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LPV observer design for PEM fuel cell system: Application to fault detection☆

S. de Lira [a,*,1], V. Puig [a,1], J. Quevedo [a,1], A. Husar [b,2]

[a] Sistemas Avanzados de Control (SAC), Universitat Politécnica de Catalunya (UPC), Rambla Sant Nebridi 10, 08222 Terrassa, Spain
[b] Instituto de Robótica i Informática Industrial (IRI), (CSIC-UPC) Parc Tecnológic de Barcelona, Edifici U, Carrer Llorens i Artigas, 4-6, Floor 2, 08028 Barcelona, Spain

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ABSTRACT

In this paper, the modelling of an energy generation system based on *polymer electrolyte membrane fuel cell* (PEMFC) system through a parameter varying approach (LPV model), that takes in to account model parameter variation with the operating point, is presented. This model has been obtained through a Jacobian linearization of the PEMFC non-linear dynamic model that was previously calibrated using real data from lab. In order to illustrate the use of the LPV model obtained its application to model-based fault detection is used. For this purposes a set of common fault scenarios, which could appear during a normal PEMFC operation, is used as case study.

1. Introduction

Low-temperature PEM fuel cells are considered as sources for rapid medium of energy generation, making these equipment suitable for automobile applications. The supply of raw materials (usually air or pure oxygen) is normally performed using an air compressor or blower and hydrogen stored in tanks. The system uses additional equipment to carry materials reaction to the optimum operating conditions, such as cooling systemsand humidifier. During the chemical reaction that is taking place into the stack, where the energy is generated, different phenomena occur, such as thermal, fluid-mechanical and electrolytic.

The complex and non linear dynamics of the power generation systems based on fuel cell technology lead to the use of linear models that includes parameter varying with operating point not only for advanced control techniques but also for fault diagnosis algorithms based on models. The use of LPV models is an alternative to the approaches presented in previous works [1,2] addressing methodologies for monitoring and fault diagnosis based on a theoretical non-linear dynamic model proposed by Pukrushpan [3,4].

Within the recent decade, state of art and background about control of LPV systems has been developed [5–10]. Because of a LPV system can be considered as a parametrized family of linear systems that change with the operating point conditions, then LPV technique allows a systematic approach for control and fault diagnosis system design. At the cost of conservatism the approach can be applied to an even wider range of systems known as quasi-LPV systems, where varying parameters are scheduled with state variables.

Since LPV models are structured as similar as a linear time-invariant (LTI) state space system, the control and fault diagnosis design methods can easily be extended. The main contribution of this paper is to obtain a linear parameter varying model for a typical PEMFC and illustrate its use for robust fault detection using interval observers.

2. Fuel cell modelling

The model proposed in [11], is a non-linear dynamic model calibrated using real data from laboratory using a *lsq*-non linear fitting approach [12,13]. This model is able to reproduce the behaviour of a commercial PEMFC (Ballard 1.2 kW, Nexa©) prototype, which has been identified in a wide range of operating conditions. Fig. 1 shows the dynamic model layout.

2.1. Dynamic non-linear model

The model is considered as SIMO system, where the input (u) is the stack current (I_{st}) and the outputs (y) are battery temperature (T_{st}), stack voltage (v_{st}), oxygen consumption ratio (λ_{O_2}), speed

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* Corresponding author. Tel.: +34 622111233; fax: +34 934015750.
E-mail address: salvador.de.lira@upc.edu (S. de Lira).
[1] http://websac.upc.es.
[2] http://www.iri.upc.edu.

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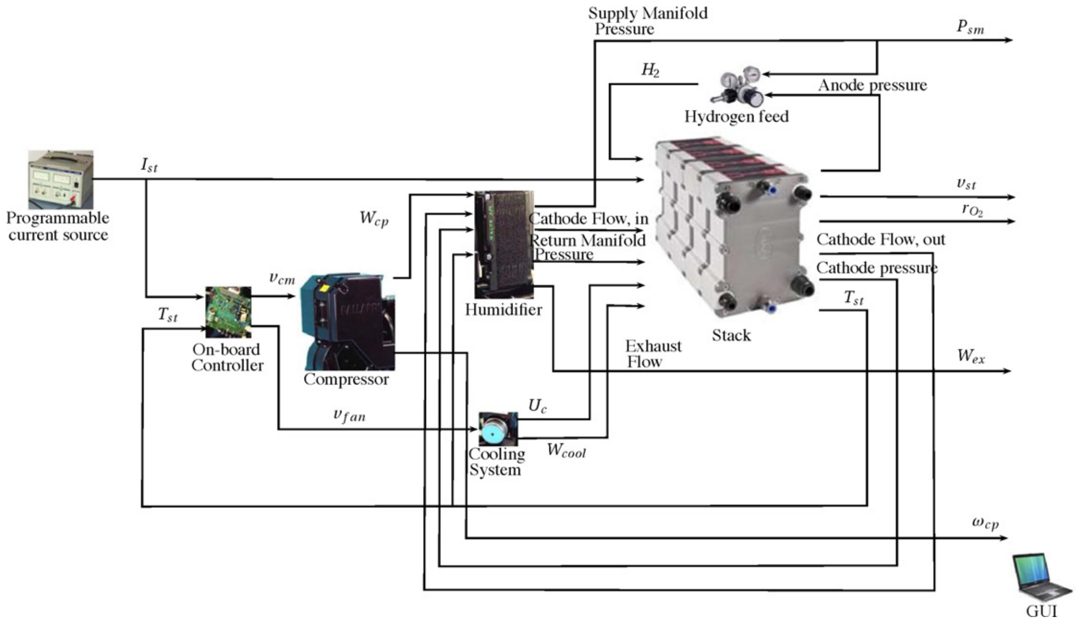

Fig. 1. Nexa© PEMFC simulator schematic.

engine (ω_{cp}) and inlet pressure to the cathode (P_{sm}). The voltage from the compressor (v_{cm}) is controlled using a static feed-forward controller. Fig. 2 shows the layout of each subsystem embedded into the PEMFC dynamic model.

The proposed model consists often state, and the state equations are listed in the following

$$
\begin{aligned}
\dot{\omega}_{cp} &= \frac{1}{J_{cp}\omega_{cp}}(\tau_{cm} - \tau_{cp}),\\
\dot{P}_{rm} &= \frac{R_{air}T_{rm}}{V_{rm}}(W_{ca,o} - W_{rm,o}),\\
\dot{m}_{rm} &= W_{ca} - W_{rm,o},\\
\dot{P}_{sm} &= \frac{\gamma R_a}{V_{sm}}(W_{cp}T_{cp} - W_{sm,o}T_{sm}),\\
\dot{m}_{sm} &= W_{cp} - W_{sm,o},\\
\dot{m}_{H_2} &= W_{H_2,i} - W_{H_2,o} - W_{H_2,r - W_{H_2,nl}},\\
\dot{m}_{w,an} &= W_{v_{an},i} - W_{v_{an},o} - W_{v_{mbr}},\\
\dot{m}_{N_2} &= W_{N_2,i} - W_{N_2,o},\\
\dot{m}_{O_2} &= W_{O_2,i} - W_{O_2,o} - W_{O_2,r},\\
m_{st}C_{st}\dot{T}_{st} &= H_{reac} - P_{elec} - Q_{rad} - \dot{Q}_{conv}.
\end{aligned}
\tag{1}
$$

The state variables ($\mathbf{x}$) of this dynamic model are the following: mass of oxygen (m_{O_2}), nitrogen (m_{N_2}), hydrogen (m_{H_2}), cathode water flow ($m_{w,ca}$), stack temperature (T_{st}), angular velocity of the compressor (ω_{cp}), supply pressure (P_{sm}) and return pressure (P_{rm}) of the humidifier, inlet flow (m_{sm}) and outlet flow (m_{rm}) of humidifier. The subindex in the variables *i*, *o*, *r*, *nl* means, input, output, reaction and natural, respectively. In the heat balance the subindex *reac*, *elec*, *rad* and *conv* are related respectively to reaction, electric, radiation and convection.

The system perturbation ($\mathbf{z}$) that have been considered are related to the weather conditions (T_{amb}, P_{atm}).

The model output equations are:

- *Stack voltage*:

$$v_{st} = n_{fc} \cdot (E - v_{act} - v_{oh} - v_{con}). \tag{2}$$

- *Oxygen excess ratio*:

$$\lambda_{O_2} = \frac{W_{O_2,i}}{W_{O_2,r}} = \frac{x_{O_2} \cdot W_{cp}}{(M_{O_2} \cdot n_{fc} \cdot I_{st})/4 \cdot F}. \tag{3}$$

- *Compressor speed motor*:

$$\omega_{cp} = \frac{U_{cp} \cdot 60}{d_c \cdot \pi}, \tag{4}$$

where v_{st}, total stack voltage (V); E, open circuit voltage (V); v_{act}, activation voltage loss (V); v_{oh}, ohmic voltage lose (V); v_{con}, concentration voltage loss (V); n_{fc}, amount of cells; λ_{O_2}, oxygen excess ratio; I_{st}, stack current (A); F, Faraday constant (col/mol); W, mass flow (g/s); U_{cp}, compressor blade (KRPM); d_c, compressor diameter blade (%); η, compressor efficiency (%); M_{O_2}, oxygen molar weight (g/mol); M_{H_2}, hydrogen molar weight (g/mol); x_{O_2}, oxygen fraction (%); φ_i, humidity ($i = ca, an$) (%).

3. Linear parameter varying model

Exist different ways to obtain LPV models. Some methods use non-linear equations of the system to derive a LPV model such as state transformation, substitution of functions and methods using the well known Jacobian linearization [14–16]. Another kind of method uses multi-model identification that consists basically in two different steps: (1) a set of LTI model is identified at different equilibrium points by classical methods (*on-line* or *off-line*), (2) then, the following step is to get a multi-model by an interpolation law that allows to commute among local LTI model at each operating point [17,18].

3.1. Problem formulation

The type of LPV system, which is considered in this paper, assumes an affine dependence with a parameter vector $\tilde{\vartheta}_k$ and can be described in discrete time state space as:

$$
\begin{aligned}
\mathbf{x}_{k+1} &= \mathbf{A}(\tilde{\vartheta}_k)\mathbf{x}_k + \mathbf{B}(\tilde{\vartheta}_k)\mathbf{u}_k + \mathbf{w}_k,\\
\mathbf{y}_k &= \mathbf{C}(\tilde{\vartheta}_k)\mathbf{x}_k + \mathbf{D}(\tilde{\vartheta}_k)\mathbf{u}_k + \mathbf{v}_k,
\end{aligned}
\tag{5}
$$

where $\mathbf{x}_k \in \mathbb{R}^{n_x}$, $\mathbf{u}_k \in \mathbb{R}^{n_u}$ and $\mathbf{y}_k \in \mathbb{R}^{n_y}$ are, respectively, the state, input, and output vectors. The process and measurement noises are $\mathbf{w}_k \in \mathbb{R}^{n_x}$ and $\mathbf{v}_k \in \mathbb{R}^{n_y}$ respectively. Both are considered unknown but bounded as $\mathbf{v}_k \in \mathbb{V}^{n_x}$ and $\mathbf{w}_k \in \mathbb{W}$ which are interval boxes.