OPTIMIZATION AND CONTROL OF FUEL CELL THERMAL MANAGEMENT SYSTEM BASED ON NEURAL NETWORK

by

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Aiming at the direct methanol fuel cell system is too complicated, difficult to model, and the thermal management system needs to be optimized. The article attempts to bypass the internal complexity of direct methanol fuel cell, based on experimental data, use neural networks to approximate arbitrarily complex non-linear functions ability to apply neural network identification methods to direct methanol fuel cell, a highly non-linear thermal management system optimization modelling. The paper uses 1000 sets of battery voltage and current density experimental data as training samples and uses an improved back propagation neural network to establish a battery voltage-current density dynamic response model at different temperatures. The simulation results show that this method is feasible, and the established model has high accuracy. It makes it possible to design the real-time controller of the direct methanol fuel cell and optimize the thermal energy management system's efficiency.

Key words: *methanol fuel cell, back propagation neural network, thermal management system, efficiency optimization*

Introduction

The fuel cell is a clean and efficient power generation technology. It is a high efficiency continuous power generation device that directly converts the chemical energy of fuel and oxidant into electrical energy by electrochemical reaction without burning. Direct methanol fuel cell (DMFC) directly uses methanol as fuel, its aqueous solution is easy to carry and store, without an intermediate conversion device, and the system structure is simple. In DMFC, methanol has higher electrochemical activity and higher volume energy density. Under the same power density, DMFC is small and low in cost and is especially suitable for portable power supplies and automotive power supplies.

To improve the DMFC power generation system's operating performance, extend its service life, and ensure the system's safe, reliable, and low cost operation, we must effectively control it. For example, the two key issues that currently affect the performance of DMFC are the low activity of the methanol electrochemical oxidation catalyst and the membrane permeability of methanol. The most important indicator for judging the performance of DMFC is the voltage/current density characteristics of the fuel cell, and these are all related to the operating temperature of the battery. Close relationship. The operating temperature range of DMFC is 50-100 °C.

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On the one hand, increasing the working temperature of DMFC can improve the anode's ability to resist CO poisoning, speed up the anode electrochemical oxidation, reduce cathode polarization, increase membrane conductivity, and improve battery performance. On the other hand, the battery's temperature increases, and water vapor's partial pressure also increases [1]. When air is used as the oxidant, the concentration of oxygen in the reaction will be reduced. More seriously, the Nafion type perfluorosulfonic acid proton exchange membrane. When it is a battery diaphragm when the battery working temperature reaches 120-130 ℃, it will cause the membrane to lose water, and the resistance of the membrane will increase considerably, causing the battery to not work correctly and shortening the battery life. Therefore, ensuring that the battery works at an appropriate temperature is the key to improving battery performance and service life.

At present, some scholars have established various mathematical models of DMFC. They have established various static or dynamic analytical models from different angles based on the electrochemical theory and physics conservation laws. The establishment of these models is essential for analysis and improvement. The performance of DMFC plays an important role. According to the DMFC system analysis, it can be known that it is a multi-input multi-output non-linear system with strong distributed parameter characteristics. The existing battery mathematical models are based on various assumptions and experiments. Due to the system's complexity, the aforementioned models have to be simplified in various ways, ignoring some uncertain factors, resulting in large differences in the models. Simultaneously, due to the complexity of the model expressions, these models cannot meet real-time control [2].

This article attempts to bypass the internal complexity of the DMFC system and uses an improved back propagation neural network to model the DMFC non-linear system [3]. With battery temperature as the input variable, battery voltage, and current density as the target variables, the neural network is analyzed according to the experiment's input and output data. Conduct training to establish the voltage/current density model of DMFC. The simulation results show that the accuracy of the model is high, and the identification results are quite ideal, which lays the foundation for the online control of DMFC.

The DMFC system description and analysis

According to the analysis of the dynamic characteristics of the DMFC power generation system, the voltage and current density model of the DMFC can be described:

$$\vec{U} = \Phi\left[\vec{U}(t), \vec{J}(t), \vec{v}(t)\right] \tag{1}$$

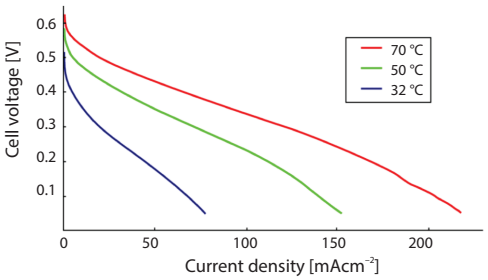

Figure 1. The DMFC voltage/current density curve at different temperatures

where $\vec{v}$ = [$v_a(t)$, $v_c(t)$] is the flow velocity of anode fuel and cathode reaction gas, $T(t)$ – the temperature change vector, and T_{a0} – the feed temperature of anode fuel. It can be seen from the eq. (1) that the working temperature of the fuel cell is mainly affected by T_{a0}, that is, adjusting T_{a0} can realize the control of the battery working temperature. To fully illustrate the fuel cell operating temperature's influence on the battery voltage and current density, we set the neural network identification model's input as the battery operating temperature. The output

vector is the battery voltage and current density, respectively, and keep v constant by adjusting the anode feed. The temperature makes the battery temperature change steadily (50-80 ℃). The corresponding experimental data is obtained as the training sample of the neural network. According to the experimental data, the voltage/current density curve of DMFC is shown in fig. 1 at different battery operating temperatures [4].

The working temperature of the battery is increased from 50-80 ℃. As the temperature rise increases the chemical reaction speed, reduces the cathode polarization, and increases the membrane's conductivity, the battery can reach a larger voltage and current density, and the battery performance is greatly improved [5]. The requirement of model identification is to dynamically simulate the change curve of battery voltage and current density under different working temperatures and complete the non-linear mapping from the input vector to the network model's output vector. In this way, the identification model can be described by a non-linear difference equation:

$$\begin{aligned} \vec{U}(k+1) &= \Phi\left[\vec{U}(k), \vec{J}(k), T(k)\vec{v}\right] \\ J(k+1) &= \Psi\left[\vec{U}(k), \vec{J}(k), T(k)\vec{v}\right] \end{aligned} \tag{2}$$

where k is a discrete-time variable.

The DMFC system identification based on improved back propagation algorithm

The back propagation neural network modelling

The proton exchange membrane fuel cell system's input and output is a very complicated non-linear time-varying mapping relationship. It's output voltage, V_{stack}, and stack temperature, I_{FC}, are related to load current, I_{FC}, anode hydrogen pressure, D, air compressor voltage, V_{cm}, and heat dissipation [6]:

$$\{V_{\text{stack}}, T_{\text{stack}}\} = F(I_{\text{stack}}, p_{\text{anode}}, V_{\text{cm}}, V_{\text{fan}}, T_{\text{room}}, T_{\text{init}}) \tag{3}$$

The back propagation network determination

According to the experimental measurable and control conditions, the input of the selected system model is load current, I_{stack}, anode hydrogen pressure, P_{anode}, air compressor voltage, V_{cm}, cooling fan voltage, V_{fan}, model output is stack voltage, V_{stack}, and stack temperature, T_{stack}.

Since the PEMFC system's output is related to both the current moment and the previous system state, the network is generally constructed in two ways to reflect the network time function. The first is by adding a delay input unit to the network input. The second is by using a local recurrent neural network, which introduces dynamic links in the neural network [7]. This article will use the first method to identify the PEMFC system. The typical system manifestation of adding a delay action input unit based on the forward neural network:

$$y(i) = f[y(i-1)\cdots, y(i-n); x(i-1)\cdots, x(i-m)] \tag{4}$$

This structure's advantage is that the network structure obtained after learning is entirely equivalent to the existing control system, but this structure cannot guarantee that the output error will approach zero. That is, it cannot guarantee the convergence of the algorithm.

The input of the model includes the delay of the input and the actual output of the system. The system's output at the last moment is used to act on the network structure so that the structure has a trend of dynamic change. The existing system's output and input are bound-

ed, which is more stable than the parallel structure. Based on the forward network, most of the series-parallel structure is adopted. According to the experimental system conditions, the model mapping relationship based on the series-parallel forward neural network identification structure can be described:

$$\{V_{FC}, T_{FC}\} = F[I_{stack}(k-1), V_{cm}(k-1), V_{fan}(k-1), p_{anode}(k-1), V_{FC}(k-1), T_{FC}(k-1)] \tag{5}$$

Determine the learning sample

To obtain a model with a strong generalization ability, we need to determine a learning sample that can comprehensively and accurately reflect the system's characteristics to be identified. Learning samples should have three characteristics: compactness, ergodicity, and compatibility. Density means that to accurately reflect the actual system model structure, corresponding data must be provided and ergodicity refers to the global concept [8]. To improve the generalization ability of the model, a global data range is a necessary condition, and the more data coverage is extensive, the generalization ability of the obtained model will be relatively improved. Compatibility refers to the impact on network learning when there are overlapping areas in the input space of different samples. Corresponding the experimental data processing, removing part of the data that cleaned the air inside the stack during the startup state, and removing obviously inconsistent data. Finally, the data we get is 4763 groups.

Normalization

The back propagation neural network's input layer can have various variables and is suitable for various models, but the unit and magnitude of each model's input variables may be very different. For example, the unit and the magnitude of the input variables of the fuel cell are different. Differ greatly. To make all input variables in the same position, the input data must be processed:

$$\overline{x_i} = \frac{x_i - x_{i\min}}{x_{i\max} - x_{i\min}} \tag{6}$$

According to the previous formula, the network input obtained after processing the sample is normalized to 0-1. For the output of the network model, the output result corresponds to denormalization processing.

Implementation of back propagation network

According to the data of the learning sample, the number of input neurons in the network is selected to be six, and the number of output neurons is two to meet the minimum input and output requirements of the system while reducing the complexity of the model, which can speed up the convergence time of the model and make the model small computational complexity. According to the forward feedback type back propagation neural network characteristics, theoretically, a three-layer network can approximate arbitrarily complex functions with arbitrary precision. The initial network model is set to three layers [9]. The function code:

$$\begin{aligned} &\text{net} = \text{new}ff \\ &\text{net} = \text{new}ff\ (PR, [S_1, S_2 ... S_N], \{TF_1, TF_2 ... TF_N\} BTF, BLF, PF) \end{aligned} \tag{7}$$

Weight or threshold learning function and performance function. The structural block diagram of DMFC system identification is shown in fig. 2, where TDL is the time-division multiplex delay link.

In Newton's method:

$$\Delta x = -[\nabla^2 E(x)]^{-1} \nabla E(x) \tag{8}$$

we set the error-index function

$$E(x) = \frac{1}{2}\sum_{i=1}^{N} e_i(x) \tag{9}$$

where $e(x)$ is the error. Then:

$$\nabla E(x) = J^T(x)e(x) \tag{10}$$

$$\nabla^2 E(x) = J^T(x)e(x) + S(x) \tag{11}$$

where $J(x)$ is the Jacobian matrix and $S(x)$ – the error function

$$S(x) = \sum_{i=1}^{N} e_i(x)\nabla^2 e_i(x) \tag{12}$$

For the Gauss-Newton method, the amount of change in the weight and threshold:

$$\Delta x = -[J^T(x)J(x)]^{-1} J^T(x)e(x) \tag{13}$$

The error adjustment curve during training is shown in fig. 3. When the error drops to $5.995 \cdot 10^{-6}$, it basically no longer changes. We take the error target as $6 \cdot 10^{-6}$.

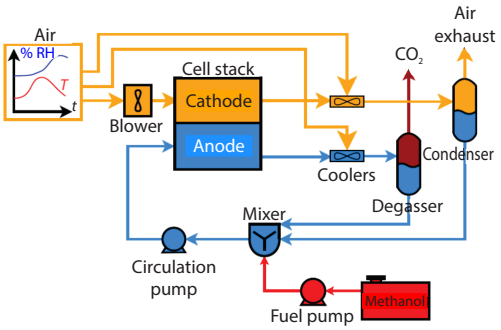

Figure 2. The DMFC system identification block diagram

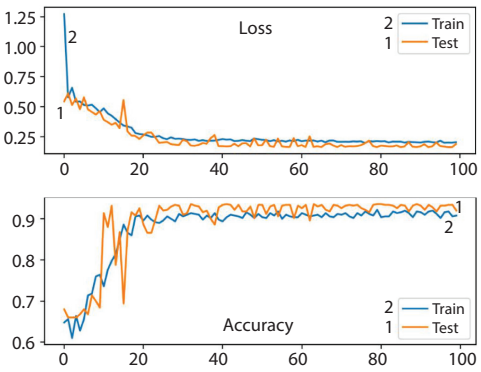

Figure 3. Network model error reduction and the target curve

The DMFC system neural network identification results

In the paper, trained neural network is used to identify the DMFC system's dynamic simulation. Under different battery operating temperatures, the battery voltage and current density changes identified by the neural network are compared with the actual battery voltage and current density response. The recognition results obtained are shown in figs. 4-7. It can be seen from the figure that the neural network identification model can basically simulate the dynamic response of the battery voltage/current density of the system, and the maximum error does not exceed 0.006 mV. The error is determined by the error target determined during training. The most suitable neural network topology can be found through multiple adjustments to improve identification accuracy.

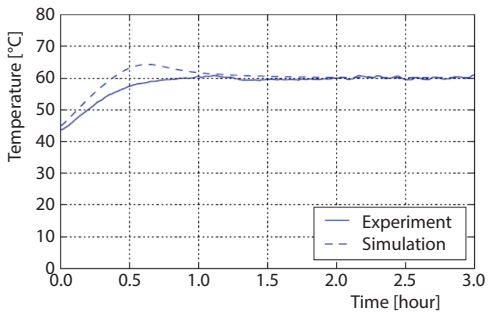

Figure 4. Identification effect at 50 °C working temperature

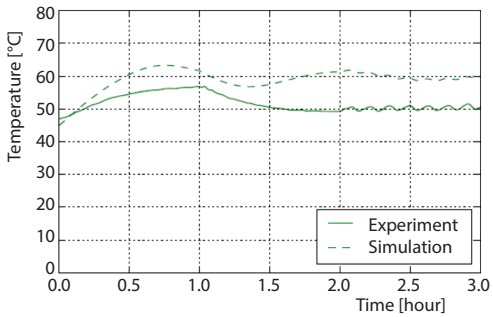

Figure 5. Identification effect at a working temperature of 60 °C

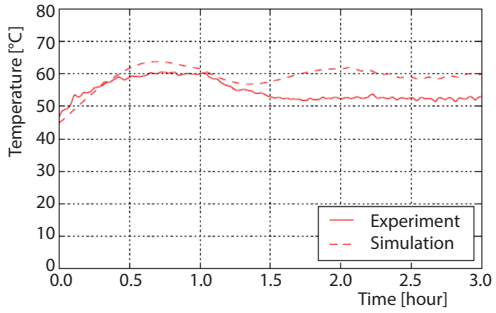

Figure 6. Identification effect at an operating temperature of 70 °C

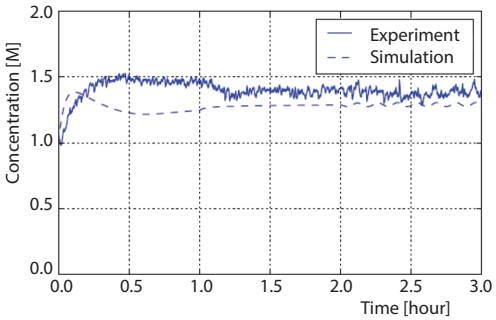

Figure 7. Identification effect at 80 °C working temperature

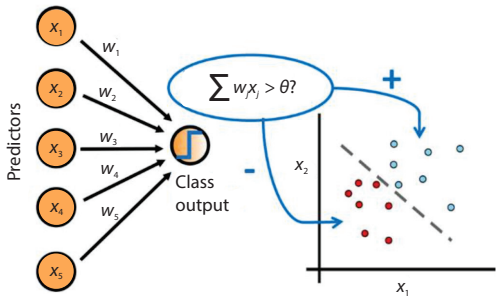

Figure 8. The hidden layer of 15 neurons is the result of model training

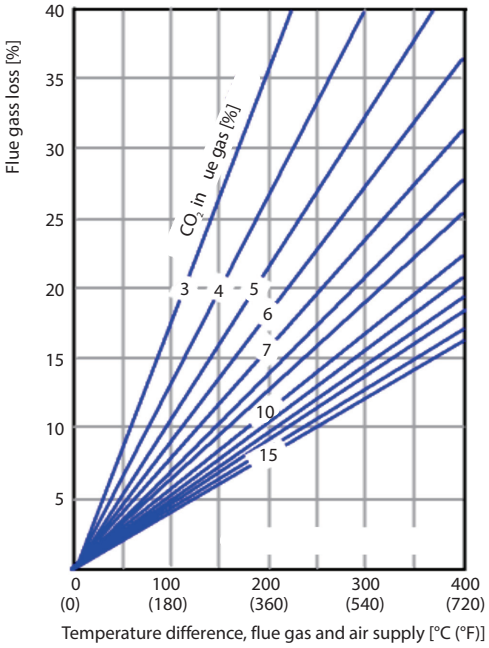

Figure 9. Stack temperature comparison

This paper uses an open air-cooled stack system. The 4763 sets of sample data obtained are used to train the network. The initial learning rate of the network is 0.01. The learning rate should be set to a small value because when the set learning rate is too large, the convergence speed can be accelerated, but it will occur when it is close to the critical point. Turbulence prevents the model from converging. Use MATLAB software to train the network. First, set the number of hidden layers of the model to 15 layers, and the maximum number of training times of the model is 1000. The model's minimum error is 0.0046549 after 93 times of training, and there is no lower error in the next six iterations. Therefore, the training is ended at 99 times of learning. The error learning curve of the back propagation neural network model is shown in fig. 8. The 60% of the sample data is training data, 20% is the validation data set, and the last 20% is used to test the model's generalization ability.

In the case of a sudden change in the stack's output current, the output voltage line of the stack drops and then rises, and then reaches a stable value. When the current changes suddenly, the amount of hydrogen and air demand will change, and the controller controls the auxiliary components. There will be a certain lag in providing the corresponding flow and pressure, so the fuel and oxidant flow delay will be affected when the reactor internally reacts. The I-V curve of the back propagation network model basically reflects this dynamic characteristic. Therefore, it is believed that the model struc-

ture identified by the back propagation network can effectively reflect the characteristics of the fuel cell system. The back propagation neural network model compares the stack temperature output with the actual stack output when the load current changes suddenly, as shown in fig. 9. When the current changes suddenly, the controller needs to output PWM to control the cooling fan voltage to ensure that the stack temperature does not exceed set temperature. The stack temperature output by the back propagation network model is basically the same as the stack temperature when the actual current changes can accurately reflect the change curve of the fan control stack temperature when the current changes.

Conclusion

We use neural network identification methods to realize the modelling of complex non-linear systems such as DMFC. It is entirely feasible, and the accuracy of modelling is relatively high. Most importantly, it avoids the complex analytical modelling process and makes the non-linear system. The input and output characteristics can be quickly obtained. Although it cannot have an apparent physical meaning like the analytical model, it can effectively express the complicated non-linear mapping relationship of the complex non-linear system's input and output.

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