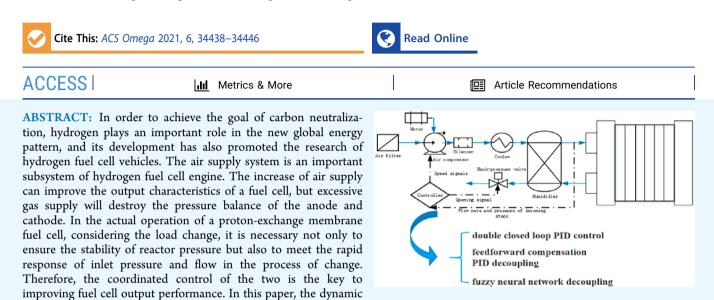


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Article

Coordinated Control of the Fuel Cell Air Supply System Based on Fuzzy Neural Network Decoupling

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model of the intake system is built based on the mechanism and experimental data. On this basis, the double closed-loop proportion integration differentiation (PID) control and feedforward compensation decoupling PID control are carried out for the air supply system, respectively. Then, the fuzzy neural network decoupling control strategy is proposed to make up for the shortcomings that the double closed-loop PID cannot achieve decoupling and the feedforward compensation decoupling does not have adaptability. The results show that the fuzzy neural network control can realize the decoupling between air intake flow and pressure and ensure that the air intake flow and pressure have a good follow-up, and the system's response speed is fast.

1. INTRODUCTION

In recent years, the burning of fossil fuels has made environmental pollution more serious. In order to improve the independent contribution, China is expected to achieve the goal of carbon neutrality in 2060. As an important exploration direction in the energy revolution, hydrogen energy has become an important way for the transportation industry to achieve low-carbon and zero-carbon emissions,¹ and more and more countries have begun to vigorously develop hydrogen fuel cell vehicles.² The hydrogen fuel cell is a multi-input and multi-output coupling system. Both the air compressor and the back pressure valve in the air supply system will have an impact on the stack inlet pressure and flow rate, and the air compressor itself has a coupling relationship between the flow rate and pressure. Therefore, how to effectively control the stack inlet flow rate and pressure will affect the stack output performance.³ At the same time, when the proton-exchange membrane fuel cell (PEMFC) is running, if the required power changes, the flow rate and pressure in the reactor will also change to meet different power requirements.⁴ Therefore, for the air supply system, to realize the coordinated control of the flow rate and pressure, it is necessary not only to ensure the stability of the pressure in the reactor but also to meet the

rapid response of the pressure and flow rate in the reactor when the load changes. ${}^{\rm 5}$

In recent years, many scholars have put forward the corresponding control strategies for air pressure and flow control. Liyan and Shuhai⁶ theoretically analyzed the coupling between the air inflow and pressure of the air intake system and suggested decoupling control between them. Sun et al.⁷ compared the opening of the back pressure valve with the open-loop control through proportion integration differentiation (PID) controller on the basis of matching the rotating speed of the air compressor. However, the pressure response speed of the open-loop control is slow, and the overshoot phenomenon of the closed-loop control is serious, which cannot well respond to the requirements of the system. On this basis, Chen et al.⁸ took the speed of the air compressor and the opening of the back pressure valve as operating

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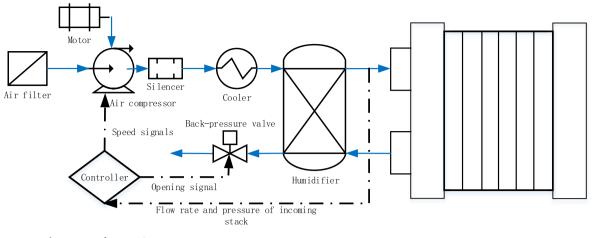


Figure 1. Air supply system of PEMFCs.

variables. The air supply system is identified as a linear system with two inputs and two outputs through experiments. The transfer function matrix of the system is diagonalized by using the multivariable decoupling control theory, so that the feedforward compensation decoupling control is carried out, and the coupling relationship between the flow and pressure is effectively released. However, when the system load changes or the environment changes greatly, the model will be mismatched, and the performance of the system will be reduced. To solve this problem, the internal model decoupling control strategy is adopted in the literature^{9,10} to decouple the flow and pressure, and the simulation shows that it has better robustness than the traditional PID decoupling. The literature^{11,12} uses a differential smoothing control strategy to decouple the flow and pressure. However, all the above control strategies need a detailed and accurate mathematical model, and the model controlled by the differential smoothing algorithm includes multiple differential terms, so it is very sensitive to the disturbance in practical application. The literature¹³ improves the feedforward decoupling control model by using the adaptive look-up table method. The results show that the improved method can realize online adaptive adjustment of parameters, which makes the control effect of the system better. However, the increased adaptive look-up table method only acts on the air compressor to correct the speed calibration table and does not control the back pressure valve.

The decoupling control of the air supply system has been studied extensively, but there are still some challenges.¹⁴ By summarizing the control scheme of the air supply system, it can be concluded that the system model built by many decoupling controllers is only in the form of transfer function. Therefore, it is assumed that the model of the fuel cell intake system is linear, and the external disturbances such as the hydration process of the exchange membrane and the frequent change of load current are not taken into account, but the air mass flow and pressure have extreme coupling characteristics since the air supply subsystem is a strongly nonlinear system, traditional decoupling methods are usually ineffective for nonlinear systems, variable structure systems, and complex systems whose coupling relationship and coupling strength vary with time and load, which makes the control of air flow and pressure unsuitable, resulting in system overshoot, slow response, or oscillation.^{14,15}

Therefore, compared with a simple transfer function used for fuel cell system modeling, this paper combines the mechanism and experimental data to build the dynamic model of the intake system, which include the transient behavior of the air compressor, the manifold filling-emptying dynamics, and the stack gas pressure. This model is identified using 40 kW fuel cell experimental data, which is proven to be capable of predicting the air mass flow response and cathode inlet pressure response accurately. Then, an intelligent control algorithm based on a fuzzy logic and neural network is proposed to control the system, which makes up for the shortcomings of the neural network in fuzzy data processing and the defects of pure fuzzy logic in learning.¹⁵ When the system changes and is subject to external interference, the fuzzy neural network can adjust the parameters through online learning to reduce the fluctuation of the system. Even if the air supply system has obvious nonlinearity, it can also have a good decoupling effect by treating various disturbances and uncertainties as total disturbances and real-time adjustment compensation, realizing the coordinated control of inlet pressure and flow of the air supply system, which is verified by simulation in this paper.

2. AIR SUPPLY SYSTEM

2.1. Air Supply System Structure. The air supply system mainly includes a two-stage air filter, an air compressor, a silencer, a cooler, a humidifier, and a back pressure valve, as shown in Figure 1.

The air filter consists of physical filtration and chemical adsorption.¹⁶ Physical filtration mainly removes particles such as dust, while chemical adsorption mainly strips off harmful gases that have not been physically adsorbed. After double purification by an air filter, clean air is sent into the compressor, and the air compressor boosts the air to reach the target pressure of stacking.¹⁷ Because the air compressor adopts centrifugal pump body, the high-speed rotation of blades will produce huge noise, which will affect the comfort of the whole vehicle,¹⁸ so a silencer will be connected at the rear end of the air compressor to eliminate the noise. After the air compressor pressurizes the air, the temperature of the air will rise correspondingly. Excessive temperature will reduce the humidity of the membrane, resulting in the membrane cracking and damage, affecting the battery life. The pressurized air needs to be cooled down to make the temperature fall within the suitable working temperature range of the stack. The air



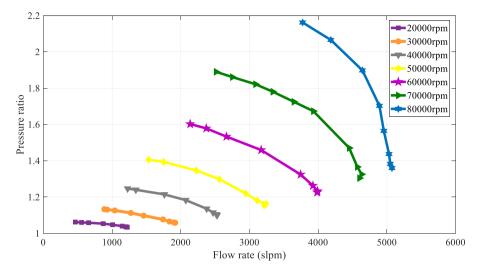


Figure 2. Static MAP of the air compressor.

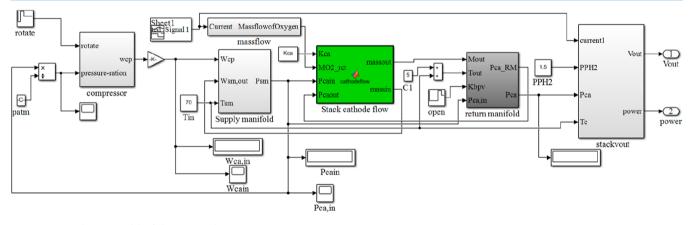


Figure 3. Simulation model of the air supply system.

compressor not only makes the gas temperature rise but also makes the water in the gas almost evaporate completely, so it needs a humidifier to make the dry air reach proper humidity, which will improve the performance of the fuel cell. The air remaining from the final reaction will be discharged through the back pressure valve at the outlet of the cathode side, which can adjust the gas flow resistance by changing the opening of the valve, so as to adjust the pressure inside the cathode cavity of the stack.¹⁹

As we can see from the above, both the air compressor and the back pressure valve can affect the pressure and flow rate into the stack, so the coordinated control of the air compressor and the back pressure valve is needed in order to obtain a suitable flow rate and pressure for the stack.²⁰

2.2. Air Supply System Characteristic Analysis. According to the above system structure, based on the manifold absolute pressure (MAP) of the air compressor measured by the experiment, as shown in Figure 2, the air supply system model was built, as shown in Figure 3 in Simulink.

The fuel cell system has two controlled variables in the model: the air compressor speed and the throttle opening, from which the flow rate $W_{ca,in}/W_{cp}$ and the pressure P_{cain}/P_{sm} into the stack are calculated by simulation. The air compressor model through its input speed, intake pressure and atmospheric pressure ratio to calculate its output flow value.

The input quantities of the supply pipeline model are the flow W_{cp} output by the air compressor and the flow mass in/ $W_{sm,out}$ entering the stack and the stack temperature T_{in} , and the pressure value P_{cain}/P_{sm} entering the stack is calculated by the state equation. According to the cathode flow field model, the inlet flow mass in and the output flow mass out of the Ballard stack are obtained by calculating the coefficient K_{ca} of the Ballard stack, the inlet and outlet pressures $P_{\text{cain}}/P_{\text{caout}}$ and the oxygen consumption MO2_rct at the current. The exhaust model includes a back pressure valve model and an exhaust pipe model. The back pressure valve through its own opening value to calculate the flow rate. The exhaust pipe model is similar to the supply pipe, and the outlet pressure Pca RM of the stack is obtained through the state equation, thus constituting the simulation model of the air supply system. The system model simulation parameters are shown in Table 1.

According to the model shown in the above figure, the simulation analysis is carried out in Simulink. By changing the setting of air compressor speed and back pressure valve opening, the variation characteristics of the intake pressure and intake flow of the air supply system are analyzed, and the analysis results are compared with the experimental data measured under the condition of the same air compressor speed and back pressure valve opening so as to verify the

parameter	physical meaning	value
F	Faraday constant	96 485 c/mol
R	ideal gas constant	8.314 J/mol K
R _a	air gas constant	286.9 J/mol K
$N_{\rm cell}$	number of fuel cells	216
$T_{\rm fc}$	temperature of the stack	70 °C
L	exchange film thickness	$1.78 \times 10^{-4} \text{ m}$
A	stack activation area	268 cm ²
$A_{ m T}$	maximum opening area	$0.002 m^2$
M_{O_2}	molar mass of oxygen	32 g/mol
$M_{ m v}$	molar mass of water	18 g/mol
λ	excess air coefficient of the cathode	2
$V_{ m sm,ca}$	volume of the cathode inlet pipe	0.01 m ³
$V_{ m rm,ca}$	volume of the exhaust pipe	0.01 m ³
ω_{O_2}	oxygen mass fraction	0.21
$k_{ m ca}'$	flow resistance constant of the cathode stack	0.0852

Table 1. System Model Simulation Reference

accuracy of the simulation model. System simulation conditions are shown in Table 2.

 Table 2. Simulation Conditions of Air Supply System

 Dynamic Characteristics

	0-20 s	20-40 s	40-60 s	60-80 s	80-100 s
air compressor speed (rpm)	40 000	60 000	50 000	50 000	50 000
opening of back pressure valve (%)	60	60	60	70	50

By setting the above simulation conditions, the obtained simulation results of the response characteristics of the air supply system and the comparison with the experimental data are shown in Figures 4 and 5.

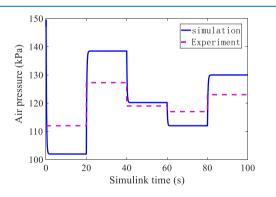


Figure 4. Simulation model of the air supply system.

It can be seen from the response characteristic graph that the flow rate and pressure entering the stack gradually stabilize with the operation of the air compressor and the back pressure valve in the air system of the fuel cell stack. When the rotational speed of the air compressor is changed separately in 20 and 40 s, the pressure and flow rate entering the stack will increase with the increase of rotational speed and decrease with the decrease of rotational speed. This is because the rotational speed of the air compressor increases with the increased rotational torque, which leads to the increase of the outlet flow rate of the air compressor. When the opening of the back pressure valve is changed separately in 60 and 80 s, the intake flow will change correspondingly with the increase and

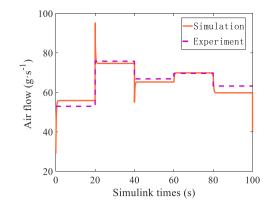


Figure 5. Simulation model of the air supply system.

decrease of the opening, but the change of the intake pressure is opposite, because with the increase of the opening of the back pressure valve, the gas resistance flowing out of the cathode of the stack becomes smaller, which makes the speed of the outgoing gas increase, and at the same time, the inflow gas flow becomes larger due to the decrease of the flow resistance, so the change trend in the above figure appears.

According to the response characteristic curve and Table 2, when the speed of the air compressor is 40 000 rpm and the opening of the back pressure valve is 60%, the relative errors between the intake pressure and the intake flow are the largest. which are 8.93 and 5.49%, respectively; when the speed of the air compressor is 50 000 rpm and the opening of the back pressure valve is 60%, the relative error of intake pressure is the smallest, which is 1.01%. When the speed of the air compressor is 50 000 rpm and the opening of the back pressure valve is 70%, the relative error of the intake air flow is the smallest, which is 0.34%. Therefore, within the simulation time, the average relative error of the inlet pressure is 5.74%, and the average relative error of the inlet flow is 3.03%. The main reasons for the error with the experimental data are as follows: (1) the air compressor flow output model is obtained by polynomial fitting, which makes it deviate from the actual flow. (2) When determining the parameters of the simulation model, there are errors in the measurement of the volume of the supply pipe, the volume of the exhaust pipe, and the maximum opening area of the back pressure valve, which will cause the error between the simulation results and the experimental data. (3) In the experimental process, the external environment interference, such as temperature, humidity, and other changes, will affect it. Therefore, there is an error between the simulation model and the experimental data, within the allowable error range, on the one hand, the established model can reflect the coupling characteristics of the inlet flow and pressure of the air supply system; on the other hand, it has the same trend with the experimental data, that is, the pressure and flow entering the stack will change with the change of speed and opening, so it is believed that the air supply system model is credible. The above results show that the speed of the air compressor and the opening of the back pressure valve have a strong influence on the intake pressure and flow rate, which reflects the coupling effect between the intake pressure and the intake flow rate.

3. CONTROL STRATEGY DESIGN

3.1. Double Closed-Loop PID Control. Two PID control loops are used to control the rotation speed of the air

compressor and the opening of the back pressure valve of the air supply system to realize the adjustment of the air pressure and flow rate. The control structure is shown in Figure 6.

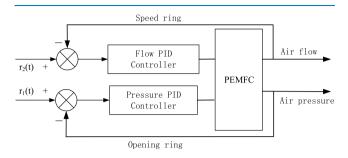


Figure 6. Schematic diagram of the double closed-loop PID control of the air system.

3.2. Feedforward Compensation Decoupling PID Control. Feedforward compensation decoupling is a decoupling controller based on the invariance principle, which eliminates the coupling relationship between systems by serially connecting the characteristic matrix of feedforward compensation in front of the controlled object to be decoupled. Figure 7 is a schematic diagram of the designed feedforward compensation decoupling control system for two input variables and output variables.

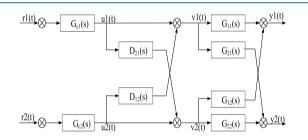


Figure 7. Schematic diagram of feedforward compensation decoupling.

According to the feedforward compensation principle, the following formula can be calculated

$$\begin{aligned} u_1(t)D_{21}(s)G_{22}(s) + u_1(t)G_{21}(s) &= 0\\ u_2(t)D_{12}(s)G_{11}(s) + u_2(t)G_{12}(s) &= 0 \end{aligned}$$
(1)

The transfer function of feedforward compensation decoupling can be expressed as

$$D_{21}(s) = -\frac{G_{21}(s)}{G_{22}(s)} \tag{2}$$

$$D_{12}(s) = -\frac{G_{12}(s)}{G_{11}(s)}$$
(3)

where $G_c(s)$ is the controller transfer function and G(s) is the transfer function of the controlled system.

3.3. Fuzzy Neural Network Decoupling Control. In this paper, the fuzzy neural network structure shown in Figure 8 is used to decouple the air intake pressure and flow rate.

Compared with the traditional five-layer fuzzy neural network structure, the fuzzy neural network has a four-layer structure, and the physical meaning of each layer is clearer. The first layer is the input layer, which inputs the actual physical

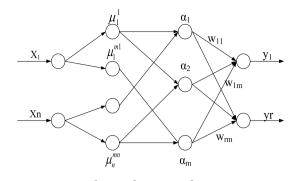


Figure 8. Fuzzy neural network structure diagram.

value of the controlled quantity of the system; the second layer is the membership function layer set according to the actual situation. Each node transforms the input variable into a fuzzy language variable in fuzzy rules, such as NB (negative big), PO (positive zero), and so forth. That is to say, by calculating the membership function of each language variable, the membership degree of the fuzzy set is obtained, so that the input language that the fuzzy control algorithm can identify is realized. In this paper, the Gaussian function is used for fuzzification

$$\mu_i^{\ j} = \mathrm{e}^{-(x_i - a_{ij})^2 / b_{ij}^2} \tag{4}$$

In the formula, $i = 1, 2, ..., n; j = 1, 2, ..., m_i$.

The third layer is a fuzzy reasoning layer, and each neuron represents a fuzzy reasoning rule with practical significance. Each node in this layer is only connected with one of the m nodes and one of the n nodes in the second layer, and there are $m \times n$ rules in total, the outputs of which are algebraic products of the upper Gaussian functions connected to each node

$$\alpha_{j} = \mu_{1}^{i_{1}} \mu_{1}^{i_{2}} \mu_{1}^{i_{n}} \tag{5}$$

In the formula, $i_1 \in \{1, 2, ..., m_1\}$; $i_2 \in \{1, 2, ..., m_2\}$; $i_n \in \{1, 2, ..., m_n\}$; j = 1, 2, ..., m; $m \le m_i$, i = 1, 2, ..., n.

The fourth layer is the output layer, and the fuzzy variables are converted into the required physical accurate values by setting the connection weights between the third layer and the fourth layer to realize clear calculation

$$y_{i} = \sum_{j=1}^{m} w_{ij} \alpha_{j} (i = 1, 2, ..., r)$$
(6)

In the running process of the fuzzy neural network, error back propagation is used to adjust and train the whole network constantly. The quality of network training results is evaluated by the following objective function formula

$$E = \frac{1}{2}(Y - y)^2$$
(7)

where Y is the expected output, y is the actual output, and E is the square error function.

The closer the value of the objective function is to 0, the smaller the error of the network. If the function value cannot reach the predetermined accuracy, it is necessary to further adjust the center value a_{ij} of the Gaussian function, the scale factor b_{ij} of the Gaussian function, and the weight w_{ij} of the output layer by the following formula

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$$\begin{cases} w(k+1) = w(k) - m\frac{\partial E}{\partial w} + \lambda^* \Delta w(k) \\ a(k+1) = a(k) - m\frac{\partial E}{\partial a} + \lambda^* \Delta a(k) \\ b(k+1) = b(k) - m\frac{\partial E}{\partial b} + \lambda^* \Delta b(k) \end{cases}$$
(8)

where *m* is the learning rate and λ is the momentum factor.

It can be seen from the literature²¹ that the simplified fuzzy neural network has also the property of global approximation and will not fall into the local minimum, so this structure is used to decouple the pressure flow on the air side.

4. CONTROL SIMULATION ANALYSIS

According to Chen et al.'s⁵ identification of the multichannel M sequence of the cathode side intake system through the experimental study, the model between pressure and flow of the cathode gas can be expressed by the transfer function matrix. The state matrix of the air intake system is extracted from the air intake system model built in Simulink, and then, the transfer function of this system can be obtained from the ss2tf function. Therefore, the transfer function of the air supply system is obtained as follows

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \frac{1}{0.016s^2 + 0.642s + 1.127} \begin{bmatrix} 0.012s & 0.001 \\ 39.435 & -2.022 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$
(9)

In the formula, y_1 is the inlet flow of air, Y_2 is the import pressure of air, U_1 is the speed of the air compressor, and u_2 is the valve opening of the back pressure valve.

In this paper, the double closed-loop PID algorithm, feedforward compensation decoupling algorithm, and fuzzy neural network algorithm are simulated with this as the system's transfer function. The simulation conditions of the system are shown in Table 3.

Table 3. Simulation Conditions of the Air Supply System

	0-20 s	20-40 s	40-60 s	60-80 s	80-100 s
flow setting (kg/s)	0.04	0.07	0.06	0.06	0.06
pressure setting (kPa)	120	120	120	150	140

4.1. Double Closed-Loop PID Control Simulation. Based on the pressure-flow double closed-loop control strategy, the simulation environment and the control strategy are integrated, and the control strategy mainly includes the reference input calculation and the control module of the intake system.

After the constant adjustment of PID parameters, the proportional parameter of the flow control loop in the model is 2.0, the integral parameter is 80, and the differential parameter is 0. In the pressure control loop, the proportional parameter of PID is -2.0, the integral parameter is -2.5, and the differential parameter is 0.

4.2. Feedforward Compensation Decoupling PID Control Simulation. According to the theoretical knowledge of feedforward compensation decoupling, the transfer function of feedforward compensation decoupling designed in this paper is

$$\begin{cases}
D_{21}(s) = 19.505 \\
D_{12}(s) = -\frac{0.001}{0.012s}
\end{cases}$$
(10)

The parameters of the PID controller in the model are the same as those of double closed-loop PID.

4.3. Simulation of the Fuzzy Neural Network Decoupling Control. Aiming at the shortcomings of feedforward compensation decoupling and air systems' multivariable, nonlinear and strong coupling characteristics, this paper adopts the fuzzy neural network control method which does not depend on the precise mathematical model of the object to decouple the flow and pressure of the air supply system. After continuous training, the response characteristics of decoupled air pressure and flow rate can achieve the desired characteristics of the system.

The M file of fuzzy neural network decoupling of the air supply system is written in MATLAB, and the basic structure of the fuzzy neural network corresponding to the written program is shown in Figure 9.

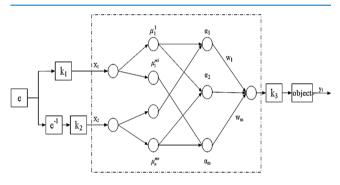


Figure 9. Membership function fuzzy neural network.

In the program, first, the transfer function of the above system needs to be discretized into different equations, as follows

$$y_{1}(k) = 0.854y_{1}(k-1) - 0.018y_{1}(k-2) + 0.017u_{1}(k-1) - 0.017u_{1}(k-2) + 1.2 \times 10^{-4}u_{2}(k-1) + 3.6 \times 10^{-5}u_{2}(k-2)$$
(11)

$$y_{2}(k) = 0.854y_{2}(k-1) - 0.018y_{2}(k-2) + 4.445u_{1}(k-1) + 1.303u_{1}(k-2) - 0.228u_{2}(k-1) - 0.067u_{2}(k-2)$$
(12)

Within the dashed box in Figure 9 is the fuzzy neural network described above, which is a four-layer network with two inputs and one output. Therefore, on the basis of determining the decoupling structure of the fuzzy neural network, the initial values of the parameters of the system and network are set, in which k_1 , k_2 , and k_3 are quantization factors. Both the input fuzzification and the output clarity of the fuzzy neural network need to use quantitative factors to adjust the size of the input and output values. The purpose is to convert the clear value of the error between pressure and flow and the clear value of its change rate from the actual range of the fuzzy control and vice versa. The quantization factors k_1 of the input error signal e in the two decoupling control loops of pressure and flow are 0.02

and 0.05, respectively. The quantization factors k_2 of error change rate e^{-1} are 0.02 and 0.05, respectively. The values of scale factor k_3 corresponding to the output variables of the two decoupling controllers are 0.4 and 1.5, respectively. The learning rate *m* of the two decoupling controllers is 0.65, the momentum factor λ is 0.5, and the training times are 20 times. During the program's running, the actual pressure and flow output are compared with the set reference input. Through continuous training, the center value, scale factor, and output weight of the Gaussian function in the decoupling controller are constantly adjusted through the error back propagation correction, formula 8, so that the value of the objective function, 7 mentioned above can reach the predetermined precision value or the system reaches the training times, and the decoupling training ends now.

The change of the objective function in the decoupling process of the fuzzy neural network obtained by simulation is shown in Figure 10. After the set value changes, its value

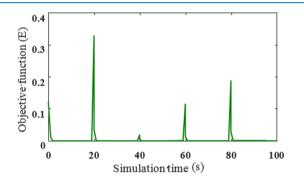


Figure 10. Change curve of the objective function.

decreases monotonously and quickly to close to the zero value, which shows that the initial value selection of the fuzzy neural network is correct, and the system starts to work stably.

4.4. Simulation Comparison of the Flow and Pressure Control. After the simulation of the above-mentioned three control strategies, the response characteristics of the air intake flow and pressure are shown in Figures 11 and 12.

By analyzing the simulation results, we can obtain the following conclusion:

- (1) When the air pressure setting value does not change in the first 50 s, the changes of the air flow setting values in the given 20 and 40 s are +0.03 and -0.01 kg/s, respectively. Under the double closed-loop PID control, the air pressure fluctuations are +6.50 and -2.10 kPa, respectively. This is because the increase or decrease of the rotation torque of the air compressor makes the air flow rate increase or decrease so as to promote the corresponding change of air flow and pressure. Under the feedforward decoupling PID control, due to the compensation of the feedforward structure, the change of flow will not cause pressure fluctuations. Under the action of the fuzzy neural network decoupling control, although the decoupling is not completely realized as the feedforward compensation decoupling, the fuzzy neural network can make the system output better follow the expected output by online adjusting the controller parameters. Therefore, the air pressure change caused by the air flow change is reduced compared with the double closed-loop PID control. The pressure change is reduced by 5.1 kPa in 20 s and 1.7 kPa in 40 s, and it reaches a stable state after 4.01 and 4.03 s, respectively.
- (2) When the set value of air flow does not change in the last 50 s, the changes of the set value of air pressure in the given 60 and $\overline{80}$ s are +30 and -10 kPa, respectively. Under the double closed-loop PID control, the fluctuations of air flow caused by pressure changes are -0.01 and +0.003 kg/s, respectively. This is because the change of the opening of the back pressure valve makes the gas resistance of the cathode of the outflow reactor change, which leads to the decrease or increase of the gas flow. Under the action of the feedforward decoupling PID control, pressure change will not cause pressure fluctuation; under the action of the fuzzy neural network decoupling control, it is not as good as the feedforward compensation decoupling control, but compared with the double closed-loop PID control, the change value of flow also decreases, which decreases by 0.009 kg/s in 60 s and 0.002 kg/s in 80 s, and it reaches a stable state again after 1.02 and 2.01 s, respectively.

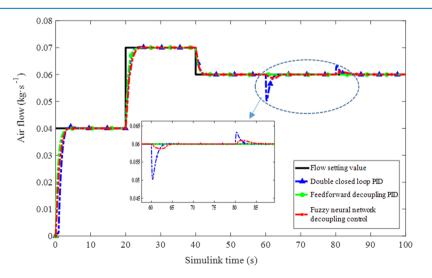


Figure 11. Response diagram of air flow.



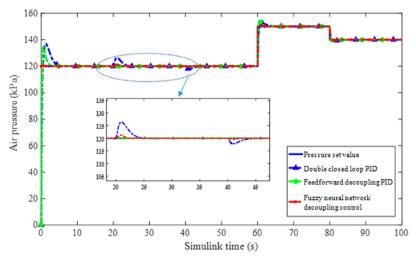


Figure 12. Response diagram of air pressure.

5. CONCLUSIONS

The air supply system adopts the double closed-loop PID control. Although the system's response speed is fast, the coupling relationship between pressure and flow cannot be realized, and they still influence each other. Feedforward PID decoupling can achieve a complete decoupling effect through the invariance principle, so that the pressure and flow circuits do not interfere with each other, and its decoupling effect depends on whether the air supply system can obtain an accurate mathematical model. However, the intake system actually participates in many parts and has a large number of variable parameters, so it is difficult to obtain its accurate control model when the fuel cell is in different working environments and working conditions, which may lead to the designed decoupling system not conforming to the actual operation model of the air system. Fuzzy neural network decoupling cannot completely decouple the coupling relationship between pressure and flow, but it can constantly adjust the network parameters and weights through online learning. Therefore, within the allowable range of the system error, we think that it realizes the generalized decoupling of pressure and flow. Besides, there are several problems to be treated in future studies:

- (1) First, the proposed algorithm needs to be written into the application layer of the fuel cell system control unit, and the actual experiment is required to verify the effectiveness of the algorithm thoroughly.
- (2) The surge boundary of the air compressor needs to be considered in the following work.

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Notes

The authors declare no competing financial interest.

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