



Neural Network Based Model for a PEM Fuel Cell System

I. Zamora¹, J.I. San Martín², J.J. San Martín², V. Aperribay², P. Eguía¹

Department of Electrical Engineering - University of the Basque Country

¹ Escuela Técnica Superior de Ingeniería de Bilbao

Alda. Urquijo s/n, 48013 Bilbao (Spain) – e_mail: inmaculada.zamora@ehu.es

² Escuela Universitaria de Ingeniería Técnica Industrial de Eibar

Avda. Otaola, 29, 20600 Eibar (Spain) – e_mail: iepadij@sb.ehu.es

Abstract. Usually, modelling of fuel cell systems uses complex expressions, based on the knowledge of physical-chemical phenomena. These models require a good knowledge of the parameters involved in the processes that, in many cases, are difficult to determine. A solution to avoid this difficulty consists in using black-box models, such as those based on artificial neural networks (ANN).

This paper presents the modelling of a PEM fuel cell system, using ANNs. The selected ANN structure has been validated for the transient state, during the start up of the system, and in steady state. Results are shown for a commercial PEM fuel cell system.

Keywords

Fuel Cells, PEMFC, System Identification, Modelling, ANN.

1. Introduction

Fuel cells are highly non-linear systems. So, appropriate system identification techniques should be used to obtain, in an experimental way, a good model. This model should reproduce, with enough accuracy, the dynamic characteristics of the analysed process.

Currently, a high number of models that describe the behaviour of a fuel cell exist, estimating the voltage for a given group of parameters. However, few models are able to predict the transition process between two steady state points. In this sense, around 80% of the operating situations in fuel cells applied to road transport is dynamic [1]. For that reason, dynamic simulations are needed to improve the reliability of fuel cell systems. However, the models based on physical principles, described by means of differential equations, are quite complex and need a high computing time.

In this context, this paper presents the modelation of fuel cell systems behaviour by means of ANNs. This technique needs to know the inputs and its corresponding outputs, without necessity of additional information. These required data have been obtained from measurements taken in a commercial PEM fuel cell system.

2. PEMFC modelling with ANNs

The empiric equations used to model a PEMFC stack, give the fuel cell voltage as indicated in expressions (1) and (2), [3], [4].

$$E = E_o - b \log i - R \cdot i - m \exp(ni) \quad (1)$$

$$E = E_o - b \log i - R \cdot i - a \cdot i^k \cdot \ln(1 - \beta i) \quad (2)$$

Where: E_o is the open circuit voltage; b and R represent the Tafel slope and the ohmic resistance, respectively, and m , n , α , β and K are constants of the empiric equation. These parameters are derived from mathematical and statistical considerations.

The problem is that the value of the aforementioned constants depends on the physical properties and the operating conditions of the fuel cell. On the other hand, the mathematical relationship between these constants and the physical properties or operating conditions is not well defined [5].

In [6] and [7], these constants are presented, under representative operating conditions. However, to avoid the calculation of those constants in a wide range of operating conditions, techniques based on ANNs can be used to model the physical processes [8].

ANNs simulate the behaviour of natural systems by means of the interconnection of basic processing units called neurons. Neurons are highly connected with each other by means of links. They can receive external signals or signals coming from other neurons affected by a factor called 'weight'. The output of the neuron is the result of applying a specific function, known as 'activation or transfer function', to the sum of its inputs, plus a threshold value called 'bias'. With these general characteristics it is possible to develop different network structures.

Depending on the type of problem we are dealing with and its specific conditions, the most adequate network structure will be different. Besides, within the same type of neural network, there are several configurations: number of layers, number of neurons in each layer, transfer functions and learning rules.

Although the modelling using ANNs has great advantages, also presents some disadvantages. Among them, the complexity in selecting the right type of network and its architecture (number of layers, number of neurons per layer, activation functions, learning algorithm parameters, etc) can be emphasized. In fact, the number of structures that can be used for solving a problem is very large, and so, it is necessary to make a good selection of the network to use. For this purpose a software tool, called SARENEUR [11], has been used. This software has been developed in the Matlab environment and allows selecting and verifying the performance of neuronal networks.

First of all, the type of ANN and the learning rule must be defined. For our model, the Multi-Layer-Perceptron with the Backpropagation learning rule has been selected.

Besides, one factor in determining the right size and structure for the network is the number of inputs and outputs which it must have. The lower the number of inputs, the smaller the network can be. However, sufficient input data to characterize the problem must be met. Thus, the following parameters have been considered:

- Input parameters: fuel cell temperature, hydrogen consumption, hydrogen pressure, oxygen flow and inlet air temperature.
- Output parameters: fuel cell voltage and current.

When applying the SARENEUR tool, two different situations have been considered: the fuel cell in steady state and the start up transient. Initially, several valid structures have been obtained for the steady state, and their performance have been validated with data measured during the start up transient. Afterwards, a solution has been proposed that uses the same ANN structure for both situations, with good agreement with the measurements. Thus, with the aim of obtaining only one structure of ANN, which can be applied in both situations, it was decided to apply a logarithmic scale, as shown in expression (3).

$$\text{new data} = \log(\text{old data} + 10) \quad (3)$$

3. Results

A group of experimental measurements have been made of a commercial Fuel Cell System Nexa Ballard of 1.2 kW to obtain enough data to train and test the selected ANN structure. These measurements include different parameters, such as: temperature of the stack of the fuel cell system, current, voltage, hydrogen consumption, hydrogen pressure, air flow stoichiometry, etc. For each parameter, a total of 2004 samples have been recorded.

As it has been justify, for this fuel cell, the ANN structure which presents good results in the start up transient and the steady state is the structure MLP 5-5-2, with activation functions L-P. It means that the selected ANN structure is a Multilayer Perceptron with 5 input data (fuel cell temperature, hydrogen consumption, hydrogen pressure, oxygen flow and inlet air temperature) and 2 output data (voltage and current). Besides, the ANN structure has a hidden layer with 5 neurons and the activation functions are log-sigmoid and linear. Finally, a logarithmic scale has been applied to the input data, as shown in expression (3)

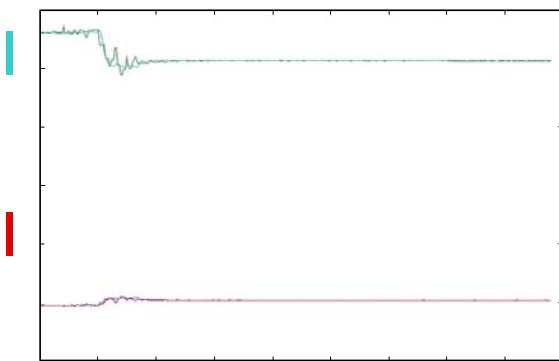


Fig. 1. PEMFC system voltage and current, in transient and steady state

Figure 1 shows the voltage and current curves of the fuel cell system Nexa Ballard of 1.2 kW. This figure shows the

simulated values and the measured data, from the start up to the steady state. It can be appreciated that the results obtained with the selected ANN structure and the real data are almost superimposed.

4. Conclusions

This model allows predicting the behavior of the PEMFC technology in the transient (start up) and steady state.

The training strategy and the ANN topology have been tested with numerous parameters and network structures, to obtain high precision results. The software tool SARENEUR has been used in this process. The final selected ANN structure has been validated with experimental data obtained from the commercial device Nexa Ballard, of 1.2 kW. Finally, it is interesting to point out that it has been necessary to normalize the input data with a logarithmic scale.

Acknowledgements

The work presented in this paper has been carried out by the research team of Project ENE2006-15700-CO2-02/CON, supported by the Ministry of Education and Science of Spain and by the Regional Council of Guipuzcoa.

References

- [1] M. Meiler, O. Schmid, M. Schudy, E.P. Hofer, "Dynamic fuel cell stack model for real-time simulation based on system identification", *Journal of Power Sources*, Vol.176, pp.523-528, 2008.
- [2] R. Dittmar, B.M. Pfeiffer, "Modellbasierte prädiktive Regelung, Eine Einführung für Ingenieure", Oldenbourg Wissenschaftsverlag, München, Berlin, 2004.
- [3] J.C. Amphlett, R.M. Baumert, R.F. Mann, B.A. Peppley, P.R. Roberge, T.J. Harris, "Performance Modeling of the Ballard Mark IV Solid Polymer Electrolyte Fuel Cell, I. Mechanistic Model", *Journal of the Electrochem Society*, Vol.142, pp.1-8, 1995.
- [4] J.H. Lee, T.R. Lalk, "Modeling fuel cell stack systems", *Journal of Power Sources*, Vol.73, pp.229-241, 1998.
- [5] W.Y. Lee, G.G. Park, T.H. Yang, Y.G. Yoon, H.S. Kim "Empirical modeling of polymer electrolyte membrane fuel cell performance using artificial neural networks", *International Journal of Hydrogen Energy*, Vol.29, pp.961-966, 2004.
- [6] J.H. Lee, T.R. Lalk, A.J. Appleby, "Modeling electrochemical performance in large scale proton exchange membrane fuel cell stacks", *Journal of Power Sources*, Vol.70, pp.258-268, 1998.
- [7] G. Squadrito, G. Maggio, E. Passalacqua, F. Lufrano, A. Patti, "An empirical equation for polymer electrolyte fuel cell behaviour", *Journal Applied of the Electrochem Society*, Vol.29, pp.1449-1455, 1999.
- [8] S. Jemei, D. Hissel, M.C. Pera, J.M. Kauffmann, "On-board fuel cell power supply modeling on the basis of neural network methodology", *Journal of Power Sources*, Vol.124, pp.479-486, 2003.
- [9] C.M. Bishop, "Neural Networks for Pattern Recognition", Oxford University Press, 1995.
- [10] S. Haykin, "Neural Networks: A Comprehensive Foundation", 2nd ed., Prentice-Hall, Inc., 1999.
- [11] A.J. Mazon. I. Zamora. J. Gracia. K.J. Sagastebeitia. J.R. Saenz. "Selecting ANN structures to find transmission faults". *IEEE Computer Applications in Power*. Vol.14, n°3, pp.44-48, July 2001.