International Conference on Renewable Energies and Power Quality (ICREPQ'14)
Cordoba (Spain), 8th to 10th April, 2014
Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, No.12, April 2014

Control of a PEM fuel cell based on maximum power tracking using radial basis function neural networks

A. Ruiz[1], J.E. Jiménez[1]

[1] Department of Computer Science and Numerical Analysis
E.P.S., Córdoba University
Campus of Rabanales, 14071 Córdoba (Spain)
Phone/Fax number: +0034 957 218729, e-mail: aruiz@uco.es, jjimenez@uco.es

Abstract. This article presents the proposal of a two-level control approach for a type of commercial PEM fuel cell. Thus, in the external control level a model based on neural networks of the FC is used together with a tracking algorithm to follow the maximum efficiency points as a function of the oxygen excess and in the internal level, a PI control strategy is used to guarantee the compressor motor voltage that satisfies the oxygen excess ratio demanded. The neural model of the FC response is developed through the steady-state FC response provided by the physical modelling using a multimodel approach. This approach allows a good relation between the computational cost of the training and the performance that the network offers. The performance of the global controller and the tracking algorithm are evaluated for variable load conditions by simulations and conclusions are drawn.

Key words

PEM fuel cell, radial basis function neural networks, maximum power tracking.

1. Introduction

The progressive increasing in electrical energy demand together with environment constraints have made the fuel cells one of the most promising renewable sources of electrical energy. The commercial fuel cells can generate electrical power ranging milliwatts to kilowatts covering numerous applications from the area of distributed power grids up to residential or the propulsion of vehicles. Specifically, the PEM FCs (protom exchange membrane fuel cells) are environment friendly as the only derived byproducts are water and heat [1] and because of their high power density, solid electrolyte, low corrosion and low temperature operation they have became a popular technology for ground vehicle applications [2-4].

However, in order to be able to compete with internal combustion engines, PEM fuel cells should operate and function at least with similar performance. The abrupt changes caused by transient behaviour in the power demanded by vehicles are particularly critical since it entails the control of several coupled devices such as the air and fuel flow, pressure regulation and heat and water management to maintain optimal temperature, membrane hydration and thus preventing fuel cell stack voltage degradation and extending the fuel cell life [3]. The main losses are caused by the compressor consumption and therefore, its operation point optimization is one of the main control objectives [5]. The difficulty lies in providing sufficient oxygen excess to ensure fast transient responses and minimize auxiliary power consumption. High oxygen excess ratio improves the power provided by the FC but, after an optimum value is reached, further increase causes an excessive increment in compressor power reducing the system net power. In contrast, abrupt reductions of the oxygen excess during the transitory responses could degrade the FC as a result of the oxygen starvation phenomenon.

The development of PEM FCs and the testing of their transient behaviour are quite costly and time consuming, and thus the use and simulation of mathematical models has become an important tool in fuel cells study. In this context, over the last decade, numerous fuel cell models based on neural networks have been proposed. Some examples are described in [6-7]. Most of these models are focused on understanding the effect of various operating, geometrical and material parameters on the fuel cell performance and have been successfully used in the optimization of fuel cell design but they are not suitable for analysis and control of the transient behaviour of fuel cells [4,8-9] or they are very computational demanding. In this context, this paper stresses the use of the control-oriented models and proposes an intelligent approach based on low computational cost neural networks to improve the maximum net power point following for variable load conditions.
The organization of the paper is as follows. The model of the FC employed in simulations is briefly outlined in section 2. The control strategy is described in section 3. The main results obtained are presented and discussed in section 4. The main conclusions resulting from this work are summarized in section 5.

2. Fuel Cell Model

To evaluate the control approach, this work has considered the fuel cell model proposed in [4]. This model is implemented as a non-linear dynamic model for control study of a commercial PEM fuel cell and is widely accepted and useful as test-bench where evaluating control strategies. The model developed by Pukrushpan describes with reasonable precision the overall dynamic behaviour, which consists of four interacting sub-models; the stack voltage, the anode flow, the cathode flow, and the membrane hydration models (see Fig. 1). Thus, the voltage model contains an equation to calculate the FC voltage $\boldsymbol{E_{fc}}$ that is based on the FC temperature, pressure, reactant gas partial pressures and membrane humidity and is described as

$$\begin{aligned} E_{fc} &= 1.229 - 0.85 \cdot 10^{-3}\left(T_{fc} - 298.15\right) \\ &+4.3085 \cdot 10^{-5} T_{fc}\left[\ln P_{H_2} - \ln P_{O_2}\right] \end{aligned} \tag{1}$$

Particularly, this model assumes that internal temperature and humidity conditions are under control and can be considered to be constant. The hydrogen supply is considered controlled by a proportional controller that regulates an inlet valve such that the reference of hydrogen pressure at the anode follows the air pressure at the cathode. Assuming such premises, the fuel cell is operated by controlling the oxygen air pressure using the compressor voltage as the input manipulated variable. The demanded current is considered as a disturbance input. The controlled variable corresponds with the oxygen excess ratio named as λ_{O2} (ratio between the rate at which oxygen is supplied, $W_{O2,in}$ and the rate at which oxygen is consumed in the cathode, $W_{O2,reac}$). The main features of the FC physical model are described in [4].

$$\lambda_{O2} = \frac{W_{O2,in}}{W_{O2,reac}} \tag{2}$$

Although the coefficient λ_{O2} does not constitute a measurable variable, this directly or indirectly represents one of the most typical controlled variables because of its importance to avoid the oxygen starvation phenomenon. This effect is caused by insufficient hydration of the membrane and can degrade the FC performance and deteriorate it. This value is assumed to be inferred as of the non-linear model of the FC by using an observer [3]. The reference value for λ_{O2} to avoid starvation is set equal to 2.

In this context, there are two control objectives and for this reason the control system is defined as a two-level cascade control configuration. Firstly, the membrane should be sufficiently hydrated to avoid the starvation phenomenon and secondly, the FC should give a fast response providing the maximum net power, that is, it should achieve the lowest losses caused by the compressor according to the following equation

$$P_{net} = P_{fc} - P_{comp} \tag{3}$$

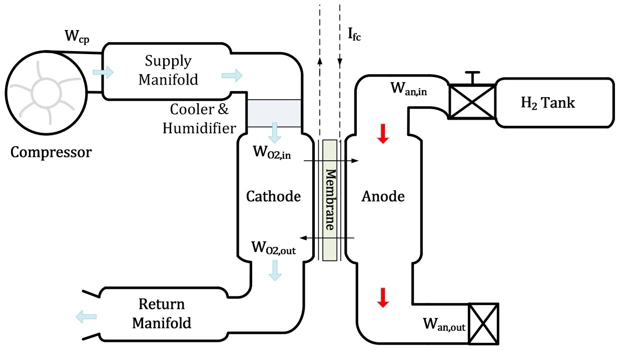

Fig. 1. Schematic diagram of the FC system [4]

where P_{comp} is the motor compressor consumption which is derived from the FC model, and P_{fc} is the power supplied by the fuel cell stack, which is given by

$$P_{fc} = I_{fc} E_{fc} \tag{4}$$

3. Control Strategy

Since the FC is a system difficult to control, a more advanced controller has to be used to satisfy the requirements. As aforementioned, a two-level cascade control strategy is proposed in this work to follow the maximum efficiency path. In the external level an optimizer based on neural networks is used to estimate the path of maximum net power (or minimum compressor losses) in terms of oxygen excess ratio λ_{O2}, and to improve the transitory response. In the internal level a classical PI controller is used to avoid the starvation phenomenon and to follow the set-points described by the optimizer.

3.1 Maximum net power tracking based on Neural Models

Artificial neural networks (ANNs) are a type of technique in the field of artificial intelligence that allows approximate non-linear relationship between the inputs and the outputs of a complex system without requiring an explicit mathematical model. They are capable of learning from experience, improving its performance and adopting to the changes in the environment. Specifically, the RBFNNs (Radial Basis Function Neural Networks) are easy to design because they have just three layers and they provide good generalization, high tolerance of input noises, and the ability of online learning and can be used to approximate functions with zero error on the design vectors.

In this paper a set of RBFNNs is used as a semi-empirical model to estimate the optimal values of the oxygen excess ration that follows the maximum net power points. Noted that the efficiency of a fuel cell is usually characterized by the state-steady net power behavior. Such curves define the power supplied by the cell minus the one spent by the compressor) with respect to oxygen excess ratio when the demanded current (I_{fc}) varies (Fig. 2). Blue dashed lines in Fig 2 represent the results

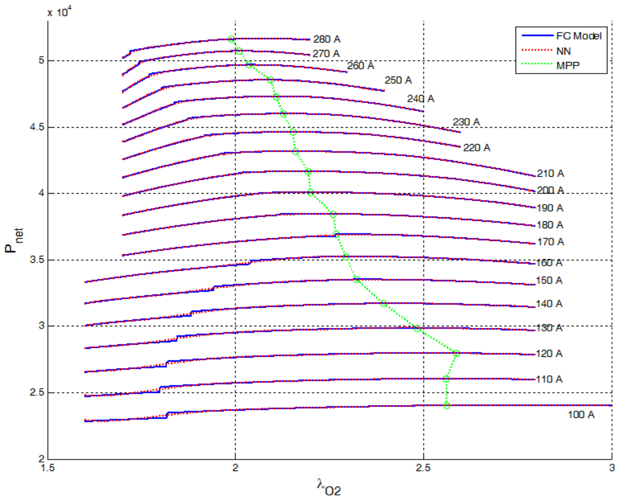

Fig. 2. Steady-state FC net power for variable oxygen excess ratio and current (blue lines). Neural networks identified trajectories (red dashed lines). Maximum net power path (green dashed lines).

obtained with the non-linear FC model considered for simulations [4]. The peaks of these curves give the optimum operation points in every situation as a function of the demanded current. To develop the neural optimizer, each RBFNN of the set is used to identify a specific curve of the Fig. 2. To this aim it was used the Matlab Neural Networks Toolbox. The training data set was obtained by experimenting with the non-linear FC model according to the configuration in Fig. 3 (which corresponds with the internal level of control).

The non-linear FC model was used to calculate approximately 1500 different cases. Main operational parameters of the cell were varied, such as, the stack current and the oxygen excess ratio are varied from 100 to 280 Amperes and from 1.5 to 3, respectively. Each point was defined as the set of values related to the compressor voltage demanded, FC output voltage, oxygen excess ratio and the net power were saved in matrixes. The results of each RBFNN are displayed for each current value in Fig. 2 (red dashed lines). As is shown, the networks perform a good fit with the training data. The optimum operation points are displayed in green. The trajectory that connects these points represents the ideal path in terms of the FC net power.

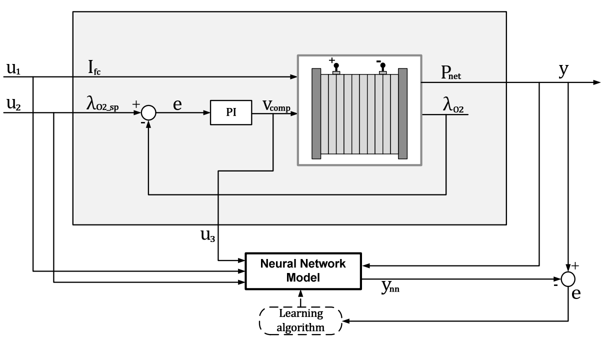

Fig. 3. Scheme setup for neural network identification.

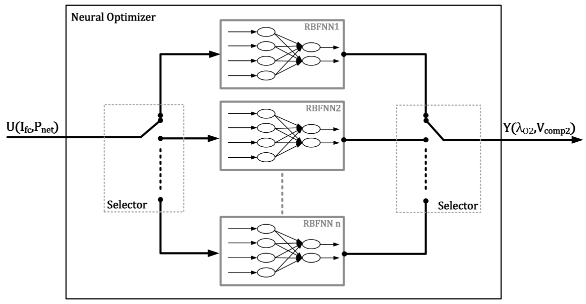

Fig. 4. Multimodel scheme based on RBFNNs.

3.2 Tracking algorithm

The set of implemented neural networks defines the optimizer as a multimodel system (Fig. 4). Each neural network can predict optimally the points of a net power curve. They are switched depending on the needed current value. In this way, for a given current value the optimizer choices which neural network estimates the set-point values to track the maximum efficiency path. This task is performed according to a proximity criterion. Thus, the neural network whose characteristic current is nearest to the demanded current would perform this task.

Regarding the maximum efficiency path, it should be noted that when a change in the load current occurs the cathode suffers the depletion effect that entails an abrupt drop of the value λ_{O2}. This effect is practically unavoidable but can be smoothed by the means of a static feedforward strategy. This is one of the objectives of the optimizer block. To perform this task the algorithm shown in Fig. 5 (in form of ASM scheme) is used to update both the internal controller set-point values and the control action applied to the compressor voltage signal.

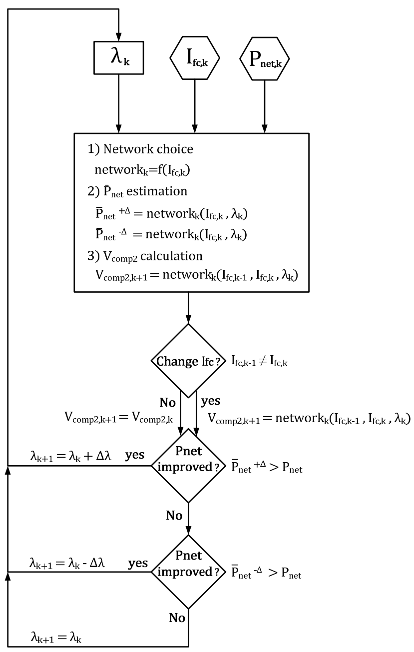

Fig. 5. Simplified ASM diagram of the tracking algorithm.

There are two possible operation modes depending on if the demanded current has changed or not. In the first mode, when a change in the current occurs, in the first algorithm step, a feedforward action updates the voltage applied to the compressor with the needed according to the new net power curve (based on which the neural networks were trained) and next, a prediction of the net power is developed for updating the current oxygen excess ratio set-points in order to follow the maximum power path. In the second mode, when the demanded current is stabilized or changes do not occur, only the set-point for λ_{O2} is updated following the maximum net power predictions of the neural network in execution.

In this way, the maximum net power points of each curve represent the attraction regions for the system state. After each execution of the algorithm, before evaluating a new iteration it is checked if the real net power has improved with respect to the prediction made and otherwise the new value of λ_{O2} is not applied.

Remark 1. The value of the parameter Δ in the algorithm should be explored for each specific FC model in order to reach a reasonable trade-off between the starvation prevention and the speed of the FC response to the load transitions.

3.3 Internal Controller

Since the underlining problem is a regulation problem, the following of the maximum net power points, the simplest solution is the adoption of a PI controller on air flow rate which would guarantee zero steady-state error [9]. It is worth remarking that the objective of the overall control scheme is not only achieving the maximum net power, but also having a fast transitory response so that the oxygen starvation is avoided. According to this control configuration, the task of the PI is made simpler thus reaching a faster response than that obtainable without the contribution of the neural network. In this case the neural optimizer can intervene with the feedforward action to improve the internal set-point tracking, while the PI controller makes the overall control scheme stable and augments the disturbance rejection. The completed scheme is shown in Fig. 6.

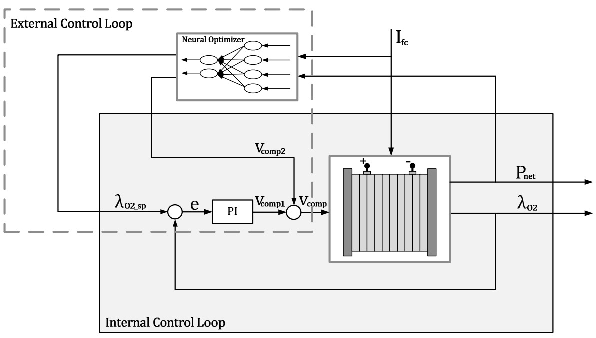

Fig. 6. Two-level FC control system. External control loop level is represented by the neural optimizer. Internal level is defined by PI control loop.

The design of the PI controller has been done considering the transfer function between the compressor voltage and the oxygen excess ratio λ_{O2} after the linearization as is described in [4]. The tuning parameters have been obtained trying to achieve the highest bandwidth and guaranteeing a phase margin of 50°.

4. Simulation Results

To prove the effectiveness of the implemented control strategy, a test signal defined as a sequence of random piecewise values has been applied to the current signal. It is depicted in Fig. 7. The test signal performs transitions that vary in the range of 10 and 20 Amperes and they practically cover the whole dynamic range of the FC system. The response of the main signals involved in the FC operation is shown in Fig. 8. The curves of the net power and oxygen excess ratio can be better appreciated in Fig. 9 where it has been depicted the lines of maximum efficiency for each current value (red dashed lines). As was expected, the current transitions cause a drop in the oxygen excess ratio but this value never exceed the lower bound of 2 required to avoid the starvation phenomenon (second plot in Fig. 9). As the results show, the proposed control strategy guarantees the following of the maximum efficiency points as well as fast transitions in the net power response. Similarly, the main signals react to the sequence of current steps quickly and without suffering remarkable overdamping. The feedforward action of the neural optimizer reduces the effects of the FC nonlinearities compensating the changes of load current with smooth transitions. Additionally, the neural optimizer gives to the PI controller the needed set-points. The control scheme makes that the compressor supply quickly more oxygen to the membrane reducing the tracking times and consequently, reducing the possibility of degrading the FC because of oxygen starvation. Thus, the control system performs a coordinated strategy that allows achieving the required control objectives of maximum net power tracking and starvation avoidance.

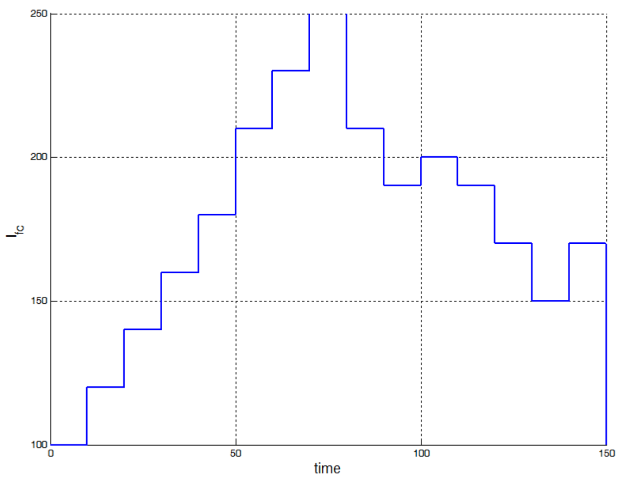

Fig. 7. Sequence of current steps for the test signal.

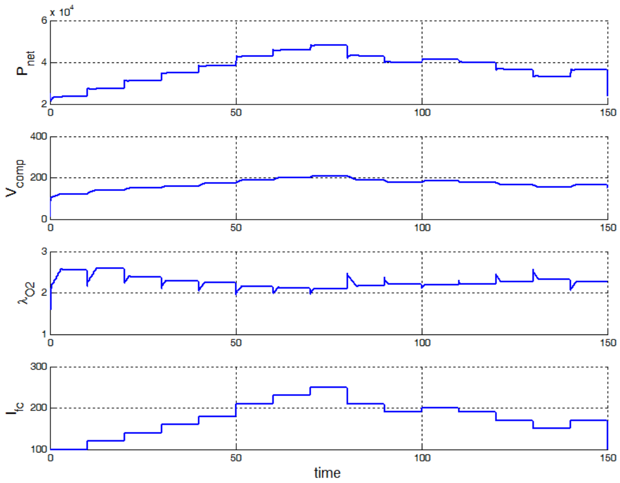

Fig. 8. Response of the main FC operation signals.

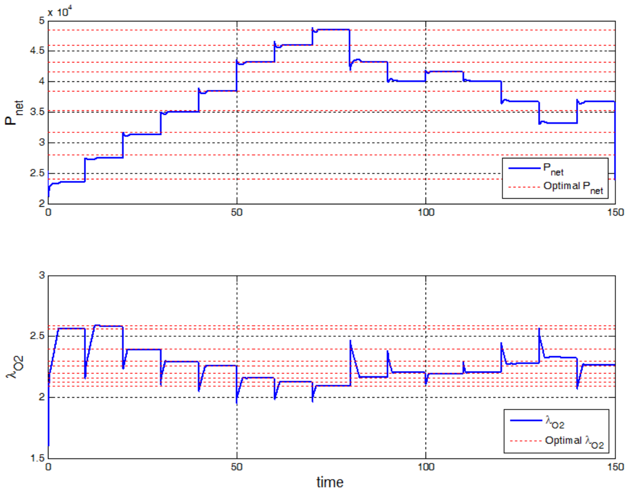

Fig. 9. Response of the two controlled variables for maximum efficiency path following. Red dashed lines define the optimal values per current value.

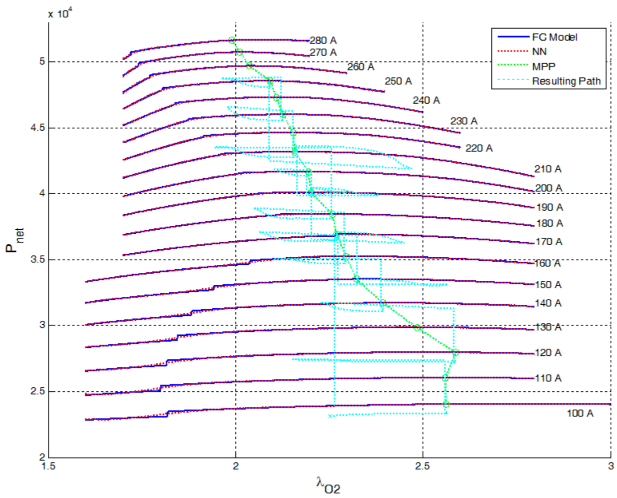

Fig. 10. Steady-state FC net power for variable oxygen excess ratio and current (blue lines). Neural networks identified trajectories (red dashed lines). Maximum net power path (green dashed lines). Path followed by the FC with the control system in the figure 6 (cyan dashed lines).

Finally, Fig. 10 shows the path followed by the FC system as a result of the test signal and the control strategy. The depletion effect separates the response of the net power from the optimal path but it is quickly recovered. As can be observed, the optimal path (remarked in green) represents an attraction domain for the state of net power signal.

5. Conclusion

A new intelligent approach to control a type of PEM fuel cell based on maximum power tracking has been presented in this work. The model employed in the analysis characterizes very well the dynamic behaviour of a real a type of PEM fuel cell without considering the thermal effects, which is assumed to be under control.

The controller has been developed as a two-level control system using artificial intelligence techniques. In the external level, a set of radial basis function neural networks has been used to identify the net power static map of the FC (as a function of the oxygen excess ratio). Additionally, an algorithm has been employed for using the knowledge acquired by the neural models in the task of tracking the maximum efficiency points. In the internal level, a classical PI controller was employed to regulate the oxygen excess ratio avoiding the starvation phenomenon. Simulation results proved the effectiveness of the approach demonstrating a good performance and a fast coordinated response of the overall control system.

The future work will be focused on analyzing the performance of the control strategy in an experimental PEM fuel cell setup including the thermal effects.

References

[1] A. Saengrung, A. Abtahi and A. Zilouchian, "Neural Network model for a commercial PEM fuel cell system", Journal of Power Sources, 2007, Nº 172, pp. 749-759.

[2] D. Feroldi, "Control and design of a PEM fuel cell-based systems", Doctoral thesis, 2009.

[3] M. Grucijic, K. M. Chittajallu, E. H. Law and J. T. Pukrushpan, "Model-based control strategies in the dynamic interaction of air supply and fuel cell", Journal of Power and Energy, 2004, Vol. 218, Nº 7, pp. 487-499.

[4] J. T. Pukrushpan, "Modelling and control of fuel cell systems and fuel processors", Doctoral thesis, 2004.

[5] W. Garcia-Gabin, F. Dorado and C. Bordons, "Real-time implementation of a sliding mode controller for air supply on a PEM fuel cell", Journal of Process Control, 2010, Vol 20, pp. 325-336.

[6] M. Hatti and M. Tioursi, "Dynamic Neural Network controller model of PEM fuel cell system", International Journal of Hydrogen Energy, 2009, Nº 34, pp. 5015-5021.

[7] S.M. Rakhtala, R. Ghaderi, A. Ranjbar, T. Fadaeian and Ali Nabavi Niaki, "PEM fuel cell voltage-tracking using artificial neural networks", in Proc. EPEC09.

[8] C. Bordons, A. Arce and J. del Real, "Constrained Predictive Control Strategies for PEM fuel cells", in Proc. ACC06, pp. 2486-2491.

[9] G. Marsala, D. Bouquin, J.T. Pukrushpan, M. Pucci, G. Vitale and A. Miraoui, "Control of a PEM-FC System by Generalized Mapping Regressor (GMR)", in Proc. IAS08.