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Parameter extraction of polymer electrolyte membrane fuel cell based on quasi-dynamic model and periphery signals

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A B S T R A C T

It is important to extract parameters of a polymer electrolyte membrane fuel cell (PEMFC) using periphery signals. The main contribution of this work is to introduce a simple yet effective method for parameter-extraction basing on a quasi-dynamic model for a single PEMFC and periphery signals. The model includes filling-and-emptying sub-models, which set up relations between periphery signals and internal states, and a static water transferring sub-model for the membrane. The parameter-extraction method with 5 steps for 9 key parameters is proposed, drawing on experiments and algorithms of nonlinear least square (NLS) and neural networks (NN). Comparison of the identified parameters to data in literature shows that, the results in our study are reasonable.

A dynamic experiment is carried out to verify the model. Relative errors within [-5, 5]% between simulating and experimental results are observed, showing the effectiveness of the results. Properties of internal states with respect to time and frequency are simulated. A net water transport coefficient $\beta \in [0.13, 0.21]$ is predicted. The normalized transfer functions of small disturbance signals from the cell current to internal states are low-frequency-pass functions. A cutoff frequency (0.0003–0.37 Hz) and a resonating frequency (3.55 Hz), which retain under different operation conditions, is found.

1. Background

Energy crises and environmental degradation have been serious global issues that have greatly affected quality of daily life and the sustainable development of human societies. The internal combustion engines (ICE) at the core of the transportation sector consume the most fossil-derived oil. However, the use of fossil-fuels by ICEs cannot deliver adequate energy efficiency, nor eliminate emissions. Therefore, hydrogen is regarded as a possible candidate for future use, as it is clean and highly efficient.

A fuel cell utilizes a fuel to generate electrical energy by means of an electro-chemical reaction. There are a variety of different fuel cell systems, e.g.: polymer electrolyte membrane fuel cells (PEMFC), alkaline fuel cells, phosphoric acid fuel cells, molten carbonate fuel cells and solid oxide fuel cells. Of these, PEMFCs are favored for automotive applications, as they feature high power density, achieve high energy efficiency, good performance at low temperatures and a quick start-up time [1].

Many countries or alliances thereof (e.g., the US, Japan, the EU, and China) have instituted development strategies and policies pertaining to fuel cell vehicles (FCVs) and considerable research and developmental progress has been devoted to these. Automotive manufacturers have also considered the use of hydrogen in conjunction with PEMFCs over the past decades, and it is considered a possible power source for future use in electric vehicles. Indeed, a number of automotive manufactures (e.g., Mercedes Benz, Ford, GM, Toyota, Honda, Nissan and Hyundai) have already launched their own FCVs.

In China, an FCV with a 30 kW-rated power PEMFC system was constructed during an initial research project that began in 2001,

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and represents a key project within the ninth five-year plan. During the tenth and eleventh five-year plans, fuel cell buses (FCB) and fuel cell passenger cars were developed by Tsinghua and Tongji Universities, respectively [2]. The configurations of the powertrain system used in both of these vehicles were similar, and included a PEMFC system, direct current (DC) converter, battery system and an electric motor. The PEMFC system exports a quasi-steady power through the DC converter, with the battery then fulfilling the dynamic power and recycling braking energy. Advanced energy management strategies have been studied and applied to vehicles, and several public demonstrations have shown the effectiveness of the technologies used; for example, at the Beijing Olympic Games of 2008, the Shanghai Expo of 2010 and the Singapore Youth Olympic Games of 2010 [3–11].

It is important to extract key parameters of a PEMFC system to understand the complex dynamic processes inside it. However, it is a challenging task to identify these parameters perfectly basing on periphery signals, such as temperatures, pressures, flow rates. The problem can be generally considered as a nonlinear multi-variable optimization problem, whose results depend on adopted models and algorithms.

A suitable numerical model is the basis for parameter extraction. Generally speaking, there are five fundamental equations to describe a PEMFC's performance: mass conservation, momentum conservation, energy conservation, species transport and charge [12]. Researchers have designed various types of models to describe the dynamic behavior of a PEMFC, such as 0/1/2/3 D models, single- or two-phase flow models and degradation models for Pt/C corrosions [13–15].

Three-dimensional models provide abundant information of a PEMFC. It is thus suitable for achieving a detailed understanding of the complex multi-physical dynamic processes inside it. Iranzo [16] developed a 3D PEMFC model which was partly validated by using the neutron imaging method. Cano-Andrade S [17] introduced a model to simulate performance of fuel cells with radial flow field patterns. Huang YX [18] studied the influences of porosity gradient in GDL on fuel cell performance basing a 3D model. Cordiner S [19] researched the water saturation distribution and its influences on fuel cell performances using a 3D model. Carton JG [20] studied the dynamic process of water droplet accumulation and motion basing on a 3D simulation and experiments. They also studied the properties of open pore cellular foam and its potential use in fuel cells [21,22] basing on numerical models. Rostami L [23] simulated the influences of bend sizes of serpentine flow channels on the performances of fuel cells.

Two-dimensional models are less complex than 3D model, yet they give rich information. Carnes [24] developed a 2D two-phase multidimensional model, which was verified by current distribution measurement. Robin [25] proposed a model for a PEMFC with a large cell surface area. The temperature and current density distributions were then simulated and validated with measurements. Tayarani-Yoosefabadi [26], meanwhile, researched a microstructural model of GDL for different liquid water saturation levels, developing and validating a stochastic, microstructural GDL modeling framework. Ramiar A [27] simulated the dynamic behaviors of fuel cells with interdigitated gas distributors and cathode flow pulsation. Xing L [28,29] proposed a 2D anode partial flooding model for investigating relations of relative humidity, stoichiometry and cell performance. A coupled model, which is composed of a 2D two-phase flow model for mass transferring and a 0D model for oxygen reduction reaction, was proposed by Xing L [30] to investigated thermal transport in the MEA.

One-dimensional models focus on dynamic distributed properties in a specific dimension, such as along the channel or through the membrane. Rakhshanpouri S [31] researched the dynamic process of water transport through a fuel cell. Iranzo A [32] proposed 1D and 2D models, which were combined by data of neutron imaging for a fuel cell. Salva JA [33] proposed and validated a model of a fuel cell using neutron imaging data.

Zero-dimensional models are much simpler than 1/2/3D models, and can capture the dynamic processes of a system. Sharifi Asl SM [34] studied a 0D model for the stable- and dynamic-properties of a fuel cell. Kang S [35] proposed a quasi-three dimensional model of a fuel cell. This model is composed of several 0D sub-models with regards to two-phase flows. Soltani [36] studied an empirical dynamic model for a Nexa PEM fuel cell module. Del Real [37] proposed and validated a nonlinear model for heat and mass transfer processes for a 1.2 kW Nexa™ fuel cell. Lee [38] designed a dynamic model with validation, which included a mass transferring process and equivalent capacitors. Experiments for static V-I curves, step current responses and frequency responses were carried out to verify this model. Wang [39] integrated an electrical equivalent circuit model into the mass transferring model and validated the entire dynamic model with experimental data. Furthermore, Liso [40] designed and verified a 0D model with a water balance in the membrane. Besides, there are also neural network models for PEMFCs [41,42] in literature.

Although 2D/3D models have high accuracy, they are always time-consuming, containing many details, most of which are not necessary for control algorithm design. 0D/1D models are relatively simple, yet provide enough information for dynamic processes. With periphery signals, it is more practical to extract key parameters for a 0D model than for a 1D model, since a 1D model requires distributed signals that are usually difficult to measure in a vehicular fuel cell system. A considerable amount of research has been performed in relation to 0D dynamic modeling and identification of the parameters of PEMFCs.

In some papers, algorithms for parameter-extraction were only regarded as parts of model validations, and were not mentioned in details [36–40]. Ziogou [43] proposed a 0D model with heat and mass transferring processes in gPROMS. Key parameters of the model were identified basing on non-linear regression algorithm. Differential evolution (DE) is a simple yet efficient evolutionary algorithm for global numerical optimization. It has been successfully used in identifying parameters for fuel cells. Gong W introduced a ranking-based DE algorithm [44] and a transferred adaptive DE algorithm [45], Sun Z [46] studied a hybrid adaptive DE algorithm, and Yang S [47] introduced an aging and challenging P systems based optimization algorithm. Moreover, there are other algorithms for fuel cells in literature, such as genetic algorithm (GA) [48], particle swarm optimization (PSO) [49], seeker optimization algorithm (SOA) [50], bio-inspired P system based optimization algorithm (BIPOA) [51], and hybrid artificial bee colony (HABC) [52].

From above we know that, it is acceptable to adopt 0D models to extract key parameters for a PEMFC. However, in most of current studies, neither the filling-and-emptying process nor the water transfer process inside the fuel cell was taken into consideration. This may cause systematic errors in identifying key parameters basing on periphery signals (such as temperatures, pressures, flow rates), which can be measured directly in the system level. This paper proposes a parameter-identification method basing on periphery signals and a quasi-dynamic model, which is composed of filling-and-empty sub-models and a static mass transferring sub-model. Section 2 describes the non-linear quasi-dynamic model with consideration of filling-and-emptying processes and mass transferring processes. Section 3 describes a parameter-identification methodology with 5 steps for 9 key parameters, drawing on experiments and algorithms of nonlinear least square (NLS) and neural networks (NN). In section 4, the key parameters are identified and the nonlinear model is verified with dynamic