

Real-Time Polymer Electrolyte Membrane Fuel Cell Parameter Estimation without Persistent Excitation (P-4FC-V)

C. Andreu^{1*}, M. Serra¹ and R. Costa-Castelló¹

¹ Institut de Robòtica i Informàtica Industrial, CSIC-UPC, Llorens i Artigas 4-6, 08028 Barcelona, Spain

(*) Corresp. author: andreu.cecilia@upc.edu

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1. Introduction

Degradation issues limit the technical and economical viability of polymer electrolyte membrane fuel cells (PEMFCs) [1]. In this context, many studies on PEMFCs systems have focused on developing models to optimize and monitor performance indices of the system. Following this line of research, a significant obstacle is that PEMFCs dynamics are described by highly nonlinear and uncertain equations, where multiple parameters may be unknown and of time-varying nature. For this reason, there is a necessity of exploiting real-time parameter estimation algorithms to compute online the unknown model parameters from easily measurable data [10][11][12].

Real-time parameter estimation algorithms have been deeply studied in the past decades and have been used in a wide variety of systems. Commonly, these algorithms generate a consistent estimation by minimizing the observed error through a gradient descent algorithm [2], least-squares method [3], or neural-network methods [4]. Nonetheless, the accuracy and robustness of these estimators is based on a persistence of excitation assumption [5]. That is, the inputs of the system have to “move” the system dynamics such that the effect of the parameters can be noticed from the measured signals. It is important to remark that this condition has to be satisfied persistently, that is, for all time. Therefore, if at any moment of the system operation the excitation condition is not satisfied, the parameter estimation is immediately degraded and the algorithm provides unreliable estimations. This is a critical limitation that prevents the practical application of such algorithms in PEMFCs and, to the author’s knowledge, has been obviated in the literature. Indeed, to minimize degradation issues, PEMFCs systems usually require minimal input variations, thus, the excitation condition is rarely satisfied in a persistent manner.

To overcome this issue, this work proposes a novel real-time parameter estimation algorithm for PEMFCs that can operate in scenarios where the excitation condition is not satisfied persistently. The algorithm is based on the results presented in [6]. The algorithm combines a memory sub-system that “stores” the parts of the measured trajectory that satisfy the excitation condition and a parameter estimator based on the dynamic regressor extension and mixing technique [7] to improve the transient performance of the algorithm.

2. Fuel Cell Model and Problem Formulation

Electrochemical models are used to predict PEMFC voltage by combining the theoretical maximum cell potential, E_r , with the major potential losses. That is, the ohmic losses, V_{ohm} , and cathode activation polarization losses, $V_{act,c}$ [8],

$$V = E_r - V_{ohm} - V_{act,c}.$$

Ohmic losses are computed from the Ohm’s law

$$V_{ohm} = R_{ohm}I$$

where I is the current and R_{ohm} is the ohmic resistance. Activation losses can be computed as a function of the current density

$$V_{act,c} = \frac{RT}{2\alpha_c F} \ln\left(\frac{I}{Ai_{0,c}}\right)$$

where α_c is the charge transfer coefficient, F is the Faraday’s constant, R is the ideal gas constant, T is the temperature and A is the cell active area. The factor $i_{0,c}$ depicts the reference exchange current, which is related to physical properties of the catalyst layer

$$i_{0,c} = \gamma_c \sqrt{a_{O_2}} e^{-\frac{E_{ca}}{RT}\left(1-\frac{T}{293}\right)}$$

where γ_c is the exchange current density at reference conditions, a_{O_2} is the oxygen activity in the catalyst layer and E_{ca} is the activation energy of the reaction.

The electrochemical model presents a pair of parameters that strongly depend on the operating conditions of the fuel cell. First, the ohmic resistance, R_{ohm} , which varies depending on the humidity of the membrane. Second, the factor $\gamma_c \sqrt{a_{O_2}}$ depends on the concentration of oxygen in the catalyst layer, which not only varies according to the oxygen concentration in the inlet, but is modified by the quantity of liquid water that blocks its transport through the porous media. For this reason, there is a necessity of estimating these factors through a real-time algorithm. Notice that the electrochemical model can be re-written as a simple linear regression of the form

$$Y = \Phi^T \theta$$

where Y and Φ are signals that can be computed as

$$Y = V - E_r - \frac{RT}{2\alpha_c F} \ln\left(\frac{I}{Ae^{-\frac{E_{ca}}{RT}\left(1-\frac{T}{293}\right)}}\right),$$

$$\Phi^T = \left[-I \quad \frac{RT}{2\alpha_c F}\right],$$

and θ are the unknown parameters to be estimated

$$\theta^T = \left[R_{ohm} \quad \ln(\gamma_c \sqrt{a_{O_2}})\right].$$

The objective is to use the trajectory information of Y and Φ to generate a consistent estimation of the unknown parameters, $\hat{\theta}$. As the model can be written in a linear regression, any of the parameter estimation algorithms presented in the Introduction can be used to solve the estimation problem. Nonetheless, these techniques require the vector ϕ to satisfy a particular excitation condition for all time t [5]. That is, there exists a constant $k > 0$ such that

$$\int_t^{t+k} \Phi \Phi^T d\tau > 0.$$

It should be remarked that for the considered PEMFC problem, such condition implies that the fuel cell current, I , and temperature, T , have to persistently modify its value, which drastically increases the degradation of the system and deteriorates the performance. Next section proposes an algorithm that provides consistent parameter estimation when the excitation condition is only satisfied for a limited amount of time, which is a more reasonable assumption in practice.

3. Proposed Estimation Algorithm

This work proposes an algorithm based on the results presented in [6]. The algorithm starts with a set of “memory dynamics” that stores the excitation information of the PEMFC measured signals. Precisely, the dynamics take the following form:

$$\begin{aligned} \dot{\hat{\theta}}_g &= \Phi(Y - \Phi^T \hat{\theta}_g), & \hat{\theta}_g(0) &= [0 \ 0]^T \\ \dot{\Omega} &= -\Phi \Phi^T \Omega, & \Omega(0) &= I_2 \end{aligned}$$

where I_2 is the identity matrix of size 2 and $\hat{\theta}_g, \Omega$ are auxiliary variables used to store the information.

The values generated by these set of dynamics are used to generate another set of signals that maintains excitation even if the original signals Y, Φ do not satisfy the excitation condition at some time range. Precisely, the following signals are generated

$$\begin{aligned} \Delta &= \det\{I_2 - \Omega\} \\ \begin{bmatrix} y_{R_{ohm}} \\ y_{O_2} \end{bmatrix} &= adj\{I_2 - \Omega\} \hat{\theta}_g. \end{aligned}$$

where $\det\{\cdot\}$ is the determinant and $adj\{\cdot\}$ is the adjugate.

Finally, the signals Δ and $y_{R_{ohm}}$ are used to estimate the ohmic resistance as:

$$\dot{\hat{R}}_{ohm} = \Delta(y_{R_{ohm}} - \Delta \hat{R}_{ohm}),$$

and Δ and y_{O_2} are used to estimate the oxygen activity factor as

$$\ln(\widehat{\gamma_c \sqrt{a_{O_2}}}) = \Delta(y_{O_2} - \Delta \ln(\widehat{\gamma_c \sqrt{a_{O_2}}}).$$

A general scheme of the algorithm is depicted in Figure 1.

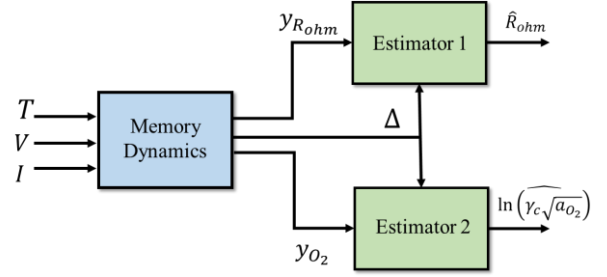


Figure 1: General scheme of the estimation algorithm

4. Preliminary Results

The benefits of the proposed architecture have been validated through a numerical simulation. In the simulation, the fuel cell model presented in [9] is excited by a particular current profile in order to generate the signals Y and Φ . Precisely, the current profile is the one depicted in Figure 2, which is a perfectly reasonable profile to implement for real fuel cells. It is noticeable that the profile only consists on a single current set-point modification. Indeed, during the set-point change, the excitation condition is satisfied, but, while the current is maintained constant, the excitation condition is not satisfied. This is an example of a scenario where the excitation condition is temporarily satisfied (during the set-point change), but is not satisfied in a persistent manner (in the whole PEMFC trajectory).

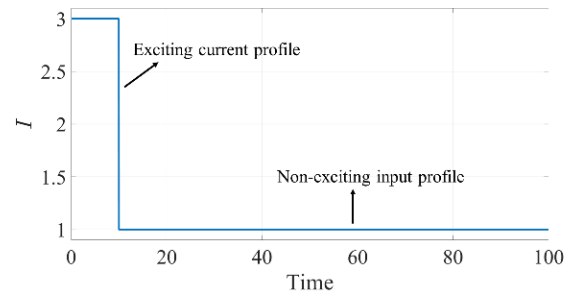


Figure 2: Introduced current profile. The PEMFC system is excited during the current set-point change. Nonetheless, the excitation is lost as the current is maintained constant.

The aim of the simulation is to compare the performance of the proposed approach with a standard gradient descent algorithm [2]. Following the discussed theory, as the system is not persistently excited, the standard gradient descent can not have a consistent estimation. Indeed, this fact can be seen in Figure 3. It can be observed that the standard gradient descent estimation oscillates at the time that the system is excited, but converges to an incorrect value when the system loses excitation. This happens because the excitation is lost before the parameter estimation has converged to the true value. On the other hand, the proposed approach provides a consistent estimation of the parameters, as the estimation eventually converges to the true value.

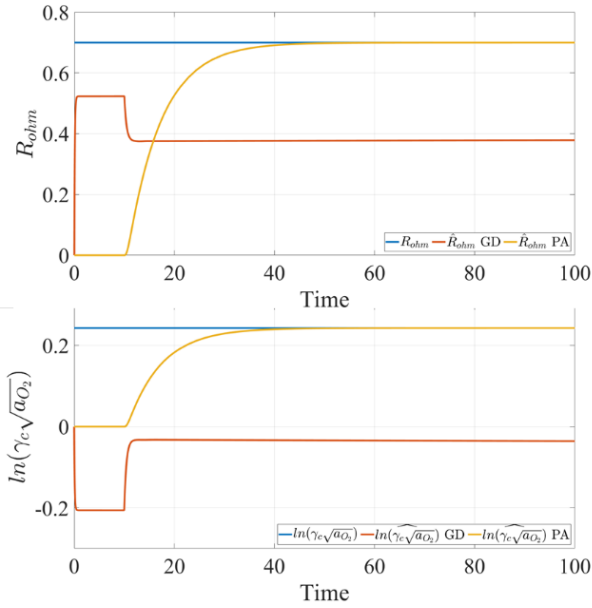


Figure 3: True value of the parameters, estimation from a standard gradient descent (GD) and estimation from the proposed algorithm (PA).

Moreover, notice that the estimation of the standard gradient descent not only converges to the wrong value, but the estimation goes to the wrong direction for some components. Indeed, the estimation \hat{R}_{ohm} in Figure 3 goes from a value of 0.52, before the current modification, to a higher-error value of 0.37 after the modification. This behaviour appears because gradient descent algorithms only guarantees a monotonic convergence of the whole parameter vector. That is,

$$\|\theta - \hat{\theta}(t_b)\| \leq \|\theta - \hat{\theta}(t_a)\|, \forall t_b \geq t_a.$$

Therefore, during the transient, some parameter estimation components may temporarily go to the wrong direction if other components get closer to the true value. Nonetheless, the proposed algorithm guarantees a monotonic convergence for each component individually. That is,

$$\|\theta_i - \hat{\theta}_i(t_b)\| \leq \|\theta_i - \hat{\theta}_i(t_a)\|, \forall t_b \geq t_a,$$

where $\theta_1 = R_{ohm}$ and $\theta_2 = \ln(\gamma_c \sqrt{a_{O_2}})$.

Consequently, the proposed algorithm presents better transient performance compared to available algorithms.

This simulation exemplifies in which ways adding memory mechanisms may help parameter estimation algorithms in common scenarios where only part of the PEMFC signals trajectory (not the whole trajectory) is sufficiently exciting to estimate the unknown parameters.

5. Conclusions

This work proposes an algorithm to estimate in real-time a PEMFC ohmic resistance and catalyst layer oxygen activity from easily measurable data. Contrary to more standard approaches, the proposed algorithm can be implemented in cases where the persistence of excitation condition is not satisfied. Consequently, the presented algorithm can be implemented in more reasonable practical scenarios where only part of the PEMFC signal trajectory (not the whole trajectory) is exciting enough to estimate the unknown parameters. The benefits of the approach have been validated through a numerical simulation. Future works will focus on

experimentally validating the proposed approach in a real fuel cell prototype.

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