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Hybrid intelligent PID control design for PEMFC anode system*

Rui-min WANG†1, Ying-ying ZHANG[2], Guang-yi CAO[1]

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

([2]*Institute of Oceanographic Instrument, Shandong Academy of Science, Qingdao 266001, China*)

†E-mail: ivywrm@yahoo.com.cn

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Abstract: Control design is important for proton exchange membrane fuel cell (PEMFC) generator. This work researched the anode system of a 60-kW PEMFC generator. Both anode pressure and humidity must be maintained at ideal levels during steady operation. In view of characteristics and requirements of the system, a hybrid intelligent PID controller is designed specifically based on dynamic simulation. A single neuron PI controller is used for anode humidity by adjusting the water injection to the hydrogen cell. Another incremental PID controller, based on the diagonal recurrent neural network (DRNN) dynamic identification, is used to control anode pressure to be more stable and exact by adjusting the hydrogen flow rate. This control strategy can avoid the coupling problem of the PEMFC and achieve a more adaptive ability. Simulation results showed that the control strategy can maintain both anode humidity and pressure at ideal levels regardless of variable load, nonlinear dynamic and coupling characteristics of the system. This work will give some guides for further control design and applications of the total PEMFC generator.

Key words: Proton exchange membrane fuel cell (PEMFC), Anode system, Single neuron, Diagonal recurrent neural network (DRNN), PID controller

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INTRODUCTION

Proton exchange membrane fuel cell (PEMFC) generator is a very complex system. Chemical reactions, reactant flow and the variable load all lead to the nonlinear dynamic and coupling characteristics of the PEMFC power generator. So coordination and control design are extremely important for achieving high efficiency and long duration of the system (Larminie and Dicks, 2002; Moore *et al*., 2005). Now PEMFC generator application is limited due to high cost and immature technology. Modeling and simulation are thus effective methods for researching the generator.

The anode pressure and humidity of the 60-kW PEMFC generator are controlled in the nonlinear dynamic and coupling system. In control designing, the coupling problem is considered as a disturbance problem, and the two-variable coupling system is treated as two single-loop control systems (Yang and Dang, 2004). A two-variable hybrid intelligent PID controller is designed based on the system model and requirements. The traditional PI control method is selected due to simple control structure and easy implementation. The single neuron has self-study ability, and DRNN has dynamic mapping and memory function. Incorporating them in the anode control system, the controller can achieve more adaptive ability. Simulation results showed that both anode pressure and humidity can be maintained very well at ideal levels in real-time operation.

ANODE SYSTEM MODELING

In the 60-kW PEMFC generator, the pressure of hydrogen stored in a high-pressure container is reduced to 0.6 MPa by a first pressure relief valve. A second valve adjusts the flow rate of hydrogen sup-

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plied to the stack anode for oxidation reaction after humidification. The system anode operates in sub-saturated condition, i.e., the relative humidity of the gas inside the anode volume $\phi_{an}<1$, to prevent anode flooding. It is assumed that the anode purge is zero. In MATLAB/SIMULINK, the simulation model of anode system is established based on the dynamic flow of reactants (Fig.1). With relatively slow responses, the stack temperature can be viewed as a separate part in the heat control subsystem of the generator (Pukrushpan *et al.*, 2004), which is not discussed here, so the stack temperature is assumed to be constant now.

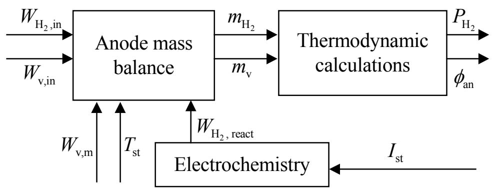

Fig.1 PEMFC stack anode model block

In the model of the second valve, the pressure drop is simplified to the square of the hydrogen flow rate. According to the state equation of ideal gas and physicochemical principles, a static model of the humidifier is used to calculate the change in hydrogen humidity due to the water injection. Based on mass and energy conservation equations, masses of hydrogen and water in the anode volume are (Caux *et al.*, 2005):

$$\dot{m}_{H_2} = W_{H_2,in} - W_{H_2,react}, \tag{1}$$

$$\dot{m}_v = W_{v,in} - W_{v,m}, \tag{2}$$

where $W_{H_2,in}$ and $W_{v,in}$ are mass flow rates of hydrogen and water entering the stack anode, respectively, $W_{v,m}$ is water transport across the membrane. $W_{H_2,react}$, the hydrogen consumed in the reaction, is a function of the stack current I:

$$W_{H_2,react} = M_{H_2} nI/(2F), \tag{3}$$

where n is the number of cells in the stack, M_{H_2} is the molar mass of hydrogen and F is the Faraday number. The total anode pressure is the sum of hydrogen and vapor partial pressures:

$$p_{an} = p_{H_2} + p_v = \frac{m_{H_2} R_{H_2} T}{V} + \frac{m_v R_v T}{V}, \tag{4}$$

where R_{H_2} and R_v are gas constant of hydrogen and vapor, respectively. T is the stack temperature and V is the anode volume. The humidity of the gas inside the anode flow is

$$\phi_{an} = p_{v,an} / p_{sat}(T), \tag{5}$$

where the saturation pressure p_{sat} is a function of the temperature, $p_{v,an}$ is the anode vapor partial pressure. The water transport across the membrane is achieved through three distinct phenomena: electro-osmotic drag, back-diffusion and migration from pressure difference (Ge *et al.*, 1999). Combining these three water transports and approximating the water concentration gradient and pressure change in the membrane to be linear over the membrane thickness, the total water transport can be calculated from

$$W_{v,m} = M_v An \left(n_d \frac{I}{AF} - D_w \frac{c_{wc} - c_{wa}}{t_m} - \lambda c_f \frac{k_p}{\mu} \frac{p_{ca} - p_{an}}{t_m} \right), \tag{6}$$

where M_v is molar mass, c_{wc} and c_{wa} the water concentrations at surfaces on cathode side and anode side respectively, A the cell active area, t_m the membrane thickness, k_p the hydraulic coefficient, μ the water viscosity, c_f the sulfonic density, p_{ca} the cathode pressure, λ the water content in the membrane, n_d the electro-osmotic drag coefficient, and D_w the water diffusion coefficient. The relation between λ and n_d is

$$n_d = 2.5\lambda / 22,$$

and the relation between λ and D_w is

$$D_w = 10^{-6} \exp\left[2416 \left(\frac{1}{303} - \frac{1}{T} \right) \right] \cdot (2.563 - 0.33\lambda + 0.0264\lambda^2 - 0.000671\lambda^3).$$

Water concentrations at surfaces on anode and cathode sides c_{wa} and c_{wc} are both calculated empirically from humidity ϕ_{an} and ϕ_{ca}:

$$c_i = \frac{\rho_{\mathrm{m}}}{M_{\mathrm{m}}}(0.043 + 17.81\phi_j - 39.85\phi_j^2 + 36\phi_j^3), \quad (7)$$

where ρ_{m} is the density and M_{m} is the equivalent weight of the dry membrane, (i, j)=(wa, an) or (wc, ca).

For accurate determination of the concentrations at the membrane-diffusion layer interface, the mole fractions for each species used in these equations are linearly extrapolated to the membrane (Dutta *et al.*, 2001).

The anode system of PEMFC generator is such a nonlinear dynamic system. In the model, p_{an} includes the vapor partial pressure, which determines ϕ_{an}. Vapor partial pressure relates to the water transport across the membrane, which is affected by p_{an} and ϕ_{an} again. So, the anode system is also a coupled system. For the 60-kW PEMFC generator, the ideal level is: anode pressure maintained at p_{an}^*=0.294 MPa, anode pressure should be 0.01 MPa lower than cathode pressure to prevent the membrane from collapsing, and anode humidity must be maintained at ϕ_{an}^*=0.98.

ANODE SYSTEM CONTROL DESIGN

To focus on the anode system, the cathode variables including pressure and humidity are all assumed to be constant. Hydrogen flow rate through the relief pressure valve and the water injection to the hydrogen cell by the pump are input variables in the anode system. The current I, cathode pressure p_{ca} and humidity ϕ_{ca} are all regarded as disturbances in the anode system. The coupling problem between p_{an} and ϕ_{an} is considered as a disturbance problem, so that the two-variable coupling system is treated as two single-loop control systems (Yang and Dang, 2004).

Fig.2 presents the total control strategy for anode system. The traditional PI control method is simple in structure and easy to implement. But in view of so many disturbances and the dynamic characteristic of the system and more other problems in real applications, this method is not enough. So, the self-study ability of the single neuron is incorporated in anode humidity control. The dynamic mapping and memory function of DRNN are used for anode pressure control, which is relatively complex but provides more stable and exact control result.

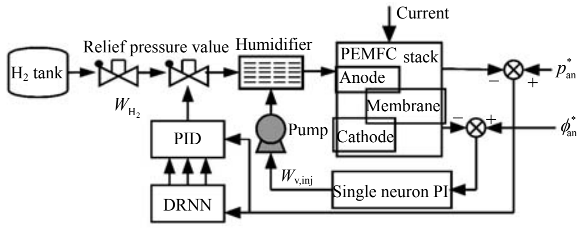

Fig.2 Control design for the anode system of a 60-kW PEMFC generator

Single neuron PI controller of anode humidity

Anode humidity control is aimed at maintaining the desired humidity $\phi_{\mathrm{an}}=\phi_{\mathrm{an}}^*$ by adjusting $W_{\mathrm{v,inj}}$, i.e., the water injected to the hydrogen cell by the pump. The control error is defined as $e_1(k)=\phi_{\mathrm{an}}-\phi_{\mathrm{an}}^*$. The quadratic index $J_1=e_1^2(k)/2$ based on optimal control theory is introduced in the single neuron PI control (Zhang and Cao, 2003; Wu and Shen, 2003).

In the neuron learning algorithm, weights of the single neurons are optimized along the negative gradient direction of J_1 versus w_{1i}, and then the control error $e_1(k)$ can be restricted. The learning algorithm is standardized as

$$\begin{cases} W_{\mathrm{v,inj}}(k) = W_{\mathrm{v,inj}}(k-1) + K_1 \sum_{i=1}^{2} w'_{1i}(k) x_{1i}(k), \\ w'_{1i}(k) = w_{1i}(k) \Big/ \sum_{i=1}^{2} \left| w_{1i}(k) \right|, \\ w_{1i}(k) = w_{1i}(k-1) + \eta_{1i} K_1 e_1(k) x_{1i}(k) \cdot \\ \qquad \mathrm{sign}\left[\dfrac{e_1(k) - e_1(k-1)}{W_{\mathrm{v,inj}}(k-1) - W_{\mathrm{v,inj}}(k-2)} \right], \end{cases} \quad (8)$$

where i=1, 2, η_{1i} are learning rates of proportional and integral terms, K_1 is the gain of the single neuron. Inputs $x_{1i}(k)$ are defined as

$$x_{11}(k) = e_1(k), \quad x_{12}(k) = e_1(k) - e_1(k-1). \quad (9)$$

If learning rates η_{1i} (i=1, 2) are set too large, the neuron regulator will easily overshoot; if too small, the regulator process will be slow. K_1 has a big effect on system stability. If K_1 is set too large, the system will easily oscillate; if too small, the system response will be too slow. Initial states of weights w_{1i} can be set randomly and self-adaptively change according to the error $e_1(k)$. Only if η_{1i} and K_1 are set to suitable values, can the control error $e_1(k)$ be restricted well through the self-adaptive algorithm.

PID controller based on DRNN identification for anode pressure

The objective of anode pressure control is to keep $p_{an}=p_{an}^*$ by adjusting W_{H_2}. Control error is defined as $e_2(k)=p_{an}-p_{an}^*$. As shown in Fig.1, PID controller acts according to the control error, and the identification result of the pressure system by DRNN is used to adjust PID controller parameters. The digital incremental PID controller used is given by

$$\begin{aligned} W_{H_2}(k) = W_{H_2}(k-1) + k_{2p}(k)x_{21}(k) + \\ k_{2i}(k)x_{22}(k) + k_{2d}(k)x_{23}(k), \end{aligned} \tag{10}$$

where k_{2p}, k_{2i} and k_{2d} are proportional, integral and differential parameters, respectively. Inputs are defined as

$$\begin{cases} x_{21}(k) = e_2(k) - e_2(k-1), \\ x_{22}(k) = e_2(k), \\ x_{23}(k) = e_2(k) - 2e_2(k-1) + e_2(k-2). \end{cases} \tag{11}$$

The quadratic index $J_2 = e_2^2(k)/2$ is also introduced in pressure control. Three PID control parameters are adjusted along the negative gradient direction of J_2,

$$\begin{cases} k_{2p}(k) = k_{2p}(k-1) + \eta_{21} e_2(k) x_{21}(k) \dfrac{\partial p_{an}}{\partial W_{H_2,\text{valve}}}, \\ k_{2i}(k) = k_{2i}(k-1) + \eta_{22} e_2(k) x_{22}(k) \dfrac{\partial p_{an}}{\partial W_{H_2,\text{valve}}}, \\ k_{2d}(k) = k_{2d}(k-1) + \eta_{23} e_2(k) x_{23}(k) \dfrac{\partial p_{an}}{\partial W_{H_2,\text{valve}}}, \end{cases} \tag{12}$$

where η_{2i} (i=1, 2, 3) are learning rates, $\partial p_{an} / \partial W_{H_2,\text{valve}}$ is the Jacobian information of the controlled pressure system, which is identified by DRNN.

The architecture of DRNN is a modified model of the fully connected recurrent neural network with a hidden layer, an input layer and an output layer (Liu *et al.*, 2004; Wang *et al.*, 2004). The hidden layer is comprised of self-recurrent neurons. $I_i(k)$ is the ith input, $S_j(k)$ is the sum of inputs to the jth recurrent neuron, $X_j(k)$ is the output of the jth recurrent neuron, and $O(k)$ is the output of the network. The activation function of the hidden layer $f(\cdot)$ is a Sigmoid function. As shown in Fig.3, inputs of the network are input variable $u(k)$ and output variable $y(k)$ of the identified system, and the output of the network is $y_m(k)$. Identification error is $e_m(k)=y(k)-y_m(k)$, and the network is trained according to it. The mathematical model of DRNN is described as follows:

$$y_m(k) = O(k) = \sum_j w_j^O X_j(k), \tag{13}$$

$$X_j(k) = f(S_j(k)), \tag{14}$$

$$S_j(k) = w_j^D X_j(k-1) + \sum_i w_{ij}^I I_i(k), \tag{15}$$

where $\boldsymbol{w}^O$, $\boldsymbol{w}^D$ and $\boldsymbol{w}^I$ represent the weight vectors of the output layer, diagonal layer and input layer, respectively, which are all adjusted along the negative gradient of the error function $J_m=(e_m(k))^2/2$,

$$\begin{cases} w_j^O(k) = w_j^O(k-1) + \eta_O e_m(k) X_j(k) \\ \qquad + \alpha[w_j^O(k-1) - w_j^O(k-2)], \\ w_{ij}^I(k) = w_{ij}^I(k-1) + \eta_I e_m(k) w_j^O f'(S_j) I_i(k) \\ \qquad + \alpha[w_{ij}^I(k-1) - w_{ij}^I(k-2)], \\ w_j^D(k) = w_j^D(k-1) + \eta_D e_m(k) w_j^O f'(S_j) X_j(k-1) \\ \qquad + \alpha[w_j^D(k-1) - w_j^D(k-2)], \end{cases} \tag{16}$$

where η_I, η_D and η_O are learning rates of weight vectors, and α is the inertial coefficient.

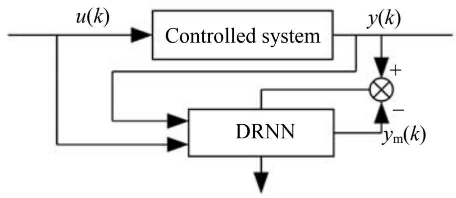

Fig.3 DRNN identification system

In the pressure control, the simulation model of anode system represents the actual controlled system. Defining the input vector of the network as $\boldsymbol{I}$=[$W_{H_2,\text{valve}}(k-1)$, $p_{an}(k)$, 1], the Jacobian information of pressure control system is

$$\frac{\partial p_{\mathrm{an}}}{\partial W_{\mathrm{H_2,valve}}}=\frac{\partial y_{\mathrm{m}}}{\partial u}=\sum_j w_j^{\mathrm{O}} f'(S_j) w_{ij}^{\mathrm{I}}. \tag{17}$$

DRNN identifies the nonlinear dynamic system rapidly and accurately. The identified convergent profile of $e_{\mathrm{m}}(k)$ is shown in Fig.4. The adaptive PID controller based on real-time identification of DRNN can provide more stable and exact control result, which favors the generator.

Based on the modeling above, SIMULINK modules are used to simulate an anode system of a 60-kW PEMFC generator. Parameters used in the model are given in Table 1. This work researched the real-time steady operation of the anode system excluding the start-up and shut-down processes, so the initial states of anode pressure and humidity are all set near their ideal values. In the test, a variable current signal I is input to the system, which is obtained by connecting some folded lines and represents the real-time load power demand in real applications, as shown in Fig.5a. Two M-function modules are used to realize the single neuron PI controller and PID controller based on DRNN identification. Selecting all control parameters as given in Table 2, Figs.5b and 5c present control results in the simulation. In Fig.5b, DRNN identifies the anode pressure very well and the pressure is maintained at the ideal level by PID controller based on DRNN identification. Compared to the single neuron PI control method, the control design presented in this paper can maintain the pressure more stably and exactly, which is favorable for power generation. Anode humidity can be controlled well

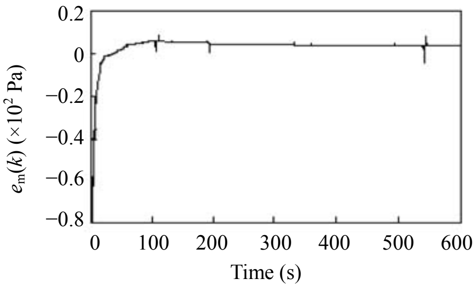

Fig.4 Output error of DRNN identification

Table 1 Parameters in the model of anode system

Parameter	Value
Stack temperature T (K)	348.15
Anode volume V_{an} (m^3)	0.01
Sulfonic density c_{f} (mol/m^2)	1.2×10^3
Cell active area A (cm^2)	600
Density ρ_{m} (kg/m^3)	2×10^3
Water viscosity μ (Pa·s)	3.565×10^{-4}
Hydraulic coefficient k_{p} (m^2)	5×10^{-19}
Equivalent weight of the dry membrane M_{m} (kg/mol)	1.1
Cathode pressure p_{ca} (Pa)	303975
Relative humidity of the gas inside the cathode volume ϕ_{ca}	1
Number of cells in the stack n	300
Membrane thickness t_{m} (m)	0.0175

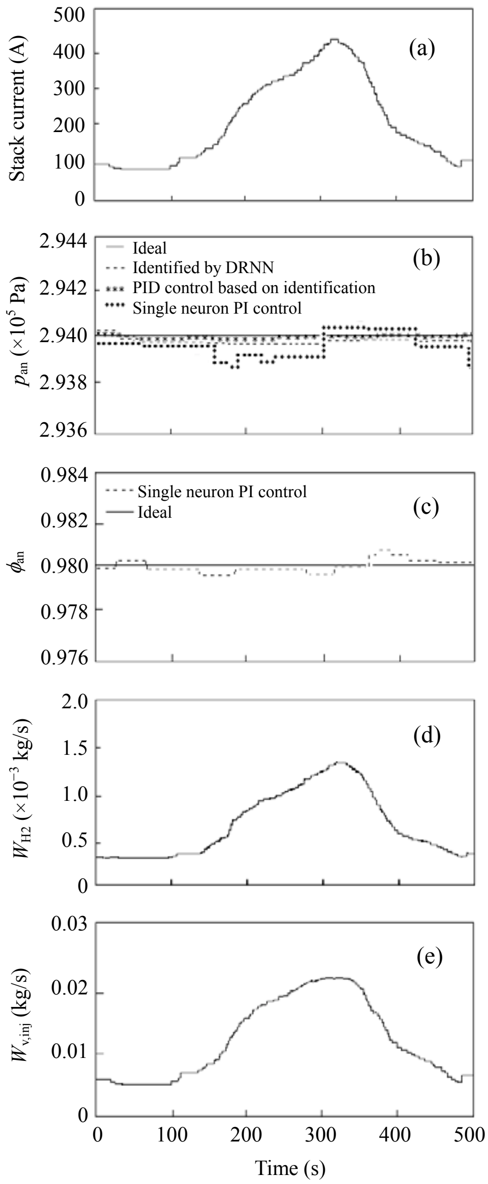

Fig.5 Control results in the simulation. (a) Input current in the simulation; (b) Anode pressure; (c) Anode humidity; (d) Hydrogen flow rate through the valve; (e) Water injection to the hydrogen cell

Table 2 Control parameters in the control simulation

Parameter	Value
Weight $w_{11}(0)$, $w_{12}(0)$	0.01, 0.01
Gain of the single neuron K_1	1×10^{-3}
Inertia coefficient α	0.0015
Proportional parameter $k_{2p}(0)$	2×10^{-6}
Integral parameter $k_{2i}(0)$	0
Differential parameter $k_{2d}(0)$	0
Learning rate	
η_I, η_O, η_D	900, 0.01, 4×10^{-6}
η_{11}, η_{12}	100, 0.10
η_{21}, η_{22}, η_{23}	8×10^{-20}, 1×10^{-21}, 1×10^{-21}

by single neuron PI controller in Fig.5c. The maximal error is 0.0001. The accuracy is enough for this anode system model. Fig.5d presents the hydrogen flow rate through the valve. Fig.5e presents water injection to the hydrogen cell. The hydrogen flow rate and the water injection to the hydrogen are both proportional to the stack current. The simulation results showed that the control design for anode system presented in this paper is effective.

CONCLUSION

Both anode pressure and humidity of a 60-kW PEMFC generator must be maintained at ideal level in real-time steady operation. The dynamic model of the anode system is established first for the control design and simulation. In the control design, the coupling problem is considered as a disturbance problem, and the two-variable coupling system is treated as two single-loop control systems. In this way, the hybrid intelligent PID controller is specifically designed to control the anode system. The hybrid intelligent PID controller, which incorporates the advantages of single neuron and DRNN, still has simple structure, so it is easy to realize. Simulation results showed that the control strategy can maintain both anode humidity and pressure at ideal level regardless of variable load, nonlinear dynamic and coupling characteristics of the system. The steady operation of PEMFC anode system in real time is realized, which will give some guides for further control design and applications of the PEMFC generator.

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