Modelling and control PEMFC using fuzzy neural networks*

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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


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.
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/cm². 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 $V(t)=\left[V_a(t), V_c(t)\right]^T$. $V_a(t)$ and $V_c(t)$ are the anode and cathode gas flow rate, respectively. According to PEMFC stack dynamic characteristics, letting $V(t)=\left[V_a(t), V_c(t)\right]^T$ and $T(t)=\left[T_a(t), T_c(t), T_e(t), T_s(t)\right]^T$, respectively. $\phi(\cdot)$ denotes the nonlinear relation between $T$ and $V$. The temperature model can be described as Eq.(1) on the basis of the analysis of dynamic PEMFC system:

$$\frac{dT}{dt} = \dot{T} = \phi(T(t), V(t)) \quad (1)$$

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:

$$T(k+1) = \phi(T(k), V(k)) \quad (2)$$

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 repre-