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DEEP LEARNING BASED HIERARCHICAL PREDICTIVE CONTROL FOR OXYGEN STOICHIOMETRY OF PROTON EXCHANGE MEMBRANE FUEL CELL ENGINE

Xuechao Wang [1,2], Jinzhou Chen [3], Shengwei Quan [1], Hongwen He [1,*], Ya-Xiong Wang [1,3*]

1 National Engineering Laboratory for Electric Vehicles, Beijing Institute of Technology, Beijing 100081, China

2 Beijing Operations, China Automotive Technology and Research Center Co., Ltd, Beijing 100070, China

3 School of Mechanical Engineering and Automation, Fuzhou University, Fuzhou 350116, China

*Corresponding Author: Hongwen He (hwhebit@bit.edu.cn); Ya-Xiong Wang (yxwang@fzu.edu.cn)

ABSTRACT

A deep learning based hierarchical predictive control is developed for regulating the oxygen stoichiometry of proton exchange membrane fuel cell (PEMFC) engine in this study. Firstly, a hierarchical predictive control scheme is proposed by designing the first-level predictor to determine the operation current of PEMFC engine, and then the second-level model predictive control (MPC) generating robust control input. BP neural network is selected to formulate the first-level prediction model and airflow model is linearized to design MPC with suitable prediction horizon and control horizon. A simulation test is carried out through operating in a mixed driving cycle MANHATTAN + (a part of) UDDS to verify the efficacy of the proposed method. The results indicate that the oxygen stoichiometry tracks the reference value well avoiding the starvation of the PEMFC engine.

Keywords: Proton exchange membrane fuel cell (PEMFC), oxygen stoichiometry, hierarchical control, deep BP neural network, model predictive control

1. INTRODUCTION

Proton exchange membrane fuel cell (PEMFC) engine has the beneficial features of the high energy density, high efficiency, and low operation temperature, which leads it to become one of the most remarkable candidates for alternative energy vehicles [1-3].

The power response of the PEMFC is slow and limited by the oxygen and hydrogen supply, and other auxiliaries. Moreover, to ensure the reliability of the PEMFC output performance, the auxiliary system is asked to satisfy the required operation condition. As one of the essential auxiliaries of PEMFC engine, an air compressor provides air flow to the cathode of PEMFC. The excess air supply increases the energy consumption of air compressor and reduces the energy conversion rate of the PEMFC engine. Too much air may also take away the heat required for the reaction, which reduces the efficiency of power generation. But if the air is insufficient, the PEMFC cannot react inadequately, reducing the utilization of PEMFC and even damaging the cell itself. Thus, many studies have conducted on the oxygen stoichiometry regulation of PEMFC engine by using various control methods, including fuzzy control, robust control, adaptive control, and so on [4]. Meanwhile, feedback and feedforward control strategies are adopted to achieve the maximum net power and prevent oxygen starvation. Xu et al. [5] studied the three internal state robust control strategies based on an adaptive second order sliding mode and a nonlinear proportional integral feedback control algorithms with a series of comparative studies. In Ref. [6], the gas supply regulation of the hybrid PEMFC generator was implemented by several robust control strategies. However, in practice, the operation conditions are changeable resulting in mass and rapid requirement oxygen that is at risk of oxygen starvation.

In this paper, a deep learning based hierarchical predictive control for oxygen stoichiometry regulation of an automotive PEMFC engine is introduced. In the first-level, the deep BP neural network is applied to predict the vehicle speed associating with the power requirement of PEMFC engine, and in the second-level, a model prediction control (MPC) is developed based on the model of oxygen stoichiometry of PEMFC engine, to prevent oxygen starvation.

In the rest of this paper, a hierarchical predictive control configuration is introduced in Section 2. Section 3 describes the oxygen stoichiometry regulation results via a simulation test. Finally, conclusion is drawn about the oxygen stoichiometry regulation methods.

2. DEEP LEARNING BASED HIERARCHICAL PREDICTIVE CONTROL SCHEME

The deep learning based hierarchical predictive control scheme is shown in Fig 1, including the first-level predictor by using deep BP neural network and second-level MPC for air mass flow control. The first-level predictor generates the vehicle driving speed to lead to a reference oxygen stoichiometry in the prediction horizon, and the second-level MPC implements the regulation of real-time oxygen stoichiometry (oxygen excess ratio).

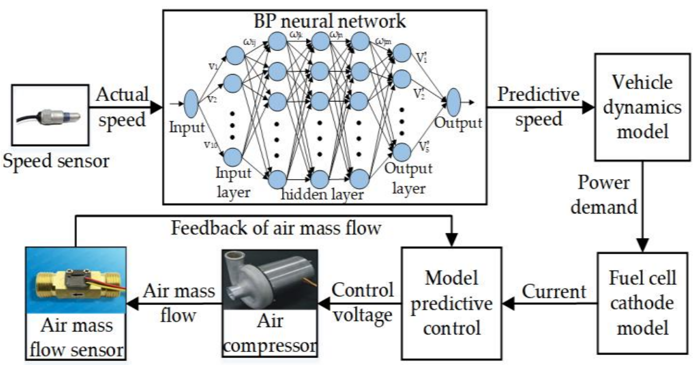

Fig 1 Hierarchical predictive control scheme

2.1 First-level Predictor

The first-level predictor takes the historical speeds measured by the speed sensor as an input, and predicts the speed sequence of the next moments, through the vehicle dynamics equation. Then, the power required of the PEMFC engine can be obtained.

Deep BP neural network prediction method [7,8] is adopted for designing the first-level predictor. The speed prediction model based on deep BP neural network was established, including the number of layer of the network L, the number of nodes in each layer m, activation function and training function. Here, L=3, m=20, and the activation function is *sigmoid* and the training function is *GradientDescent*.

The driving cycles of the training sample are configured by WVUCITY, NEDC, 1015_6PRIUS, UDDS, FTP and NYCCOMP, as shown in Fig 2. The training process is using every ten historical speeds of sample speeds as the input and the next five speeds as the output, and using the determined network structure to train 100000 times, where the prediction algorithm is shown in Fig 3.

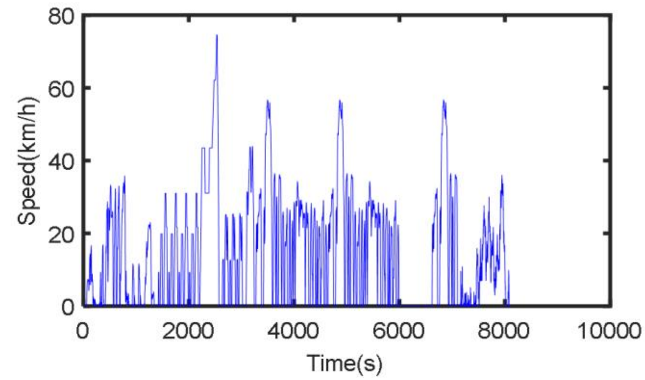

Fig 2 Driving cycles of training samples

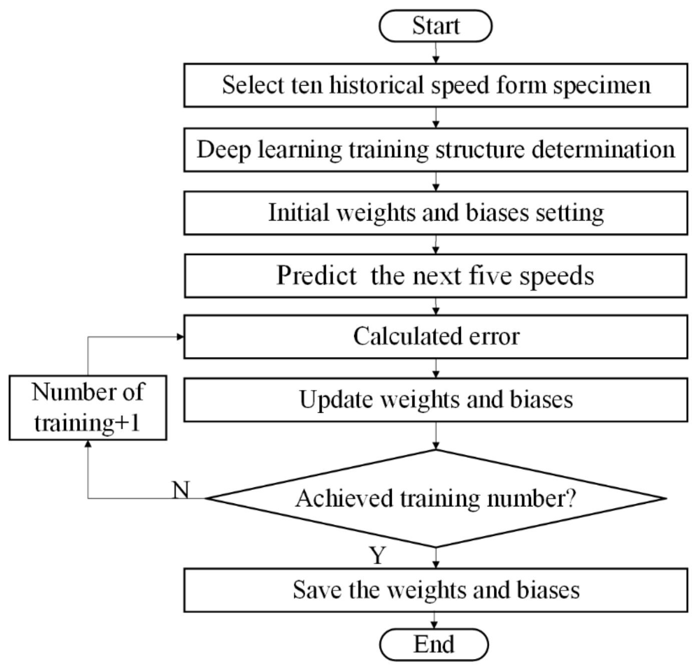

Fig 3 Predicting flow of BP neural network

Calculate the output of the hidden layer H:

$$H_j = f\left(\sum_{i=1}^{n}\omega_{ij}x_i - a_j\right),\ j=1,2,\cdots m \tag{1}$$

where x_i is the input vector, ω_{ij} and a_j are the weights and the biases between the input layer and hidden layer, respectively. $f(*)$ is the hidden layer activation function. The output of the output layer O_k is given by

$$O_k = \sum_{j=1}^{m} H_j\omega_{jk} - b_k\ ,k=1,2,\cdots,5 \tag{2}$$

where ω_{jk} and b_k are the weights and the biases between the hidden layer and output layer.

2.2 Second-level MPC for Oxygen Stoichiometry

The control objective of the second-level MPC is regulating the oxygen stoichiometry λ_{O_2} (defining as the ratio between the oxygen flowing into the cathode and the oxygen reacted in the cathode) at reference values, here λ_{O_2} =2.0 is selected as a setpoint. In this section, the air compressor and oxygen stoichiometry models are presented, and used for designing the model-based oxygen stoichiometry MPC controller.

The dynamic characteristics of the air compressor supplied PEMFC engine can be described by [9,10]:

$$\begin{aligned} \frac{d\omega_{cp}}{dt} &= \frac{1}{J_{cp}}\left(\tau_{cm}-\tau_{cp}\right) \\ \frac{dP_{sm}}{dt} &= \frac{\gamma\cdot R_a}{V_{sm}}\left(W_{cp}\cdot T_{cp,out}-W_{sm,out}\cdot T_{sm}\right) \\ \frac{dm_{sm}}{dt} &= W_{cp}-W_{sm,out} \end{aligned} \tag{3}$$

where ω_{cp} represents the compressor speed; J_{cp} denotes the combined inertia of the compressor and the motor; τ_{cp} is the required torque of the compressor; W_{cp} is the air compressor output air flow; supply manifold pressure P_{sm} and mass m_{sm} are simplified; R_a is the gas constant; γ is the ratio of the specific heats of air; $T_{cp,out}$ and $W_{sm,out}$ are the air compressor output temperature and the outlet mass flow of the supply manifold, respectively. Moreover, the compressor motor torque input τ_{cm} is related to the compressor supplied voltage U_{cm}, and the motor efficiency η_{cm}, as well as motor constants k_e, k_t and R_{cm}, which can be formulated by

$$\tau_{cm}=\eta_{cm}\cdot\frac{k_e}{R_{cm}}\left(U_{cm}-k_t\cdot\omega_{cp}\right) \tag{4}$$

Based on the air flow dynamics of the air compressor model, the oxygen flows into the cathode $W_{O_2,ca,in}$ can be calculated by

$$W_{O_2,ca,in}=\frac{y_{O_2}}{1+\Phi}\cdot W_{cp} \tag{5}$$

and the oxygen flow consumed by PEMFC is depending on the stack current [11,12]

$$W_{O_2,reacted}=M_{O_2}\cdot\frac{nI_{st}}{4F} \tag{6}$$

where Φ is the humidity ratio, y_{O_2} is the oxygen mass fraction, I_{st} is the stack current, and F is the Faraday constant.

Then, the oxygen stoichiometry λ_{O_2} is given by,

$$\lambda_{O_2}=\frac{W_{O_2,ca,in}}{W_{O_2,reacted}} \tag{7}$$

Combining with Eq. (3)-(7) and using the Taylor expansion method in a selected linearization point, the system plant can be expressed as follows

$$\dot{X}(t)=AX(t)+BU(t) \tag{8}$$

$$Y=CX(t)+DU(t) \tag{9}$$

in which $X=[P_{sm}\ m_{sm}\ \omega_{cp}]^T$ is the state variable, $Y=\lambda_{O2}$ is the control objective. $U=[U_{cm}\ I_{st}\ d(t)]^T$, I_{st} the measured disturbance, $d(t)$ is the unmeasured disturbance.

According to the linear model, MPC with P=15, M=5 and T_s=1ms, is designed under the predictive interference I_{st},

3. SIMULATION STUDY

The driving cycle used for testing the proposed deep learning based hierarchical predictive control scheme is consist of a MANHATTAN cycle and the first third of the UDDS cycle. The actual speed of the defined driving cycle and the predictive speed by using the deep BP neural network are as show in Fig 4. Moreover, the current of PEMFC engine is calculated by the vehicle dynamics, and the actual current and the predictive current results are also given in Fig 5. The results indicate that the operation condition prediction is with good fitting performance in both speed terms and current terms.

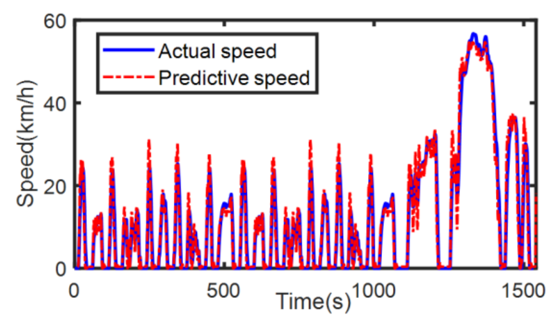

Fig 4 Comparison of prediction and actual speed

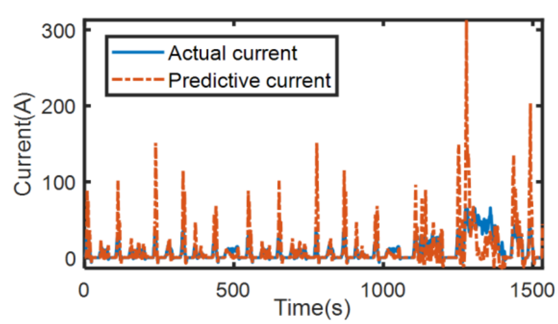

Fig 5 Comparison of prediction and actual current

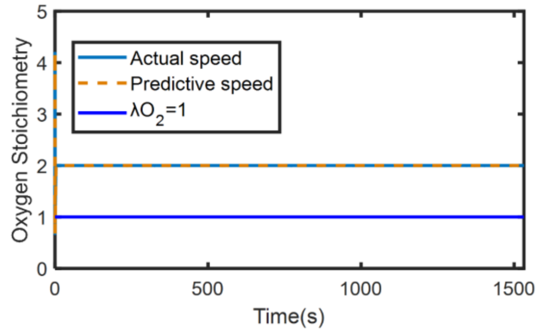

Fig 6 λ_{O_2} distribution according to predictive speed and actual speed

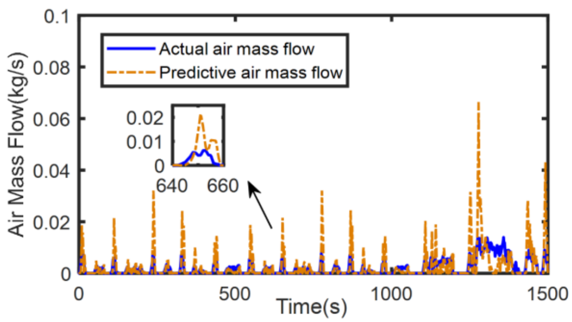

Fig 7 W_{cp} distribution according to predictive speed and actual speed

Furthermore, the oxygen stoichiometry regulation performance is tested in the condition of the defined driving cycles. The results show that the proposed hierarchical predictive control scheme can be used to control the oxygen stoichiometry for achieving the desired setpoint tracking as well as the PEMFC engine oxygen starvation preventing.

4. CONCLUSION

In this paper, a hierarchical predictive control strategy is proposed to predict and control the oxygen stoichiometry of the air supply system of PEMFC engine. From the predictive results, the prediction performance of the deep BP neural network is acceptable, providing accurate current interference for the control of the bottom air flow. Moreover, the simulation test through the defined driving cycles indicates that the oxygen stoichiometry is well regulated, and is always higher than 1 and air starvation can be avoided, which may improve the lifetime of the PEMFC engine.

ACKNOWLEDGEMENT

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