PEM Fuel Cell Modelling Using Artificial Neural Networks (ANN)

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Abstract- Fuel cells (FC) convert directly into a dc electrical energy the chemical energy of a reaction of hydrogen and oxygen. Proton Exchange Membrane (PEMFC) is a suitable alternative for both electrical transportation and stationary applications. This article deals with an Artificial Neural Network (ANN) modelling method of a PEMFC. This modelling approach permits to describe both transient and steady state behaviours of the PEMFC voltage. Furthermore, the prediction of the operating temperature of a PEMFC based only on its measured voltage and current is proposed and tested successfully. Indeed, experimental data from a 1.2 kW Nexa Ballard PEMFC is used to validate the proposed method.

Keywords- Neural network; Thermal model; Polymer electrolyte fuel cells; green energy; distributed sources.

1. Introduction

Proton Exchange Membrane Fuel Cell (PEMFC) is considered as a potential future green power source for both electrical transportation and stationary application, due to its high efficiency, zero emission if it runs with pure hydrogen and its low operating temperature. The main challenge of PEMFC systems is the design of a power converter suitable for conditioning the output power with high efficiency and reliability. Indeed, about 80% of the damage occurred in the PEMFC system are involved by the power converters. During the design phase, the power converter must be tested and adjusted with a real PEMFC, and thereafter, it must be validated. However, the design and development of PEMFC including auxiliaries such as testing an air compressor control, power and energy management and performance optimization can damage a PEMFC easily. In addition, the cost of testing (hydrogen consumption and the secure facilities requirements) is still relatively high, for experiments with a real PEMFC. These disadvantages demonstrate the great importance of the design of a PEMFC emulator in real time based on a model material for applications such as HIL (Hardware In the Loop). During the design process of the power system of PEMFC, power converters and the auxiliaries development can be initially verified and increased with a PEMFC emulator in real time without any risk for the stack, and a low system operating cost. Modelling of PEMFC met a growing interest in the literature, where it is usually done with complex models based on knowledge of the physicochemical phenomena [1-3]. These models need a good knowledge of the parameters describing the behavior of the process [4-7]. Generally, these parameters are no easy to establish for the PEMFC systems. A model describing the transient behavior of a PEMFC stack with equations is given in [8]. However, the internal parameters should be defined such as the ohmic resistance, which determines the humidity of the membrane, as well as overflowing and drying of electrodes. These internal parameters are significant when the cell voltage is considered, but they were not considered in this mathematical model, as the required parameters are difficult to calculate. Hybrid models could overcome these issues. In [9], a PEMFC model has been developed, which is able to characterize the cell either steady state or transient. Combined electrical circuit□based model and the empirical model, the proposed model presents a good agreement with the experimental results. However, this model is correct only in a small range.

Nevertheless, it is possible to obtain a behavioral modeling and without the identification of all these parameters through a models so called "black box". These models are based on readily measurable variables such as temperature, pressure, or the current of the cell and are able to estimate the output voltage of the PEMFC.

Today, dynamic models of PEMFC systems based on Artificial Neural Networks (ANN) are rare in the literature. However, a lot of substantially stationary models have been established with good results [10-13].

In [13], a static and dynamic model of the PEMFC based on ANN has been proposed and experimental results were presented. This proposed model uses the measured temperature, the fuel cells current, the stoichiometry of the two gases and humidity. This modeling approach gives good results, even if it suffers from a disadvantage concerning the evolution of the temperature which is not considered. In [14], neuronal modeling of a high power PEMFC is presented where the evolution of temperature was considered. However, due to the not recurring structure of the ANN, the model presented is static [13]. In addition the temperature was measured at the anode circuit and in the water tank which does not provides the accurate operating temperature of the fuel cell. Indeed, in [15], an infrared camera was used in order to improve acquisition of the temperature in the cells.

In this paper, a novel modelling approach of the PEMFC to provide stack voltage characteristic and the operating temperature is presented based on ANN and its performances are analyzed. This method called "black box" consists of the dynamic neural modeling with recurrent ANN structure to predict with a good accuracy the PEMFC voltage and operating temperature by the use an experimental data.

2. Development of the ANN Modelling Approach

ANN is commonly considered as an attractive and powerful tool to provide the relation of complex and nonlinear dynamic model based only on input-output data mapping [16-18]. In the literature, they are several models have been proposed for different applications [19]. Generally, the neural network has two types of structure, a feed-forward architecture networks where the direction of the signals is only from input to output. Unlike, for networks feed-back structure, the direction of the signals is from input to output and vice versa [13]. ANN learning can be classified in two categories [20]: the supervised (learning with a teacher) or unsupervised (learning without a teacher) [13]. For the supervised training which assumes the availability of a supervisor, each element in input vector represents an explicit element in the output target vector. While in the unsupervised training, the ANN model is not trained to any certain output target, and the reinforcement learning is accomplished via a trial and error learns [20, 21].

A typical feed–forward neural network perceptron with Back-propagation (BP) algorithm has been used in this study. The BP algorithm which has a large classification capacity is widely used in the area of identification and control [10]. The algorithm uses the technique of gradient descent search in order to reduce a cost function mean squared error (MSE). The minimization process is carried out by modifying the weight vector of the neural networks. Some training algorithms have been presented in order to adapt the weight values in the dynamic recurrent network. The minimized cost function, which is the error between the network output and the desired output as expressed as:

$$e = \frac{1}{2}\sum_j e_j^2(k) = \frac{1}{2}\sum_j \left[y_j^* - y_j(k)\right]^2 \tag{1}$$

Where yj(k) is the output of jth neuron and yj*(k) is the desired output.

To achieve a neuronal dynamic modelling the PEM fuel cell, the neuronal structure illustrated in Fig. 1 was chosen, which represents a typical processing element which forms a weighted sum of its inputs and puts the result via a nonlinear transfer function to the output. These transfer functions can also be linear, and then the weighted sum is transmitted directly to the output path. The multi-layer perceptron (MLP) used in this work is composed of three main layers. The first part is the input layer where experimental data are presented, then are processed and propagated via a hidden layer, to the output layer. Training a network consist to modify continuously the weights of the connecting links between processing elements as patterns of inputs and corresponding desired outputs are presented to the network [22].

Equ. (2) and Equ. (3) represent respectively the weighted summation of the inputs and the non linear transformation (transfer function) to the output of the neuron.

$$\sigma = \sum_i x_i w_i \tag{2}$$

$$Y = f(\sigma) \tag{3}$$

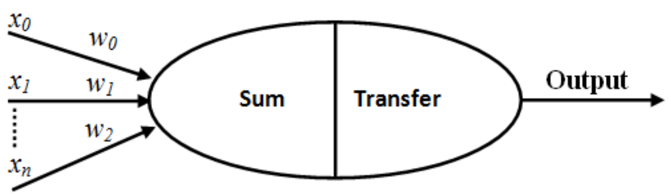

Figure 1. Schematic diagram of a basic formal neuron.

A recurrent neural structure allows, with adding time delays to take into account the time variation of input parameters to analyze the dynamics of output [13]. In order to speed up the convergence of the learning process of ANN, we choose to use the Levenberg-Marquardt (LM) method which improves the gradient decent method of back-propagation [23].

The neural electrochemical model the PEMFC consists of three layers, the input layer, hidden layer and the output layer (see Fig. 2). The activation function used for the first two layers is the tangent sigmoid function (tansig), while the linear activation function is used for the output layer.

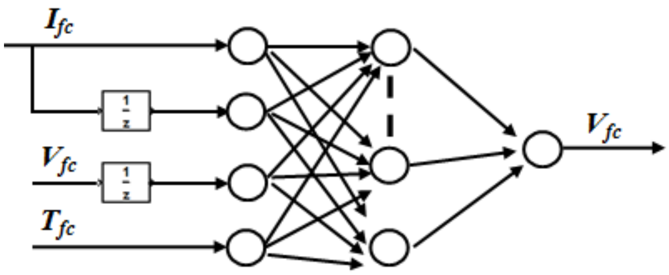

Figure 2. Schematic diagram of the neural electrochemical model the PEM fuel cell.

The structure of neural networks used to provide the operating temperature of the PEMFC is illustrated in Fig. 3. For training the ANN, having regard to the electrochemical performance of the PEMFC model presented previously, we used the same configuration in terms of type of activation and the number of neurons in each layer function. We took into account the dynamics of the current and voltage by introducing time delays to the input of ANN.

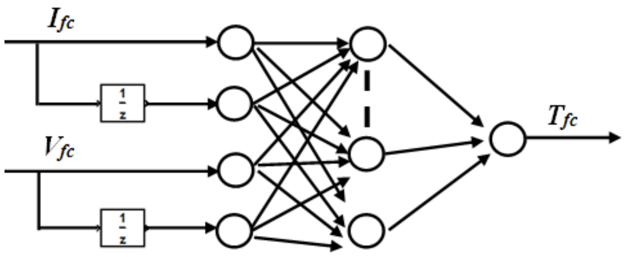

Figure 3. A block diagram of an ANN PEMFC operating temperature.

3. Experimental Setup Details

The all experimental data which are used in this paper are derived from [24]. A 1200 W Nexa Ballard with 47 cells connected in series. In order to provide an accuracy cells operating temperature, an infrared camera is used. The current profile used in this analyze is depicted in Fig. 4.

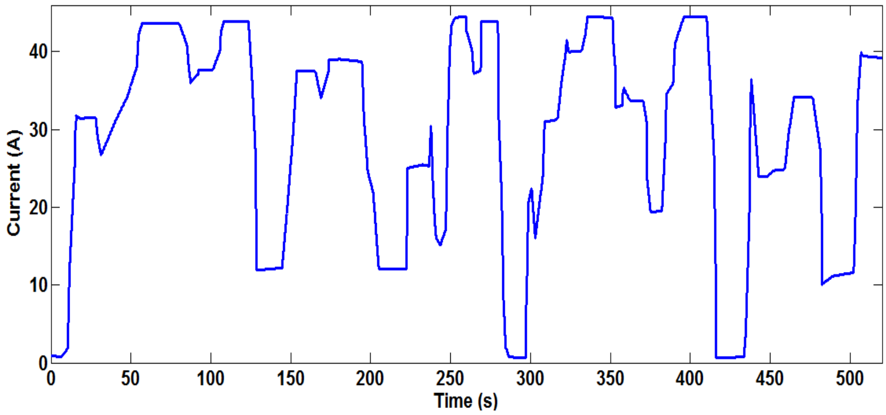

Figure 4. A very high dynamic applied current profile [24].

4. Simulation Results and Discussion

To validate the effectiveness of the neural modelling approach of PEMFC a training process using experimental data is achieved using Matlab/Simulink® and Neural Network Toolbox™. A number of epochs between displaying, maximum number of epochs, performance goal, and other training parameters are listed in Table 1. Fig. 5 depicts a training error of PEMFC stack voltage prediction during the learning process. Training performance goal was $3e^{-8}$ and the maximum training epochs was less than 25000. After 25000 epochs, the error was $3.117e^{-8}$, then the assigned performance goal was not reached, but the trained neural network has a good performances. To validate the proposed neural modelling method, a very high variation of the current is used (see Fig. 4). This current profile includes the total operating range from 0 to 45 A [24].

Table 1. PEM fuel cell output voltage model parameters

Epochs between displays	10
Maximum number of epochs to train	25000
Performance goal	$3e^{-8}$
Learning rate	0.001
Maximum validation failures	5
Ratio to increase learning rate	1.5
Ratio to decrease learning rate	0.7

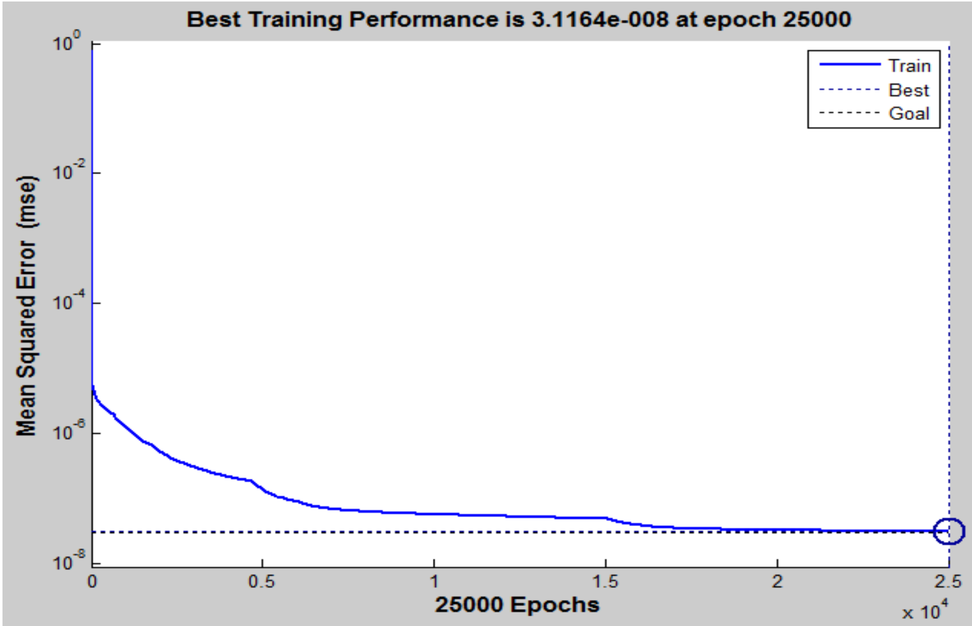

Figure 5. Training error of AE voltage prediction during the learning process.

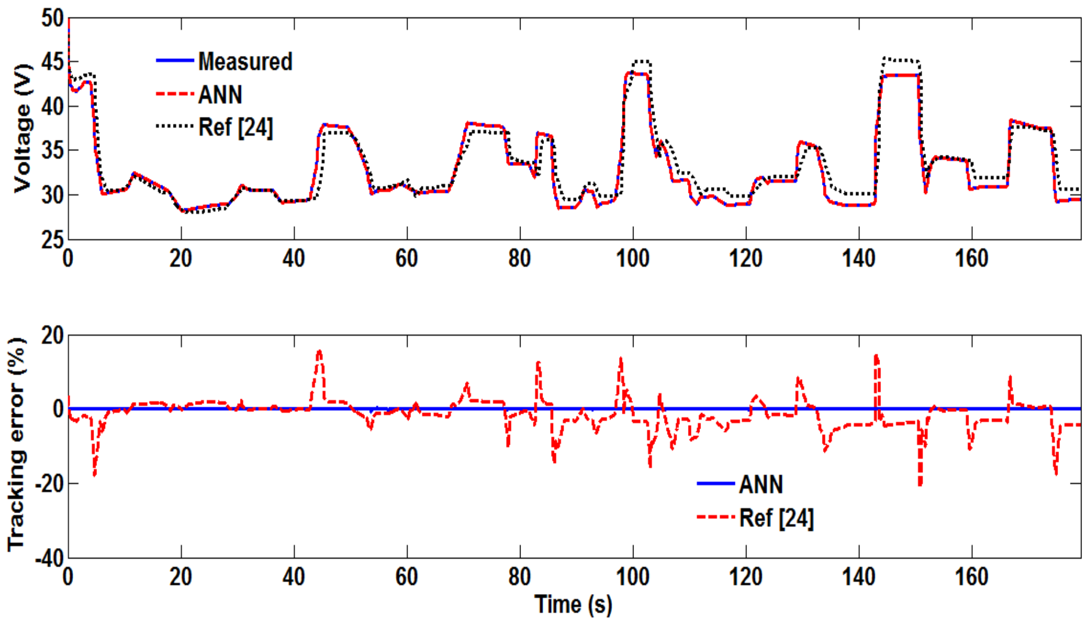

Figure 6. Neural PEM fuel cell stack voltage prediction performances.

As we can see in Fig. 6, the neural predict with a good precision the voltage of the 47 cells stack of the PEMFC than the model presented in [24]. Indeed, with the neural method, the tracking error is less than 0.5%, while it is around 20% with the method given in [24].

Table 2 summarizes the number of epochs between displaying, maximum number of epochs, performance goal, and other training parameters for the neural operating temperature prediction. Fig. 7 shows a training error of PEM fuel cell operating temperature prediction during the learning process. Training performance goal was $4.3e^{-9}$ and the maximum training epochs was less than 25000. After 12048 epochs, the error was $4.299e^{-9}$, then the assigned performance goal was reached, and the neural network trained.

Table 2. PEM fuel cell operating temperature prediction model parameters

Epochs between displays	10
Maximum number of epochs to train	25000
Performance goal	$4.3e^{-9}$
Learning rate	0.001
Maximum validation failures	5
Ratio to increase learning rate	1.5
Ratio to decrease learning rate	0.7

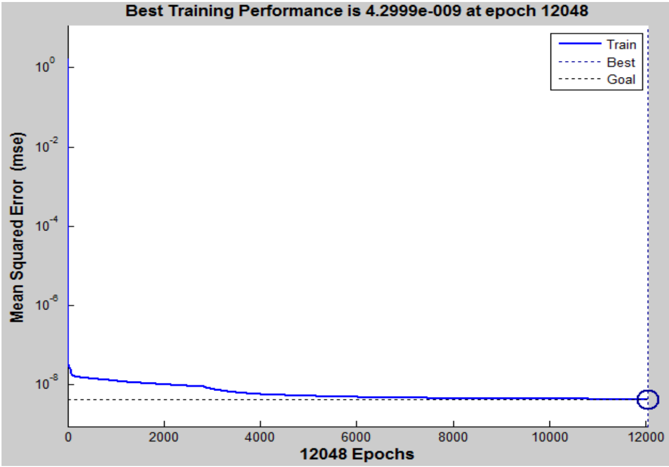

Figure 7. Training error for operating tempeature prediction during the learning process.

As we can see in Fig. 8, the neural predict with a good accuracy the voltage of the 47 cells stack of the PEM fuel cell than the model presented in [24]. Indeed, with the neural method, the tracking error is less than 0.2%, while it is around -10% and +2% with the method given in [24].

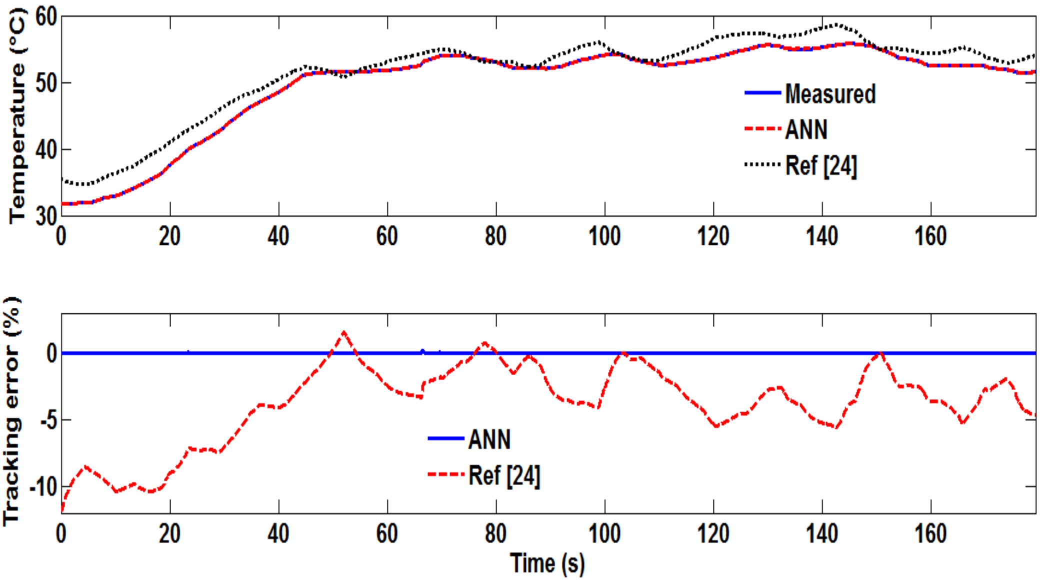

Figure 8. Neural PEM fuel cell stack voltage prediction performances.

5. Conclusion

A dynamical model of a PEMFC stack voltage behavior and operating temperature prediction based on artificial neural networks was proposed in this paper. Firstly, the feed-forward neural network (FFNN) was trained offline by using experimental data, to predict a PEM fuel cell voltage without using any analytical relations. The neural model approximates with a good accuracy a stack voltage of a PEMFC with comparison with a model existing in the literature. Indeed, with the proposed approach, a tracking error less than ±0.5%, while it is around ±20% with a compared method.

Thereafter, a neural network operating temperature of cells based on the feed-forward neural network (FFNN) was presented and tested successfully using experimental data.

The tracking error is less than 0.2% while it is around -10% and +2% with the model derived from the literature.

With this approach, a simulation model which describes both the 47 cells stack voltage and operating temperature with a good accuracy is presented and validate with an experimental data. This model can be used during the phase of development of PEMFC auxiliaries such as the power converter without any risk to damage PEMFC, and with a less cost.

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