduced from more than ten to only one.

2. Theoretical framework

For a given PEMFC system, the fuel cell terminal voltage V is influenced by many operating parameters: cell temperature T, cathode oxygen pressure P_{O_2}, anode hydrogen pressure P_{H_2}, relative humidity a, membrane humidity λ, etc. Accordingly, fuel cell voltage is given by

$$V = f(I, T, P_{O_2}, P_{H_2}, \lambda, \alpha, \ldots) \qquad (1)$$

Up to now, no model has ever been able to accommodate all these operating parameters. With the assumption that channel gas is fully saturated and membrane is fully humidified, Eq. (1) is simplified as

$$V = f(I, T, P_{O_2}, P_{H_2}) \qquad (2)$$

Although Eq. (2) is a simplified equation, it is still hard to model with traditional means due to its high dimensionality. A way to deal with large scale complex systems is to break them into independent simple submodels. Thus, we further separate Eq. (2) into two parts as

$$V = V_{P_0}(I, T) + V_{\Delta P}(\Delta P_{O_2}, \Delta P_{H_2}) \qquad (3)$$

The first part V_{P_0} denotes a LS-SVM model, which predicts cell voltages at different currents and temperatures under a constant cathode gas pressure $P^0_{O_2}$ and a constant anode gas pressure $P^0_{H_2}$. We refer to these constant pressures as reference pressures. The second part $V_{\Delta P}$ denotes a pressure-incremental model, which predicts voltage increment caused by oxygen pressure increment ΔP_{O_2} and hydrogen pressure increment ΔP_{H_2}. The structure of our proposed hybrid pressure-incremental LS-SVM model is illustrated in Fig. 1.

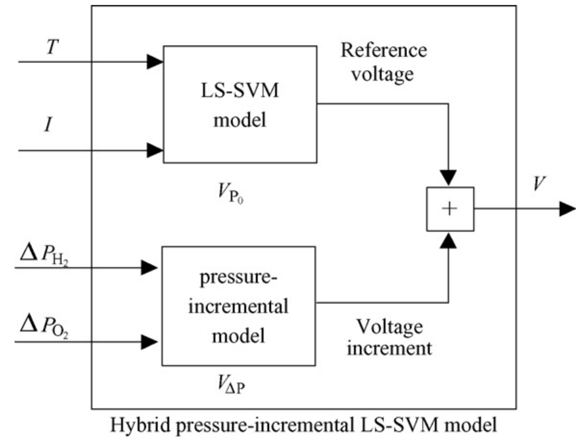

Fig. 1. Framework of the hybrid pressure-incremental LS-SVM model.

3. Optimized LS-SVM model

A support vector machine is a novel and powerful tool based on statistical learning theories. It was originally developed at AT&T Bell Laboratories by Vapnik [20] for classification in various domains of pattern recognition, then expanded successfully to deal with regression problems more recently. The SVM model possesses a high degree of precision and does not require a pre-knowledge of the fuel cell. Comparing to artificial neural networks, the SVM model has a superior capability of generalization and it is also more robust. LS-SVM proposed by Suykens and Vandewalle [21] is a least square version of the standard SVM. Compared to SVM, LS-SVM significantly reduces the computation time with a tiny precision loss. Taking advantage of the high computing efficiency of LS-SVM, PSO strategies are used to automatically optimize performance.

3.1. Modeling a PEMFC by LS-SVM

Building a LS-SVM model need three steps:

- Preparing training data.
- Selecting optimal LS-SVM parameters to train the LS-SVM model.
- Predicting with the LS-SVM model.

In this study, experimental data provided by Laurencelle et al. [22] was used to generate the training data for the LS-SVM model. This fuel cell was composed of 36 cells; each cell with a 232 cm^2 active area, graphite electrodes, and a Dow membrane. Air pressure and hydrogen pressure were both regulated to 3 atm. Training data were obtained at 24 °C, 31 °C, 39 °C, 56 °C and 72 °C and current densities from 0 mA cm^{-2} to 1000 mA cm^{-2}.