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Nonlinear modelling and adaptive fuzzy control of PEMFC

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SUMMARY

To improve stability and performance of fuel cells, the operating temperature of proton exchange membrane fuel cells (PEMFC) should be controlled within a specified range. However, the most existing mathematical models of PEMFC are too complex to be applied effectively in control process. In this paper, adaptive fuzzy identification and control models of PEMFC are developed based on input-output sampled data and experts experience. The parameters of identifier and controller are regulated by adaptive learning algorithm, the networks structure and the rule database are modified by adjusting the parameters. In the end, the simulation results of on-line control model are presented, and show the effectiveness.

Key words: *Proton exchange membrane fuel cell (PEMFC), Adaptive neural-networks fuzzy infer system (ANFIS), Adaptive neural-networks learning algorithm (ANA), Adaptive neural-networks fuzzy controller.*

1. INTRODUCTION

Proton exchange membrane fuel cells (PEMFC) is a kind of clean energy with high efficiency, which will be widely utilized soon. Without combustion, PEMFC converts chemical energy contained in reactants to electric energy via electro-chemical reaction. PEMFC has a tendency to replace the traditional oil-burning power system and to reduce pollution emission.

In the last decade, many researchers focused on improving performance and reducing cost of fuel cells, the research of control methods is not put in schedules. At present, it is urgent to increase the utilization ratio of fuel and oxidizer. This paper emphasizes on presenting an effective control method for PEMFC [1].

Performance and stability of PEMFC are greatly dependent on its operating temperature. The range of operating temperature is about *50° C~110° C*, and the normal operating temperature is about *80° C*. Operating below *50° C*, the electrical conductivity of the membrane degrades and the cells' performance drops significantly. A higher operating temperature is favorable for improving the cells' output performance, however, the dehydration of membrane shortens the cells' lifespan [2]. So controlling the operating temperature within a specified range and reducing temperature fluctuation are very important.

As we know, PEMFC systems are sealed, and work in a complicated environment, they include multiple recycling gas-flow loops and multiple phase flows in the complex electro-chemical reactions. According to analysis of PEMFC system, it is known that the dynamics of PEMFC system is a nonlinear system with multi-input and multi-output, and it is difficult to model using the traditional methodologies [3, 4]. The most existing models are based on mass, energy and momentum conservation laws, and their expressions are too complicated to be applied in control process.

It has been shown that fuzzy logic system can uniformly approximate any continuous function to a pre-specified accuracy [5]. In this paper, adaptive fuzzy neural-networks technique is considered as an attractive method to establish the identification and control models of the operating temperature of PEMFC based on input-output sampled data and experts' experience. In modelling process, ANFIS can use the data and experience obtained in experiments to infer the results of model, and applies ANA to adjust the parameters of membership functions if errors are produced between the results and data, infers and adjusts repeatedly. At last, the errors are reduced within the specified range. In control process, at first, according to the analysis results and operating experience, establish an initial fuzzy logic system, then optimize and adjust the parameters of membership functions and networks structure. At last, obtain satisfying control effect.

This paper is organized as follows. Section 2 presents a brief analysis of the characters of PEMFC. In Section 3, we give a review of ANFIS for MIMO nonlinear system, and we apply the modelling technique to overcome the internal complexity of the system, and we identify the PEMFC system, finally, we set up the nonlinear operating temperature model. A novel adaptive fuzzy neural-networks controller for PEMFC is developed in Section 4. In Section 5, a numerical experiment based on the control model is considered to show the effectiveness of the proposed control algorithm. In the end, we present our conclusion remarks.

2. DESCRIPTION AND ANALYSIS OF PEMFC

A single cell consists of anode, cathode, proton exchange membrane and bipolar plate. In anode catalyst layer, H_2 in fuel gas reacts and produces H^+ and electrons, electrons pass through external circuit to cathode, and H^+ passes through proton exchange membrane to cathode. In cathode catalyst layer, O_2 in oxidant gas reacts with H^+ and produces H_2O.

Potential of a single cell is about *0.75 V* and current density approximates $200{\sim}600\ mA/cm^2$. To supply a high power, several cells are usually connected together and separated from each other by bipolar plates [6].

In the sequel, we denote the operating temperature of PEMFC by $T(t)$; $V_a(t)$, $V_c(t)$ and $V_w(t)$ are the anode and cathode gas flowrate as well as cooling water flowrate:

$$\boldsymbol{V} = [v_a(t), v_c(t), v_w(t)]^T \quad (1)$$

The temperature model of PEMFC system can be described as:

$$dT/dt = \Phi(T(t), V(t)) \quad (2)$$

where $\Phi(\cdot)$ denote the nonlinear relation between $\boldsymbol{V}$ and $\boldsymbol{T}$.

The temperature response of PEMFC is dependent on three factors: heat emitted by electro-chemical reaction that increases the temperature, convection heat of exhausted gases and conduction heat taken away by cooling water that lows temperature. The flowrate of fuel and oxidant gases have great influence on convection heat. Slow flowing of gases leads to an adequate reaction, less heat lost, and less heat produced, at last the steady temperature is higher. Fast flowing results in an inadequate reaction, much more heat taken away by the remaining gases, and much reaction heat produced, the steady temperature is lower. So the steady temperature of PEMFC system varies with the flowrate of fuel, oxidant gases and cooling water in a complex manner. To simplify modelling and control designing, we use the difference form of Eq. (2):

$$T(k+1) = \Phi(V(k), T(k)) \quad (3)$$

3. MODELLING OF A NONLINEAR PEMFC SYSTEM

3.1 Adaptive neural-networks fuzzy infer system (ANFIS)

It is known that adaptive fuzzy logic system can be expressed as feedforward neural-networks. In the training process, we apply adaptive neural-works learning algorithm to adjust the parameters, and to ensure high accuracy of identification, then, the system trained by sampled data and experience can be taken as an identifier of nonlinear dynamic system. In fact, ANFIS consists of fuzzy rules, ANA and feedforward neural-networks. Comparing with simple neural-networks method, firstly ANFIS can use not only data information but also linguistic information from experts experience. Secondly, the parameters of ANFIS can show distinct physical signification, we can select initial parameters effectively. It is shown that ANFIS has better global searching capacity and stronger robustness, furthermore, people comprehend easily the method to set up model [7, 8].

The structure of ANFIS includes five layers. The functions of five layers are the calculation of inputs memberships, the memberships calculation of condition section in every rule, memberships normalization, and calculating the outputs of every fuzzy rule and ANFIS, respectively. The structure of ANFIS with *n* inputs and *M* rules is given in Figure 1.

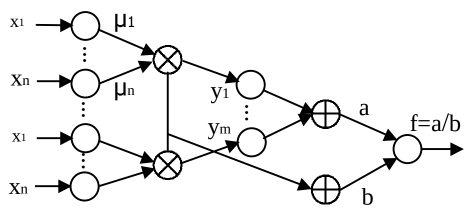


Fig. 1 ANFIS with n inputs and m rules structure

For ANFIS with *n* inputs and *M* rules, the input membership nodes can be expressed as a vector $\mu=[\mu_1,\mu_2,...,\mu_n]$, and condition section membership $\omega=[\omega_1,\omega_2,...,\omega_M]$, fuzzy rule nodes $Y=[y_1,y_2,...,y_M]^T$

and inputs $X(k)=[x_1(k), x_2(k),..., x_n(k)]^T$, $\mu_i(x_i(k))$ is a nonlinear function. Then the ANFIS output $f(x)$ can be presented as follows:

$$f(x)=\frac{\sum_{l=1}^{M}\omega^l y^l}{\sum_{l=1}^{M}\omega^l} \tag{4}$$

where:

$$\omega^l=\prod_{i=1}^{4}\mu_{F_i}^l(x_i) \tag{5}$$

3.2 Identification model of PEMFC system with ANFIS

As we know, a high-order nonlinear system can be described as the following nonlinear autoregressive model with exogenous inputs (NARX) [9]:

$$\boldsymbol{Y}(k)=F(\boldsymbol{Y}(k-1),...,\boldsymbol{Y}(k-n_y);\ \boldsymbol{U}(k-1),...,\boldsymbol{U}(k-n_u)) \tag{6}$$

where $\boldsymbol{Y}(k)$ denotes the output vector, $\boldsymbol{U}(k)$ is the input vector, n_y and n_u are the lags of the output and input respectively, and $F(\cdot)$ is a nonlinear function.

For PEMFC system, $\boldsymbol{U}(k)=[v_a(k), v_c(k), v_w(k)]^T$, $Y(k)=T(k)$ is the operating temperature. The purpose of this section is to use ANFIS to model the PEMFC system described by Eq. (2). According to the identification structure in Figure 2, the input vector of ANFIS $\boldsymbol{X}(k)$ at sample k can be written as:

$$\boldsymbol{X}(k)=[\boldsymbol{Y}(k-1),...,\boldsymbol{Y}(k-n_y);\ \boldsymbol{U}(k-1),...,\boldsymbol{U}(k-n_u)]^T \tag{7}$$

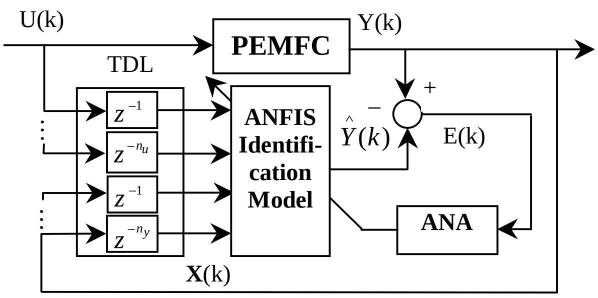


Fig. 2 Identification structure of PEMFC system with ANFIS

3.3 Training algorithm of ANFIS

In Figure 2, the predictive error is $E(k)=Y(k)-\hat{Y}(k)$, where $\hat{Y}(k)$ is the predictive output of ANFIS, and $Y(k)$ is the observation data in experiments. In this paper, we apply the Sugeno fuzzy logic system to identify and model PEMFC system, and M rules defined in ANFIS are expressed below:

$R^{(l)}$: If x_1^l is F_1^l and x_2^l is F_2^l *and* x_3^l is F_3^l and x_4^l is F_4^l

then $y^l=c_0^l+c_1^l x_1^l+...+c_4^l x_4^l$

where F_i^l is the fuzzy subset of input variables in condition section of fuzzy rule, $V_a\in F_1$, $V_c\in F_2$, $V_w\in F_3$ and $T\in F_4$. In the conclusion section, the output y^l is linear combination expression, c_0, c_1, c_2, c_3 and c_4 are the linear combination parameters of fuzzy rule output. In other words, condition section is fuzzy and conclusion section is certain in Sugeno fuzzy logic system [10]. So the training algorithm only adjusts the parameters of the inputs membership in identification process.

The adaptive neural-networks learning algorithm is used to train the ANFIS, we define the membership functions as Gaussian functions:

$$\mu_{F_i}^l=a_i^l\,exp\left[-\left(\frac{x_i-\bar{x}_i^l}{\sigma_i^l}\right)^2\right] \tag{8}$$

where $\bar{x}_i^l$ is the center and σ_i^l is width of Gaussain membership function, $a_i^l=1$. The criterion of training ANFIS is to minimize the mean square error (MES) as follows:

$$E_{MES}=\frac{1}{2}\sum_{p=1}^{P}\left[y^p(k)-\hat{y}^p(k)\right]^2 \tag{9}$$

where P is the number of training samples. The expression of ANFIS output is given:

$$\hat{y}(k)=f(x)=\frac{\sum_{l=1}^{M}\prod_{i=1}^{n}\mu_{F_i}^l(x_i(k))y^l(k)}{\sum_{l=1}^{M}\prod_{i=1}^{n}\mu_{F_i}^l(x_i(k))} \tag{10}$$

The parameters $\bar{x}_i^l$ and σ_i^l are regulated by:

$$\bar{x}_i^l(k+1)=\bar{x}_i^l(k)-\eta\left.\frac{\partial E}{\partial\bar{x}_i^l}\right|_k \tag{11}$$

$$\sigma_i^l(k+1)=\sigma_i^l(k)-\eta\left.\frac{\partial E}{\partial\sigma_i^l}\right|_k \tag{12}$$

Let $f={}^a/_b$, $b=\sum_{l=1}^{M}z^l$, then we can obtain the formula of adjusting parameters:

$$\bar{x}_i^l(k+1)=\bar{x}_i^l(k)+\eta\left[e_k(e_k-e_{k-1})\frac{y^l-f}{b}z^l\cdot\right.$$
$$\left.\cdot\frac{2\left(x_i(k)-\bar{x}_i^l(k)\right)}{\left(\sigma_i^l(k)\right)^2}\right] \tag{13}$$

$$\sigma_i^l(k+1)=\sigma_i^l(k)+\eta\left[e_k(e_k-e_{k-1})\frac{y^l-f}{b}\cdot\right.$$

$$\left.\cdot\, z^l\,\frac{2\left(x_i(k)-\bar{x}_i^l(k)\right)^2}{\left(\sigma_i^l(k)\right)^3}\right] \qquad (14)$$

where η is step, $k=0,1,2,...$; $i=1,2,3,4$; $l=1,2,...,M$.

In fact, Eqs. (13) and (14) represent the error back propagation algorithm. The parameters are regulated based on the input-output data of the previous step, and the normal error is back propagated to relative parameter processing unit with delay of one step [7].

3.4 Model training and simulation test

We used the MATLAB fuzzy logic toolbox to perform the training and simulation. The 240 groups data are used to identify the operating temperature model of PEMFC system, and they are stored in a training data file, and will be supplied for the ANFIS during the training process. The discrete values of operating temperature calculated by ANFIS are compared with the actual temperature response values of PEMFC system, the identification results are shown in Figure 3. The parameter of membership function of V_a is adjusted in training process, and the max error is about *1.1° C* between the identification result and temperature response. We can increase the identification accuracy by selecting suitable membership function and modifying ANFIS structure. Figure 3 shows the ANFIS based on model can be used to predict the temperature response on-line, which makes it possible to design online controller of PEMFC system.

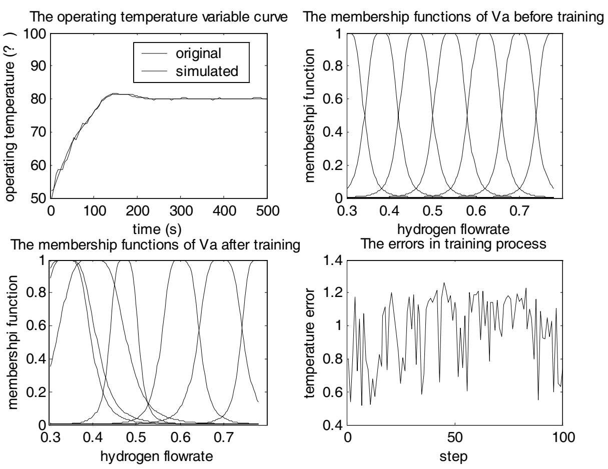


Fig. 3 Identification results of PEMFC system with ANFIS

4. ADAPTIVE FUZZY CONTROL SYSTEM OF PEMFC

4.1 Description and analysis of PEMFC system

The PEMFC system with multi-input and multi-output possesses stronger nonlinear and coupling characters. In control process, a fast flowrates of gases leads to a lower steady temperature, and the cells performance drops greatly. A slow flowrate results in a higher steady temperature, and dehydration of membrane shortens the cells lifespan.

The variation of operating temperature is relative to the regulation of v_a, v_c and v_w, so we need to resolve the coupling question of them. In the electro-chemical reactions, the stoichiometric coefficient of hydrogen is twice than oxygen, it exists a ratio relation between hydrogen flowrate and oxygen flowrate. In fact, air is used to be oxidant gas in our system, in order to ensure hydrogen to be utilized completely, air is excessive. From operating experience, air flowrate is five to ten times than hydrogen. In the same way, the operating temperature varies with the variation of v_a and v_w. In the paper, according to the different influence on T and the demand of control accuracy, we design a control method called divided-area control to resolve the coupling question between v_a and v_w. In general, we use different control variable to regulate the temperature within the different range of temperature errors.

For the PEMFC system, the experimental data indicates that cells performance is the best when operating temperature T is *80° C* and operating pressure is *0.3 MPa*. In the process of designing control system, the variable range of T is chosen between [*50*, *110° C*], and the variation of T is [-*1.5*, *1.5*]. The regulating range of v_a and v_c are [*0.28*, *0.6 m/s*] and [*1.4*, *3.0 m/s*] respectively, and the regulating range of cooling water v_w is [*0*, *0.032 m/s*], the sample period is *2 s*. We will use v_a, v_c and v_w as the manipulated variables to control T to the steady temperature value T_d, and minimize the temperature fluctuation as much as possible. The designing principles of the adaptive fuzzy control system of PEMFC are given as follows:

1 The principles for establishing fuzzy rules

The expected operating temperature T_d=*80° C*, the flowrates of v_a, v_c and v_w are reduced if T is below *80° C*, and they are increased if T is beyond *80° C*.

2 Start-up control

In operating process, we use lead acid storage battery to heat fuel cells stack to *50° C*, then, start up the PEMFC control system. For making T reach rapidly the expected temperature, we do not cool down the stack during the periods of time (the time is determined by the stack scale). At the beginning of operation, the cooling water flowrate is zero, at the same time, the flowrates of reactant gases are reduced.

3 Divided-area control

The experimental data shows that both reactant gases and cooling water are able to regulate T, but the effects are different. The method is considered that the reactant gases flowrates are used to regulate T if the temperature error is less than $4°\ C$, and the cooling water flowrate is regulated if the error is bigger than $4°\ C$. The principles of the divided-area control are given in Table 1.

4.2 Structure of adaptive fuzzy control system of PEMFC

The structure of adaptive fuzzy control system of PEMFC is shown in Figure 4. In the figure, $V_k=V(k)$ is the manipulated input vector, $V(k)=[v_a(k),v_c(k),v_w(k)]^T$. The $T_k=T(k)$ is the output of PEMFC control system, and T_d is the expected output.

In the section, the neural-networks model trained by ANFIS identifier is considered as the reference model of PEMFC control system. The errors e and errors variation Δe between the expected output and the output of reference model are taken as the inputs of neural-works fuzzy controller, according to the outputs of controller V_k, e and Δe, we use ANA to regulate fuzzy rules and parameters of membership functions. Finally, the PEMFC control system is able to obtain satisfying control effect and control accuracy by regulating the parameters again and again.

Table 1 The divided-area control method

T_d-$T > 4$℃	0℃ $< T_d$-$T \le 4$℃	0℃ $< T$-$T_d \le 2$℃	T-$T_d > 4$℃
$v_w\downarrow$; v_a: no change	v_w: no change ; $v_a\downarrow$	v_w: no change ; $v_a\uparrow$	$v_w\uparrow$; v_a: no change

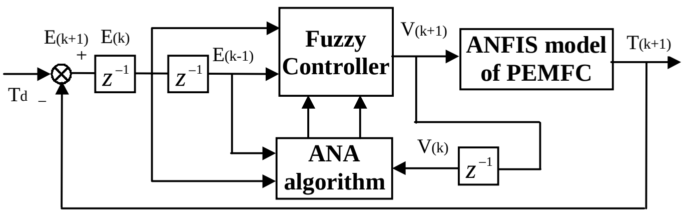


Fig. 4 Structure of adaptive fuzzy control system of PEMFC

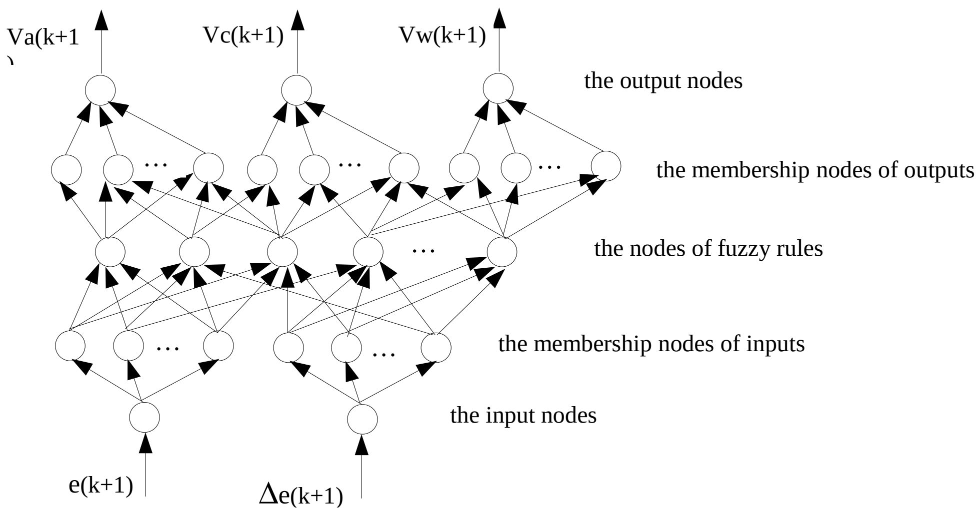


Fig. 5 Structure of the neural-networks fuzzy controller

4.3 Parameters regulation using adaptive neural-networks learning algorithm

The structure of the neural-networks fuzzy controller is given in Figure 5. In the figure, the controller is combined with the Mamdani fuzzy logic system [11] and the five layers feedforward neural networks. In control process, we use ANA to regulate the parameters of membership functions of inputs and outputs [12]. The input variables are e and Δe, and the output variables are v_a, v_c and v_w. The membership functions of inputs and outputs are adopted Gauss membership functions, and defuzzification is the center of gravity method. According to the analysis data and operating experience, 96 rules are deduced to establish a fuzzy rules base. For de-coupling the manipulated variables, the expression of fuzzy rule is shown as follows:

$$R^l : If\ x_1^l\ is\ F_1^l\ and\ x_2^l\ is\ L\,F_2^l\ then\ y_j\ is\ G_j^l$$

where F_i^l is the fuzzy subset of input variables, and G_j^l is the fuzzy subset of output variables. This system is compared with Sugeno fuzzy logic system, the fuzzy rule output of Mamdani fuzzy logic system is a fuzzy variable. The value fields of input and output variables are given in the Section 4.1. The value fields of e and Δe are defined as 13 and 7 fuzzy subsets, and the value fields of v_a, v_c and v_w are divided by 9, 9 and 11 fuzzy subsets respectively. The nodes signification of every layer and the inference process of ANA are described below:

The first layer nodes: the input nodes, transmit the inputs to the next layer nodes:

$$f^1 = u_i^1 \tag{15}$$

The second layer nodes: the membership nodes of inputs, the fuzzification of input variables:

$$f^2 = exp\left[-\left(\frac{u_i^2 - m_i^2}{\sigma_i^2}\right)^2\right] \tag{16}$$

The third layer nodes: the nodes of fuzzy rules, match the condition section with memberships:

$$f^3 = min\left(u_1^3, u_2^3, \ldots u_i^3, \ldots\right) \tag{17}$$

The fourth layer nodes: the membership nodes of outputs, the output of conclusion section in fuzzy rules:

$$f^4 = min\left(1, \sum_{i=1}^{P} u_i^4\right) \tag{18}$$

The fifth layer nodes: the output nodes of neural networks, the defuzzification of fuzzy variables:

$$f^5 = \frac{\sum_{i=1}^{P}\left(m_i^5\ \sigma_i^5\right)u_i^5}{\sum_{i=1}^{P}\sigma_i^5\ u_i^5} \tag{19}$$

where superscript presents the j^{th} layer nodes, subscript presents the i^{th} fraction. For example, u_1^3 shows the first input of the third layer nodes, m_i^5 is Gauss membership function center of the i^{th} input of the fifth layer nodes.

The criterion of regulating parameters is a minimized error function, $y(t)$ is expected output and $\hat{y}(t)$ is the output of neural networks. The formula is given below:

$$E = \frac{1}{2}\left[y(t) - \hat{y}(t)\right]^2 \tag{20}$$

We use BP algorithm to obtain the parameter regulation formulas of membership function, the parameters regulated are m_i^5, σ_i^5, m_i^2 and σ_i^2, the formulas and inference process are shown as follows:

$$m_i(t+1) = m_i(t) + \eta\left(-\frac{\partial E}{\partial m_i}\right) \tag{21}$$

$$\sigma_i(t+1) = \sigma_i(t) + \eta\left(-\frac{\partial E}{\partial \sigma_i}\right) \tag{22}$$

$$\frac{\partial E}{\partial m_i^5} = \frac{\partial E}{\partial f^5}\cdot\frac{\partial f^5}{\partial m_i^5} = -\left[y(t) - \hat{y}(t)\right]\cdot\frac{\sigma_i^5\ u_i^5}{\sum_{i=1}^{P}\sigma_i^5\ u_i^5} \tag{23}$$

$$m_i^5(t+1) = m_i^5(t) + \eta\left[y(t) - \hat{y}(t)\right]\cdot\frac{\sigma_i^5\ u_i^5}{\sum_{i=1}^{P}\sigma_i^5\ u_i^5} \tag{24}$$

$$\frac{\partial E}{\partial \sigma_i^5} = \frac{\partial E}{\partial f^5}\cdot\frac{\partial f^5}{\partial \sigma_i^5} = -\left[y(t) - \hat{y}(t)\right]\cdot\frac{m_i^5\sigma_i^5\left(\sum_{i=1}^{P}\sigma_i^5\ u_i^5\right) - \sum_{i=1}^{P}\left(m_i^5\ \sigma_i^5\ u_i^5\right)u_i^5}{\left(\sum_{i=1}^{P}\sigma_i^5\ u_i^5\right)^2} \tag{25}$$

$$\sigma_i^5(t+1) = \sigma_i^5(t) + \eta[y(t) - \hat{y}(t)] \cdot \frac{m_i^5 \sigma_i^5 \left(\sum_{i=1}^{P} \sigma_i^5 u_i^5 \right) - \sum_{i=1}^{P} \left(m_i^5 \sigma_i^5 u_i^5 \right) u_i^5}{\left(\sum_{i=1}^{P} \sigma_i^5 u_i^5 \right)^2} \tag{26}$$

$$\begin{aligned} \frac{\partial E}{\partial m_i^2} &= \frac{\partial E}{\partial f^5} \cdot \frac{\partial f^5}{\partial u_i^5} \cdot \frac{\partial u_i^5}{\partial f^4} \cdot \frac{\partial f^4}{\partial u_i^4} \cdot \frac{\partial u_i^4}{\partial f^3} \cdot \frac{\partial f^3}{\partial u_i^3} \cdot \frac{\partial f^2}{\partial m_i^2} = \\ &= \frac{\partial E}{\partial f^5} \cdot \frac{\partial f^5}{\partial u_i^5} \cdot \frac{\partial f^2}{\partial m_i^2} = -\left[y(t) - \hat{y}(t) \right] \cdot \frac{\partial f^5}{\partial u_i^5} \cdot f^2 \cdot \frac{2\left(u_i^2 - m_i^2 \right)}{\left(\sigma_i^2 \right)^2} \end{aligned} \tag{27}$$

$$\begin{aligned} \frac{\partial E}{\partial \sigma_i^2} &= \frac{\partial E}{\partial f^5} \cdot \frac{\partial f^5}{\partial u_i^5} \cdot \frac{\partial u_i^5}{\partial f^4} \cdot \frac{\partial f^4}{\partial u_i^4} \cdot \frac{\partial u_i^4}{\partial f^3} \cdot \frac{\partial f^3}{\partial u_i^3} \cdot \frac{\partial f^2}{\partial \sigma_i^2} = \\ &= \frac{\partial E}{\partial f^5} \cdot \frac{\partial f^5}{\partial u_i^5} \cdot \frac{\partial f^2}{\partial \sigma_i^2} = -\left[y(t) - \hat{y}(t) \right] \cdot \frac{\partial f^5}{\partial u_i^5} \cdot f^2 \cdot \frac{2\left(u_i^2 - m_i^2 \right)^2}{\left(\sigma_i^2 \right)^3} \end{aligned} \tag{28}$$

$$\frac{\partial f^5}{\partial u_i^5} = \frac{m_i^5 \sigma_i^5 \left(\sum_{i=1}^{P} \sigma_i^5 u_i^5 \right) - \sum_{i=1}^{P} \left(m_i^5 \sigma_i^5 u_i^5 \right) \sigma_i^5}{\left(\sum_{i=1}^{P} \sigma_i^5 u_i^5 \right)^2} \tag{29}$$

$$m_i^2(t+1) = m_i^2(t) + \eta\left[y(t) - \hat{y}(t) \right] \cdot \frac{\partial f^5}{\partial u_i^5} \cdot f^2 \cdot \frac{2\left(u_i^2 - m_i^2 \right)}{\left(\sigma_i^2 \right)^2} \tag{30}$$

$$\sigma_i^2(t+1) = \sigma_i^2(t) + \eta\left[y(t) - \hat{y}(t) \right] \cdot \frac{\partial f^5}{\partial u_i^5} \cdot f^2 \cdot \frac{2\left(u_i^2 - m_i^2 \right)^2}{\left(\sigma_i^2 \right)^3} \tag{31}$$

4.4 The simulation results of the neural-networks fuzzy control system

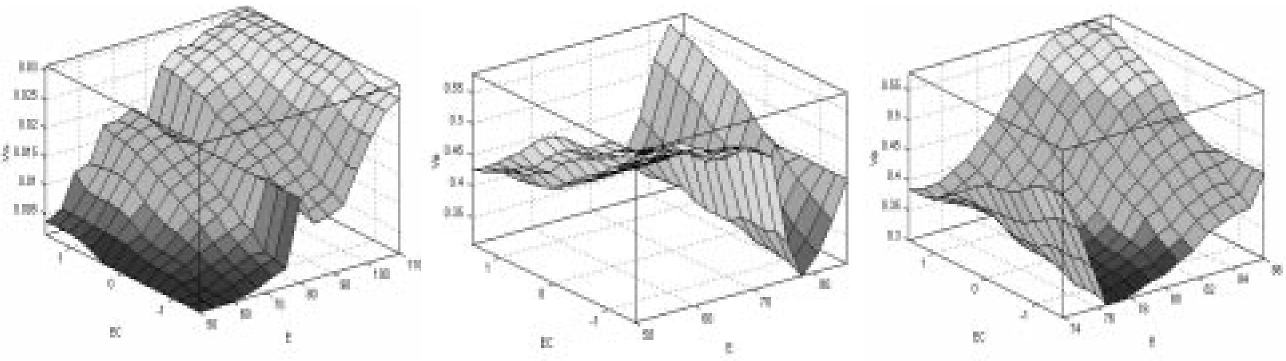
The Figure 6 shows the simulation results of the neural-networks fuzzy control system. Figure 6a is the control surface of cooling water flowrate, in this figure, we can see a gap between *76° C* and *84° C* on the surface, and v_w is zero near *50° C*. During start-up control period, in order to increase rapidly the temperature, cooling water is turned off. For divided-area control mode, the errors are less than *4° C*, regulate reactant gases flowrate to control operating temperature, at the same time, cooling water flowrate is not changed, the cooling water flowrate under steady state is *0.016 m/s*. Figure 6b is the control surface of hydrogen flowrate from *50° C* to *84° C*. It is shown that the initial hydrogen flowrate is very big, and it decreases rapidly with the temperature increase. The lowest flowrate is *0.28 m/s* in order to ensure the reactions to go on. Figure 6c is the control surface of hydrogen flowrate between *76° C* and *84° C*, it is presented that we can control the operating temperature smoothly, the hydrogen flowrate under steady state is *0.38 m/s*.

5. THE APPLICATION OF THE ADAPTIVE NEURAL-NETWORKS FUZZY CONTROL SYSTEM FOR PEMFC

The experimental parameters of PEMFC control system are given in Table 2. The variable curves obtained in experiments are shown in Figure 7.

Table 2 The experimental parameters of PEMFC control system

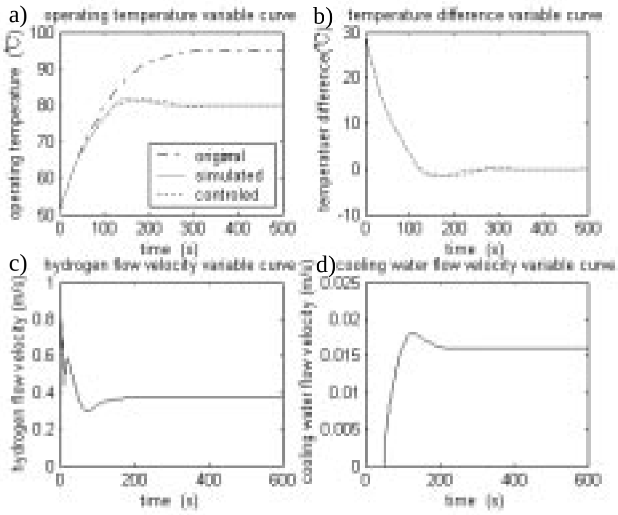
The experimental parameters of control system					
T	353 K	P_c	0.3 MPa	V_w	0 m/s
P	0.3 MPa	V_a	0.5 m/s	T_{init}	323 K
P_a	0.3 MPa	V_c	2.5 m/s	T_{humi}	60° C



(a) The control surface within [50-110º C] *(b) The control surface within [50-84º C]* *(c) The control surface within [76-84º C]*

Fig. 6 Simulation results of the neural-networks fuzzy control system of PEMFC

In Figure 7a, the original curve is the operating temperature variable curve, which is not controlled by the manipulated variables. The steady temperature is about *100° C*, the dehydration of exchange membrane is very serious, and cells performance drops significantly (current density approximate *1000 mA/cm²*, the potential of cells drops rapidly). The neural-networks identification model is taken as the reference model, we use the controller to control the operating temperature, and we obtain the simulated curve in simulation process. In experiments, we apply adaptive neural fuzzy technique to control the PEMFC system and obtain the controlled curve. In the figure, the simulated curve makes the PEMFC system go into steady state faster than controlled curve, it is the reason that disturbances, lags and other uncertain factors are produced in the control process. In general, the adaptive neural-networks fuzzy controller can regulate and control the operating temperature to the destination more quickly, and maintain it with smaller fluctuation, the experimental results prove the effectiveness of the control system.



(a) The operating temperature variable curves
(b) The temperature errors variable curve
(c) The hydrogen flowrate variable curve
(d) The cooling water flowrate variable curve

Fig. 7 Experimental results of the neural-networks fuzzy control technique of PEMFC

6. CONCLUSION

The operating temperature of PEMFC system must be controlled within a specific range. It is difficult to model with the traditional methodologies. The existing models are analytical, which can not be applied to system synthesis. In the paper, the ANFIS identification model of PEMFC system is developed, then, an online adaptive neural-networks fuzzy controller is presented. Comparing with simple neural-networks method and other control methods, ANFIS and adaptive neural-networks fuzzy control can use not only data information but also a linguistic information from the experts experience, and the parameters can show a distinct physical signification, we can select initial parameters effectively. The validity of ANFIS identification model of PEMFC system and the good performance of the adaptive neural-networks fuzzy controller are demonstrated by simulations and experiments.

It is concluded that it is feasible to establish the model of the complex nonlinear system based on ANFIS and it can be used to predict the temperature responses online. The adaptive neural-networks fuzzy controller designed is efficient, it can control the operating temperature to change smoothly to ideal stabilization value and it performs much better than the traditional control method.

7. ACKNOWLEDGEMENTS

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NELINEARNO MODELIRANJE I PRIMJENA FUZZY KONTROLA PEMFC

SAŽETAK

Da bi se poboljšala stabilnost kao i rad ćelija goriva, potrebno je kontrolirati radnu temperaturu protonski izmjenjive membrane ćelija goriva (PEMFC) unutar određenih granica. Postojeći matematički modeli PEMFC previše su složeni da bi se efikasno primijenili u kontrolnom procesu. U ovom radu primijenjeni su fuzzy identifikacijski i kontrolni modeli PEMFC koji se baziraju na iskušanim input-output podacima te iskustvu stručnjaka. Parametri indikatora i kontrolora određeni su primjenjivim naučenim algoritmom, strukture mreža i baza podataka pravila preinačeni su podešavanjem parametara. Na kraju, prikazani su rezultati simulacije on-line kontrolnog modela koji pokazuju efikasnost.

Ključne riječi: *protonski izmjenjiva membrana ćelije goriva (PEMFC), fuzzy kontrola, neuralna mre•a .*