Analysis of Optimal Oxygen Excess Ratio and Nonlinear Tracking Control of Vehicle PEMFC Air Supply System

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To a large extent, the efficiency and durability of the proton exchange membrane fuel cell (PEMFC) depend on the effective control of air supply system. However, dynamic load scenarios, internal and external disturbances, and the characteristics of strong nonlinearity make the control of complex air supply systems challenging. This paper mainly studies the modeling of PEMFC air supply system and the design of a nonlinear controller for oxygen excess ratio tracking control. First, we analyze and calibrate the system’s optimal oxygen excess ratio control target and explore how the system temperature and humidity impact it, respectively; second, a second-order affine oriented control model which can represent the static and dynamic characteristics of the air supply system is derived, and a disturbance observer is designed to estimate and compensate the “lumped error” online. Then, aiming at the problem of unmeasurable cathode pressure, a state observer based on Kalman optimal estimation algorithm is proposed to realize the real-time estimation of cathode pressure; finally, a dynamic output feedback control system based on observer and backstepping nonlinear controller is proposed, and the comparison and evaluation of two control strategies based on constant oxygen excess ratio tracking and optimal oxygen excess ratio tracking are carried out. The simulation results show the effectiveness and superiority of the designed control system compared with the reference controller.

1. Introduction

With the increasingly serious problems of energy crisis and environmental pollution, the development and utilization of new nonpolluting renewable energy sources such as wind energy, solar energy, and hydrogen energy have become an important direction of scientific and technological development. Hydrogen is widely considered as the most promising new renewable energy in the 21st century due to its large specific energy, low pollution, and wide source. In the engineering application of hydrogen energy, proton exchange membrane fuel cell (PEMFC), as an electrochemical device with high efficiency, high power density, low operating temperature, and low noise [1], has been widely used and developed in electric vehicles [2]. In recent years, PEMFC has been widely concerned by the scholars and its principle is to produce almost nonpolluting emissions, such as electricity, heat, and water, through hydrogen and oxygen reactions as shown in Figure 1. However, the vehicle PEMFC is a complex system with strong nonlinearity, varying time, and randomness. Especially in the driving condition of frequent load changes, whether it can be controlled stably, accurately, and efficiently determines the life, efficiency, and performance of the entire system [3].

Vehicle PEMFC is mainly divided into four subsystems: temperature subsystem, humidity subsystem, hydrogen supply system, and air supply system [4]. Since the dynamic change of temperature and humidity subsystem is slower than that of the other subsystems, it can be stripped out for decoupling control. The hydrogen subsystem mainly controls the high-pressure hydrogen tank through the solenoid valve, and its control goal is to minimize the pressure difference between the cathode and the anode. Therefore, this control goal can be achieved by simple proportional control.
However, in the process of controlling the vehicle PEMFC cathode air supply system, the operating conditions of the vehicles are complex, and the air compressor has a certain hysteresis characteristic for the adjustment of the air flow. When the load current suddenly changes, resulting in too low or too high air flow will have a very serious impact on the system. When the air flow is too low, oxygen deficiency will occur. At this time, due to the insufficient supply of materials, the power generation of the reactor cannot meet the demand of the upper load, the output voltage and power are reduced, the system efficiency is greatly cut down, and thus the overheating phenomenon of the proton exchange membrane will curtail the life of the reactor and even affect the whole system in serious cases, leading to safety problems [5]. In contrast, when the air flow is too high, the oxygen saturation will occur, and the output power of the stack does not change significantly, but the power loss of the compressor power increases greatly which reduces the net power of the whole system. For the vehicle PEMFC system with limited power, the power loss of the air supply system with an air compressor as the core component accounts for more than 25% of the overall output of the system [6]. Hence, how to avoid oxygen saturation is also a problem to be considered. Similar to the concept of excess air coefficient in internal combustion engines, the oxygen excess ratio (OER) of fuel cells is the ratio of the actual oxygen mass flow into the cathode to the oxygen mass flow involved in the reaction [7], which is an important indicator for characterizing the oxygen supply status and power generation performance in the PEMFC stack. Kim et al. [8] showed that the appropriate oxygen excess ratio can not only avoid the above adverse phenomena but also improve the net power of the system. Therefore, to avoid the problem of too high or too low oxygen excess ratio in the running of vehicle PEMFC system and meet the high requirements of cathode air flow under complex working conditions, it is necessary to control the oxygen excess ratio in real time efficiently and accurately.

Many scholars have done a lot of research on the modeling and control of air supply systems. Pukrushpan [7] proposed the earliest nine-order dynamic semiempirical model of air supply system which is established based on the theory of gas dynamics and thermodynamics. The model has nine state variables, which is more complex and more computational than the low-order model, so it is difficult to realize in the model-based control system. Meanwhile, there will be more measurement errors and signal fluctuations in the control system based on the high-order model, so the stability of the closed-loop system may be difficult to be guaranteed. On this basis, Suh [9] made some reasonable assumptions and simplified them into four state variables: oxygen partial pressure, nitrogen partial pressure, gas supply pipeline pressure, and compression motor speed, to put forward the fourth-order dynamic model of the air supply system. Talj et al. [10] combined the partial pressure of oxygen and nitrogen into the cathode pressure under further assumptions, and a control-oriented third-order system model was proposed, which was more suitable for the design of control systems. Niane et al. [11] proposed a theoretical result to prove that the oxygen excess ratio value can be controlled by using continuous state feedback.

In terms of the researches on the nonlinear control method, Beirami et al. [12] applied a fuzzy logic controller and in the feedback a filtered PID controller to improve the fuel cell system performance and prevent oxygen starvation. Ou et al. [13] proposed a new fuzzy-PID controller based on feedforward approach to regulate oxygen excess ratio, and simulation results revealed that the efficacy of the proposed feedforward fuzzy-PID approach is proved in regulating the...
oxygen excess ratio and in reducing parasitic power loss. Zhixiang [14] proposed a compound feedforward PID control method for the air system and proved that the control method was able to make full use of the fast response characteristic of centrifugal air compressor, with dynamic response time greatly shortened and the steady control accuracy requirements achieved. Baroud et al. [15] proposed a novel hybrid fuzzy-PID controller, which consists of three parts: a fuzzy logic controller (FLC), a fuzzy-based self-tuned PID (FSTPID) controller, and a fuzzy selector. Yang et al. [16] provided a novel modeling and control method based on Takagi-Sugeno fuzzy theory and predictive control, which can control the oxygen excess ratio in the ideal range and effectively suppress the fluctuation caused by the load change, and the results proved the proposed method can accurately control the air supply at desire values. Han et al. [17] proposed a model reference adaptive control (MRAC) method to deal with various inherent characteristics of the air supply system and the results showed that the presented MRAC strategy performed better than the nominal feedback control method with less wear and less control effort on the compressor. Kim et al. [18] established an approximation-based adaptive control strategy to ensure robust regulation of the OER, and, using the Lyapunov stability theorem, the boundedness of all closed-loop signals and the convergence of the output tracking error to the vicinity of zero were proved. Li and Yu [19] proposed an intelligent controller based on distributed deep reinforcement learning which exerts better control over the air flux of a PEMFC air supply system, which exhibited better control performance and robustness compared with other control methods. Liu et al. [20] presented an adaptive-gain second-order sliding mode (SOSM) control applied to a hybrid power system for electric vehicle with a PEMFC and proved that the proposed approach is effective and feasible. Chen et al. [21] designed an active disturbance rejection controller (ADRC) to regulate back-pressure valve (BPV) for the cathode outlet flow in a high-pressure PEMFC engine. Simulations and extensive experiments were conducted with the xPC Target and showed that the proposed controller can achieve good dynamic and static performance. Zhou et al. [22] established a novel adaptive fuzzy finite-time pure feedback switching control method by using the dynamic surface control (DSC) and the backstepping technique, and an example was given to illustrate this method and verify its validity and effectiveness. Chang et al. [23] developed a resilient controller by considering the randomly occurring uncertainty, and an illustrative simulation was given to show the effectiveness of the proposed method. Chang et al. [24] constructed a finite-time adaptive output feedback tracking controller via the backstepping technique based on designing an observer and demonstrated the high efficiency of the proposed control method in the end. Wang et al. [25] established an adaptive neural network controller by utilizing the multiple Lyapunov function method and the backstepping technique together with the prescribed performance bounds, which can ensure that all the signals in the closed-loop system are bounded under a class of switching signals with average dwell time and the tracking error converges to the predefined bounds. However, in the current researches on the vehicle PEMFC air supply system, there are common problems; for example, the model order is too high or the accuracy is insufficient, the cathode pressure is an unmeasurable value in engineering practice, and the general linearization methods do not work well.

To further solve existing problems, avoid the undesirable phenomena of oxygen deficiency and oxygen saturation, and maximize the net power and efficiency of the PEMFC system, this paper focuses on the oxygen excess ratio control of PEMFC air supply system and proposes a backstepping control strategy based on Kalman filter optimal estimation state observer to ensure the oxygen excess ratio of the system can always be maintained in an ideal range, when the load current changes frequently due to the complex driving conditions of the vehicle. The main contributions of this paper are as follows:

(i) According to the tracking objective of the designed control system, the optimal oxygen excess ratio of the system is calibrated and analyzed, and its sensitivity to different load currents, temperature, and humidity conditions is explored, respectively

(ii) A control-oriented model of a second-order affine air supply system is established, and an extended state observer is designed to estimate and compensate the "lumped error" in real time, thereby improving the accuracy of the model

(iii) Aiming at the problem that the cathode pressure cannot be measured, a state observer based on Kalman optimal estimation algorithm is designed to estimate the cathode pressure online by using the simplified model

(iv) A dynamic output feedback control system based on the observer + backstepping controller architecture is proposed, and the two schemes of fixed-value oxygen excess ratio tracking and optimized oxygen excess ratio tracking are compared and evaluated

The main content of this paper is as follows. Section 2 analyzes the control objectives, establishes the second-order affine oriented control model of the air supply system, and designs the model error compensation link. Section 3 designs a Kalman state observer to estimate the cathode pressure. In Section 4, the system control law is derived in detail and the stability is analyzed. Section 5 provides the simulation analysis results. Section 6 summarizes the content of the full text and puts forward conclusions.

2. Control Objective Analysis and Model Building

Figure 2 shows a schematic diagram of the structure of the vehicle PEMFC system. The air supply system mainly includes an air compressor, an intercooler, a humidifier, and corresponding pipelines. When the system works, the air compressor continuously provides air for the stack, and the oxygen in the air is used as an oxidant to participate in the reaction. Since air pressure, flow rate, temperature, and
humidity have different effects on the performance of the reactor, real-time adjustment is needed. By controlling the input voltage of the air compressor, the air flow into the stack can be adjusted. The intercooler is responsible for cooling the air into the stack, and the humidifier is used to adjust the air humidity in real time.

2.1. Control Objective Analysis. The oxygen excess ratio is an important variable that affects the net output power of the fuel cells at all times, which is defined as

$$\lambda_{O_2} = \frac{W_{O_2, in}}{W_{O_2, react}} = \frac{b_1 (p_{atm} - p_{ca})}{b_2 I_{st}}$$

(1)

where $W_{O_2, in}$ is the mass flow of oxygen into the cathode; $W_{O_2, react}$ is the oxygen mass flow for chemical reaction; $p_{atm}$ is the air pressure in the supply manifold; $p_{ca}$ is the internal pressure of the cathode; $I_{st}$ is the load current, given by the upper energy management system; $b_1$ and $b_2$ are the constants; see the Appendix for the specific values.

When the value of the oxygen excess ratio is too high or too low, oxygen saturation or oxygen deficiency will occur, resulting in a decrease in the net output power of the stack. Therefore, when the vehicle is running, the oxygen excess ratio should be adjusted to the best value of the current working condition as much as possible to maximize the net power. The net output power of the stack is defined as the difference between the output power of the stack and the power of the auxiliary components (mainly borne by the air compressor), which is expressed as

$$P_{net} = P_{st} - P_{cp},$$

(2)

where $P_{net}$ is the net output power of the fuel cell stack, $P_{st}$ is the total power output of the stack, and $P_{cp}$ is the power loss of the air compressor. The total output power of the stack can be calculated by the following equation:

$$P_{st} = I_{st} V_{st},$$

(3)

where $V_{st}$ is the output voltage of the fuel cell stack; the expression is

$$V_{st} = n (E_{Nernst} - E_{loss}),$$

(4)

where $n$ is the number of single fuel cells in the stack, $E_{loss}$ is the voltage loss caused by the polarization phenomenon, and $E_{Nernst}$ is the reversible voltage of the single fuel cell, which can be expressed by Nernst equation:

$$E_{Nernst} = E_0 + \frac{RT}{2F} \ln \left( \frac{p_{H_2}^{1/2}}{p_{H_2O}} \right),$$

(5)

where $E_0$ is the reversible voltage for the standard state (20°C, one standard atmospheric pressure), R is a constant representing the general gas constant, $T$ is the stack temperature, F is the Faraday constant, and $p_{H_2}$, $p_{O_2}$, and $p_{H_2O}$ are hydrogen partial pressure, oxygen partial pressure, and vapor partial pressure, respectively. It can be seen from equations (3)–(5) that, with the increase of oxygen partial pressure, the output power of the stack will also increase accordingly. At the same time, since the oxygen excess ratio is positively correlated with the oxygen partial pressure, it can be seen that increasing the oxygen excess ratio can improve the output power of the fuel cell stack. However, with the elevation of the oxygen excess ratio, the parasitic power of the air compressor will also increase. The compressor power consumption expression is

$$P_{cp} = C_{p} T_{atm} \eta_{cp} \left( \frac{p_{atm}}{p_{in}} \right)^{y-1} W_{cp},$$

(6)

where $C_p$ is the specific heat capacity of air, $T_{atm}$ is the atmospheric temperature, $\eta_{cp}$ is the compressor efficiency, $p_{atm}$ is the air pressure in the supply manifold, $p_{in}$ is the atmospheric pressure, $y$ is the ratio of the specific heat ratio of air, and $W_{cp}$ is the air mass flow through the compressor. It can be seen from equation (6) that, with the increase of inlet pressure and compressor flow, the power consumption of the compressor will also increase, and the oxygen excess ratio is also positively correlated with the inlet pressure and compressor flow.
Therefore, when the vehicle PEMFC is running, each load current will correspond to an optimal oxygen excess ratio, so that the net output power of the fuel cell reaches the maximum. Most of the existing studies used a fixed oxygen excess ratio ($\lambda_{O^e} = 2$) as the objective value for air supply system control. Although reaching this objective value can avoid oxygen deficiency and oxygen saturation, it cannot maximize the net power output of the system. In response to this problem, this paper uses the fuel cell air supply system simulation model built in Section 5 to test and calibrate. Under different load current conditions (100–300 A) of the given system, the compressor voltage is controlled to gradually increase and the values of the system oxygen excess ratio and the output net power are collected. This process is repeated to make the load current cover the entire range of working conditions. Finally, after collecting data and processing, the oxygen excess ratio and the net output power of the system under different load currents are obtained as shown in Figure 3. After fitting, the relationship curve between the load current and the optimal oxygen excess ratio is obtained, as shown in Figure 4, which is used as the objective value of this control strategy tracking in this paper.

### 2.2. Control Model Construction and Simplification

#### 2.2.1. Initial Model Building

Since the focus of this paper is the cathode flow control based on the optimal oxygen excess ratio, the anode is supplied by a high-pressure and high-purity hydrogen tank through a pressure reducing valve, so it is assumed that the anode pressure can track the cathode pressure well. At the same time, the dynamic change speed of the gas temperature and humidity when the load current changes transiently is much smaller than the dynamic change of the airflow. Therefore, the range of temperature and humidity is negligible, so here it is assumed that the temperature and humidity of the air entering the reactor are always controlled at ideal values, and it is assumed that they are all gases in an ideal state [7]. According to the literature [7, 9, 10], the following simplified reduced-order control-oriented third-order system model can be further obtained:

\[
\dot{x}_1 = a_1 x_1 + a_2 x_2 + a_3 I_{st} + a_4, \tag{7}
\]

\[
\dot{x}_2 = a_5 x_1 + a_6 x_2 + a_7 W_{cp} (x_2, x_3), \tag{8}
\]

\[
\dot{x}_3 = a_8 x_3 + a_9 (a_{10} x_2^{a_{11}} - 1) \frac{W_{cp} (x_2, x_3)}{x_3} + a_{12} u, \tag{9}
\]

where the state variable $x = [x_1, x_2, x_3]^T \approx [p_{ca}, p_{sm}, \omega_{cp}]^T$, $x_1 = p_{ca}$ is the cathode pressure, $x_2 = p_{sm}$ is the supply manifold pressure, $x_3 = \omega_{cp}$ is the speed of the compressor motor, $x_1$ is the unmeasurable variable, and $x_2$ and $x_3$ are measurable variables. Control input of the system $u = v_{cp}$ is the input voltage of the compressor, and $I_{st}$ is the load current given by the upper layer, which is regarded as the disturbance input of the system. $a_1, \ldots, a_{12}$ are system constant value parameters; refer to Appendix A for details.

#### 2.2.2. Formal Transformation of Model and Control Objective

To facilitate the derivation of the control law, the original system model is processed. According to equations (7)-(8), a new state variable is defined as

\[
X = x_2 - x_1, \tag{10}
\]

where $X$ represents the difference between the inlet pipe pressure and cathode pressure. According to equation (1), the new control objective of the system is defined as

\[
\min J(X) = \int \left( X \right)^2 dt.
\]
\[ X \rightarrow X^* = \frac{b_2 I_{a1} A_{a1}^*}{b_1}. \]  

(11)

The model form is organized as follows:

\[ \dot{X} = (a_1 - a_5)X + (a_2 + a_6 - a_1 - a_2)x_2 + a_2 W_{cp} - a_3 I_d - a_4, \]

\[ X = (a_1 - a_5)X + (a_2 + a_6 - a_1 - a_2 + a_1 \frac{\partial W_{cp}}{\partial x_2}) + a_2 \frac{\partial W_{cp}}{\partial x_3}. \]

(12)

Substituting equations (8)-(9), the second-order affine model is further sorted out:

\[ \dot{X} = f_1 \dot{X} + f_2 X + f_3 + gu. \]  

(13)

The details are as follows:

\[ f_1 = a_1 - a_5, \]
\[ f_2 = a_2 \left( a_1 + a_2 - a_5 - a_6 - a_7 \frac{\partial W_{cp}}{\partial x_2} \right), \]
\[ f_3 = \left( a_5 + a_6 - a_1 - a_2 + a_7 \frac{\partial W_{cp}}{\partial x_2} \right) \left[ \left( a_2 + a_6 \right) x_2 + a_7 W_{cp} \right] \]
\[ + a_7 \frac{\partial W_{cp}}{\partial x_3} \left\{ a_3 x_3 + a_9 \left( a_{10} x_2^a + 1 \right) W_{cp} (x_1, x_3) \right\}, \]
\[ g = a_7 a_12 \frac{\partial W_{cp}}{\partial x_3}. \]  

(14)

### 2.2.3. Disturbance Observer Design

According to some of the system variables are omitted from the simplified reduced-order control-oriented model, although the calculation amount of the model is greatly reduced, the accuracy of the model is difficult to meet the control requirements, and there is a certain signal transmission interference in the actual operation of the system. Therefore, a lumped error interference quantity \( d \) is considered in the model. Then the model is updated from equation (13) to

\[ \dot{X} = f_1 \dot{X} + f_2 X + f_3 + gu + d. \]  

(15)

The extended state observer (ESO) in active disturbance rejection control is used to estimate the amount of interference. Define \( z_1 = X, z_2 = \dot{X}, \) and \( z_3 = d. \) The ESO is designed as follows:

\[ \dot{z}_1 = z_2, \]
\[ \dot{z}_2 = f_1 z_2 + f_2 z_1 + f_3 + gu + z_3, \]
\[ \dot{z}_3 = C. \]  

(16)

Define estimation error \( \tilde{z}_1 = z_1 - \hat{z}_1; \) the designed ESO form is as follows:

\[ \dot{\hat{z}}_1 = \hat{z}_2 + 3a \tilde{z}_1, \]
\[ \dot{\hat{z}}_2 = f_1 \hat{z}_2 + f_2 \hat{z}_1 + f_3 + gu + \tilde{z}_3 + 3a^2 \tilde{z}_1, \]
\[ \dot{\hat{z}}_3 = \alpha^3 \tilde{z}_1, \]  

(17)

where \( \tilde{z}_1, \tilde{z}_2, \) and \( \tilde{z}_3 \) are the corresponding observations, and \( d = \tilde{z}_3. \) The original model is updated:

\[ \dot{\hat{X}} = f_1 \dot{\hat{X}} + f_2 \hat{X} + f_3 + gu + \tilde{d}. \]  

(18)

### 3. State Observer Design

Since the pressure state variable inside the PEMFC cathode is unmeasurable in engineering applications, a suitable state observer should be selected to estimate it online. Kalman filter is an optimal recursive estimation algorithm for system state variables by processing the system inputs and measurable outputs using the system state-space equation. Because it can estimate the state variables of a dynamic system from a series of incomplete and noise-containing measurement data combined with the state-space equation of the system, it is widely used in the field of state observation. The observability analysis of the system has been given in the literature [7], since the purpose of designing the state observer here is only to obtain the cathode pressure, equation (9) in the state equations is omitted, and the load current and the air compressor flow rate are set as the input of the model, which is simplified to a linear model to facilitate observer design and reduce the amount of model calculations. Finally, the measured value of \( x_3 = p_{am} \) and the calculated value of the second-order equation of state model are used to obtain a more accurate cathode pressure value by distributing the weight of the Kalman gain.

Equations (7)-(8) are rewritten in the following form:

\[ \dot{x} = Ax + BU + C, \]  

(19)

where \( x = [x_1, x_3]^T, A = \begin{bmatrix} a_1 & a_2 & a_9 \end{bmatrix}, B = \begin{bmatrix} a_9, 0, 0, a_9 \end{bmatrix}, \) \( C = \begin{bmatrix} a_4, 0 \end{bmatrix}^T, \) and observer input \( U = [I, W_{cp} W_{cp}^T]^T. \) The model is discretized to get

\[ x_k = A_0 x_{k-1} + B_0 U_{k-1} + C, \]  

(20)

where \( A_0 \) and \( B_0 \) are the discrete model gain, and the subscripts \( k \) and \( k - 1 \), respectively, represent the current sampling time and the previous sampling time. Since \( x_3 = p_{am} \) is a measurable variable, it is the measurable output of the system; namely,

\[ Z_k = H x_k. \]  

(21)

where \( H = [1, 0]. \) Due to the interference of the model and environment in the actual system, the process noise and measurement noise are introduced here, and the system state equation is updated as follows:

\[ x_k = A_0 x_{k-1} + B_0 U_{k-1} + C + w_{k-1}, \]
\[ Z_k = H x_k + v_k. \]  

(22)

It is assumed here that the process noise \( w \) and measurement noise \( v \) in equation (22) conform to the Gaussian
distribution, and their covariance matrices are $Q$ and $R$, respectively. According to the literature [26], the Kalman optimal estimation algorithm is designed in two stages: prediction and correction.

3.1. Prediction Stage. Because the process noise $w$ and measurement noise $v$ are not considered in the original system state equation, the prediction is not accurate enough. According to equation (20), a priori estimated value is defined:

$$\hat{x}_k = A_0\hat{x}_{k-1} + B_0U_{k-1} + C.$$ \hspace{1cm} (23)

Prior error covariance is as follows:

$$P_k = A_0P_{k-1}A_0^T + Q,$$ \hspace{1cm} (24)

where $Q$ is the covariance matrix of the process noise.

3.2. Correction Stage. Update the Kalman gain $k_k$ by using the prior estimation value and the prior error covariance obtained by equations (23)-(24):

$$k_k = \frac{P_kH^T}{HP_kH^T + R},$$ \hspace{1cm} (25)

where $R$ is the covariance of the measurement noise. To calculate the value of the prior error covariance for the next sampling time, update the error covariance:

$$P_k = (I - k_kH)P_k^{-1},$$ \hspace{1cm} (26)

where $I$ is the identity matrix. Finally, calculate the posterior estimate obtained by the Kalman filter at the current sampling time:

$$\tilde{x}_k = \hat{x}_k + k_k(Z_k - H\hat{x}_k).$$ \hspace{1cm} (27)

In each sampling time, the two processes of equations (23)–(27) will cycle once. By reasonably selecting the covariances of the process noise and the measurement noise, the estimated value and the measured value are combined to obtain a more accurate observation value. The schematic diagram is shown in Figure 5.

4. Controller Design

4.1. Backstepping Control Law. Let $y_1 = X$ and $y_2 = \hat{X}$. Then the system model is updated to

$$\dot{y}_1 = y_2,$$ \hspace{1cm} (28)

$$\dot{y}_2 = f_1y_2 + f_2y_1 + f_3 + gu + \dot{d},$$ \hspace{1cm} (29)

and, according to equation (11), the control objective is

$$y_1 \rightarrow y_1^* = X^*.$$ \hspace{1cm} (30)

The design of the backstepping controller is as follows. Define the tracking error:

$$e_1 = y_1^* - y_1.$$ \hspace{1cm} (31)

Take the derivative of equation (31) and substitute equation (28):

$$\dot{e}_1 = y_1^* - y_2.$$ \hspace{1cm} (32)

The Lyapunov function needs to be defined here. In practical applications, in order to ensure the asymptotic stability of the defined error, the function should have the desired boundary form according to the needs of the required proof, and let the derivative of the function include an upper bound inequality that is expected to be proved. The specific definition is as follows:

$$\dot{V}_1 = \frac{1}{2}e_1^2 \geq 0.$$ \hspace{1cm} (33)

Take the derivative of equation (33) and substitute equation (32) to get

$$\dot{V}_1 = e_1\dot{e}_1 = e_1(y_1^* - y_2).$$ \hspace{1cm} (34)

Let $\dot{y}_1^* - y_2 = -k_1e_1 (k_1 > 0)$; then

$$\dot{V}_1 \leq 0.$$ \hspace{1cm} (35)

The system satisfies the asymptotic stability condition, so another objective value is introduced:

$$y_2^* = y_1^* + k_1e_1.$$ \hspace{1cm} (36)

Take the derivative of (36) and substitute equation (32):

$$\dot{y}_2^* = \dot{y}_1^* + k_1(y_1^* - y_2).$$ \hspace{1cm} (37)

Since $y_2$ is not always equal to $y_2^*$, define another tracking error here:

$$e_2 = y_2^* - y_2.$$ \hspace{1cm} (38)

Take the derivative of equation (38) and substitute equations (29) and (37):

$$\dot{e}_2 = \dot{y}_1^* + k_1(y_1^* - y_2) - (f_1y_2 + f_2y_1 + f_3 + gu + \dot{d}).$$ \hspace{1cm} (39)

Substituting equation (36) into (34), the following can be obtained:

$$\dot{V}_2 = V_2 + \frac{1}{2}e_2^2 \geq 0.$$ \hspace{1cm} (40)

Define the Lyapunov function again:

$$V_2 = V_1 + \frac{1}{2}e_2^2 \geq 0.$$ \hspace{1cm} (41)

Take the derivative of equation (41) and substitute equation (40):

$$\dot{V}_2 = -k_1e_1^2 + e_2(e_1 + \dot{e}_2).$$ \hspace{1cm} (42)

Here $V_2$ needs to meet the asymptotically stable condition for the system to converge; namely,

$$\dot{V}_2 \leq 0.$$ \hspace{1cm} (43)

To satisfy the convergence condition of equation (43), define
\[ e_1 + e_2 = -k_2 e_2 \]  \quad (k_2 > 0).  

Substitute equation (39) into equation (44) and sort out the final input control law:

\[ u = \frac{1}{g} \left[ k_1 e_2 + e_1 + y_1^* + k_1 (y_1^* - y_2) - f_1 y_1 - f_2 y_2 - f_3 - d \right], \]

where \( k_1 \) and \( k_2 \) are control parameters, and both are greater than zero, which can be adjusted until the system requirements are met. For the rest of the system parameters, refer to equation (16). The block diagram of the proposed control method is shown in Figure 6.

4.2. Lyapunov Stability Analysis. Substitute equations (36) and (38) into equation (32):

\[ \dot{e}_1 = -k_1 e_1 + e_2. \]  

Substitute equation (45) into (39):

\[ \dot{e}_2 = -e_1 - k_2 e_2. \]

Rewrite equations (46)-(47) into state-space form:

\[
\begin{bmatrix}
    \dot{e}_1 \\
    \dot{e}_2
\end{bmatrix} =
\begin{bmatrix}
    -k_1 & 1 \\
    -1 & -k_2
\end{bmatrix}
\begin{bmatrix}
    e_1 \\
    e_2
\end{bmatrix}. \]  

Since both \( k_1 \) and \( k_2 \) are positive, the system eigenvalues \( \lambda_1 \) and \( \lambda_2 \) are as follows:

\[ \lambda_1 + \lambda_2 = -k_1 - k_2 < 0, \]

\[ \lambda_1 \lambda_2 = k_1 k_2 + 1 > 0. \]

The eigenvalues \( \lambda_1 \) and \( \lambda_2 \) are all less than zero, and, from equation (48), it can be known that the balance point of the system is at the origin of the coordinate. Therefore, according to the principle of invariance, the system satisfies the asymptotic stability condition, and the errors will eventually tend to zero; that is, satisfy \( y_1 \to y_1^* = X^* \).

5. Simulation Verification and Analysis

To verify the designed control strategy, a high-precision semimechanical simulation model was built based on the MATLAB/Simulink platform [7], and a series of random step load current signals were input to the built-up fuel cells system-controlled object model to simulate a variety of complex operating conditions when the actual vehicle is running, as shown in Figure 7.

5.1. The Influence of Temperature and Humidity on the Optimal Oxygen Excess Ratio. Since the temperature and humidity of the system are assumed to be an ideal control state in the calibration process of the optimal oxygen excess ratio, the analysis and exploration of the influence of temperature and humidity on the net power of the system and the optimal oxygen excess ratio are as follows.

5.1.1. Temperature Influence. As shown in Figure 8, the curves of the relationship between the oxygen excess ratio and the net power of the system under the conditions of load current of 120 A, 160 A, 200 A, 240 A, and 280 A and temperature of 40, 50, 60, 70, and 80°C are obtained by simulation experiments (humidity changes with temperature); the symbol “×” on each curve in the figure represents the maximum net power point under this condition.

According to the experimental results, it can be seen that temperature will not only affect the net output power of the system but also affect the optimal oxygen excess ratio of the system under a certain load current. The effect on the net power can be explained by equations (3)-(5). As the temperature increases, it will directly affect the monolithic fuel
cell voltage and voltage loss of the stack, thereby affecting the net power output of the stack. From Table 1, we can further obtain the variation of the optimal oxygen excess ratio of the system within this temperature range. It can be seen that it is relatively large under low current conditions, but its variation gradually decreases as the current increases. The reason is that the change of temperature will affect the internal pressure of the cathode, which will cause the change of the value of the optimal oxygen excess ratio under the current working conditions. Therefore, after the above analysis, it can be known that the control of the stack temperature has a certain influence on the value of the optimal oxygen excess ratio, especially under the condition of low load current.

5.1.2. Humidity Influence. As shown in Figure 9, \( \lambda_m \) represents the average water content of the proton exchange membrane, calculated from the relative humidity of the gas [7]. Through simulation experiments, the relationship curves between the oxygen excess ratio and the net power of the system when the stack temperature is 80°C (353 K), the load current is 120 A, 160 A, 200 A, 240 A, and 280 A, and the membrane water content is 6, 8, 10, 12, and 14 are obtained. The symbol “×” on each curve in the figure represents the maximum net power point under this condition.

From the simulation results in the figure, it can be seen that the change of the membrane water content will also affect the net power of the system. This is because the membrane water content determines the ohmic loss in the polarization phenomenon of the fuel cell, thus affecting \( E_{loss} \) in equation (4), which ultimately leads to a change in the net power of the system. In addition, it can be seen that changes in the water content of the membrane have little influence on the optimal oxygen excess ratio.

5.2. Observer Verification. To verify the performance of the designed Kalman optimal estimation state observer, considering its working conditions in the actual environment, process noise and measurement noise with a mean value of 0 and a variance of \( 10^{-8} \) and \( 10^{-4} \) were added to the system. At the same time, in order to optimize the performance of the observer, take its parameters as \( Q = \text{diag} \ (0, 10) \) and \( R = 0.05 \). The simulation result is shown in Figure 10.

5.3. Control-Oriented Model Verification. To eliminate certain model errors and signal interference, an error compensation link based on ESO is added to the control strategy. After many simulation experiments, the parameter \( a \) is set to be 1000 to ensure the optimal performance. The performance and error comparison before and after model optimization are shown in Figure 11. It can be seen from the figure that the control model does not work well before optimization, and the transient error and convergence speed are relatively terrible. After adopting the error compensation link of ESO, good results have been achieved. The transient error of the model is controlled within 2%, and it can converge to zero with a faster response speed and meet the requirements of model-based controller design.

5.4. Controller Performance Verification and Analysis. In order to better verify the performance of the designed control strategy, first set the oxygen excess ratio equal to 2 as the control objective, and compare the PID controller with the designed control strategy. After many simulation experiments, the optimal parameters of the PID controller are summarized as \( k_p = 55, k_i = 580, \) and \( k_d = 0.6 \). The designed controller parameters are \( k_1 = 920 \) and \( k_2 = 130 \). The simulation result is shown in Figure 12. It can be seen from Figure 12(a) that both controllers have achieved better tracking results. In addition, Figures 12(b) and 12(c) show the transient response effects of the controller when the load current demand increases and decreases at 8 s and 12 s, respectively. Clearly, the designed controller is superior to the PID controller in terms of transient response quality. At
Figure 8: The influence of different stack temperature on net power and optimal oxygen excess ratio under (a) 120 A, (b) 160 A, (c) 200 A, (d) 240 A, and (e) 280 A load current conditions.
### Table 1: Variation range of optimal oxygen excess ratio under the condition of stack temperature of 40–80°C.

| Load currents | Range of optimal OER | Change of optimal OER |
|---------------|----------------------|-----------------------|
| 120 A         | 2.452–2.73           | 0.278                 |
| 160 A         | 2.294–2.589          | 0.295                 |
| 200 A         | 2.161–2.299          | 0.138                 |
| 240 A         | 2.098–2.199          | 0.101                 |
| 280 A         | 1.999–2.067          | 0.068                 |

### Figure 9: Continued.

(a) ![Graph](image1)

(b) ![Graph](image2)

(c) ![Graph](image3)

(d) ![Graph](image4)
the same time, there is no overshoot phenomenon and it has good steady-state characteristics.

5.5. Control Objective Optimization Effect. In order to optimize the performance of the system, simply tracking the fixed oxygen excess ratio is surely unable to meet the demand. According to the relationship curve between the optimal oxygen excess ratio and the load current obtained by fitting the calibration data, the optimal oxygen excess ratio of the system can be calculated online and output to the controller in real time when the system is running. The performance of tracking the optimal oxygen excess ratio using the designed control strategy is shown in Figure 13. Obviously, the designed control strategy still has better tracking performance than the PID controller. From the amplification effect in Figures 13(b) and 13(c), it can be seen that, at 12 s and 16 s, the load current and the objective of oxygen excess ratio occur simultaneously. In case of changes, the controller still has better transient response and steady-state characteristics.

Figures 14(a) and 14(b) show the comparison diagrams of output voltage and output power when the constant value and the optimal oxygen excess ratio are the tracking objective. It can be seen that the output voltage and power after the optimization of the objective value have been improved to a certain extent, especially when the load current is low. Figure 14(c) is a comparison chart of the output net power. Compared with the fixed oxygen excess ratio objective, it can be seen that the net power after adopting the optimal oxygen excess ratio is always higher than the former. At the same time, the performance improvement effect is more significant under low current conditions.
Figure 11: Comparison of the original model and the optimized model.

Figure 12: Comparison of the proposed control strategy and PID control performance.
Figure 13: Comparison of the control effect of using the optimal oxygen excess ratio as the tracking objective.

Figure 14: Continued.
6. Conclusion

This paper proposes a nonlinear control strategy for tracking control of the oxygen excess ratio. Through the feedback processing of the operating parameters of the vehicle PEMFC air supply system, the precise control of the input voltage of the core component air compressor is realized, and the goal of optimizing the oxygen excess ratio of the core parameter is achieved. The following conclusions can be drawn:

(1) The mechanism analysis of the fuel cell is carried out, and the optimal oxygen excess ratio curve under different working conditions is calibrated. The simulation results show that the output characteristics of PEMFC have been improved to different degrees under various working conditions, compared with the tracking objective of fixed oxygen excess ratio.

(2) A second-order affine form-oriented control model is derived through reasonable simplification, and a disturbance observer is designed to improve the accuracy of the model. The simulation results show that the transient error of the optimized model is controlled within 2%, and the convergence rate has been greatly improved.

(3) Aiming at the problem that the cathode pressure cannot be measured, a state observer based on the Kalman optimal estimation algorithm is designed to realize the online cathode pressure estimation. The simulation results show that the transient error is controlled within 2%, and the steady-state relative error is controlled within 0.5%, which meets the system requirements.

(4) Based on the established model and Kalman observer, a dynamic output feedback controller of observer + backstepping controller is proposed and Lyapunov analysis is carried out to ensure the stability of the closed-loop system. Two control strategies are compared and evaluated, and the simulation results show that the proposed controller is superior to the benchmark controller in both dynamic tracking performance and steady-state performance.

(5) The sensitivity of the model is analyzed, and the results show that the stack temperature has a certain effect on the optimal oxygen excess ratio, while the membrane water content slightly impacts on the optimal oxygen excess ratio.

Through simulation experiments at each stage, it is verified that the proposed control strategy can ensure the stable operation of the vehicle PEMFC air supply system under complex working conditions, and it also has good transient response performance under sudden load changes. On this basis, after adopting the optimal oxygen excess ratio as the tracking target, the output performance of the system has been improved to varying degrees. In summary, the results show that the proposed method achieves precise control of air supply, avoids unfavorable phenomena caused by system air flow imbalance, and improves system output performance, thereby increasing its life and efficiency, which has certain guiding significance for actual engineering applications. However, there are some problems that need to be solved in future work, the sensitivity analysis results for the optimal oxygen excess ratio need to be further applied to the optimization of the control target, and the performance of the proposed method needs to be verified on the test bench.
Appendix

A. PEMFC Model Parameters

\[ a_1 = \frac{RT_a}{V_{ca}} \left( x_{O_2, atm} k_{sm, out} + \frac{(1 - x_{O_2, atm}) k_{sm, out}}{1 + \omega_{atm}} \right) \]

\[ a_2 = \frac{RT_a}{V_{ca}} \left( \frac{x_{O_2, atm} k_{sm, out}}{1 + \omega_{atm}} + \frac{(1 - x_{O_2, atm}) k_{sm, out}}{1 + \omega_{atm}} M_{N_2} \right) \]

\[ a_3 = \frac{nRT_a}{4FV_{ca}} \]

\[ a_4 = \frac{RT_a C_D A_T}{kV_{ca}} r_{sat} = \frac{(2 \gamma + 1) y^{1/2} (y - 1)}{2 \gamma + 1} \]

\[ a_5 = -a_6 \]

\[ a_7 = \frac{RT_a}{V_{sm} M_{a, atm}} \]

\[ a_8 = \eta_{cm} k_{\Omega} k_{\Phi} \]

\[ a_9 = \frac{C_p T_{atm}}{J_{cp} R_{cm}} \]

\[ a_{10} = \frac{1}{P_{atm}} \]

\[ a_{11} = \gamma - 1 \]

\[ a_{12} = k_{v} J_{cp} R_{cm} \]

\[ b_1 = \frac{k_{sm, out} x_{O_2, atm}}{1 + \omega_{atm}} \]

\[ b_2 = \frac{1}{n M_{O_2}} \]

\[ M_{a, atm} = y_{O_2, atm} M_{O_2} + (1 - y_{O_2, atm}) M_{N_2} \]

\[ x_{O_2, atm} = \frac{y_{O_2, atm} M_{O_2}}{M_{a, atm}} \]

\[ \omega_{atm} = \frac{M_{v} \Phi_{atm} P_{sat}}{M_{a, atm} P_{atm} - \Phi_{atm} P_{sat}} \]

(A.1)

B. PEMFC Physical Parameters

| Sign | Implication | Unit | Value |
|------|-------------|------|-------|
| n | Number of cells in fuel cells stack | | 381 |
| \( \mathbb{R} \) | Universal gas constant | J/(mol·K) | 8.3145 |
| \( P_{atm} \) | Atmospheric pressure | Pa | 101325 |
| \( P_{sat} \) | Saturation pressure | Pa | 42404 |
| \( T_{atm} \) | Atmospheric temperature | K | 298.15 |
| \( T_{st} \) | Stack temperature | K | 353 |
| \( \Phi_{atm} \) | Average ambient air relative humidity | | 0.5 |
| \( C_{p} \) | Constant pressure specific heat of air | J/(kg·K) | 1004 |
| \( \gamma \) | Ratio of specific heat of air | | 1.4 |
| \( M_{O_2} \) | Oxygen molar mass | kg/mol | 0.032 |
| \( M_{N_2} \) | Nitrogen molar mass | kg/mol | 0.028 |
| \( M_{v} \) | Vapor molar mass | kg/mol | 0.018 |
| \( J_{cp} \) | Compressor inertia | kg·m² | \( 5 \times 10^{-5} \) |
| \( k_{\Omega} \) | Motor parameter | N·m/Amp | 0.0153 |
| \( R_{cm} \) | Compressor motor resistance | Ω | 0.82 |
| \( k_{v} \) | Motor parameter | V/(rad/sec) | 0.0153 |
| \( \eta_{cm} \) | Compressor efficiency | | 0.8 |
| \( \eta_{m} \) | Motor mechanical efficiency | | 0.98 |
| \( V_{sm} \) | Supply manifold volume | m³ | 0.02 |
| \( V_{ca} \) | Cathode volume | m³ | 0.01 |
| \( k \) | Parameter for model simplification | | 0.02585 |
| \( k_{sm, out} \) | Supply manifold outlet orifice constant | kg/(s·Pa) | \( 0.3629 \times 10^{-5} \) |
| \( C_{D} \) | Cathode outlet throttle discharge coefficient | | 0.0124 |
| \( A_T \) | Cathode outlet throttle area | m² | 0.00175 |
| \( \gamma_{O_2, atm} \) | Oxygen mole fraction | | 0.21 |

Data Availability

The data (specifications for the PEMFC stack) supporting the simulation model dynamic model of the PEMFC are from previously reported studies. These studies are cited at relevant places within this paper as references [7] and [10].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

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References

[1] H. Chen, B. Liu, T. Zhang, and P. Pei, “Influencing sensitivities of critical operating parameters on PEMFC output performance and gas distribution quality under different electrical load conditions,” Applied Energy, vol. 255, Article ID 113849, 2019.

[2] M. Li, Y. Bai, C. Zhang et al., “Review on the research of hydrogen storage system fast refueling in fuel cell vehicle,” International Journal of Hydrogen Energy, vol. 44, no. 21, pp. 10677–10693, 2019.

[3] O. Z. Sharaf and M. F. Orhan, “An overview of fuel cell technology: fundamentals and applications,” Renewable and Sustainable Energy Reviews, vol. 32, pp. 810–853, 2014.

[4] H. Deng, Q. Li, W. Chen, and G. Zhang, “High order sliding mode observer-based OER control for PEM fuel cell air-feed system,” IEEE Transactions on Energy Conversion, vol. 99, p. 1, 2018.

[5] H. Chen, S. Xu, P. Pei, B. Qu, and T. Zhang, “Mechanism analysis of starvation in PEMFC based on external characteristics,” International Journal of Hydrogen Energy, vol. 44, no. 11, pp. 5437–5446, 2019.

[6] R. Tirnovan and S. Giurgea, “Efficiency improvement of a PEMFC power source by optimization of the air management,” International Journal of Hydrogen Energy, vol. 37, no. 9, pp. 7745–7756, 2012.

[7] J. T. Pukrushpan, Modeling and control of fuel cell systems and fuel processors, Ph.D. thesis, University of Michigan, Ann Arbor, MI, USA, 2003.

[8] B. Kim, D. Cha, and Y. Kim, “The effects of air stoichiometry and air excess ratio on the transient response of a PEMFC under load change conditions,” Applied Energy, vol. 138, pp. 143–149, 2015.

[9] K. W. Suh, Modeling, Analysis and Control of Fuel Cell Hybrid Power Systems, University of Michigan., Ann Arbor, MI, USA, 2006.

[10] R. J. Tali, D. Hissel, R. Ortega, M. Becherif, and M. Hilairet, “Experimental validation of a pem fuel-cell reduced-order model and a moto-compressor higher order sliding-mode control,” IEEE Transactions on Industrial Electronics, vol. 57, no. 6, pp. 1906–1913, 2009.

[11] M. Niane, M. Zerrougui, and R. Oubib, “A theoretical result on stabilizability of oxygen excess ratio for PEM fuel cell,” in Proceedings of the International Conference on Electromechanical and Power Systems (SIELMEN), Iasi, Romania, October 2017.

[12] H. Beirami, A. Z. Shabestari, and M. M. Zeratif, “Optimal PID plus fuzzy controller design for a PEM fuel cell air feed system using the self-adaptive differential evolution algorithm,” International Journal of Hydrogen Energy, vol. 40, no. 30, pp. 9422–9434, 2015.

[13] K. Ou, Y.-X. Wang, Z.-Z. Li, Y.-D. Shen, and D.-J. Xuan, “Feedforward fuzzy-PID control for air flow regulation of PEM fuel cell system,” International Journal of Hydrogen Energy, vol. 40, no. 35, pp. 11686–11695, 2015.

[14] L. Zhixiang, L. Li, Y. Ding, H. Deng, and W. Chen, “Modeling and control of an air supply system for a heavy duty PEMFC engine,” International Journal of Hydrogen Energy, vol. 41, no. 36, pp. 16230–16239, 2016.

[15] Z. Baroud, M. Benmiloud, A. Benalia, and C. Ocampo-Martinez, “Novel hybrid fuzzy-PID control scheme for air supply in PEM fuel-cell-based systems,” International Journal of Hydrogen Energy, vol. 42, no. 15, pp. 10435–10447, 2017.

[16] D. Yang, R. Pan, Y. Wang, and Z. Chen, “Modeling and control of PEMFC air supply system based on T-S fuzzy theory and predictive control,” Energy, vol. 188, Article ID 116078.1, 2019.

[17] J. Han, S. Yu, and S. Yi, “Oxygen excess ratio control for proton exchange membrane fuel cell using model reference adaptive control,” International Journal of Hydrogen Energy, vol. 44, no. 33, pp. 18425–18437, 2019.

[18] B. M. Kim, H. C. Yun, and S. J. Yoo, “Adaptive control of proton exchange membrane fuel cell air supply systems with asymmetric oxygen excess ratio constraints,” IEEE Access, vol. 99, p. 1, 2019.

[19] J. Li and T. Yu, “Intelligent controller based on distributed deep reinforcement learning for PEMFC air supply system,” IEEE Access PP, vol. 99, p. 1, 2021.

[20] J. Liu, Y. Zhao, B. Geng, and B. Xiao, “Adaptive second order sliding mode control of a fuel cell hybrid system for electric vehicle applications,” Mathematical Problems in Engineering, vol. 2015, Article ID 370424, 14 pages, 2015.

[21] F. Chen, L. Liu, S. Liu, and T. Zhang, “Modeling, parameters identification, and control of high pressure fuel cell back-pressure valve,” Mathematical Problems in Engineering, vol. 2014, Article ID 246015, 10 pages, 2014.

[22] P. Zhou, L. Zhang, S. Zhang, and A. F. Alkhateeb, “ Observer-based adaptive fuzzy finite-time control design with prescribed performance for switched pure-feedback nonlinear systems,” IEEE Access, vol. 99, p. 1, 2020.

[23] X. H. Chang, Y. Liu, and S. Chen, “Resilient control design for lateral motion regulation of intelligent vehicle,” IEEE/ASME Transactions on Mechatronics, vol. 99, p. 1, 2019.

[24] Y. Chang, S. Zhang, N. D. Alotaibi, and A. F. Alkhateeb, “Observer-based adaptive finite-time tracking control for a class of switched nonlinear systems with unmodeled dynamics,” IEEE Access, vol. 99, p. 1, 2020.

[25] Y. Wang, B. Niu, H. Wang, N. Alotaibi, and E. Abozinadah, “Neural network-based adaptive tracking control for switched nonlinear systems with prescribed performance: an average dwell time switching approach,” Neurocomputing, vol. 435, p. 6, 2020.

[26] A. Valade, P. Acco, P. Grabolosa, and J.-Y. Fourniols, “A study about kalman filters applied to embedded sensors,” Sensors, vol. 17, no. 12, p. 2810, 2017.