A virtual sensor for a cell voltage prediction of a Proton-Exchange Membranes based on intelligent techniques

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Abstract. The use of Proton-Exchange Membranes Fuel Cells is presented as a key alternative to face the increasing and concerning problems related to global warming. The international expansion of green policies, has resulted in the need of ensuring their quality and reliability performance. Although fuel cells can get to play a significant role, this technology is still under development, paying special attention to the problems related to gas starvation and degradation. In this context, the present work deals with the virtual sensor implementation of one of the voltage cells present in a stack, whose operation is subjected to several degradation cycles. The proposal predicts indirectly the voltage of one cell from the current state of the rest of the cells by means of an intelligent model.

Keywords: Fuel Cell · Virtual Sensor · Intelligent modelling · MLP

1 Introduction

During last century, the global society has faced a significant development in terms of technology, industry and life standard, among others. However, this has resulted in an increase of greenhouse gasses emission derived by fossil fuels use. Then, modern societies started to focus their efforts on palliating this critical problem, and, consequently, most governments promoted green policies [6, 18] and, nowadays, there is a legislation whose restriction level tend to be higher [28, 4, 17].

Given this situation, different alternatives are presented to contribute for preserving the environment by slowing down the climate change [10, 7, 8]. A common solution consists of the use of renewable energy sources such as solar, wind, hydraulic or even ocean energy [20, 11, 7]. On the other hand, an interesting research line is focused on Proton-Exchange Membranes Fuel Cells (PEMFC) [21, 19]. This technology can be efficiently used in micro-combined heat and power units (CHP) and electric vehicles [3, 27].

Although the PEMFC can get to play a significant role, its technology is still under development [3, 2]. One of the main research lines is related to the development of devices which works over 100 °C, also denoted as as High-Temperature PEM fuel cells (HT-PEMFC). The High-Temperature Proton-Exchange Membrane Power Cell commonly works with a phosphoric acid doped polybenzimidazole (PBI) membrane [30], that raises the allowed temperature to a range between 120 °C and 180 °C. This features give significant advantages compared to the low-temperature PEMFCs [30, 5]. First, it is important to emphasise the CO tolerance and the simplification of water management systems [26]. Furthermore, it is demonstrated that the electrochemical kinetics of cathode and anode reactions are enhanced [26]. Finally, these high-temperature devices are simpler and more reliable since sophisticated humidification subsystems can be dispensable. Hence, cooling systems are highly simplified due to the increase in temperature gradient between fuel cell stack and coolant [26].

One of the common problems of power cells is the degradation induced by gas starvation, considerably decreasing the durability of the electrodes [9]. In this context, having an accurate model of a power cell could present a useful tool to determine normal operation of the device. This work deals with the implementation of a virtual sensor to determine the voltage cell, which offers the possibility of estimating the current state of the system. To achieve this goal, an empirical dataset registered from different operating conditions and degradation levels, ensuring a good generalisation [1].

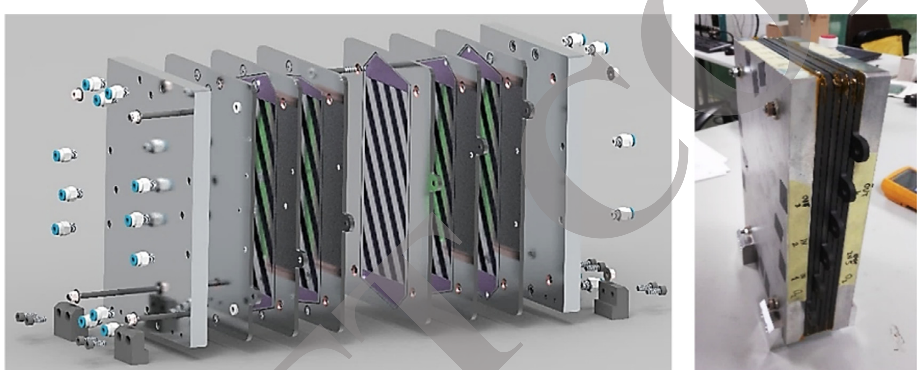
The present document is structured as follows. After this introduction, a brief description of the case of study is presented in next section. Then, the model approach is detailed, followed by the Experiments and Results section. Finally, the reached conclusions are exposed in the last section.

2 Case study

In spite of the significant breakthroughs made in PEMFC technology, some key aspects regarding performance durability and degradation are still under development [22]. In this sense, several research works are focused on improving lifetime of HT-PEMFCs under variable load conditions [22]. This work deals with a laboratory equipment to test the battery degradation due to gas starvation, whose main features are described in this section.

2.1 Physical system

The starvation experiments have been developed in a stack consisting of five different cells whose gas supply is independent. It has six JP-945 graphite bipolar plates of 280 mm x 195 mm x 5 mm whose temperature can reach up to 200 °C. Furthermore, there are two more plates, made of stainless steal, in charge of connecting the reactant gasses lines (H_2 and O_2). The flowfield geometry of both cathode and anode sides consisted of straight parallel channels with a land-to-channel ratio of 1, as recommended by the manufacturer. The cathode side flowfield geometry consisted of 87 channels with a width of 1 mm and a depth of 2 mm, and a total length of 120 mm. The anode side was formed by 47 channels with a width of 1 mm, a depth of 1.5 mm, and a total length of 210 mm. Figure 1 shows the 3D design of the fuel cell and the physical system.



a) b)

Fig. 1. Fuel cell 3D desing (a) and physical system (b)

The stack was assembled inside a greenhouse in the laboratory to guarantee adequate humidity conditions. To decrease the relative humidity inside the greenhouse, dry compressed air was injected using two pipes connected to the main air pressure line. A complete description and illustrative photos of this facility can be consulted in [3].

2.2 Dataset description

To check the HT-PEMFC degradation performance and durability, the stack was subject to a series of starvation cycles. These tests followed the next structure:

- **Day 1**
  1. The stack is warmed up to 160 °C.
  2. A constant current of 32.7 A is demanded for 3 hours.

3. The flow rate of one cell is reduced a 20 % of that corresponding to stoichiometric flow conditions for 30 minutes.

– **Day 2**
  1. The stack is warmed up to 160 °C.
  2. A constant current of 32.7 A is demanded for 3 hours.
  3. The flow rate of one cell is reduced a 50 % of that corresponding to stoichiometric flow conditions for 30 minutes.
– **Day 3**
  1. The stack is warmed up to 160 °C.
  2. A constant current of 32.7 A is demanded for 3 hours.
  3. The flow rate of one cell is reduced a 50 % of that corresponding to stoichiometric flow conditions for 120 minutes.
– **Day 4**
  1. The stack is warmed up to 160 °C.
  2. A constant current of 32.7 A is demanded for 1 hour.

During the operation, the voltage measured at each of the 5 fuel cells is registered with a sample rate of five minutes. The data available are the following:

– Operation at constant current from days 1, 2, 3 and 4: 130 samples.
– Degradation stage of day 1: 60 samples.
– Degradation stage of day 2: 40 samples.
– Degradation stage of day 3: 55 samples.

3 Model approach

As the main goal of this research is the implementation of a virtual sensor capable of estimating the voltage value of one cell from the values of the other cells, the topology of the proposal and the technique applied are described in this section.

3.1 Model Topology

The general topology of the proposed model is shown in Figure 2. This consists in the prediction of voltage in cell 1 from the voltage of cells 2, 4 and 5. Furthermore, to incorporate the system dynamic to the model, the possibility of adding the previous states of the measurements is considered.

In this case, the voltage of cell 3 is not considered because it is the one subjected to a gas starvation during the test. The idea is to check if it is possible to model the behaviour of one cell from data measured on other cells.

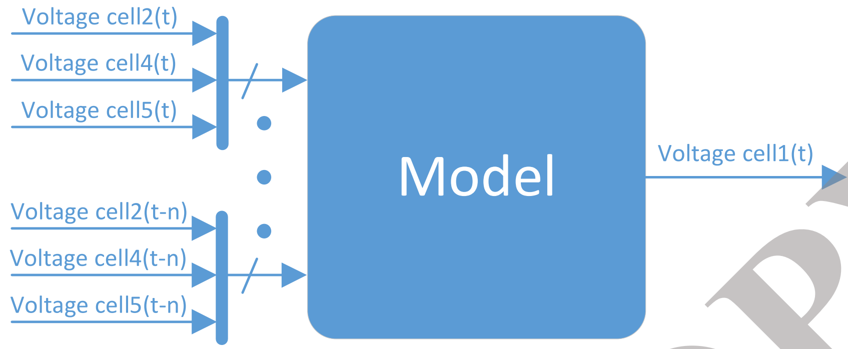


Fig. 2. Model topology

3.2 Multilayer Perceptron

The modelling process is carried out using the Multilayer Perceptron (MLP) technique, which is one of the most used supervised learning ANN due to its simple structure and its robustness. An artificial neural network (ANN) is a system designed to emulate the brain operation in a specific functions of interest or tasks. In this century, ANN have been applied successfully to solve real and challenging problems [29, 16]. The MLP presents the structure shown in Figure 3, which presents one input layer, one output layer and one or more hidden layers. These layers are made of neurons and weighted connections links different layer neurons [12, 23, 13, 15]. The values of the weights are adjusted following an error reduction criteria, being the error the difference between real and estimated output. In the most common configuration, the same activation function is assigned to all neurons from a layer. The activation function can be linear, tan-sigmoid or log-sigmoid.

The employed learning algorithm was Gradient descent, and the algorithm for model training was Levenberg-Marquardt. Also, to measure the network performance, the MAE (Mean Absolute Error) method was applied.

4 Experiments and Results

To achieve the best model performance, a wide range of configurations is checked. The MLP parameters were swept according the following configurations:

- Three MLP topologies are tested: the current state of the inputs, the current and one previous state of the inputs and the current and two previous states of the inputs.

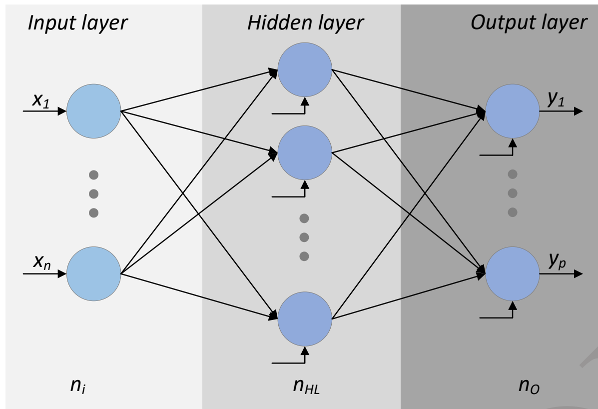


Fig. 3. MLP structure

– The activation function of the hidden layer was set to linear, tan-sigmoid or log-sigmoid.
– The number of neurons in the hidden layer was tested from 1 to 50.

From the combination of all these configurations, a total amount of 450 models have been implemented and validated. To validate the proposal, a k-fold cross validation with k = 5 is implemented. The process followed by this method is depicted in Figure 4.

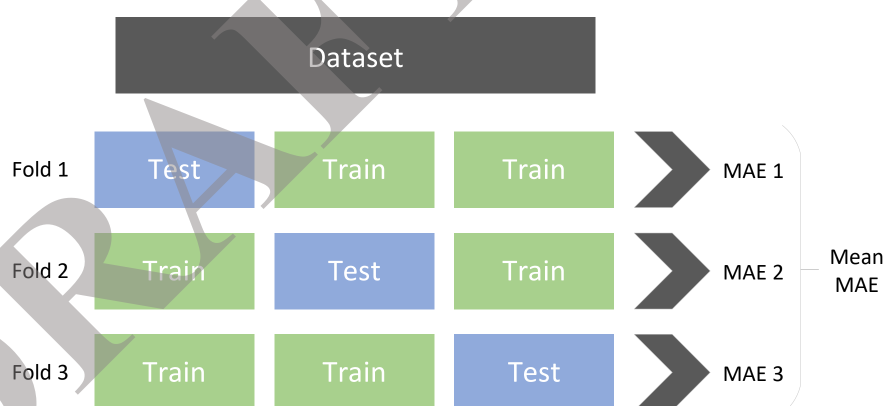


Fig. 4. Implementation of k-fold with k=3

The results obtained for each MLP topology and their corresponding configuration are summarised in Table 1.

Input states	Activation function	Hidden layer size	MAE (mV)
Current	log-sigmoid	22	1.1029
Current and previous	tan-sigmoid	16	1.3690
Current and two previous	log-sigmoid	24	1.2258

Table 1. Best results for each tolopogy

It is important to remark that the best configuration achieves an error of 1.1029 mV in the prediction, which is a significantly low value. This result is reached with a log-sigmoid activation function in the hidden layer and 22 neurons and taking into consideration only the current state of the rest of cells.

5 Conclusions and future works

The present work dealt with the voltage prediction of a cell located in a HT-PEMFC that has been subjected to different gas degradation process. The model proposed gives successful results, especially when the model takes into consideration the current state and previous state of the inputs.

The proposal is presented is a useful tool to estimate the the real state of the fuel cell as a previous step to detect anomalous situations. The difference between the real and predicted values is presented as a good indicator about the correct performance of the fuel cell. Furthermore, the model is trained taking into consideration different degradation cycles, so it represents a wide range of cell operation.

As future works, in spite of using data from steady state, the use of data from the degradation cycles could be considered to determine the voltage value at the degraded cell. This model, combined with expert system knowledge [24, 25] and imputation techniques [14], could help to determine the degradation level of the fuel cell.

Acknowledgements

CITIC, as a Research Center of the University System of Galicia, is funded by Consellería de Educación, Universidade e Formación Profesional of the Xunta de Galicia through the European Regional Development Fund (ERDF) and the Secretaría Xeral de Universidades (Ref. ED431G 2019/01).

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