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ELECTRICAL AND THERMAL TIME CONSTANTS FUEL CELL SYSTEM IDENTIFICATION – A LINEAR VERSUS NEURAL NETWORK APPROACH

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ABSTRACT

The energy generated by PEM fuel cells can be used in many different applications with emphasis to commercial power generation and automotive application. It requires the integration of various subsystems such as chemical, mechanical, fluid, thermal and electrical ones. Their electrical and thermal time constants are important variables to analyze and consider in the development of control strategies of electronic converters. For this purpose, a mathematical model of the PEM fuel cell system was developed in Matlab/Simulink based on a set of equations describing cell operation. The model considers static and dynamic operating conditions of the PEM. Using experimental measurements at different load conditions made in a Nexa™ PEM fuel cell system, analysis based on linear ARX (Autoregressive with Exogenous Input) and neural network methods were made in Matlab in order to identify the electrical and thermal time constant values. Both linear ARX and neural network approaches can successfully predict the values of the time constants variables. However, the identification by the linear ARX is appropriated around the most significant operation points of the PEM system while neural network allows at obtaining a nonlinear global model. The paper intends to be a contribution for the identification of the electrical and thermal time constants of PEM fuel cells through these two methodologies. The linear approach is simple but presents some limitations while the non-linear one is widespread but more complex to be implemented.

Keywords: PEM fuel cell, Dynamic operation, nonlinear system, Parameters identification, Models comparison.

NOMENCLATURE

A	cell active area (cm2)
C	equivalent electrical capacitance (F)
E_{Nernst}	thermodynamic potential
Jn	no-load current density (A/cm2)
Jmax	maximum current density (A/cm2)
l	membrane thickness (μm)
n	number of cells in stack
PO_2	oxygen partial pressure (atm)
PH_2	hydrogen partial pressure (atm)
R_C	contact resistance (Ω)
T	cell operating temperature (K)
V_{act}	activation voltage drop (V)
V_{ohmic}	ohmic voltage drop (V)
V_{con}	concentration voltage (V)
ξi , ψ	parametric coefficients

INTRODUCTION

Fuel cells are considered clean and efficient energy systems. The overall efficiency of fuel cells can be 80% instead of the net electrical efficiency that varies between 40% and 60%, which are higher than that of almost all other energy conversion systems. They occupy actually an important place in the scenario of renewable energies sources environmentally friend.

There are several different types of fuel cells, most often categorized by the type of electrolyte present. Four of the more common fuel cells are proton exchange membrane fuel cells (PEMFC), phosphoric acid fuel cells (PAFC), molten carbonate fuel cells (MCFC), and solid oxide fuel cells (SOFC). However, the PEMFC is a well known fuel cell and shows to be appropriated for applications in the medium power range.

Because of its efficiency and relatively low operating temperature range, the PEMFC is ideal for residential applications. The PEMFC is especially attractive for automotive applications due to its higher power density (power per fuel cell active area) and lower operating temperature compared to other types of fuel cells [1]. There are many papers presenting and discussing models of fuel cells, particularly the PEMFC [2-6]. These models are based on one of the following approaches: The first approach includes mechanistic models, which aim at simulating the heat, mass transfer and electrochemical phenomena encountered in fuel cells and the second approach includes models that are based on empirical or semi-empirical equations, which are applied to predict the effect of different input parameters on the voltage–current characteristics of the fuel cell, without examining in depth the physical and electrochemical phenomena involved in the operation. The model adopted in this paper is based on the second approach and applies the semi-empirical equations proposed in [5]. This model enables estimation of overall performance of a PEM fuel cell in terms of operation conditions without extensive calculations.

PEMFC has the advantage of this low operation pressure and temperature with higher power density compared to other types of fuel cells. For an adequate design of fuel cells applied to power generation systems subjected to different load changes, it is essential to have an accurate dynamic model for the cell and an adequate control system. So the knowledge of the electrical and thermal time constants has to be got. The main contribution of the present work is the knowledge of electrical and thermal time constants based on linear and nonlinear techniques, which are critical for improving PEMFC performance and lifetime [2]. Although such effects may not be so significant in the case of large fuel cells where the large thermal mass may prevent an excessive temperature excursion but, for smaller fuel cells in the range of a few kW levels, it can have an enormous effect.

In order to predict the values of the time constants variables a linear ARX and a nonlinear or neural network method approaches are presented. The linear ARX approach is used for the identification of the most significant operation points of the PEM system. The neural network approach has the ability to learn the nonlinear function and establishing the mathematical relationship of the dynamic system based on the input-output data. The load current imposed to the fuel cell is considered as input variable and the working temperature of the stack is used as output variable in the neural network identification method.

FUEL CELL OPERATION

Although fuel cell technology development requires a complex multidisciplinary effort, with various subsystems such as; chemical, mechanical, fluid, thermal, electrical ones, the basic concept of fuel cell operation is very simple.

A fuel cell is an electrochemical device that converts chemical energy typically from hydrogen, directly into electrical energy. Similar to a battery, a fuel cell consists of two electrodes (anode and cathode) and an electrolyte. A basic scheme for a single cell is shown in Figure 1.

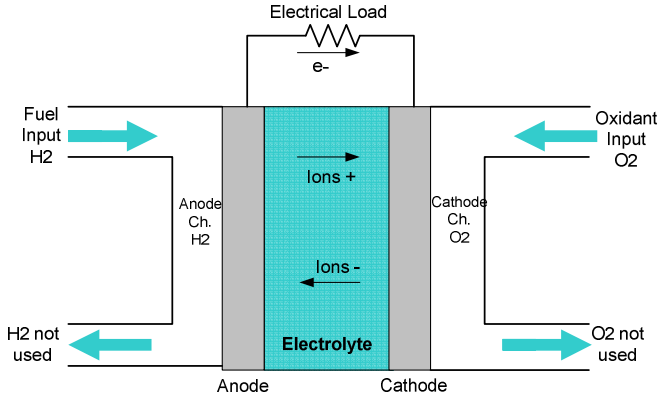

Figure 1 - Scheme of a single cell.

The electrochemical reactions involved in the process can be described by the equations:

In the anode side: $$H_2 \rightarrow 2H^+ + 2e^- \quad (1)$$

In the cathode side: $$2H^+ + \tfrac{1}{2}O_2 + 2e \rightarrow H_2O \quad (2)$$

The overall reaction is: $$H_2 + \tfrac{1}{2}O_2 \rightarrow H_2O \quad (3)$$

MATHEMATICAL MODEL

Equations describing cell operation need to have some knowledge on several parameters which are dependent on cell operation as well as on operating temperature. The electrical equivalent circuit presented in Figure 2 can be used to model the fuel cell dynamical behavior. Equations (4) and (5) represent the fuel cell stack static electrochemical behavior.

For a single cell, the output voltage can be defined as the result of the following expression [4, 5].

$$V_{FC} = E_{Nernst} - V_{act} - V_{Ohmic} - V_{con} \quad (4)$$

For n cells connected in series, forming a stack, the voltage Vs can be calculated by:

$$V_s = n \times V_{FC} \quad H_2 \rightarrow 2H^+ + 2e^- \tag{5}$$

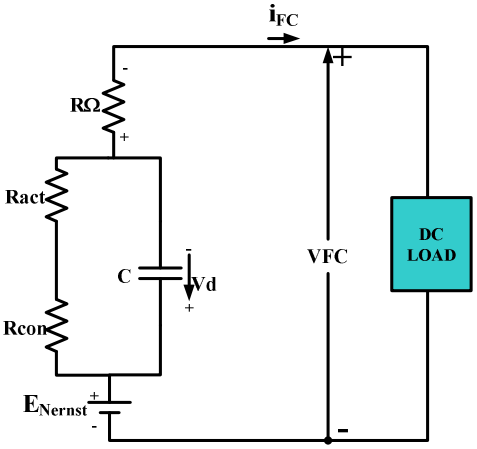

Figure 2 – Electrical equivalent circuit of PEMFC.

In Eq. (4), E_{Nernst} is the thermodynamic potential of the cell and it represents its reversible voltage; Vact is the voltage drop due to the activation of the anode and cathode (also known as activation overpotential); Vohmic is the ohmic voltage drop (also known as ohmic overpotential), a measure of the ohmic voltage drop resulting from the resistances of the conduction of protons through the solid electrolyte and the electrons through its path; and Vcon represents the voltage drop resulting from the reduction in concentration of the reactants gases or, alternatively, from the transport of mass of oxygen and hydrogen (also known as concentration over potential). But there is another voltage drop associated to the internal currents and the fuel crossover. This voltage drop is considered in the model using a fixed current density even at no-load operation (represented by Jn). The first term of Eq. (4) represents the fuel cell open circuit voltage, and the three last terms represent reductions in this voltage to supply the useful voltage across the cell electrodes, V_{FC}, for a certain operation current.

The dynamic behavior of fuel cells and the equations for electrical power generation and efficiency are shown. Each individual term is defined by [5].

$$E_{Nernst} = 1.229 - 0.85 \times 10^{-3} \times (T - 298.15) + \\ + 4.31 \times 10^{-5} \times T \times \left[\ln(P_{H2}) + \frac{1}{2} \ln(P_{O2}) \right] \tag{6}$$

$$V_{act} = -[\xi 1 + \xi 2 \times T + + \xi 3 \times T \times \ln(C_{O2}) \\ + \xi 4 \times T \times \ln(i_{FC})] \tag{7}$$

where ξ1, ξ3, and ξ4 are constant parameters and ξ2 is given by;

$$\xi 2 = 0.00286 + 0.0002 \times \ln A + (4.3.10^{-5}) \times \ln C_{H2} \tag{8}$$

$$V_{ohmic} = i_{FC} \ (R_M + R_C) \tag{9}$$

$$V_{con} = -B \times \ln\left(1 - \frac{J}{J_{max}}\right) \tag{10}$$

$$C_{O_2} = \frac{P_{O2}}{5.08 \times 10^6 \times e^{-\left(\frac{498}{T}\right)}} \tag{11}$$

where, P_{H2} and P_{O2} are partial pressures (atm) of hydrogen and oxygen, respectively. T is the cell absolute Kelvin temperature.

The cell operating current is i_{FC} (A) and CO_2 is the concentration of oxygen in the catalytic interface of the cathode (mol/cm3). The ξi (i = 1,...4) and ψ represent the parametric coefficients for each cell model [5]. R_M is the equivalent membrane resistance to proton conduction. RC is the equivalent contact resistance to electron conduction. Jmax is the maximum current density. B (V) is a constant dependent on the cell type and its operation state. J is the actual cell current density (A/cm2) including the permanent current density Jn.

The equivalent membrane resistance (R_M) can be calculated by [6]:

$$R_M = \frac{\rho_M \times l}{A} \tag{12}$$

where ρ_M is the membrane specific resistivity (Ω. cm) obtained by:

$$\rho_M = \frac{181.6\left[1 + 0.03 \times \left(\frac{i_{FC}}{A}\right) + 0.062 \times \left(\frac{T}{303}\right)^2 \times \left(\frac{i_{FC}}{A}\right)^{2.5}\right]}{\left[\psi - 0.634 - 3 \times \left(\frac{i_{FC}}{A}\right)\right] \times \exp\left[4.18 \times \left(\frac{T - 303}{T}\right)\right]} \tag{13}$$

To account the phenomenon known as "charge double layer" on which the interface electrode/electrolyte acts as storage of electrical charges and energy, represented by an electrical capacitor in the electrical equivalent circuit of Figure 3, the dynamical equation of the model is represented by:

$$\frac{dV_d}{dt} = \left(\frac{1}{C} \times i_{FC}\right) - \left(\frac{1}{\tau} \times V_d\right) \tag{14}$$

where Vd represents the dynamical voltage across the equivalent capacitor (associated with Vact and Vcon); C is the equivalent electrical capacitance; and, τ is the fuel cell electrical time constant defined as:

$$\tau = C \times Ra = C \times (R_{act} + R_{con}) = C \times \left(\frac{V_{act} + V_{con}}{i_{FC}}\right) \tag{15}$$

where, Ra is an equivalent resistance.

Including the dynamic behavior represented by Eq. (14), the resulting fuel cell voltage is then defined by:

$$V_{FC} = E_{Nernst} - V_{Ohmic} - V_d \qquad (16)$$

The electrical output of the cell can be linked to any load, with no restriction related to the load type since the power supplied by the stack is enough to feed it.

EXPERIMENTAL SETUP

In order to validate the proposed approach a commercial fuel cell system was used. The experimental setup consists of a Nexa™ PEM fuel cell, the resistor load, the measurement system and cooling system. The set of resistor load provides a variable load to the fuel cell, which will be used to test its static and dynamic performance for different temperature conditions.

The Nexa™ PEM fuel cell is a Ballard Power Systems Inc. and has been projected for providing 1.2kW of unregulated dc output .This stack has 43 elements and each ones produces about 1 volt at open-circuit and about 0.6 volts at full current output. Figure 3 below shows the overview of the Nexa™ and load banc, which was used for the experimental results.

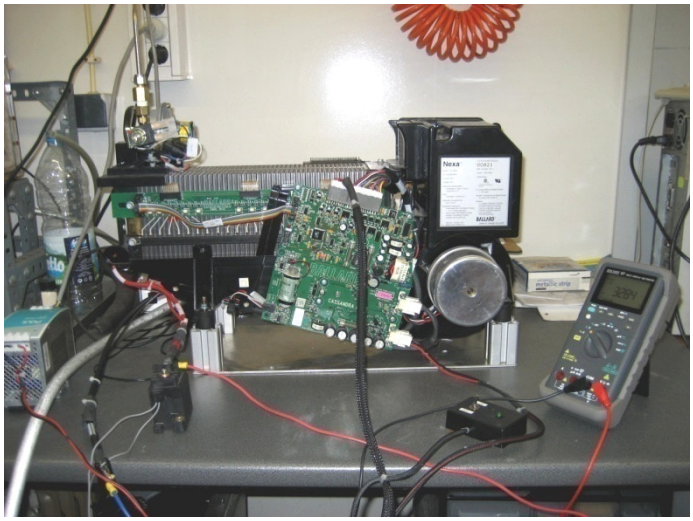

Figure 3 – Overview of the experimental setup.

LINEAR IDENTIFICATION OF TIME CONSTANTS

The problem of system identification is the estimation of a system model based on the observed input-output data. There are several ways to describe a system and to estimate such descriptions. The procedure to determine a model of a dynamic system from observed input-output data involves three basic components:

1. The input-output data.
2. A set of candidate models (the model structure).
3. A criterion to select a particular model in the set, based on the information in the data (the identification method).

Linear identification methodologies are techniques for estimating parameters for a given model structure. This model describes the relationships between input signals and output signals, such that the outputs are partly determined by the inputs.

The identification of the electrical and thermal time constants of the PEM system uses ARX and residue functions where: ARX function is applied to determine the polynomial vectors of the model using the least square method and residue function is used to convert the quotient of these polynomials to pole-residue representation. The methodology adopted is as follows.

A. Linear identification methodology

A typical identification process consists of stages that iteratively select a model structure, compute the best model in this structure, and evaluate the model properties. In the present study the parameters were estimated through the ARX function. ARX function can be applied in continuous and discrete time domains. In the present, the data to be analyzed are in discrete time domain and the ARX function returns a model containing the correspondent coefficients of numerator and denominator of a discrete time transfer function that characterizes the system.

Syntax of ARX function:

m=arx(**data**,orders)

m=arx(**data**,'na','na','nb','nb','nk','nk')

where:

data is an **iddata** object that contains the input-output data. Both time and frequency-domain signals are supported, and data can also be a frd or idfrd frequency-response data object. However, multioutput continuous-time models are not supported by ARX.

orders is given as *orders = [na nb nk]* defining the orders and delay of the ARX model.

The parameters of ARX model structure can be estimated using the least squares method.

$$A(q)\,y(t) = B(q)u(t) + e(t) \qquad (17)$$

Specifically, in discrete time application of ARX function is represented by:

$$na: A(q) = 1 + a_1 q^{-1} + ... + a_{na} q^{-na} \qquad (18)$$
$$nb: A(q) = 1 + b_1 q^{-1} + ... + b_{nb} q^{-nb+1}$$

For models with one output, continuous-time models can be estimated from continuous-time (frequency-domain) data. The orders are then interpreted as *na* being the number of estimated denominator coefficients and *nb* being the number of estimated numerator coefficients. This means that if na = 4 and nb = 2 the model can be;

$$G(s) = \frac{b_1 s + b_2}{s_4 + a_1 s^3 + a_2 s^2 + a_3 s + a_4} \qquad (19)$$

For continuous-time models the delay parameters nk have no meaning and should be omitted.

B. Poles system determination

Residue function is applied in the identification of the poles system. The number of poles is n=length (A)-1= length (R) = length (P). Function residue converts a quotient of polynomials to pole-residue representation, and back again.
Syntax of residue function:
[r,p,k]=residue(B,A)
where;
r:Column vector of residues
p:Column vector of pole locations
k:Row vector of direct terms

Vectors A and B specify the coefficients of the numerator and denominator polynomials in descending powers of s as follows.

$$\frac{B(s)}{A(s)} = \frac{R(1)}{s - P(1)} + \frac{R(2)}{s - P(2)} + \ldots + \frac{R(n)}{s - P(n)} + K(s) \quad (20)$$

C. Transfer function in continuous- domain

The expression of transfer function of the system in continuous-time domain corresponds to estimated data and is represented by eq.(20).

$$f(t) = A \times \left[1 - \left(k1 \times e^{-(t/\tau 1)} + k2 \times e^{-(t/\tau 2)}\right)\right] \quad (21)$$

where:
A: is the step value or input u(t)
K1: is the constant value
τ1: electrical time-constant of fuel cell system
K2: is the constant value
τ2: thermal time-constant of the fuel cell system

D. Validation of the linear methodology

The methodology explained above for the linear time constants identification was validated using experimental results obtained with the Nexa™ PEM fuel cell system, considering a sampling time of one second (Tsample=1s), as represented in Figure 4. These results show that the stack temperature changes proportionally to the load level applied to the stack. The Nexa™ fuel cell stack is air-cooled. A cooling fan located at the base of the unit blows air through vertical cooling channels in the fuel cell stack. The fuel cell operating temperature is maintained at 65°C by varying the speed of the cooling fan. Figure 4 also shows the existence of a typical time delay which is associated with the internal control of the system. The methodology adopted does not consider this delay time for the identification of the electrical and thermal time constants as can be observed in Figure 5.

The error between the experimental and estimated results has validated by Eq. (22).

$$\tau_{\exp} = \left[\frac{\tau_{sim} - \tau_{\exp}}{\tau_{\exp}}\right] \times 100\% \qquad (22)$$

where $\tau_{sim} = \tau_1 + \tau_2$ and corresponds to the estimated time constant and τexp corresponds to the experimental one.

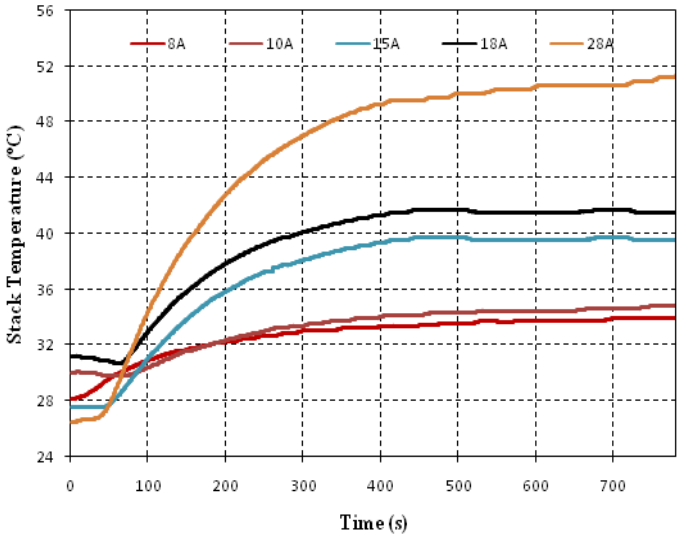

Figure 4 – Experimental results for different load levels.

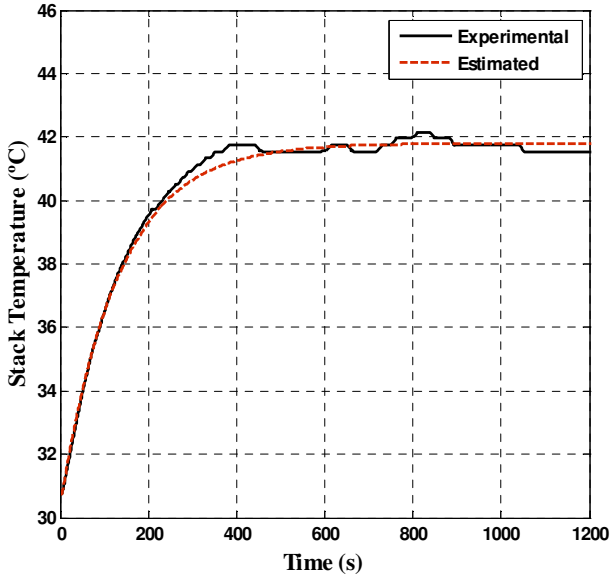

Figure 5 – Experimental and estimated results for the load level of 18A by linear approach.

Experimental and estimated plots are practically coincident as can be observed in Figure 5 for the step current of 18A.

Therefore, it can be concluded that the identification using linear ARX methodology is appropriated around the most significant points of operation and serves perfectly the purpose. Similar plot results were obtained for other step values of the load.

Table 1 and Table 2 summarize the information obtained with this methodology considering the experimental results of Figure 4.

From table 1 it can be concluded that:

1. Results obtained through the tests made with the PEM fuel cell system clearly presents two time constants $\tau 1$ and $\tau 2$, which corresponds to a second-order system.
2. The thermal time-constant value $\tau 2$ is clearly higher than the electrical time-constant value $\tau 1$.
3. The experimental time-constant value τexp of the Nexa system is the sum of electrical time-constant $\tau 1$ and thermal time-constant $\tau 2$.
4. The electrical time-constant value $\tau 1$ depends of the operation condition of fuel cell system. It increases with the increase of the load current.
5. The thermal time-constant value $\tau 2$ is much higher than the electrical time-constant and does not depend on the load current. The mean value of $\tau 2$ is approximately 153.2 s.
6. The error between experimental and estimated results is less than 1%.
7. The mean value of the error is 0.64% with a standard deviation of 0.19%.

From table 2 the main conclusions are:

The gain of the system is dependent on the step current value applied and it is always less than one. A linear methodology can be successfully used to identify the time-constant variables of a PEM fuel cell. However, although good results have been obtained in this method, it is necessary to define a transfer function for each condition. Considering that they are non-linear relationships and taking into account that all transfer functions are of same type, the problem can be analyzed as follows:

$$G(z) = \frac{Y(z)}{U(z)} = \frac{b_1 z}{z^2 + a_1 z + a_2} = \frac{b_1 z^{-1}}{1 + a_1 z^{-1} + a_2 z^{-2}} \quad (23)$$

The output can be expressed through the expression:

$$Y(z) = -a_1 Y(z) z^{-1} - a_2 Y(z) z^{-2} + b_1 U(z) \quad (24)$$

Or,
$$y_k = f(y_{k-1}, y_{k-2}, +u_{k-1}) \quad (25)$$

The use of neural networks can overcome this disadvantage since it enables to find a transfer function satisfying any condition. The adopted methodology, the network structure and obtained results with neural network approach to this problem are presented below.

Table 1: Time constants and errors for several load levels (steps).

Step	τexp (s)	Simulation				$\tau error$ (%)
		K1 (int)	K2 (int)	$\tau 1$ (s)	$\tau 2$ (s)	
8A	140	-0.012	0.69	1.11	138.47	0.30
10A	190	-0.007	0.51	1.47	187.03	0.78
15A	140	-0.013	0.81	1.01	140.08	0.77
18A	130	-0.015	0.63	2.10	131.65	0.53
28A	170	-0.020	0.92	2.63	168.77	0.82
					Mean value (%):	0.64
					Standard deviation (%):	0.19

NOTE: $\tau 1$: Electrical time-constant, $\tau 2$: Thermal time- constant, $\tau exp \approx \tau 1 + \tau 2$.

Table 2: System poles, transfer function and gain of the system.

Step	System Poles		Transfer function	Gain system
8A	0.9928	0.3773	$G(z) = \frac{0.0030z}{z^2 - 1.3701z + 0.3746}$	0.6667
10A	0.9947	0.4928	$G(z) = \frac{0.0014z}{z^2 - 1.4875z + 0.4902}$	0.5185
15A	0.9929	0.3395	$G(z) = \frac{0.0038z}{z^2 - 1.3323z + 0.3377}$	0.8085
18A	0.9924	0.6150	$G(z) = \frac{0.0018z}{z^2 - 1.6075z + 0.6104}$	0.6207
28A	0.9941	0.6802	$G(z) = \frac{0.0017z}{z^2 - 1.6743z + 0.6762}$	0.8947

NEURAL NETWORK IDENTIFICATION OF TIME CONSTANTS

Neural networks (NN) have been described as a representation of a mathematical formulation that receives values (inputs) and gives results (outputs). The NN has the ability to learn a specific process for which it is trained. It allows obtaining at the output the expected value whatever the value placed in the input (assuming that it was well trained). Because of their inherent design features they can be applied to linear and nonlinear problem domains.

There are many different types of neural network (NN) models that have been developed for various applications, the most popular include multilayer perceptron (MLP) in which the neurons are organized by layers, trained generally with the algorithm, back-propagation (BP) of error, radial basis function (RBF), learning vector quantization in among others.

NNs can be classified as feed-forward while others are recurrent ones (i.e. implement feedback) depending on how data is processed through the network. NNs can also be classified by their learning method or training as some employ supervised training while others are self-organized or unsupervised [7- 9].

As observed earlier, the prediction of the time constant variables by linear ARX approach was successful but the method is appropriated only around the most significant operation points of the PEM system. So, an analysis on a method allowing at establishing a nonlinear global model should be developed. The approach based on NNs shows to be appropriate to.

In order to select a good NN configuration, there are several factors to take into consideration such as, the network design, the training method and practical considerations [9]. Next point presents the methodology adopted of the NN architecture for this case study.

A. Neural network architecture

The architecture of the network is defined by the organization on the neurons. The design considerations include determining the number of input and output nodes to be used, the number of hidden layer in the network and the number of hidden nodes used in each hidden layer [7-9]. The number of input nodes is typically the same as the number of state variables. In the case of feed-forward architecture, the outputs of a layer are the inputs of the following one. The hidden layer is composed by an adequate number of neurons, specified by the user, while the output layer possesses the neurons as the outflow of the system, which in this case is only one. The schematic diagram of Figure 6 represents the neural network architecture used in this study.

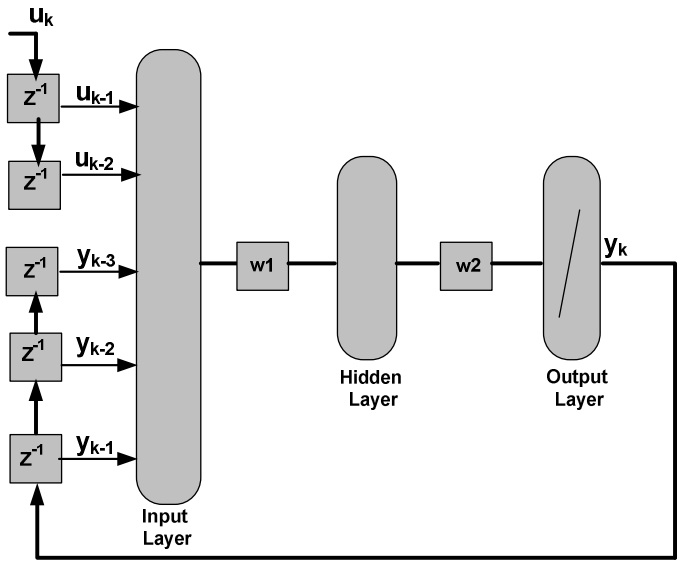

Figure 6 –NN architecture with three layers and dynamical memory.

The input layer should present a number of entries ($y_{k-1}, y_{k-2}, \ldots \; u_{k-1}, \ldots$) in accordance with the stipulated memories. As this type of neural network is said to proactive network model or NARX model (Nonlinear Autoregressive with Exogenous Input). It can be represented by Eq. (26):

$$y_k = f\left(y_{k-1}, y_{k-2}, \cdots, y_{k-n_a}, u_{k-1}, u_{k-2}, \cdots, u_{k-n_b}\right) \quad (26)$$

B. Neural network methodology

The fuel cell system was operated with the load bank in order to use the data in the proposed neural network algorithms. The data sets collected are the stack current (A) as input data and the stack temperature (◦C) as output data.

Range of input data: stack current (A) range from 1 to 42.8A, with a total of 1008 data points.

Range of output data: stack temperature range from 28 to 56 ◦C.

1. Data manipulation for training and validation

Normally it is chosen a set of training data and a set of validation data that are statistically significant and representative of the system under consideration. The training data set is used to train the NN, while the validation data is used to validate the network performance, after the finish of the training phase [7]. Training data set needs to be fairly large and contains variety of data in order to contain all the needed information. Therefore, in the present case study, from the 1008 points of collected data, 770 points are used for the training phase and all data points are used for validation phase. Figure 7 shows the graphs of input and output data used in the NN training process.

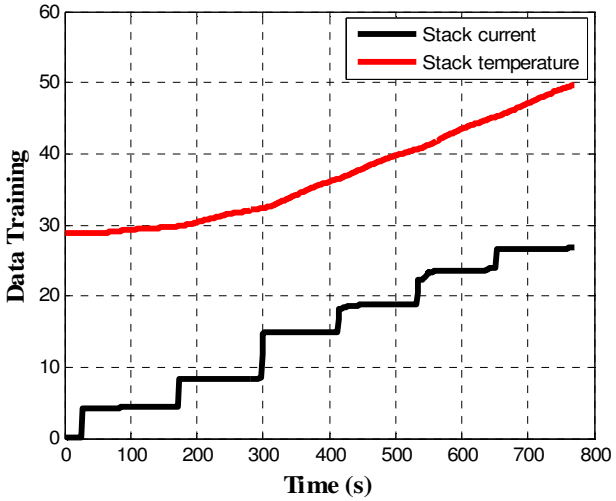

Figure 7 – Data used for training the network.

When training data set is presented to the network, the weights and biases are up until the entire training data set is completed. This process is called one "epoch". The number of "epoch" indicates the speed of the training method. The training phase is repeated until the network performs well according to an error goal defined by the user. In consequence, the validation data is presented to ensure that the network has learned the general patterns, not just simply has memorized the data set. If the network still performs well, in this phase, the training is completed and the neural network can be used for whatever input data placed in the input.

2. Network initialization and training

To be able to produce the correct output data, various training algorithms of backpropagation (BP) and radial basis function (RBF) networks were tested. Levenberg_Marquardt – BP algorithm shows to be the best solution for this case study, since it is efficient, easy to implement and is not time consuming. Through the function *newff* included in Neural Network library of MATLAB [10] the feed-forward backpropagation network was created.

3. Performance evaluation

The criteria selected to investigate the performances of the neural network on the evolution of the stack temperature of the 1.2kW Nexa™ fuel cell system are:

(a) Number of epochs: indicates the training speed.

(b) Error (E): indicates the average error of the prediction by the equation.

$$E = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \quad (27)$$

During the training process the error function (E) is minimized with the increasing number of epochs. During this process, the network will adjust its weights and biases until the output error reaches the designated error goal. Figure 8 corresponds to the Levenberg_Marquardt–BP performance during the training process, and Figure 9 shows the performance of the NN model for the validation process.

C. Validation of NN methodology

For the step current of 18A, for example, as can be observed through Figure 10 and by comparison with the correspondent Figure 5, both linear ARX and neural network approaches can successfully predict the values of the time constants variables. However, the identification by the linear ARX is appropriated around the most significant operation points of the PEM system while neural network allows at obtaining a nonlinear global model. Therefore the non-linear representation with the NNs allows obtaining good results for any value of the input current.

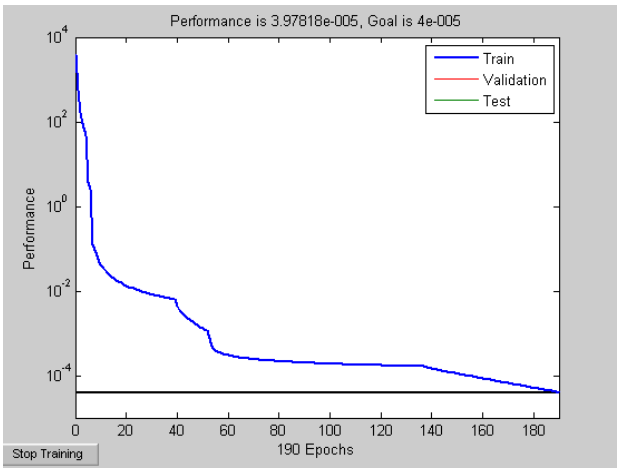

Figure 8 – Levenberg_Marquardt–BP performance during the training process.

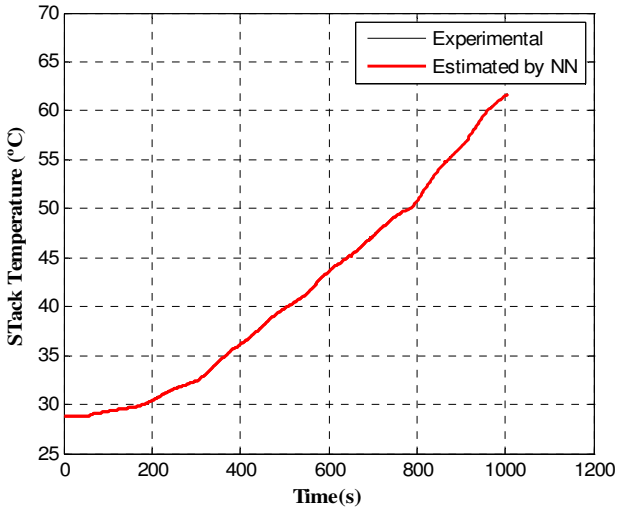

Figure 9 – Performance data for NN validation.

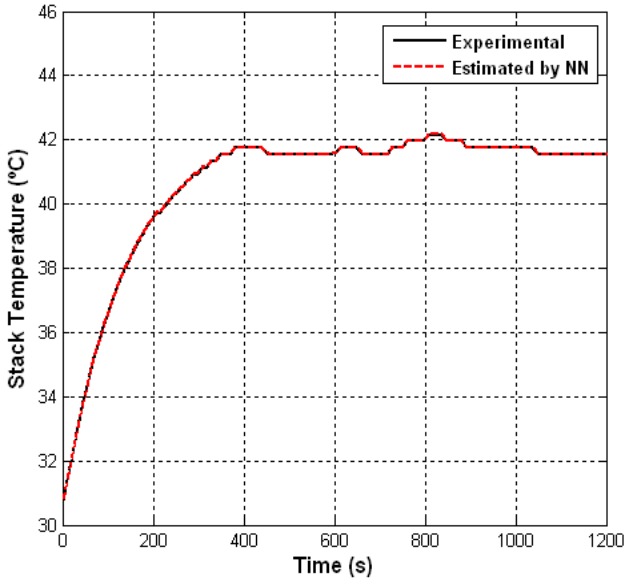

Figure 10 –Experimental and estimated results for the load level of 18A by NN approach.

CONCLUSIONS

The performance of the PEM fuel cells is known to be influenced by many parameters, such as operating temperature, pressure and discharge current. In order to improve the fuel cell performance, it is important to understand the effects of these parameters on the operation of the PEM fuel cell. The electrical and thermal time constants are important variables and need to be considered on the development of control strategies of power electronic converters applied to these systems.

In this paper a mathematical model of the PEM fuel cell was presented based on a set of equations describing the cell operation. For the identification of electrical and thermal time constants, linear versus non-linear approaches were considered.

Both linear and non-linear approaches showed to be suitable to predict the values of the time constants variables. However, the identification by the linear approach is appropriated around the most significant operation points of the PEM system while the nonlinear one allows at obtaining a global model. The linear approach is simple but presents some limitations while the non-linear one is widespread but more complex to be implemented.

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