Journal of Zhejiang University SCIENCE
ISSN 1009-3095
http://www.zju.edu.cn/jzus
E-mail: jzus@zju.edu.cn

Modelling and control PEMFC using fuzzy neural networks*

SUN Tao (孙 涛)†1, YAN Si-jia (闫思佳)[2], CAO Guang-yi (曹广益)[1], ZHU Xin-jian (朱新坚)[1]

([1]*Fuel Cell Institute, Department of Automation, Shanghai Jiao Tong University, Shanghai 200030, China*)

([2]*Department of Applied Chemistry, Shanghai Normal University, Shanghai 200234, China*)

†E-mail: xiaosuntao@sjtu.edu.cn; xiaosuntao@126.com

Received Dec. 10, 2004; revision accepted Apr. 10, 2005

Abstract: Proton exchange membrane generation technology is highly efficient, clean and considered as the most hopeful "green" power technology. The operating principles of proton exchange membrane fuel cell (PEMFC) system involve thermodynamics, electrochemistry, hydrodynamics and mass transfer theory, which comprise a complex nonlinear system, for which it is difficult to establish a mathematical model and control online. This paper first simply analyzes the characters of the PEMFC; and then uses the approach and self-study ability of artificial neural networks to build the model of the nonlinear system, and uses the adaptive neural-networks fuzzy infer system (ANFIS) to build the temperature model of PEMFC which is used as the reference model of the control system, and adjusts the model parameters to control it online. The model and control are implemented in SIMULINK environment. Simulation results showed that the test data and model agreed well, so it will be very useful for optimal and real-time control of PEMFC system.

Key words: Proton exchange membrane fuel cell, Adaptive neural-networks fuzzy infer system, Modeling, Neural network
doi:10.1631/jzus.2005.A1084 **Document code:** A **CLC number:** TP183

INTRODUCTION

With worldwide increase of air pollution and the environmental consciousness of governments, people have to look for new resources to mitigate the energy crisis and improve the present environmental status (Baschuk and Li, 2000; Rowe and Li, 2001). Fuel cells are highly efficient and environmentally clean electricity generators (Berning *et al*., 2002) that convert the chemical energy of a gaseous fuel directly into electrical energy and play an important role in solving the energy problem. Therefore worldwide attention has been focused on the development of fuel cells which will become alternative energy resources in the future (Bender *et al*., 2003). A fuel cell system can have overall efficiency of up to 80% and net electrical efficiency of 40% to 60%, which are higher than that of almost all other energy conversion systems. Among five different kinds of fuel cells, the proton exchange membrane fuel cell (PEMFC) has advantages of low operational temperature (20~100 °C), little noise, rapid startup, high power density and light weight; and has become the investigative focus of fuel cells (Berning and Djilali, 2003). PEMFC is being applied to vehicle, portable, and distributed power generation systems (such as district power station, family power supply) successfully and is considered as the most promising fuel cell technology in the future.

The thermal management is critical for improving PEMFC performance and lifetime. Increasing the operating temperature can decrease mass transport limitations and increase the electrochemical reaction rates; but also has adverse effect on the maximum cell potential due to thermodynamic considerations and the increase in water vapor partial pressure (Rowe and Li, 2001). So maintaining the appropriate working temperature is the key factor affecting the cell performance.

* Project (No. 2003AA517020) supported by the Hi-Tech Research and Development Program (863) of China

The neural network has the ability to learn and approach the nonlinear function, and has been considered as a powerful computing tool for establishing the mathematical relationship of the dynamic system based on the input-output data. It had been shown that feed-forward neural networks with one hidden layer can uniformly approximate any continuous function. A large number of structures and algorithms for identification and control using neural networks have been proposed (Chen and Bilings, 1992).

This paper adopts the neural network identification method to establish the nonlinear model in order to avoid the internal complexity of the PEMFC. The flow rates of fuel and air are used as input variables and the working temperature of the stack is used as output variable in this temperature model of PEMFC set up based on neural network identification. In order to maintain the ideal temperature value, the neural fuzzy controller was designed to regulate the gas flow rate.

PEM FUEL CELL SYSTEMS

Fig.1 in (Sun *et al*., 2005) shows the basic structure of a single cell consisting of anode, cathode, electrolyte plate, membrane and catalyst. The key part of the cell is the membrane electrode assembly made up of two porous gas diffusion electrodes pressed against the membrane sides and the catalysis layer of the electrode near the membrane. The membrane and the two electrodes are assembled into a sandwich structure to form a membrane-electrode assembly (MEA) placed between two bipolar plates with machined groves that provide flow channels for distributing the hydrogen and oxygen (Fowler *et al*., 2002; Rowe and Li, 2001). Hydrogen is fed to the anode along the gas channel, and separated into hydrogen protons and electrons under the action of the anode catalyst. The hydrogen protons migrate through the polymer electrolyte membrane driven by an electric field. Released electrons are collected by the bipolar plates and then pass from the anode to the cathode, where the oxygen reacts with the hydrogen protons and the electrons, thus producing water. The anode and cathode are connected to form an external load equipment. Generally speaking, the potential of a single cell is about 0.7 V and current density is approximately 400~800 mA/cm^2. To supply higher power, several cells are usually assembled into a PEMFC stack, where the cells are electrically connected in series and separated from each other by bipolar plates.

The anode temperature is denoted by $T_a(t)$, the cathode temperature is denoted by $T_c(t)$, the electrolyte membrane temperature is denoted by $T_e(t)$, and the gas flow by $\boldsymbol{V}(t)=[V_a(t), V_c(t)]^T$, $V_a(t)$ and $V_c(t)$ are the anode and cathode gas flow rate, respectively. According to PEMFC stack dynamic characteristics, letting $\boldsymbol{V}(t)=[V_a(t), V_c(t)]^T$ and $\boldsymbol{T}(t)=[T_a(t), T_c(t), T_e(t), T_s(t)]^T$, respectively. $\phi(\cdot)$ denotes the nonlinear relation between $\boldsymbol{T}$ and $\boldsymbol{V}$. The temperature model can be described as Eq.(1) on the basis of the analysis of dynamic PEMFC system:

$$\frac{\mathrm{d}T}{\mathrm{d}t} = \dot{T} = \phi(\boldsymbol{T}(t), \boldsymbol{V}(t)) \tag{1}$$

The stack temperature is mainly affected by the flow rate of inlet gas (Bender *et al*., 2003; Arriaqada *et al*., 2002). When the input air temperature is lower than the fuel cell temperature, some of the gas would be consumed, and the remaining gas would take away some heat. Slower gas flow rate leads to adequate reaction and less heat loss, the ultimate temperature of the stack would rise; on the other hand, faster gas flow rate would lead to inadequate reaction and carry away much more heat, so that the ultimate temperature of the stack would fall. The model should simulate the temperature variation curve at different gas flow rates, as well as complete the dynamic nonlinear map from input vector to output vector. The identification model can be described by the nonlinear differential equation:

$$T(k+1) = \phi(T(k), V(k)) \tag{2}$$

where k is the discrete time variable.

ANFIS LEARNING ALGORITHM AND PEMFC IDENTIFICATION

The PEMFC system identification structure is shown in Fig.6 in (Sun *et al*., 2005), where TDL denotes a tapped delay line whose output vector represents the delayed values of the input signal. Since the above model has no feedback loop, training procedures can be used to adjust the parameters (Shen and Cao, 2002; Kim and Kim, 1999). So we adopt the adaptive fuzzy neural network as the nonlinear system identifier, which can use the neural network's learning mechanism to compensate for the shortage of fuzzy inference system.

After the PEMFC system is identified, the membership function and fuzzy rules are used to learn the temperature values at different moments under the best steady working state, which are then combined with neural networks and their back propagation learning algorithm in order to improve the identification precision. The typical structure of Sugeno's ANFIS includes five layers: fuzzification layer, rule layer, normalization layer, defuzzification layer, summation neuron layer, which has M fuzzy rules (Sakhare and Davari, 2003; Efe and Kaynak, 1999):

R^l: IF x_1 is F_1^l and …, and x_n is F_1^l,
THEN $\boldsymbol{y}$ is G^l (l=1, 2, …, M) (3)

where F_1^l and G^l are both fuzzy set. $\boldsymbol{x}=(x_1, \ldots, x_n)^{\mathrm{T}}$ and $\boldsymbol{y}$ are input and output language variable, respectively. Gaussian function was adopted as the input membership function:

$$\mu_{F_i^l} = \alpha_i^l \exp\left[-\left(\frac{x_i - \overline{x}_i^l}{\sigma_i^l}\right)^2\right] \tag{4}$$

where α_i^l ($0<\alpha_i^l<1$), $\overline{x}_i^l$ denoting the center of the Gaussian membership function and σ_i^l denoting the width of the membership function, are adjustable parameters, respectively. Given an input-output pair (x^p, d^p), $x^p \in U$, $d^p \in V$, the designed fuzzy system f expressed below:

$$f(x) = \frac{\sum_{l=1}^{M} \overline{y}^l \left[\prod_{i=1}^{n} \alpha_i^l \exp\left(-\left(\frac{x_i - \overline{x}_i^l}{\sigma_i^l}\right)^2\right)\right]}{\sum_{l=1}^{M} \left[\prod_{i=1}^{n} \alpha_i^l \exp\left(-\left(\frac{x_i - \overline{x}_i^l}{\sigma_i^l}\right)^2\right)\right]} \tag{5}$$

minimizes the following expression:

$$e^p = \frac{1}{2}[f(x^p) - d^p]^2 \tag{6}$$

For ANFIS network, we adopt the hybrid algorithm of error back propagation and least square method to identify the above parameters. In the forward pass of the inputs, the parameters of membership function (premise parameters) are fixed, and the parameters in the decision part of fuzzy are fixed if rules (consequent parameters) are identified with least square method. In the backward, the consequent parameters are fixed, the premise parameters $\overline{x}_i^l$ and σ_i^l are modified by the following algorithm (Wang and Jerry, 1992):

$$\overline{x}_i^l(k+1) = \overline{x}_i^l(k) - \beta \frac{\partial E}{\partial \overline{x}_i^l} + \eta \Delta \overline{x}_i^l(k) \tag{7}$$

$$\sigma_i^l(k+1) = \sigma_i^l(k) - \beta \frac{\partial E}{\partial \sigma_i^l(k)} + \eta \Delta \sigma_i^l(k) \tag{8}$$

where β denotes the learning speed, η denotes momentum coefficient of reduced oscillation during the course of learning.

One hundred groups of training data on the PEMFC stack working temperature were collected under hydrogen (anode) flow rate of 1.2 L/min and air (cathode) flow rate of 5 L/min. The number of fuzzy rules M was selected as 18, the speed of learning β=0.7, the momentum coefficient η=0.1. After adjusting the premise parameters (V_a for example in Fig.1), the neural networks model can in a short time simulate test data with high precision. The maximal error was less than 2 °C. From the identification results of PEMFC system (Fig.2), we can also know it is feasible to establish the model of PEMFC nonlinear complicated system, and avoid to solving the differential equation during the course of mechanism modelling.

NEURO-FUZZY CONTROL SYSTEM OF PEMFC

The operating principle of PEMFC involves theories on thermodynamics, electrochemistry, hydrodynamics and mass transfer so it is difficult to establish a mathematical model of this complicated nonlinear system. So adopting the above mentioned

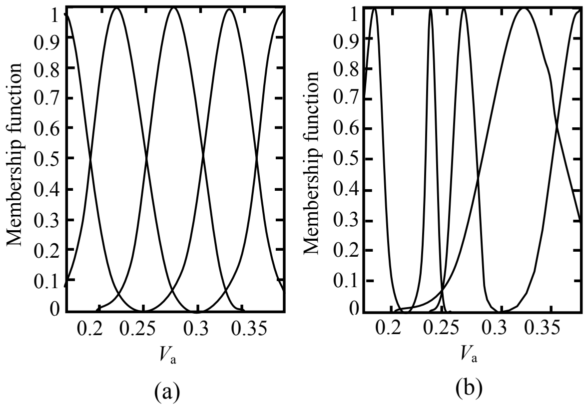

Fig.1 Membership function of V_a
(a) Before training; (b) After training

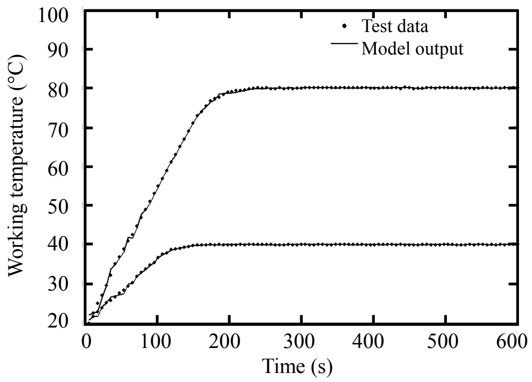

Fig.2 Identification results of PEMFC

neural network model as the PEMFC model, and designing fuzzy neural controller for researching the structure and realizing the fuzzy neural controller of PEMFC system.

The working temperature T_s and ΔT_s of the PEMFC were selected as fuzzy variables, the desired temperature was set at T_s=80 °C. The flow rates of anode and cathode gas in the system would increase when the working temperature exceeds T_s; the gas flow rate would decrease when the working temperature falls below T_s. Under the condition of the given working pressure, the basic range of T is 40 °C~100 °C, the basic range of ΔT is −2 °C~2 °C, the sampling period of system is 2 s. Fuzzy variables are expressed by linguistic variables such as positive big (PB), positive medium (PM), positive small (PS), zero (ZO), negative small (NS), negative medium (NM), negative big (NB). Similarly, linguistic variables were established for output variables. The basic range of the flow rate of anode and cathode gas are 15~20 and 30~38, respectively. Each value of linguistic variable adopts Gaussian function to express it. The Mamdani method is used in fuzzy inference, and the centroid defuzzification method determines the output value from the center of gravity of the output membership function. The actual and the reference working temperature are compared which generates the error. This becomes one of the inputs and the change in the error derived from this error becomes the other input. These inputs then based on the fuzzy rules generate the desired control signal for the system to work as desired and control the unregulated working temperature coming from the PEMFC (Fowler *et al.*, 2002; Rowe and Li, 2001). The structure of fuzzy controller is shown in Fig.3.

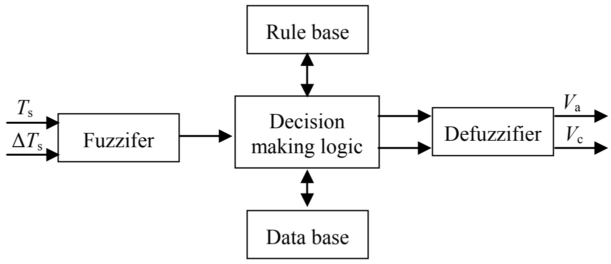

Fig.3 Fuzzy controller of PEMFC

The parameters in rules and membership function of fuzzy system are designed based on operating experience only, and which is difficult to adjust on-line. Neural networks and fuzzy inference systems are well-recognized tools for designing an identifier/controller capable of perceiving the operating environment and imitating a human operator with high performance (Sakhare and Davari, 2003). So adopting a neural networks to construct the fuzzy system, which can use the learning method of neural networks to design and adjust the parameters to realize the self study and self adapting function of fuzzy system according to input and output sample.

Neuro-fuzzy controller utilizes the input [T_s, ΔT_s] and the output [V_a, V_c] of the previous PEMFC fuzzy controller to train neural networks, let it learn and remember the abstract fuzzy rules, and neural networks would store the knowledge of expression in its weight and structure. Therefore the controller of PEMFC can associate and make use of rules. We adopt an error back propagation training algorithm to adjust the value of parameters $\bar{y}^l$, $\bar{x}_i^l$ and σ_i^l (Wang and Jerry, 1992). The objective is to determine a fuzzy logic system described by Eq.(5), so as to minimize the value of Eq.(6). $\bar{y}^l$ is the desired value of the controller output. Assuming α_i^l=1, and the number of rules M=24, the training algorithm for $\bar{y}^l$ is shown as follows:

$$\bar{y}^l(k+1)=\bar{y}^l(k)-\alpha\frac{\partial E}{\partial \bar{y}^l}\Big|_k \tag{9}$$

l=1, 2, …, M; k=0, 1, 2, …, α. α is the given step.

Let f=a/b, $a=\sum_{l=1}^{M}(\bar{y}^l z^l)$, $b=\sum_{l=1}^{M}z^l$ and $z^l=\prod_{l=1}^{k}\exp\left[-\left(\frac{x_i-\bar{x}_i^l}{\sigma_i^l}\right)\right]$. We can see f and e depends on $\bar{y}^l$ only through α. From Eq.(9), we deduce the following learning algorithm:

$$\bar{y}^l(k+1)=\bar{y}^l(k)-\alpha\frac{f-d}{b}z^l \tag{10}$$

$$\bar{x}_i^l(k+1)=\bar{x}_i^l(k)-\frac{f-b}{b}(\bar{y}^l-f)z^l\frac{2(x_i^p-\bar{x}_i^l(k))}{\sigma_i^{l2}(k)} \tag{11}$$

$$\sigma_i^l(k+1)=\sigma_i^l(k)-\alpha\frac{f-b}{b}(\bar{y}^l-f)z^l\frac{2(x_i^p-\bar{x}_i^l(k))}{\sigma_i^{l3}(k)} \tag{12}$$

The parameters are adjusted based on the input-output data of the previous step, and the normal error is back propagated with delay of one step to the relevant parameter processing unit. The structural scheme of PEMFC system with neuro-fuzzy control is shown in Fig.4.

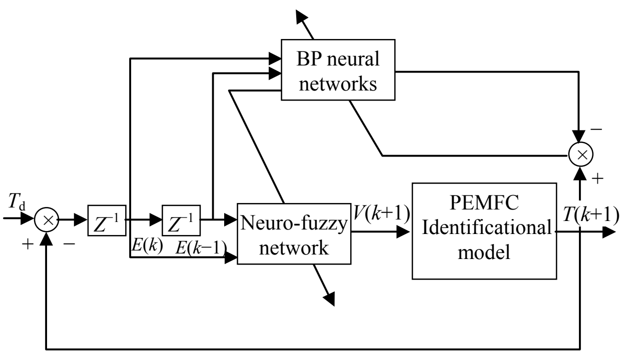

Fig.4 Structure of the neuro-fuzzy control system of PEMFC

The dynamic temperature characteristic of PEMFC is replaced with the ANFIS identification model on-line in order to faster response. The program of simulation is compiled in MATLB environment, which includes the following content: the current temperature value is inputted to the neural networks model, where the current temperature value reduces the previous value, and inputs the result to the neuro-fuzzy control network. In the end, the corresponding flow rate of gas is calculated and outputted. Table 1 shows the parameters of experiment and simulation in PEMFC system.

Table 1 Operating conditions of PEMFC

Item	Value
Number of cell	30
Proton exchange membrane	Nafion115
Cathode pressure	2.52×10^5 Pa
Anode pressure	2.52×10^5 Pa
Cathode gas flow rate	30~38 L/min
Anode gas flow rate	15~20 L/min
Humidification temperature	70 °C
Hydrogen inlet temperature	75 °C
Air inlet temperature	65 °C
Stack operating temperature	40~80 °C
Active area of cell	128 cm^2
Fuel gas	H_2/H_2O=0.86/0.14
Relative humidity	100 %
Electrode thickness	0.3 mm
Membrane thickness	0.13 mm
Current collector thickness	4 mm

In the condition of the rated output power, we only consider adopting the fuzzy neural controller to control the flow of gas to regulate the fuel cell operating temperature. In fact, the change of the gas flow would influence the transmittance process of the reacting gas more or less, thus impact the current and power of the stack. But the influence is smaller in case the gas utilization ratio is lower. From the simulation results in Fig.5 and Fig.6, we can see that the operating temperature reaches the desired value smoothly during shorter time through the neuro-fuzzy controller's adjustment of the gas flow rate. So PEMFC system adopting neuro-fuzzy control method can reach the desired temperature rapidly, and the temperature fluctuation is smaller.

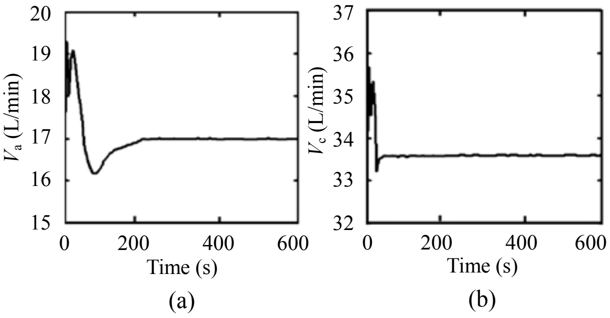

Fig.5 The flow rates of V_a (a) and V_c (b)

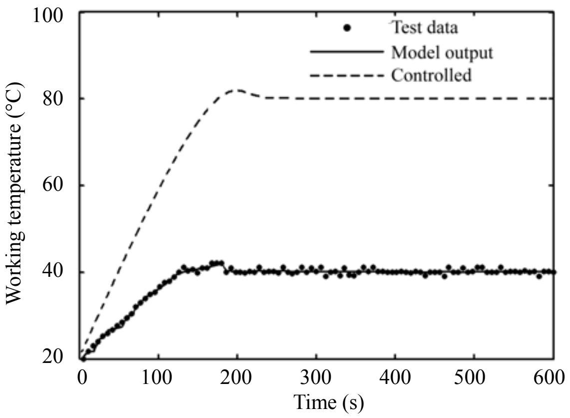

Fig.6 The control results of PEMFC

CONCLUSION

An ANFIS identification model of PEMFC was first developed in this work. Then an online neuro-fuzzy controller of PEMFC system was set up. The proposed procedure overcomes the limitations of the traditional fuzzy control method. The validity of ANFIS identification of PEMFC system and the good performance of neuro-fuzzy controller were validated by simulation, from which we can know that it can establish the model of the complicated PEMFC nonlinear complicated system with ANFIS method and can be used to predict the temperature response online.

References

Arriaqada, J., Olausson, P., Selimoric, A., 2002. Artificial neural network simulator for SOFC performance prediction. *Journal of Power Sources*, **112**:54-60.

Baschuk, J.J., Li, X., 2000. Modelling of polymer electrolyte membrane fuel cells with variable degrees of water flooding. *Journal of Power Sources*, **86**:181-196.

Bender, G., Wilson, M.S., Zawodzinski, T.A., 2003. Further refinements in the segmented cell approach to diagnosing performance in polymer membrane fuel cells. *Journal of Power Sources*, **123**:163-171.

Berning, T., Djilali, N., 2003. Three-dimensional computational analysis of transport phenomena in a PEM fuel cell−A parametric study. *Journal of Power Sources*, **124**:440-452.

Berning, T., Lu, D.M., Djilali, N., 2002. Three-dimensional computational analysis of transport phenomena in a PEM fuel cell. *Journal of Power Sources*, **106**:284-294.

Chen, S., Bilings, S.A., 1992. Neural networks for nonlinear dynamic system modeling and identification. *International Journal of Control*, **56**(2):319-346.

Efe, M.O., Kaynak, O., 1999. Neuro-fuzzy Approaches for Identification and Control of Nonlinear Systems. Proceedings of the IEEE International Symposium on Industrial Electronics, p.TU2-TU11.

Fowler, M.W., Mann, R.F., Amphlett, J.C., Peppley, B.A., Roberge, P.R., 2002. Incorporation of voltage degradation into a generalized steady state electrochemical model for a PEM fuel cell. *Journal of Power Sources*, **106**:274-283.

Kim, Y.H., Kim, S.S., 1999. An electrical modeling and fuzzy logic control of a fuel cell generation system. *IEEE Transactions on Energy Conversion*, **14**(2):239-244.

Rowe, A., Li, X., 2001. Mathematical modeling of proton exchange membrane fuel cells. *Journal of Power sources*, **102**:82-96.

Sakhare, A., Davari, A., 2003. Control of Stand Solid Oxide Fuel Cell Using Fuzzy Logic. Proceedings of the 35th Southeastern Symposium on System Theory, p.473-476.

Shen, C., Cao, G.Y., 2002. Nonlinear modeling and adaptive fuzzy control of MCFC stack. *Journal of Process Control*, **12**:831-839.

Sun, T., Cao, G., Zhu, X., 2005. Nonlinear modeling of PEMFC based on neural networks identification. *J Zhejiang Univ SCI*, **6A**(5):365-370.

Wang, L.X., Jerry, M.M., 1992. Back Propagation Fuzzy System as Nonlinear Dynamic System Identifiers. IEEE International Conference on Fuzzy Systems, p.1409-1418.