Energy Proceedings
Vol 45, 2024
ISSN 2004-2965

Reinforcement Learning-Based Energy Management for Fuel Cell Vehicles Incorporating Temperature Dynamics

Qilin Shuai[1], Yiheng Wang[1], Zhengxiong Jiang[1], Qingsong Hua [1*]

1 College of Nuclear Science and Technology , Beijing Normal University, Beijing, China;

(*Corresponding Author: 11112019039@bnu.edu.cn)

ABSTRACT

The energy management system and thermal control of fuel cell in fuel cell vehicles plays a crucial role in ensuring their stable and efficient operation. This study presents a novel fuel cell powertrain energy management system control strategy considered the temperature fluctuation based on deep reinforcement learning. A comprehensive SIMULINK model, encompassing fuel cell cooling system and stack models, was constructed for the fuel cell, followed by simulation testing under various temperature scenarios. To validate the robustness and stability of the control system, the standard operating conditions - US06 were employed for experimental verification. The experimental results highlight the effectiveness of the designed fuel cell energy management system in achieving transient temperature stabilization. Additionally, the results revealed that stable operation temperatures correlate with reduced hydrogen consumption. Furthermore, it's noted that fuel cell hydrogen consumption displays substantial variation under uniform operating conditions at varying temperatures. This highlights the key role of temperature in fuel cell performance. These findings serve as valuable reference points for the refinement of energy management system designs with thermal control of fuel cell, contributing to the advancement of fuel cell vehicle technology.

Keywords: fuel cell vehicle, energy management system, temperature, deep reinforcement learning, PEMFC model, Hydrogen consumption

NONMENCLATURE

Abbreviations	
PEMFC	proton exchange membrane fuel cell
EMS	energy management system
ECM	Equivalent consumption minimization strategy
DQL	deep Q learning
SOC	the stat of charge
Symbols	
E_{nerst}	the Nernst electromotive force
V_{act}	activation overpotential
V_{ohm}	ohmic overpotential
V_{con}	concentration overpotential
N_{cell}	the number of cell units
M_{H2}	the molar mass of hydrogen gas
F	the Faraday constant
P_{aux}	the parasitic power of the system
LHV_{H2}	the low calorific value of hydrogen
P_b	the output power of battery
U_b	the output voltage of battery
E	The open circuit voltage of battery
R_b	the internal resistance of battery
η_b	the battery efficiency
Q_b	the rated capacity of a lithium battery
R	the immediate reward
a	the action of agent

1. INTRODUCTION

Presently, the progress of electric vehicles faces constraints, primarily related to factors such as range limitations and battery life. The adoption and utilization of fuel cells offer a promising solution to address the endurance challenges in electric vehicles.[1],[2] Among various types of fuel cells, proton exchange membrane fuel cell (PEMFC) has been widely used in the field of transportation and energy due to its advantages such as small size, long service life, low pollution, low operating temperature, high power generation efficiency, and fast start-up and shutdown.[3] Nevertheless, comprehensive research and development efforts dedicated to the performance and reliability of fuel cell vehicles remain

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

essential prerequisites for their further commercialization. Among the most critical research domains, the integration and thermal control of fuel cell systems for fuel cell vehicles play a key role.

The thermal system of fuel cell vehicles mainly includes PEMFC stack temperature control. The placement and control strategy of the thermal management system determines vehicle performance and efficiency.[4] During the operation of fuel cell vehicles, the PEMFC stack releases a large amount of waste heat during the power generation process, which affects the output power of the stack. During the operation of fuel cell vehicle, the PEMFC produce a substantial amount of waste heat , which subsequently influences the stack's power output.[5] For example, an increase in operating temperature can increase the catalyst activity of the gas diffusion layer, while also increasing the saturated vapor pressure of water and accelerating the evaporation rate of water, resulting in a decrease in the polymer electrolyte content in the proton exchange membrane and catalyst layer and an increase in ohmic losses. On the contrary, if the temperature of the stack is low, the catalyst cannot reach the most active point, the reaction rate slows down, and the corresponding operating point cannot be reached during rapid load changes, which affects the life of the stack.[6] In addition, frequent fluctuations in temperature can also cause thermal fatigue of the membrane layer accelerates the aging of the proton exchange membrane and catalyst layer, and uneven temperature distribution will also reduce the output voltage and power of the stack. Therefore, this heat must be effectively dissipated to avoid degradation of fuel cell performance and durability. So, how to establish an integrated thermal management system and design a reasonable control strategy is the main difficulty in the current development of fuel cell vehicles. The purpose of the integrated thermal management system for fuel cells is to integrate all subsystems into one.[7] However, there is currently relatively little literature on such integrated thermal management, with most of the literature related to electric vehicles and hybrid vehicles. Wang et al. constructed a fuel cell vehicle cooling system that integrates target components, including a fuel cell stack, DC/DC, drive motor, and air compressor. The simulation results investigated the impact of temperature on the stack and thermal management system, and analyzed the impact of high load conditions on the thermal capacity of the system.[8] Xu developed an integrated thermal management model utilizing KULI software, with a specific emphasis on analyzing heat generation and transfer mechanisms in components such as engines, fuel cells, and air boosters. The model incorporated PID algorithms to control the water pump and fan speeds. Simulation outcomes demonstrated that the maximum coolant outlet temperature of the fuel cell and motor, along with the maximum air inlet temperature of the fuel cell, remained within permissible limits, thus validating the soundness of the proposed system.[9] Xing et al. proposed a vehicle integrated thermal management system model for fuel cell/lithium battery hybrid vehicles and analyzed the characteristics of a 30kW PEMFC battery pack under its cooling system conditions under actual driving conditions.[10] However, the above research mainly focuses on obtaining the optimal temperature of the fuel cell stack based on the optimal performance or efficiency of the stack, and then proposes traditional control algorithms (such as fuzzy logic control, self disturbance rejection control, etc.) to achieve the optimal temperature of the fuel cell. There is less research on intelligent control algorithms, which have better control effects and faster response time compared to traditional control algorithms. Considering the above issues, this article proposes a fuel cell vehicle energy management system based on reinforcement learning that takes into account both fuel cell thermal management and provides a virtual platform for system integration and powertrain coupling analysis. The thermal management control strategy of fuel cell proposed in this study integrates energy management strategies to better support simulation experiments. Simulations were conducted in various standard operating conditions to analyze the operating mechanism, thermal performance, and coupling phenomena of each key thermal system. The research results of this article demonstrate the rationality of the system model and control strategy, which can be used for the design and development of fuel cell vehicle energy management systems and the thermal control of fuel cell.

The organizational structure of this article is as follows. Firstly, it introduces the thermal management structure, theoretical model, and cooling system of fuel cell vehicles; Subsequently, a fuel cell thermal management model and corresponding algorithm principles were proposed, and the training process and simulation results were presented in Section 4, and summarized in Section 5.

2. MODEL

In order to study the operational characteristics of various components of the thermal management system, analyze the impact of coupling of various heat sources in practical applications, and study control strategies, a fuel cell powertrain model based on actual vehicles is proposed. The powertrain of the vehicle includes a 65kW PEMFC and a 1.6 kWh lithium-ion battery. This model considers the cooling of a hybrid power system with integrated fuel cells and lithium-ion batteries. As shown in Fig. 1.

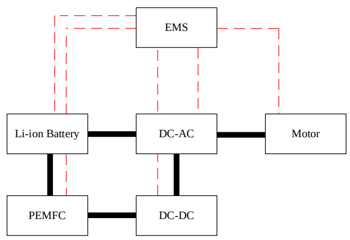

Fig. 1. The Structural schematic diagram of FCV

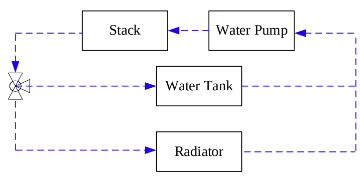

Fig. 2. The Cooling Circuit of fuel cell

2.1 System Configure

The key components of the powertrain thermal management system include PEMFC stack, coolant pumps, and air compressors. The model is established based on the main structural information and test data provided by the supplier, mainly focusing on one-dimensional heat generation and energy exchange mechanisms. Due to the similarity of modeling methods, the modeling principles of similar components in the drive system and other cooling circuits will no longer be repeated below.

2.2 Fuel Cell

2.2.1 The Electrical Model of Fuel Cell

During the operation of a fuel cell, irreversible losses of its electrodes are inevitable during the energy conversion process. The expression for the output voltage ***V*** of the fuel cell is:

$$V = E_{\text{nernst}} - V_{loss} \tag{1}$$

Where $\boldsymbol{E_{nerst}}$ is the Nernst electromotive force. Without considering losses, the Nernst electromotive force can be obtained based on the Nernst equation and the variation of Gibbs free energy.

$$\begin{aligned} E_{\text{nernst}} &= 1.229 - \left(8.5 \times 10^{-4}\right) \times (T - 298.15) \\ &+ \frac{RT}{2F} \times \left(\ln P_{H_2,an} + \frac{1}{2} \ln P_{O_2,ca} \right) \end{aligned} \tag{2}$$

Among them, the irreversible loss of overpotential in fuel cells mainly includes activation overpotential V_{act}, ohmic overpotential V_{ohm}, and concentration overpotential V_{con}. Among them, the activation overpotential and concentration overpotential can be calculated by empirical formulas

$$V_{loss} = V_{act} + V_{ohmic} + V_{con} \tag{3}$$

In the formula, $\boldsymbol{T}$ is the operating temperature of the battery stack, $\boldsymbol{C_{O2}}$ is the oxygen concentration dissolved at the gas-liquid interface in the battery stack, and $\boldsymbol{B}$ is a constant that depends on the fuel cell and its operating state; $\boldsymbol{i_{lim}}$ Represents the actual current density of the stack; Represents the ultimate current density in a fuel cell stack. The hydrogen consumption of fuel cells is represented as follows:

$$\dot{m}_{fc} = \frac{N_{cell} \cdot I \cdot M_{H_2}}{2 \cdot F} \tag{4}$$

Where $\boldsymbol{N_{cell}}$ represents the number of cell units in the fuel cell, $\boldsymbol{M_{H2}}$ represents the molar mass of hydrogen gas, ***F*** is the Faraday constant, and ***I*** is the output current of the fuel cell. Therefore, the heat generation of fuel cell stacks is as follows:

$$\begin{cases} P_{fc} = VI - P_{aux} \\ \eta_{fc} = \dfrac{VI - P_{aux}}{m_{fc} LHV_{H_2}} \end{cases} \tag{5}$$

Where $\boldsymbol{LHV_{H2}}$ represents the low calorific value of hydrogen and $\boldsymbol{P_{aux}}$ represents the parasitic power of the system.

2.2.2 The Thermal Model of Fuel cell

The thermal model of the fuel cell is shown in the Fig. 2, following the law of energy conservation and the heat balance equation. The stack temperature of the fuel cell is mainly determined by the heat generated during operation minus the heat carried away.

$$\dot{Q}_{heat} = C_{st} m_{st} \frac{dT_{st}}{dt} = N_{cells} \cdot I_{st} \left(E_{equal} - \frac{E_{st}}{N} \right) \tag{6}$$

Where $\boldsymbol{C_{st}}$ is the specific heat capacity of the proton exchange membrane fuel cell stack (kJ/K × kg); $\boldsymbol{m_{st}}$ is the mass of the stack; $\boldsymbol{T_{st}}$ is the stack temperature; $\boldsymbol{E_{equal}}$ is the equal voltage of the stack; E_{st} is the output voltage of the fuel cell; ***N*** is cells number; $\boldsymbol{I_{st}}$ is the current of the fuel cell. The heat dissipation of a radiator is mainly related to air flow rate and environmental temperature difference.

2.3 Li-ion Battery

This article uses an internal resistance model to establish a one-dimensional model for lithium-ion batteries, as shown in the following equation.

$$I_b = \frac{E - \sqrt{E^2 - 4R_b P_b}}{2R_b} \tag{7}$$

In the formula, P_b represents output power, U_b represents output voltage, I_b represents lithium battery current, and E represents open circuit voltage; R_b represents internal resistance. The current of a lithium battery can be calculated based on its output power. The state of charge (SOC) of lithium batteries is a key control parameter in energy management strategies. This article uses the ampere hour integration method to calculate SOC:

$$SOC(t) = SOC_0 - \frac{\eta_b \int_0^t I_b(\tau)d\tau}{Q_b} \tag{8}$$

Where ***SOC(t)*** represents the current SOC value of the lithium battery and SOC_0 represents the initial SOC value of the lithium battery; η_b Represents battery efficiency; Q_b represents the rated capacity of a lithium battery. The voltage and capacity of its battery pack are shown below.

$$V_{bat} = V_{batcell} N_{\mathrm{mod}} \tag{9}$$

Therefore, the voltage and capacity of the battery pack are 48V and 35Ah, respectively. The heat generation during its discharge process is shown below.

3. METHOD

Deep Q Learning (DQL) is a deep reinforcement learning algorithm based on deep Q learning, used to solve the problem of continuous action space. Its core is the optimization of the deep neural networks by optimizing weight. The energy management strategy framework and design are based on DQL algorithm mainly consists of several parts, such as deep Q network, weight updating, gradient, policy, mini batch and experience pool, as shown in the Fig. 3.

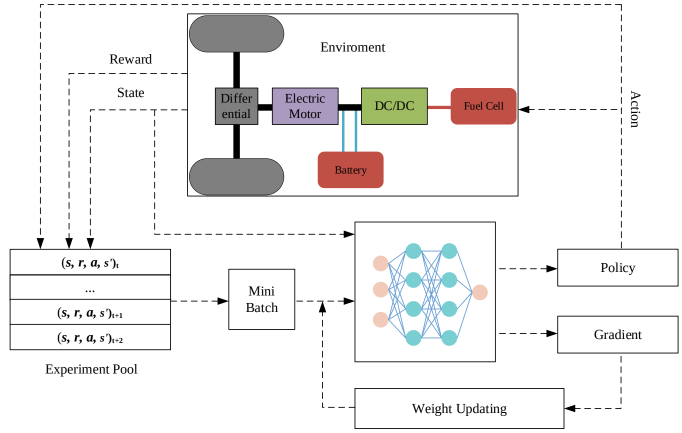

Fig. 3. Energy Management Strategy Framework Based on DQL Algorithm

Enviroment State: The required power of the entire vehicle, the ***SOC*** of the lithium battery, and the temperature composition state space of the fuel cell system [P_{req}, ***SOC***, T_{fc}];

Control Action: The output power of the fuel cell is a control action, which is different from the DQL algorithm. DQL directly outputs the action to the system through the Q network.

Reward function: The reward function directly affects the adjustment of deep network parameters. This article takes hydrogen consumption as the main indicator, while considering the retention capacity of lithium battery SOC, temperature changes in fuel cells, and fuel cell attenuation, and designs the following reward function:

$$R = \left\{ \alpha \frac{dFuel}{dt} + \beta (Soc_{ref} - Soc)^2 + \lambda |\Delta T| \right\} \tag{10}$$

Where R is the immediate reward for taking action a in state s to state s'; ***Fuel*** represents hydrogen co nsumption; ΔT represents the rate of change in tem perature.

4. TRAINING AND SIMULATION RESULT

This section provides a comprehensive analysis of the proposed DQL based energy management strategy. Prior to validation, the network was trained and the simulation results were analyzed and discussed.

4.1 Training Setting

In this study, the Fuel Cell Energy Management System is trained and validated using the US06 operating conditions, as illustrated in the Fig. 4. The simulation results of the DQL-based energy management system are then compared and elucidated alongside those of the ECM-based energy management system.

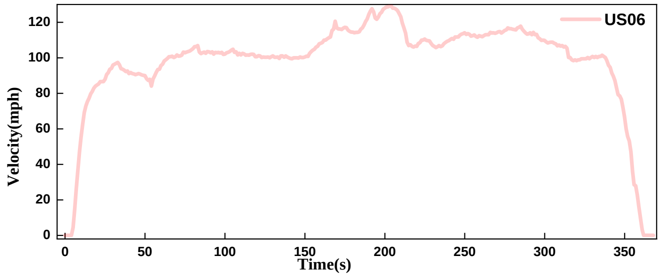

Fig. 4. The Velocity of US06

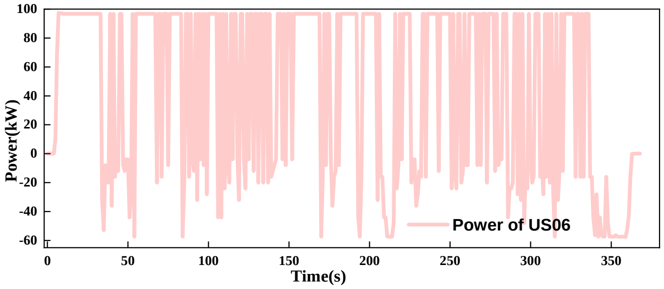

Fig. 5. The power request of US06

4.2 Impact of the reward settings on convergence

Fig. 6 Fig. 6. The reward of DQL–EMS training progressillustrates the training progression of the energy management system for fuel cell vehicles. It demonstrates the evolution of the reward function in relation to the number of training iterations. As depicted, the DQL agent engages in continuous exploration from episodes 0 to 130, aimed at maximizing the reward function value. Over the course of 290 iterations, the neural network progressively stabilizes across episodes, thereby facilitating the exploration of an improved global optimal solution. Ultimately, as indicated in the figure, the system reaches a state of gradual stabilization after 280 iterations.

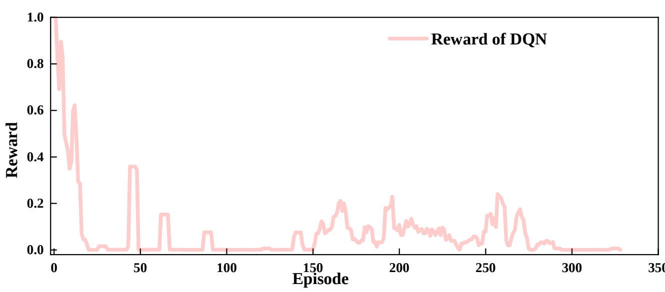

Fig. 6. The reward of DQL–EMS training progress

4.3 Simulation results and analysis

In evaluating the effectiveness of the proposed DQL strategy, the assessment of fuel cell vehicles under US06 standard operating conditions encompasses three vital dimensions: State of Charge (SOC) maintenance, hydrogen consumption optimization, and temperature regulation. These dimensions will be further elucidated in the subsequent sections.

4.3.1 Battery's charge-sustaining

Fig. 7. SOC trajectory of DQL -EMS and ECM-EMSdisplays the State of Charge (SOC) trajectory of the lithium battery within DQL-EMS. The DQL-EMS consistently regulates the fuel cell power to remain under 50kW. Notably, during acceleration phases, the system optimally strives to maintain fuel cell power as close to 50kW as possible, thereby preserving the initial and final SOC states. This strategy effectively reduces the load on the lithium batteries, as depicted in Fig. 7. The SOC states are evidently maintained at approximately 0.6, attesting to the success of our proposed DQL-based EMS in achieving charge maintenance.

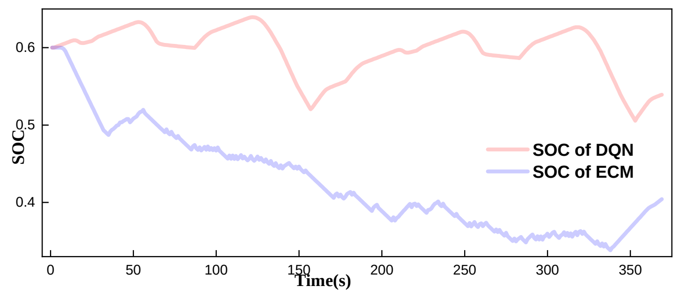

Fig. 7. SOC trajectory of DQL -EMS and ECM-EMS

4.3.2 Optimality of operational cost

Fuel cell operational expenditures are primarily driven by hydrogen consumption. To assess the cost-effectiveness of our DQL-EMS, we employ Equivalent Consumption Minimization (ECM) as a benchmark for validation. The Fig. 8 presents hydrogen consumption fluctuations at different time points. Evidently, maintaining stable fuel cell power during charge maintenance mode emerges as a cost-effective strategy. In essence, our proposed DQL-EMS effectively reduces hydrogen consumption, thus curbing operational costs.

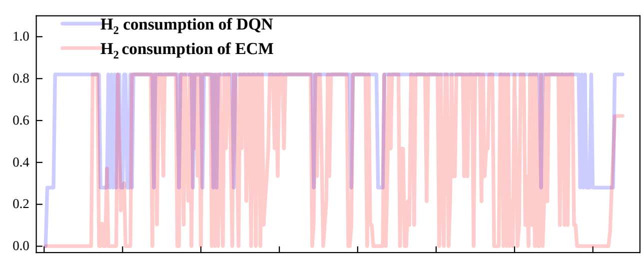

Fig. 8. H_2 consumption of DQL -EMS and ECM-EMS

4.3.3 Temperature

The temperature dynamics in fuel cells predominantly arise from the waste heat generated during their operation, as shown in the Fig. 9. Given the critical need to sustain the fuel cell at its optimal operating temperature, approximately 80 degrees Celsius, this study emphasizes the reduction of power conversion frequency. By minimizing the frequency of power output transitions, this research aims to ensure the fuel cell remains within a high-efficiency power output range, thus enhancing its overall operational efficiency.

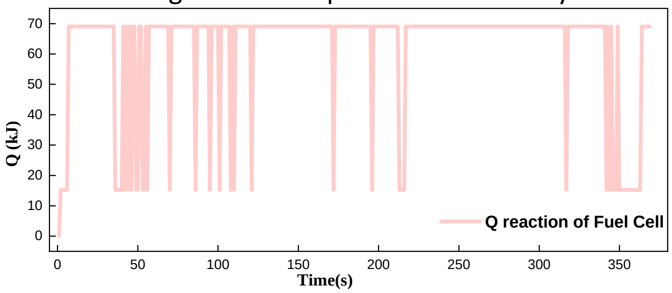

Fig. 9. The heat of chemical reaction of Fuel Cell

5. CONCLUSION

This study reports a fuel cell energy management strategy based on deep reinforcement learning, which considers the temperature dynamic of fuel cells. In order to maintain the optimal temperature for fuel cell operation and the consistency of SOC initial and final states, an optimization method based on reinforcement learning is proposed, which can adjust and optimize the strategy online. Based on the vehicle model, an energy management problem is created using a reinforcement learning structure, and then solved using one of the most advanced DRL algorithms, DQL. A random training environment based on US06 is used to generate realistic simulations and prevent overfitting. Complete training by interacting with the environment through DQL agents. After training, the simulation results show that the proposed strategy has good ability in maintaining the consistency of SOC initial and final states and the thermal stability of fuel cells. In addition, the strategy was compared with an energy management strategy based on ECM, and the results showed that the strategy had lower fuel consumption and better thermal stability.

ACKNOWLEDGEMENT

This work was financially supported by “the National Key Research and Development Program of China Research and Application Demonstration of Intelligent loT and Control Technology for Urban Integrated Energy, China (grant number: 2020YFB2104500)”.

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] Han J. A review of key components of hydrogen recirculation subsystem for fuel cell vehicles. Energy Conversion and Management 2022.

[2] Hua Z. A review on lifetime prediction of proton exchange membrane fuel cells system. Journal of Power Sources 2022.

[3] Krithika V, Subramani C. A comprehensive review on choice of hybrid vehicles and power converters, control strategies for hybrid electric vehicles[J]. International journal of energy research, 2018, 42(5): 1789-1812.

[4] Yang Q, Zeng T, Zhang C, et al. Modeling and simulation of vehicle integrated thermal management system for a fuel cell hybrid vehicle[J]. Energy Conversion and Management, 2023, 278: 116745.

[5] Şefkat G, Özel MA. Experimental and numerical study of energy and thermal management system for a hydrogen fuel cell-battery hybrid electric vehicle. Energy 2022;238:121794.

[6] Li X, Deng Z H, Wei D, et al. Novel variable structure control for the temperature of PEM fuel cell stack based on the dynamic thermal affine model[J]. Energy Conversion and Management, 2011, 52(11): 3265-3274.

[7] Sun L, Li G, Hua Q S, et al. A hybrid paradigm combining model-based and data-driven methods for fuel cell stack cooling control[J]. Renewable Energy, 2020, 147: 1642-1652.

[8] Wang Y, Li J, Tao Q, et al. Thermal management system modeling and simulation of a full-powered fuel cell vehicle[J]. Journal of Energy Resources Technology, 2020, 142(6): 061304.

[9] Xu J, Zhang C, Fan R, et al. Modelling and control of vehicle integrated thermal management system of PEM fuel cell vehicle[J]. Energy, 2020, 199: 117495.

[10] Xing L, Xiang W, Zhu R, et al. Modeling and thermal management of proton exchange membrane fuel cell for fuel cell/battery hybrid automotive vehicle[J]. International Journal of Hydrogen Energy, 2022, 47(3): 1888-1900.