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Nonlinear modeling and identification of proton exchange membrane fuel cell (PEMFC)

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ABSTRACT

The nonlinear autoregressive moving average model with exogenous inputs (NARMAX) approach is employed to analyze time-frequency domains for the proton exchange membrane fuel cell (PEMFC) system. The time-domain nonlinear NARMAX model of PEMFC system is modeled from measured experimental input and output data. The outputs obtained by using the time-domain NARMAX model were confirmed by model validation tests which compare the model's predictive outputs with actual system outputs, in an interactive environment. This provides a potentially nondestructive tool for the modeling of a nonlinear PEMFC system. Then, the generalized frequency response function (GFRF) is employed in the frequency-domain, which is computed directly from the time-domain NARMAX model, to provide information about the types of nonlinearities in a PEMFC. The analysis revealed that the time-domain model provides better parameter estimation and a good forecasting ability. The frequency-domain response function is consistent with actual reaction mechanisms. The results illustrate that the time-frequency domain NARMAX approach can be effectively employed in modeling and identifying of PEMFC system. Crown Copyright © 2015, Hydrogen Energy Publications, LLC. Published by Elsevier Ltd. All rights reserved.

Introduction

Over the past decade, many types of fuel cells (FCs) have been developed for various applications and have been extensively described in the literatures [1–3]. A PEMFC is considered one of the most promising candidates for FC development because it is not only light and compact but also possesses features such as rapid start up and a low operating temperature. Despite these potential advantages, the performance of PEMFC is influenced by numerous operational obstacles including material properties, operating conditions, thermal conduction, and electrochemical processes [4–9]. In order to

address commercialization challenges for FCs such as low cost, a long life and reliability, the development of the comprehensive model representing an authentic system with inner reaction mechanisms of PEMFC is required.

Modeling the characteristic internal physicochemical processes occurring in the PEMFC system is not an easy task. It is especially difficult to develop suitable types of nonlinear multi-input and multi-output (MIMO) models for PEMFC systems using traditional methodologies. In many literatures, researchers have made significant efforts to develop model-based (MB) analytical approaches for various transport phenomena, physical conservation laws, governing equations, and computational modeling for PEMFC [10–16]. An increase

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in computing power and a corresponding increase in the case in which, complex computational results are obtained, have greatly influenced on the field of mathematical modeling. Although these models are very useful in analyzing the internal steady-state characteristics, they have many limitations, complicated expressions, and need a priori hypotheses to describe an FC system accurately. In the recent decades, a great number of researchers have developed models using non-model methodologies such as data-driven modeling (DDM) [17–24]. DDM concentrates on computational intelligence (CI) and soft-computing (SC) methods to establish models for complementing or replacing physical models. The results obtained from those methodologies are promising for predictions but do not reveal PEMFC nonlinear behavior. On the other hand, alternating current (AC) impedance modeling, based on electrochemical impedance spectroscopy (EIS) measurement, has been applied frequently in many literatures [25–29]. In order to understand the effects of each variable and the frequency domain spectrum, the experiment focuses on one-factor at a time in steady-state period of an EIS measurement. However, when the number of experimental iterations increase, certain disadvantages of measuring an EIS spectrum appear, such as high time consumption and high cost. As mentioned above, a novel nonlinear modeling and identification methodology is needed to provide a better solution in time and frequency domain.

Black-block system identification techniques can model nonlinear systems directly from experimental input–output data by estimating the model structure form and the numerical values of the unknown parameters. Driven by such motivation, the recursive system modeling and identification methodology in the time-frequency domain based on the nonlinear autoregressive moving average model with exogenous inputs (NARMAX) approach is proposed for PEMFC system. The time-domain NARMAX model is a nonlinear difference equation that relates the system output at a given time instant to values of the inputs, outputs, and noises at previous time instances. The process of identifying time-domain NARMAX model involves model structure determination, significant terms of unknown nonlinear equations, parameter estimation associated with the coefficients of a particular structure, and validating the resulting model in order to assess the model's correctness. Thereafter, the identified NARMAX model can be applied to compute the frequency-domain generalized frequency response function (GFRF) directly. The frequency-domain approach based on GFRF is a new insight in PEMFC systems. The results of GFRF can show inner nonlinear mechanisms and can explain the dynamic behavior of PEMFC modeling system.

The purpose of this study is to develop and implement NARMAX approach, in both time and frequency domains, for PEMFC output voltage response in the period of the current step change under normal operating conditions that can describe dynamic polarization characteristics. The model is extended to include activation, concentration, and mass-transfer losses. The time-domain NARMAX model structure is estimated by the orthogonal least square algorithm (OLS) and error reduction ratio (ERR) to model PEMFC system. Furthermore, model validation tests are conducted to check the accuracy of the time-domain NARMAX model. Then, the

frequency-domain response function is computed directly from time-domain fitted model by applying recursive probing to depict reaction mechanics. The procedure of validation provides both good long-term and short-term predictions of system outputs of PEMFC. The scope of the basic nonlinear system modeling and the identification concept of PEMFC is depicted in Fig. 1.

NARMAX time-frequency domain approaches

Modeling is a critical step in a successful system identification process because it is the basis for data fitting interpretation. The NARMAX method was first proposed by Billings and Leontaritis [30]. The NARMAX model has been applied extensively to represent the relationship between the system output and input in the presence of noise in many nonlinear stochastic dynamic systems [31–34]. The identification problem of nonlinear systems such as PEMFC can be described by a NARMAX model in our study. The time-domain nonlinear difference NARMAX model equation that involves the system inputs, outputs and the effect of measurement noise is described by Ref. [35]:

$$y(k) = F^l [y(k-1), \dots, y(k-n_y), u(k-1), \dots, u(k-n_u) \times \zeta(k-1), \dots, \zeta(k-n_\zeta)] + \zeta(k) \quad (1)$$

where $F[\cdot]$ is an unknown nonlinear function; l is the degree of nonlinearity; $y(k)$ is the output vector, $u(k)$ is the input vector,

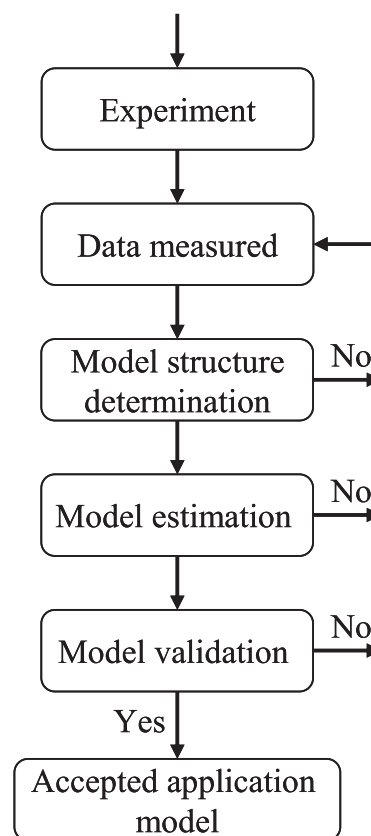


Fig. 1 – Steps of the system identification procedure.

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