Energy Proceedings
Vol 45, 2024
ISSN 2004-2965

Particle swarm optimization Fuzzy algorithm applied to temperature control in PEM fuel cell systems

Zhanglin Ruan[1], Handong Wu[3], Ruilin Wang[4], ZhenYu Tian[1], Wenjia Li [2*]

1 School of School of Mechanical Engineering, Tianjin University, Tianjin, 300072, China

2 South University of Science and Technology, Shenzhen, 518055, China

3 State Power Investment Corporation Hydrogen Energy Co.LTD., Beijing, 102209, China

4 School of Energy and Mechanical Engineering, Nanjing Normal University, Nanjing, 210023, China
(*Corresponding Author: liwj@sustech.edu.cn)

ABSTRACT

Working temperature is a key issue that affects the performance of proton exchange membrane fuel cells (PEMFCs). Proper thermal management can improve the PEMFC output performance and longevity. To deal with the problems of poor robustness and slow response time of traditional temperature control curves, this paper establishes a dynamic temperature model of PEMFC. It proposes a particle swarm optimized fuzzy proportional-integral-derivative (PSO-Fuzzy-PID)-based temperature control strategy to achieve dynamic control of the electric reactor temperature. The performance of PSO-Fuzzy-PID temperature control is verified for step load, dynamic load, and variable target conditions, and its effectiveness is compared with that of an ordinary PID controller. The results show that the proposed method has the advantages of fast convergence speed, good dynamic performance, and strong disturbance immunity. The PSO-Fuzzy-PID temperature controller ensures temperature fluctuations within 0.5°C of dynamic perturbations and is capable of strong tracking control of variable targets.

Keywords: PEMFC, Temperature management, Thermal model, Particle Swarm Optimization Fuzzy Control

NONMENCLATURE

Abbreviations	
PEMFCs	Proton exchange membrane fuel cells
PID	Proportional-integral-derivative
PSO	Particle swarm optimization
FC	Fuel cell
Symbols	
E	The Nernst voltage
V_{act}	The activation voltage loss
V_{conc}	The concentration voltage loss
V_{ohm}	The ohmic voltage loss
T_f	The working temperature of the FC
V_f	The output voltage
P_{H_2}	The partial pressures of hydrogen
P_{O_2}	The partial pressures of oxygen
P	Stack pressure
ξ_1-ξ_4	Empirical coefficient
I_f	Working Current
A_{ac}	Active area
C_{O_2}	The concentration of O_2
λ	The membrane water content
r_m	The resistivity of the membrane
t_m	Membrane thickness
R_m	Membrane resistance
R_c	The leads' ohmic resistance
I_i	Current density
I_{imax}	Maximum current density
Q_{tot}	Total power of electrochemical Reaction
N	Cell number
P_{st}	The output electrical power of the Stack
Q_{gas}	The thermal power from anode and cathode reactants
Q_{cl}	Thermal power discharge through the cooling

This is a paper for 15th International Conference on Applied Energy (ICAE2023), Dec. 3-7, 2023, Doha, Qatar.

Q_{amb}	The thermal power radiated outwards from the stack
m_f	The mass of the stack
F	The Faraday's constant
C_w	The constant pressure specific heat capacity of cooling water
T_{in}	The cool water temperature into the stack
K_p	Proportionality coefficient
K_i	Integration coefficient
K_d	Differentiation coefficient
Δe	Amount of error variation
ec	The rate of change of error
t	Time
ω_s	The start inertia weight
ω_e	The inertia weight
k_m	Maximum number of iterations
k_n	The current number of iterations

1. INTRODUCTION

In a world where energy crises and environmental issues are a major concern, it is essential to discover clean and efficient energy solutions. The proton exchange membrane fuel cell (PEMFC) is a cutting-edge technology that has gained wide-ranging attention, especially in the new energy vehicle industry, due to its high efficiency, zero greenhouse gas emissions, low noise, and high specific power [1]. PEMFC reactors' efficiency and lifetime are mainly affected by the operating temperature, water content of the proton exchange membrane, and the partial pressure of the reaction gas [2]. Control of the operating temperature is essential to maintain cell performance. Effective thermal management and control of the stack is crucial to ensure stable operation and prolong its service life, especially in practical applications like PEMFC vehicles where batteries often face load variations that cause temperature fluctuations.

Several researchers have explored and proposed various methods for controlling the temperature of PEMFC, including an adaptive sparrow search algorithm [4] by Zhu et al. for PEMFC control model parameter identification, model reference adaptive control (MRAC) [5], model predictive control [7], artificial neural network control [8], and deep learning [9]. Wang et al. [6] established three-dimensional fuzzy control rules to regulate the temperature of PEMFC, and their experimental and simulation results indicate that the three-dimensional fuzzy control method has a strong regulation ability and low static error.

Two issues need to be resolved in the thermal management control strategy. Firstly, the traditional controller is not robust enough due to the nonlinear characteristics of the thermal management model system. Secondly, fuzzy controllers are complex and time-consuming to tune. Effective control algorithms for PEFC temperature regulation are lacking and more robust control methods are needed. This paper proposes a particle swarm optimization fuzzy control strategy based on real-time optimization of PID parameters to regulate the temperature of the power reactor by controlling the cooling water flow and achieve dynamic control of the temperature.

2. SYSTEM DESCRIPTION AND MODEL BUILDING

2.1 Thermal management system structure

In order to manage the temperature of an 80kW PEMFC power stack, a thermal management model has been established as shown in Figure 1. The thermal management model was established after experimental verification, And the parameters of the model are listed in Table 1.

Table 1 The stack parameters

Parameter	Value (Unit)
Number of cells	330
Active area	282 (cm^2)
Partial pressure of hydrogen	1 (atm)
Partial pressure of oxygen	1 (atm)
Anode channel volume	0.008 (m^3)
Cathode channel volume	0.014 (m^3)
Rated power	80 (kW)
Maximum power	80.5 (kW)
Operation Temperature	50-80 (°C)
Environment temperature	25 (°C)
PEM thickness	0.078 (mm)

In the face of different working conditions, the controller is responsible for regulating the speed of the pump so as to release the heat generated by the stack to the environment, in accordance with the set control objectives.

2.2 Voltage model

The fuel cell stack produces electrical energy by using hydrogen as fuel and oxygen as the oxidizer in an electrochemical reaction. The voltage of the electric stack is a non-linear function that factors in the ohmic voltage loss, concentration loss, and activation loss in the electrochemical reaction. The output voltage of each cell can be expressed as follows:

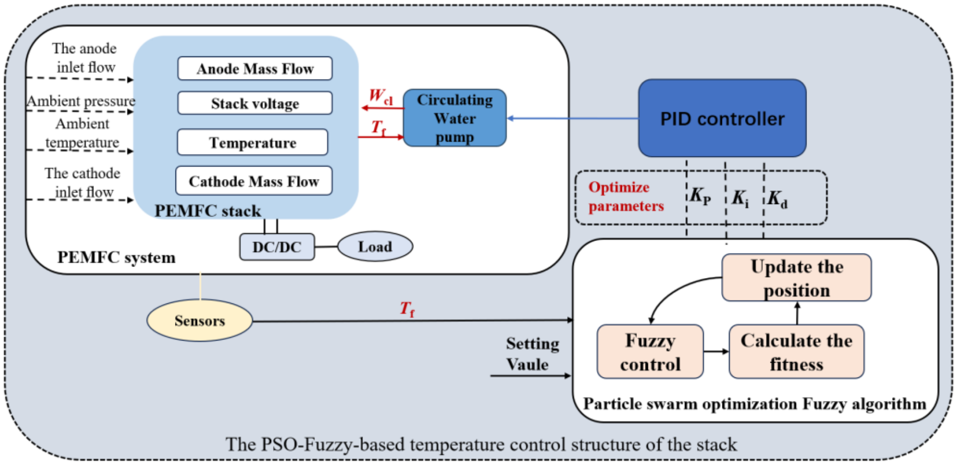

Fig. 1. Cooling circuit structure

$$V_f = E - V_{act} - V_{ohm} - V_{conc} \tag{1}$$

Where E is the Nernst voltage, V_{act} is the activation voltage loss, V_{ohm} is the ohmic voltage loss, and V_{conc} is the concentration voltage loss. The Nernst voltage is expressed as follow:

$$E = 1.229 - \left(8.5\times10^{-4}\right)\left(T_f - 298.15\right) + 4.308\times10^{-5} T_f \times \left[\ln\left(\frac{P_{H_2}}{P}\right) + \frac{1}{2}\ln\left(\frac{P_{O_2}}{P}\right)\right] \tag{2}$$

Where T_f is the working temperature of the FC, P_{H_2} is the partial pressure of hydrogen, P_{O_2} is the partial pressure of oxygen, and P is stack pressure. The activation voltage loss is expressed as follows:

$$V_{act} = \xi_1 + \xi_2 T_f + \xi_3 T_f \ln\left(C_{O_2}\right) + \xi_4 T_f \ln\left(I_f\right) \tag{3}$$

$$C_{O_2} = \frac{P_{O_2}}{5.08\cdot10^6}.e^{498/T_f} \tag{4}$$

Where ξ_1-ξ_4 are empirical coefficients, C_{O_2} is the concentration of O_2, and I_f is the pull current. The concentration voltage loss is expressed as follows:

$$V_{ohm} = I_f\left(R_m + R_c\right) \tag{5}$$

$$R_m = \frac{r_m \times t_m}{A_{ac}} \tag{6}$$

$$r_m = \frac{181.6\left[1 + 0.03\left(\frac{I_f}{A_{ac}}\right) + 0.062\left(\frac{T_f}{303}\right)^2\left(\frac{I_f}{A_{ac}}\right)^{2.5}\right]}{\left[\lambda - 0.634 - 3\left(\frac{I_f}{A_{ac}}\right)\right]\cdot\exp\left[4.18\left(\frac{T_f - 303}{T_f}\right)\right]} \tag{7}$$

Where A_{ac} is the active area, λ is the membrane water content, r_m is the resistivity of the membrane, t_m is membrane thickness, R_m is membrane resistance and R_c is the leads' ohmic resistance. The concentration voltage loss is expressed as follows:

$$V_{con} = \frac{\beta\times T_f}{N\times F}\ln\left(1 - \frac{I_i}{I_{imax}}\right) \tag{8}$$

Where I_i is the current density, I_{imax} is the maximum current density, N is the cell number, and β is the universal gas constant.

2.3 Thermal model

Based on the conservation of energy, the heat balance equation of the fuel cell electric stack follows:

$$m_f C_f \frac{dT_f}{dt} = Q_{tot} - P_{st} - Q_{gas} - Q_{cl} - Q_{amb} \tag{9}$$

$$Q_{tot} = \frac{NI_f}{2F}\Delta H \tag{10}$$

$$P_f = V_f I_f \tag{11}$$

$$Q_{cl} = W_{cl} C_w \left(T_f - T_{in}\right) \tag{12}$$

Where Q_{tot} is the total power of the electrochemical reaction, P_{st} is the output electrical power of the stack, and Q_{gas} is the thermal power from anode and cathode reactants, Q_{cl} is the thermal power discharge through the cooling, Q_{amb} is the thermal power radiated outwards from the stack, m_f is the mass of the stack, C_f is the specific heat capacity of the stack, F is the Faraday's constant, V_f is the actual output of the monolithic fuel cell voltage, W_{cl} is the cooling water flow rate, ΔH is the low-level heat generation of hydrogen, C_w is the constant pressure specific heat capacity of cooling water, and Tin is the cooling water temperature into the stack. About 90% of the waste heat is discharged through cooling water. Thus, Q_{gas} and Q_{amb} are neglected in this model.

3. CONTROL STRATEGY DESCRIPTION

3.1 PID control

The PID control algorithm is as follows:

$$u(t)=K_p e(t)+\frac{1}{K_i}\int_0^t e(t)dt+K_d\frac{de(t)}{dt} \tag{13}$$

Where e(t) is the difference between the current output value and the desired value, K_p is the proportionality coefficient, K_i is the integration coefficient; and is the differentiation coefficient.

3.2 Fuzzy PID control

The fuzzy PID control structure is shown in Fig. 2. The fuzzy PID control system combines fuzzy and PID control in a closed-loop system. The controller fuzzifies the obtained exact quantities of deviation *e* and deviation change rate *ec* through K_e and K_{ec}, then makes *e* and *ec* fall into the corresponding thesis domains and assigns them fuzzy linguistic values by means of the subordinate function, then carries out fuzzy inference by means of the fuzzy rules, and finally defuzzifies the obtained results by means of the proportionality factor Ku, obtaining ΔK_p , ΔK_i and ΔK_d , and then amends the three characteristic parameters of the PID, K_p , K_i , and K_d . The equation as follows: The equation as follows:

$$\begin{aligned} K_{p(n)}&=K_{p(n-1)}+\Delta K_{p(n)}\\ K_{i(n)}&=K_{i(n-1)}+\Delta K_{i(n)}\\ K_{d(n)}&=K_{d(n-1)}+\Delta K_{d(n)} \end{aligned} \tag{14}$$

Where $K_{p(n-1)}$ $K_{i(n-1)}$ and $K_{i(n-1)}$) are the PID characterization parameters before Update, $\Delta K_{p(n)}$ $\Delta K_{i(n)}$, $\Delta K_{d(n)}$ are the increments of the PID characteristic parameters, and $K_{p(n)}$ $K_{i(n)}$ and $K_{i(n)}$ are the updated PID characteristic parameters.

$$e=T-T_0 \tag{15}$$

$$ec=\frac{\Delta e}{t} \tag{16}$$

Where *T* is the coolant out of stack temperature, T_0 is the target temperature, Δe is amount of error variation, *ec* is the rate of change of error.

The fuzzy PID control structure is shown in Fig. 2, set fuzzy domains and fuzzy subsets for controller inputs and outputs. The fuzzy subsets of input and output are NB (negative large), NM (negative medium), NS (negative small), ZO (zero), PS (positive small), PM (positive medium), and PB (positive large). The affiliation functions of fuzzy subsets NB and PB corresponding to *e*, *ec*, ΔK_p , ΔK_i , and ΔK_d are Gaussian-type functions, and the affiliation functions corresponding to the remaining fuzzy subsets are trigonometric-type

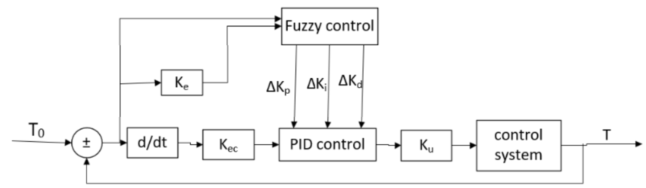

Fig. 2. Fuzzy control structur

functions. K_e K_c and K_u are computed by iterative particle swarm optimization.

3.3 Particle swarm optimization fuzzy PID

Particle swarm optimization is a technique that imitates the flight behavior of a group of birds searching for food. In this technique, the birds in the flock are represented as particles, and each particle is considered as a possible solution. The particles' velocity and position are continuously updated to find the optimal solution in the entire search space. The principle is as follows: suppose there are m particles with arbitrary velocities in the n-dimensional search space, the position of each particle is $X_i=\left(x_{i_1},x_{i_2},\cdots,x_{i_n}\right)$, the velocity of each particle is $V_i=\left(v_{i_1},v_{i_2},\cdots,v_{i_n}\right)$ and the optimal position of the particle is $P_i=\left(p_{i_1},p_{i_2},\cdots,p_{i_n}\right)$, The optimal position of the whole particle swarm is $P_g=\left(p_{g_1},p_{g_2},\cdots,p_{g_n}\right)$ $i=1,2,3,\cdots,m$. The principle of the algorithm is to initialize a group of particles with random velocities and positions, and then search for them through iterations. In each iteration, the particles update themselves by tracking the optimal solutions found by individual particles, i.e., the individual extremes, and the optimal solutions found by the group of particles, making constant adjustments to the particles' velocities and positions, and finally finding the optimal values in the search space.

ITAE is the absolute value of the error multiplied by the integral of the time term over time, which reflects both the size of the error (control accuracy) and the speed of convergence of the error, taking into account both the control accuracy and the speed of convergence. The expression of the fitness function is as follows:

$$J(ITAE)=\int_{-\infty}^{+\infty} t|e(t)|dt \tag{17}$$

Where t is the time.

The velocity update equation is as follows:

$$V_{i_d}^{k+1}=w(k)V_{i_d}^k+c_1r_1\left(P_{i_d}^k-X_{i_d}^k\right)+c_2r_2\left(P_{g_d}^k-X_{i_d}^k\right) \tag{18}$$

The position update formula is as follows:

$$X_{i_d}^{k+1}=X_{i_d}^{k}+V_{i_d}^{k+1} \quad (19)$$

The inertia weights are calculated as follows:

$$w(k)=\frac{w_s-(w_s-w_e)(k_m-k_n)}{k_e} \quad (20)$$

Where w_s is the start inertia weight, w_e is the inertia weight at the termination of the algorithm, k_m is the maximum number of iterations, k_n is the current number of iterations, r_1 and r_2 are random numbers between [0,1], $c_1$and c_2 are the acceleration factors.

The particle swarm optimized fuzzy PID control structure is shown in Fig. 3. This paper proposes a particle swarm optimized fuzzy PID control algorithm consisting of the following steps:

Step 1: Initialize the parameters related to the PSO algorithm.

Step 2: Calculate the fitness value of the particle. The optimal individual solution and the global optimal resolution are updated by the fitness update obtained from each operation.

Step 3: Update the particle state. The velocity and position of the particle are updated using equations (18) to (20).

Step 4: Check whether the termination condition is satisfied. If the set maximum number of operations is reached or the preset adaptation degree is derived, terminate the operation. Otherwise, return to step 2 to continue the operation.

4. RESULTS AND DISCUSSION

4.1 Model validation

To validate the electrochemical model, Compared simulation results to experimental data from the supplier in Fig. 3.. Results showed a deviation within 0.10% to 3.58%, confirming the accuracy of the heat generation calculation. Only relevant modifications should be described, as indicated by reference.

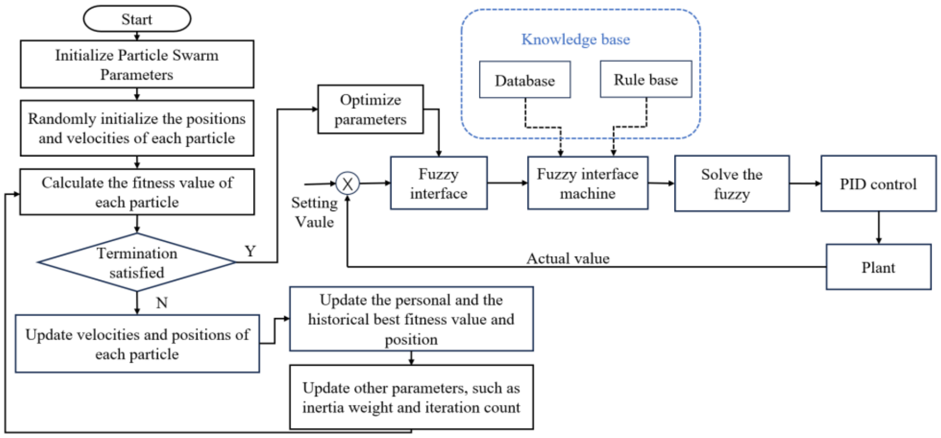

Fig. 3. PSO-fuzzy control structure

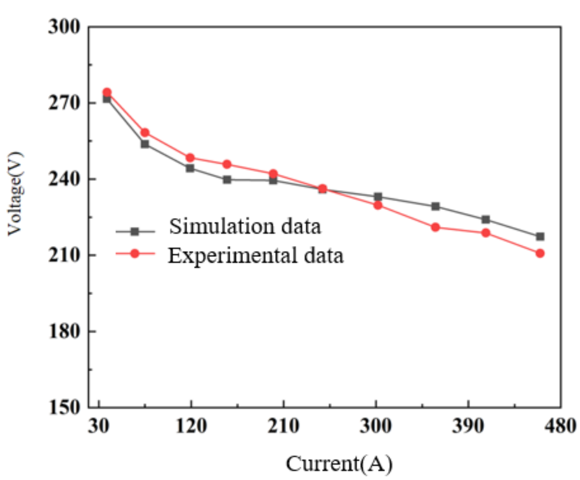

Fig. 4. Current-voltage relationship

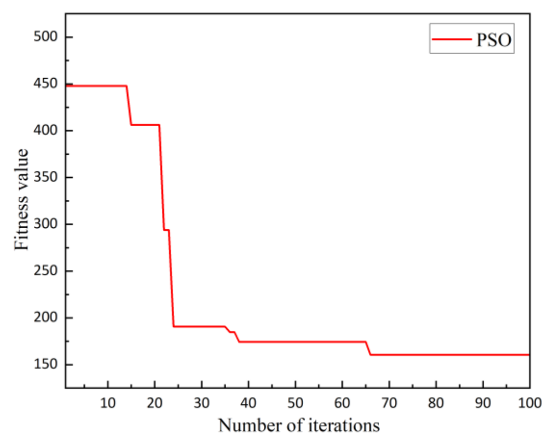

Fig. 5. Fitness curve

4.2 Temperature regulation results under step load

Two control strategies were compared by analyzing the current of pull load step and optimizing control using particle swarm optimization algorithm. The optimization process is depicted in Fig.5 and resulted in a 15.3%

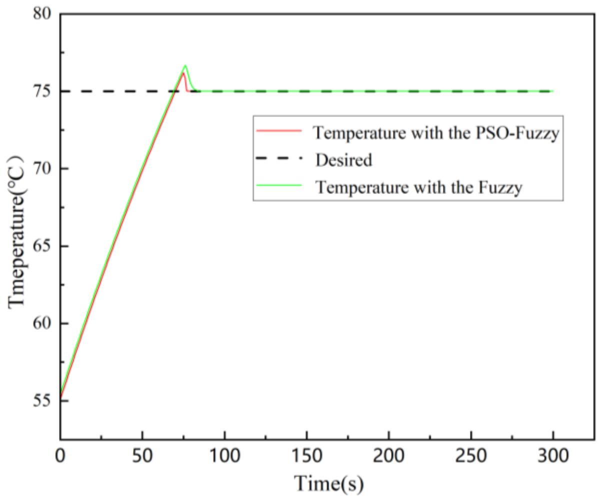

Fig. 6. Temperature control under step load

acceleration of pre-optimization system regulation time and an 11.9% reduction in overshooting, as shown in Fig.6.

4.3 Temperature regulation results under dynamic load

To further validate the performance of the PSO-Fuzzy-PID temperature control strategy, a dynamic load current was applied to the stack. As shown in Fig. 7 and in Fig. 8. The maximum deviation of the temperature of the stack was 0.48°C when the load current was dynamically varied, indicating the effectiveness and superiority of the control.

4.4 Temperature regulation in a variable target situation

The optimum operating temperature of the system will change due to fuel cell life and aging. The control strategy in the case of target change requires good target

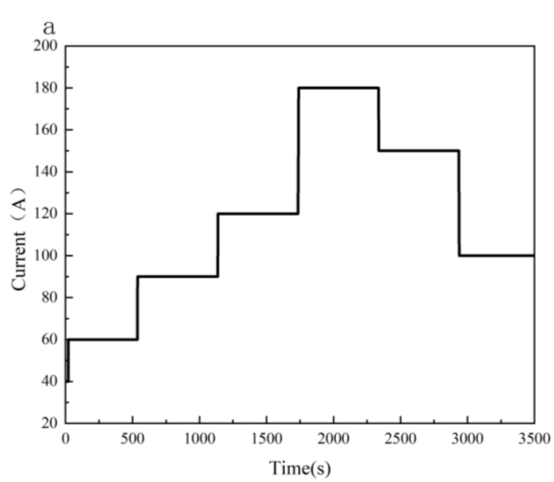

Fig. 7. Pattern of current changes

tracking ability, and the results are shown in Fig. 9 and in

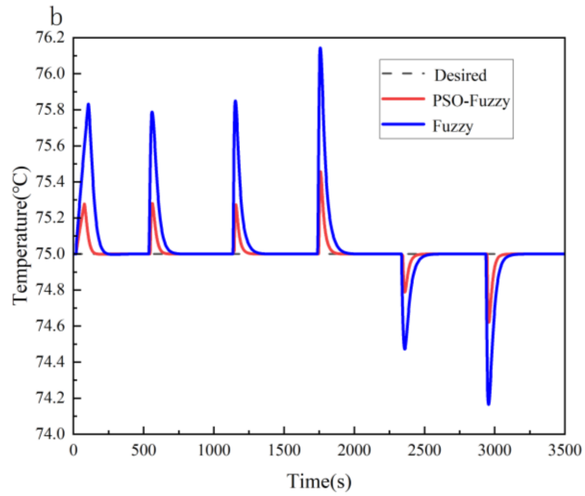

Fig. 8. Stack temperature under dynamic load

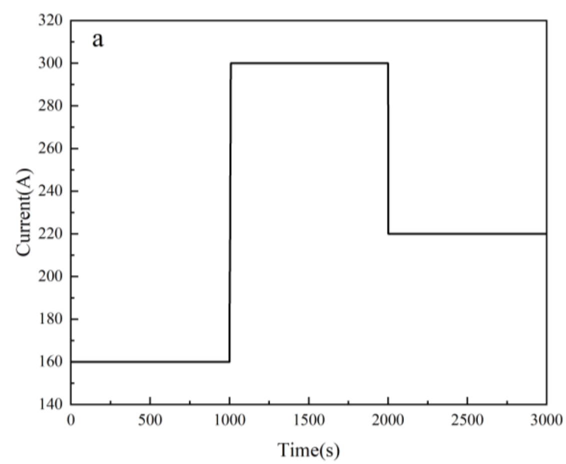

Fig. 9. Pattern of current changes

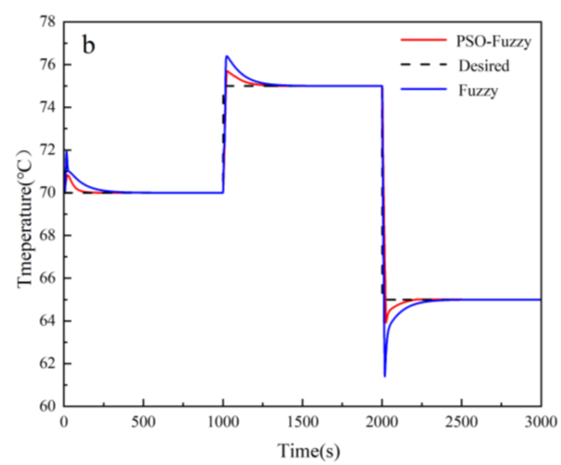

Fig. 10. Stack temperature with variable targets

Fig. 10, where the optimized fuzzy control has a much greater ability to track the target than the pre-optimized fuzzy control.

5. CONCLUSIONS

This paper presents a novel temperature control strategy for the PEMFC power stack, which employs a particle swarm algorithm optimized fuzzy control approach and a newly developed 80 kW dynamic power stack model. The proposed strategy is tested under varying operational conditions. The cooling water flow rate is used as a control variable to regulate the operating temperature of the electric stack in real-time. The main conclusions drawn from the study are as follows:

(1) The temperature control strategy is evaluated against Fuzzy control, specifically in scenarios where the stack temperature needs to be changed from its initial value to a predetermined value as quickly as possible. The comparison showcases the benefits of the PSO-Fuzzy approach, which exhibits the fastest convergence speed, shortest adjustment time, and the smallest temperature overshoot.

(2) The performance of the new strategy has been assessed under different conditions, including step current, dynamic load, and variable target. The results demonstrate that the temperature control based on this new strategy exhibits better dynamic performance and disturbance resistance. By applying this strategy, the temperature fluctuation of the electric stack can be reduced to less than 0.5°C.

ACKNOWLEDGEMENT

This study was partially supported by the Major Program of the National Natural Science Foundation of China (52293414), and the National Natural Science Foundation of China (5210060338).

DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

REFERENCE

[1] K. Ou, W.W. Yuan, M. Choi, et al. Performance increase for an open-cathode PEM fuel cell with humidity and temperature control. J Int. J. Hydrogen Energy 2017; 42 (50) 29852–29862.

[2] S.H. Hwang, M.S. Kim. An experimental study on the cathode humidification and evaporative cooling of polymer electrolyte membrane fuel cells using direct water injection method at high current densities. J Applied Thermal Engineering 2016;99: 635–644.

[3] Amir Faghri, Zhen Guo, Z. Guo. Challenges and opportunities of thermal management issues related to fuel cell technology and modeling. J International Journal of Heat and Mass Transfer 2005;48: 3891-3920

[4] Yan long Zhu, Nasser Yousefi. Optimal parameter identification of PEMFC stacks using Adaptive Sparrow Search Algorithm. J International Journal of Hydrogen Energy 2021;46: 9541-9552

[5] S. Cheng, C. Fang, L. Xu, et al. Model-based temperature regulation of a PEM fuel cell system on a city bus. J Int. J. Hydrogen Energy 2015 40 (39) 13566–13575.

[6] Y.-X. Wang, F.-F. Qin. Temperature Control for a Polymer Electrolyte Membrane Fuel Cell by Using Fuzzy Rule. J IEEE Trans. Energy Convers 2016; 31 (2) 667–675.

[7] B. Zhang, F. Lin, C. Zhang, et al. Design and implementation of model predictive control for an open-cathode fuel cell thermal management system. J Renew. Energy 2020;154 1014–1024.

[8] Y. Li, H. Wang, Z. Dai. Using artificial neural network to control the temperature of fuel cell.2006 International Conference on Communications, Circuits and Systems, 2006; IEEE 3 2159–2162.

[9] J. Li, T. Yu. Distributed deep reinforcement learning for optimal voltage control of PEMFC. J IET Renew. Power Gener2021; 15 (12) 2778–2798.