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Proton exchange membrane fuel cell voltage-tracking using artificial neural networks

Seyed Mehdi RAKHTALA†, Reza GHADERI, Abolzal RANJBAR NOEI

(*Faculty of Electrical and Computer Engineering, Babol Industrial University, P. O. Box 47144-484, Babol, Iran*)

†E-mail: mhj_g@yahoo.com

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Abstract: Transients in load and consequently in stack current have a significant impact on the performance and durability of fuel cells. The delays in auxiliary equipments in fuel cell systems (such as pumps and heaters) and back pressures degrade system performance and lead to problems in controlling tuning parameters including temperature, pressure, and flow rate. To overcome this problem, fast and delay-free systems are necessary for predicting control signals. In this paper, we propose a neural network model to control the stack terminal voltage as a proper constant and improve system performance. This is done through an input air pressure control signal. The proposed artificial neural network was constructed based on a back propagation network. A fuel cell nonlinear model, with and without feed forward control, was investigated and compared under random current variations. Simulation results showed that applying neural network feed forward control can successfully improve system performance in tracking output voltage. Also, less energy consumption and simpler control systems are the other advantages of the proposed control algorithm.

Key words: Feed forward control, Neural network, Proton exchange membrane (PEM) fuel cell, Terminal voltage tracking
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1 Introduction

A fuel cell is an electrochemical device that can convert chemical energy into electrical and thermal energy. There are types of fuel cells which can generate electrical power ranging from mW to MW (Wang *et al*., 2005).

To design and control a fuel cell system for maximum power performance, a designer needs to acquire sufficient knowledge of the physical process, the internal structure of the process, and the dominant input/output variables of the system, in order for an accurate mathematical representation of the system to be developed. On the other hand, accurate modeling of a fuel cell system requires specific knowledge of parameters, i.e., membrane thickness and resistance, which are either unknown or known only to the manufacturer.

In most control applications the designer may be interested in relationships between inputs and outputs as well as the internal structure of the system. Such a prediction may be performed using artificial neural networks (Saengrung *et al*., 2007).

These systems model the brain neurosynaptic structure. One of the significant specifications is that they do not need programming and are trained based on experimental data (Arriagada *et al*., 2002). Neural networks are used for two objectives, first as a representation for plant dynamics (identification) and second as a controller (Wu *et al*., 2008).

Two artificial neural networks (ANNs) including the back propagation (BP) and radial basis function (RBF) networks are constructed based on experimental data. Speed and accuracy of several prediction algorithms are determined and investigated (Saengrung *et al*., 2007). An ANN model is used to predict the performance of a solid oxide fuel cell (SOFC) through the BP algorithm. Voltage and temperature are considered as input variables and current and air flow rate as output variables (Arriagada *et al*., 2002).

A nonlinear model predictive control method is proposed to control the stack terminal voltage of SOFC, and the fuel flow rate is considered as the control signal. A genetic algorithm is used to minimize the parameters of the RBF neural network (Wu *et al*., 2008).

Since fuel cell voltage is varied under various parameters such as input air pressure and load current, this will lead to performance degradation in practical applications, so the objective of the proposed control strategy is to use a fast and accurate model to predict proper control signals and keep the terminal voltage at a constant value.

2 Proton exchange membrane fuel cell nonlinear model

The ideal potential of a fuel cell is 1.229 V. The actual fuel cell potential is decreased from its equilibrium point because of irreversible losses. Several sources contribute to irreversible losses in a practical fuel cell. The losses, often called polarization over voltage, originate from three sources: activation polarization, ohmic polarization, and concentration polarization (Iqbal, 2003; Wang *et al.*, 2005).

These losses result in a cell voltage for a fuel cell that is less than its ideal potential:

$$V_{fc}=E-\text{losses}, \tag{1}$$

where losses=$\eta_{act}+\eta_{ohm}+\eta_{conc}$, and η_{act}, η_{ohm}, and η_{conc} are as described in the following. Thermodynamic potential E is defined from a Nernst equation in expanded form (Iqbal, 2003; Wang *et al.*, 2005):

$$\begin{aligned} E &= 1.229 - 0.85\times10^{-3}(T-298.15) \\ &\quad + 4.3085\times10^{-5}T(\ln P_{H_2} + 0.5\ln P_{O_2}). \end{aligned} \tag{2}$$

The parametric equations for the over voltage due to activation, internal resistance, and concentration are discussed in the following (Iqbal, 2003; Wang *et al.*, 2005).

1. Activation over voltage. This loss is caused by the slowness of the reactions taking place on the surface of the electrodes.

$$\begin{aligned} \eta_{act} &= -9.514 + 0.00312T - 0.000187T(\ln i_{fc} \\ &\quad + 7.4\times10^{-5}T\ln C^{*}_{O_2}). \end{aligned} \tag{3}$$

2. Ohmic over voltage. This voltage drop is the straightforward resistance to the flow of electrons through the material of the electrodes and various interconnections (Iqbal, 2003; Wang *et al*., 2005; Rakhtala *et al*., 2008).

$$\eta_{ohm} = -i_{fc}R_{int}. \tag{4}$$

3. Concentration over voltage. This voltage drop results from the change in the concentration of the reactants at the surface of the electrodes as the fuel is used.

$$\eta_{conc} = -\frac{RT}{nF}\ln\left(1-\frac{i_{fc}}{i_{lim}}\right). \tag{5}$$

The combined effect of thermodynamics, mass transport kinetics, and ohmic resistance determines the output voltage of the cell as (Iqbal, 2003; Wang *et al*., 2005; Rakhtala *et al*., 2008)

$$V_{cell} = E - \eta_{act} + \eta_{ohm} + \eta_{conc}. \tag{6}$$

A fuel cell stack consists of several cells in series to increase the voltage from the fuel cell. Fuel cell stack voltage is described by (Rakhtala *et al*., 2008)

$$V_{stack} = N_{cell}V_{cell}, \tag{7}$$

where N_{cell} is the number of cells in series.

The dynamics of a fuel cell voltage can be modeled by the addition of a capacitor C to the steady state model. The capacitor represents the effect of a double charge layer and is connected in parallel with activation resistance (Iqbal, 2003; Wang *et al.*, 2005).

Fig. 1 shows the electrical equivalent model of the fuel cell. Here,

$$\begin{cases} V_C = \dfrac{1}{C}\displaystyle\int i_C \mathrm{d}t \Rightarrow \dfrac{\mathrm{d}V_C}{\mathrm{d}t} = \dfrac{i_C}{C} \Rightarrow \dfrac{\mathrm{d}V_{\mathrm{act}}}{\mathrm{d}t} = \dfrac{i_C}{C} - \dfrac{V_{\mathrm{act}}}{RC}, \\ i_C = i_{\mathrm{fc}} - i_a, \end{cases} \tag{8}$$

where i_C (in A) is the current of capacitance C and i_{a} (in A) is the current of R_{act}.

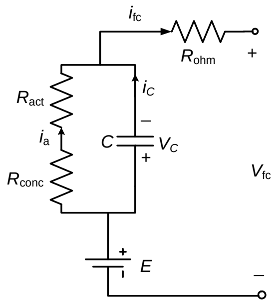

Fig. 1 The electrical equivalent model of the fuel cell

Table 1 shows the proposed specific characteristics of a proton exchange membrane (PEM) fuel cell. The fuel cell *V-I* and *P-I* curves are presented in Fig. 2. The parameters used for modeling the PEM fuel cell are shown in Table 2.

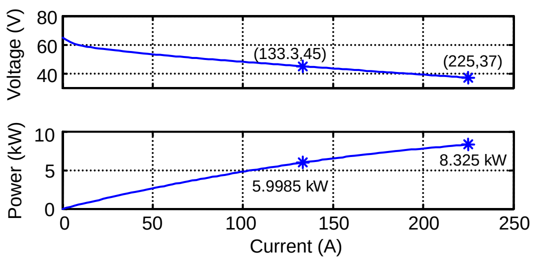

Fig. 2 *V-I* and *P-I* curves of the proton exchange membrane (PEM) fuel cell

Table 1 Specific characteristics of the proton exchange membrane (PEM) fuel cell

Parameter	Value
Number of cells	65
Nominal stack power (W)	6000
Maximal stack power (W)	8300
Open circuit voltage (V)	65
Nominal stack efficiency	55%
System temperature	65°

Table 2 Parameters used for modeling the proton exchange membrane (PEM) fuel cell

Parameter	Meaning
N_{cell}	Number of cells
E (V)	Nernst voltage
V_{fc} (V)	Fuel cell output voltage
T (K)	Temperature of the fuel cell
P_{H_2}, P_{O_2}, P_{H_2O} ($\times 10^5$ Pa)	Partial pressure of each gas inside
F (C/mol)	Faraday's constant (=96 485)
i_{lim} (A)	Maximum output current
i_{fc} (A)	Output current
$C^*_{O_2}$	Oxygen concentration at gas interface
R_{int} (Ω)	Internal resistance
R	Universal gas constant
n	Number of electrons

3 Neural network model for fuel cell dynamic model estimation

An ANN is a type of artificial intelligence technique that mimics the behavior of the human brain. It can approximate a nonlinear relationship between the input and output variables of nonlinear, complex systems without requiring explicit mathematical representations (Entchev and Yang, 2007).

Multilayer feed forward networks can be used to estimate the nonlinear functions. In system identification, the plant neural network model is constructed and can be a proper alternative for plant dynamic modeling.

The estimation error between the actual output and the neural network output is used as a training signal. This process is presented in Fig. 3 (Huang *et al.*, 2008).

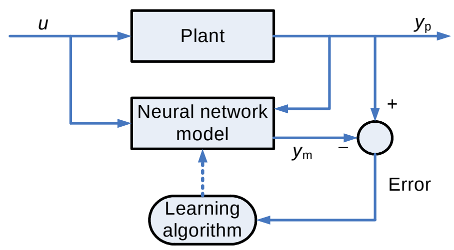

Fig. 3 Neural networks as a function evaluator

To achieve the internal relationship that governs the plant, the neural network is given a suitable set of training data for which the correct outputs or targets are available.

The most frequently used method for training multilayer neural networks is the BP algorithm. The idea of the BP algorithm is to send back through the network the error generated, when the actual output differs from the target. For this reason, a least mean square error function (MSE) is introduced (Arriagada *et al.*, 2002):

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N} e_k^{\ 2}. \tag{9}$$

The weights, which at the beginning are random numbers close to zero, are successively updated in the direction of decreasing the error gradient. The weight correction is proportional to error gradients, with a constant η, known as the learning rate (Arriagada *et al.*, 2002):

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}}. \tag{10}$$

The ANN used in this study is a three-layer BP network with two hidden layers. The input layer has one neuron and the output layer has two neurons. The input parameters are the stack voltage and current, and the output parameter is the air pressure (Fig. 4).

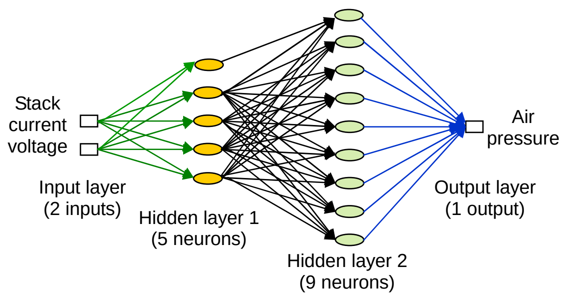

Fig. 4 Three-layer back propagation network diagram

The dynamic model of the PEM fuel cell was used to calculate approximately 400 different operational cases. The main operational parameters of the cell were varied, i.e., a stack current from 1 to 20 A and an inlet air pressure from 0.5×10^5 to 3.15×10^5 Pa in 20 steps. The output voltage values were saved in a matrix.

The maximum cell temperature was set to be constant (80 °C); in consequence, the dynamic model was used to generate 400 input data and resulted in 400 output data as the target. Fig. 5 shows the 3D polarization curve considering the inlet air pressure.

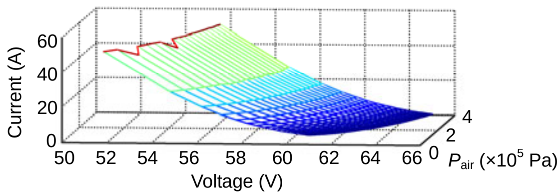

Fig. 5 Polarization curve considering the inlet air pressure

To produce correct output data, the network was trained with an improved version of the BP algorithm, i.e., the Levenberg-Marquardt algorithm (Trainlmn). During the learning process the error function was minimized with an increasing number of training epochs (El-Sharkh *et al.*, 2004; Entchev and Yang, 2007).

The compatibility of the two models was easily observed (Fig. 6). The developed model showed a good agreement with the other model.

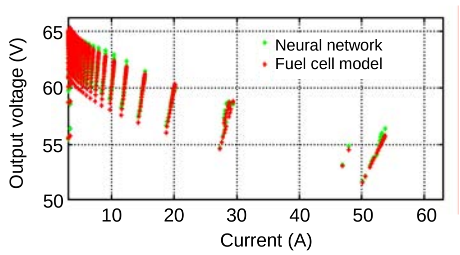

Fig. 6 *V-I* characteristics based on generated data

4 Output voltage tracking

A feed forward control system including a neural network together with a proportional-integral-derivative (PID) controller is presented in Fig. 7 (Huang *et al.*, 2008). In this work P_{air} is the control signal applied to the plant and V_{ref} is the output reference voltage. Fig. 8 shows the plant control diagram without feed forward control.

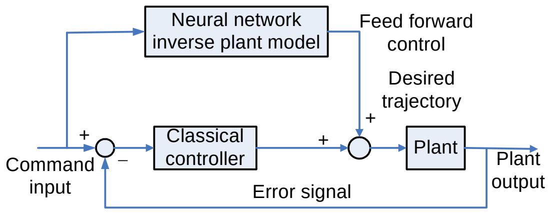

Fig. 7 Feed forward control system including a neural network together with a PID controller

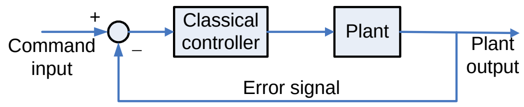

Fig. 8 Plant control diagram without feed forward control

A feed forward control system including a neural network was applied to stabilize the fuel cell terminal voltage. The delay existing in applying the proper pressure to the stack was also considered and set to 2 s. The simulation results were compared to those of the system without a feed forward controller.

A PID controller was used in both systems. Its parameters were calculated through the Ziegler-Nichols method and finely tuned to optimize the output response. The corresponding values were as follows:

The system with feed forward control: K_i=2, K_p=0.8, K_d=1e-7; the system without feed forward control: K_i=0.3, K_p=0.1, K_d=1e-7.

4.1 Inlet air pressure impact on fuel cell performance

According to the previous simulation results (Rakhtala *et al.*, 2008), as the inlet air pressure increases, the *P-I* and *V-I* curves rise dramatically and the cell voltage and current increase in turn. The above mentioned results were completely compatible with dynamic equations. Thus, the air pressure is considered to be a tuning parameter in controlling the fuel cell output voltage.

5 Simulation results

The main weak point of the fuel cell is its slow dynamic response dominated by temperature, inlet flow rate, and pressure. Load transients will therefore cause a high voltage drop in a short time. Thus, applying fast current pulses to the fuel cell system is evidently harmful for the stack or will lead to a reduced lifetime (Thounthong *et al.*, 2006; Wu *et al.*, 2008). Therefore, the transients in current must be omitted by a fast predictive control system along with a PID controller. The neural network simulation model is as presented in Fig. 9.

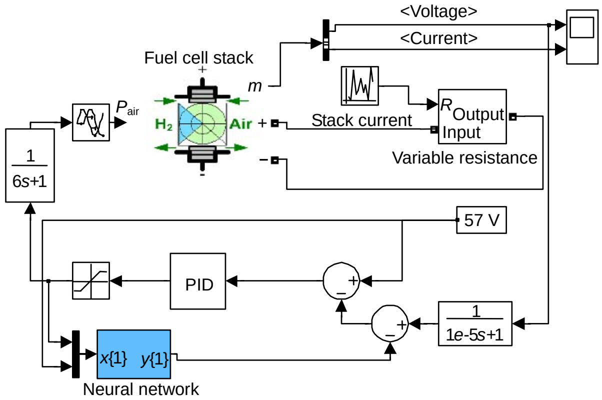

Fig. 9 Neural network simulation model

In normal operating conditions, system voltage and current were 57 V and 33 A, respectively. A current step from 20 A to 33 A at t=20 s and a current step from 33 A to 18 A at t=45 s were applied to the system. The stack current step variations during 550 s and the details during the first 100 s are presented in Figs. 10a and 10b, respectively.

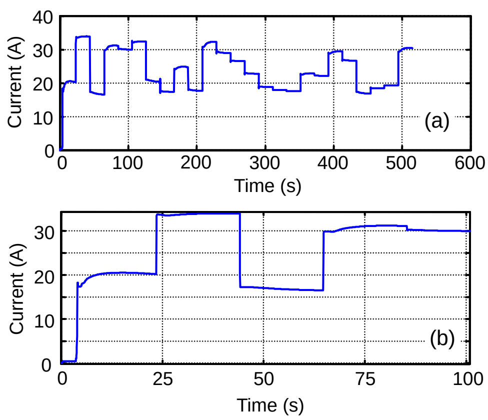

Fig. 10 Stack current step variations during 550 s (a) and the details during the first 100 s (b)

The plant terminal voltage variation under a random step current is illustrated in Fig. 11a.

Together with current variations, the terminal voltage was scarcely tracked via a PID controller. Consequently, fluctuations in terminal voltage were too large due to the time delay in auxiliary equipment and will degrade fuel cell efficiency and performance in industrial applications. In contrast, in a feed forward neural network control system, the output voltage fluctuations due to load current variations were well declined (Fig. 11b).

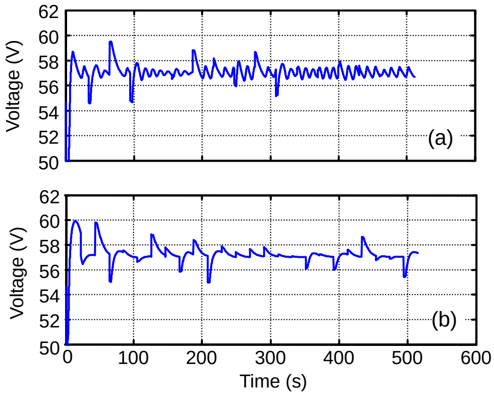

Fig. 11 Plant output voltage without (a) or with (b) feed forward control

Comparing the control signals in both systems (Figs. 12a and 12b), it is obvious that the inlet air pressure in the system with a feed forward controller had fewer fluctuations and that the pressure value was applied in a very short time.

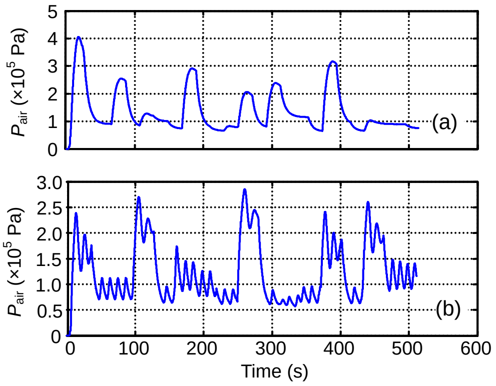

Fig. 12 The control signal P_{air} in the plant model with a feed forward controller (a) or with a PID controller (b)

In the proposed control strategy, the output voltage control was performed using only a back pressure and hence consumed less energy and employed a simpler control system. However, applying this strategy using a stack temperature control signal led to much more energy consumption and increased the system complexity.

6 Conclusions

Transients in dynamic loads will damage one of the significant parts of the fuel cell stack, membrane electrode assembly (MEA). Hence, this will degrade the fuel cell performance in a very short time. This is due to the delay in electrical and mechanical parts of auxiliary equipment (such as pumps and heaters) and back pressures. To remove the harmful effects of fast pulse currents, a neural network model together with a PID controller is employed in this study. The control signal is the inlet air pressure. The overall system behavior is investigated under random current variations and compared to the fuel cell nonlinear dynamic model. Simulation results show that the proposed neural network model is a fast and proper control system for controlling the fuel cell terminal voltage and improving the system performance. Moreover, it leads to less energy consumption and lower control system complexity.

The proposed control strategy can be extended to an overall artificial neural network control scheme for proton exchange membrane fuel cells including temperature and fuel and air flow rate control to improve the transient response of the output voltage.

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