Hindawi
Mathematical Problems in Engineering
Volume 2023, Article ID 9848695, 1 page
https://doi.org/10.1155/2023/9848695

Retraction

Retracted: Multienergy Management Strategy of Fuel Cell Hybrid Vehicle Based on Distributed Parameter Model

Mathematical Problems in Engineering

Received 13 September 2023; Accepted 13 September 2023; Published 14 September 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] M. Li, Q. Liang, J. Hu, Y. Liang, and J. Zhao, "Multienergy Management Strategy of Fuel Cell Hybrid Vehicle Based on Distributed Parameter Model," *Mathematical Problems in Engineering*, vol. 2022, Article ID 4883228, 8 pages, 2022.

Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 4883228, 8 pages
https://doi.org/10.1155/2022/4883228

Research Article

Multienergy Management Strategy of Fuel Cell Hybrid Vehicle Based on Distributed Parameter Model

Mengjie Li, Qianchao Liang, Jinyi Hu, Yifan Liang, and Jianfeng Zhao

Department of Power Engineering, Naval University of Engineering, Wuhan, Hubei 430033, China

Correspondence should be addressed to Qianchao Liang; 18407161@masu.edu.cn

Received 1 June 2022; Revised 2 July 2022; Accepted 5 July 2022; Published 20 July 2022

Academic Editor: Naeem Jan

To increase the fuel efficiency of fuel cells, lengthen their useful lives, and fulfil the demands for high energy and high power during the operation of hybrid electric vehicles. This paper's goal is to thoroughly examine the distributed parameter model-based multienergy management technique of fuel cell hybrid electric vehicles. Firstly, the simplified model of a hybrid system is constructed according to the distributed parameter model, and the fuel cell model, unidirectional DC/DC converter, and battery are described in detail. The multienergy management of hybrid electric vehicles based on improved deep Q-learning is adopted, the multienergy management strategy based on deep Q-learning is designed, so as to reduce fuel consumption and improve the working efficiency of fuel cells, optimize the energy distribution of lithium batteries and fuel cells, and adopt the experience playback mechanism of summation tree structure in the process of strategy training to complete the multienergy management of hybrid electric vehicles. The strategy described in this study can successfully increase the overall power performance of fuel cell hybrid vehicles, extend the battery's service life, and increase fuel economy, according to simulation results, which has a certain practical value.

1. Introduction

With the increasingly serious environmental pollution and the gradual depletion of energy in the global environment, the development of renewable new energy automobiles are the general trend of the times. Fuel cell hybrid vehicle is the focus of worldwide attention in new energy automobiles. However, because the response of fuel cell to start-up and operation is slow and cannot meet the change of power requirement during the driving process of the hybrid vehicle, the combination of fuel cell and multienergy is the main way to effectively solve this problem. The matching of fuel cell hybrid vehicle parameters and the multienergy management and other parts performance of the vehicle play a decisive role in the overall power and economy of the vehicle. Among them, the research of multienergy management strategy is how to rationally distribute the current of vehicle load among different energy sources. For this reason, the appropriate multienergy management strategy has an important impact on the power and economy of hybrid vehicles. The multienergy management method of fuel cell hybrid vehicles is investigated in order to decrease fuel cell usage, and the distributed parameter model is utilized for this purpose. By using the distribution parameters, the characteristics of the fuel cell are described, which has a good ability to resist the influence of the distribution current. The model has a good protection range and has certain research value.

The innovations of this paper are as follows:

(1) First, a simplified model of a hybrid power system is built based on the distributed parameter model. The multienergy management of hybrid vehicle based on improved deep Q learning is adopted, and the multienergy management strategy based on deep Q learning is designed. The experience playback mechanism of the summation tree structure is used in the process of strategy training to complete the multienergy management of the hybrid vehicle.

(2) Compared with the multienergy management strategies of other hybrid vehicles, the methods presented in this paper can effectively improve the overall dynamic performance of fuel cell hybrid

vehicles, extend the battery life cycle, and improve fuel economy. This study has the potential to extend the service life of batteries, increase fuel efficiency, and effectively improve the overall power performance of fuel cell hybrid cars, all of which have potential practical applications.

The rest of the article is as follows: Section 2 defines the numerous related works. Section 3 analyzes the dynamic system model building based on distributed parameter model. Section 4 explains the multi-energy management strategy based on improved deep Q-learning. Section 5 evaluates the experimental results. Section 6 concludes the article.

2. Related Work

All countries in the world are actively developing fuel cell hybrid vehicles and have achieved corresponding results. Hong et al. to improve the efficiency of fuel cells and power vehicles and maintain the charging status of batteries, based on the corresponding parameters in the real hardware system and the vehicle working conditions, puts forward the energy management strategy of fuel cell hybrid electric vehicle based on the principle of small gold value. The proposed energy management strategy is scientifically validated on the hardware system of the fuel cell hybrid vehicle and compared with the equivalent minimum hydrogen consumption strategy. The results show that, regardless of the initial battery value, the proposed energy management strategy is slightly more efficient than other energy management strategies, which can effectively reduce the actual hydrogen consumption and better maintain the SOC value of the battery. However, this method has the shortage of fuel cell life [1]. In order to improve the fuel economy of fuel cell hybrid vehicle, Zhao et al. choose three typical working conditions to formulate corresponding optimal energy management strategies, uses the optimized support vector machine to identify the operating conditions of the vehicle, and dynamically chooses the multienergy management strategies to make the selected representative conditions more adaptive, thereby reducing the hydrogen consumption. The simulation results demonstrate that, in comparison to the nonoperating condition identification and the conventional support vector machine identification, the suggested method can minimize and stabilize the change of the charging state of the accumulator. Although this method can effectively prolong the life of the battery, the overall fuel economy is poor [2]. In order to improve fuel economy and prolong the battery life of hybrid vehicles, Liu et al. proposed a multienergy management strategy for hybrid vehicles based on multiobjective optimization. Based on the power flow of the hybrid power system and the efficiency of key components, a model of hydrogen consumption in the drive system was proposed. In addition, the impact of load changes on the lifetime of fuel cells is considered comprehensively, and an intelligent power allocation method is proposed to achieve multienergy management. That is, based on the fuzzy control strategy, in the process of in-depth research, in order to improve the proposed multienergy management strategy, the corresponding parameters of the fuzzy controller are optimized by using a genetic algorithm, and the multiobjective optimization problem is solved by using the improved nondominant genetic algorithm, and the control parameters are optimized reasonably. Comparing with other management strategies, the simulation results show that the fuel cell life cycle is prolonged effectively, but the overall fuel economy has not been significantly improved [3]. Wang et al. proposed a multienergy management control strategy based on a tiny variable for Fuzzy Control Fuel Cell based on the combination of Fuel Cell Hybrid Vehicle and Power Battery, which combines the current situation, that frequent discharge of Fuel Cell Hybrid Vehicle results in the shorter battery life cycle and higher power consumption and increases economic costs. By optimizing the secondary development of the fuel cell hybrid vehicle, experiments are carried out to verify the scientificity of the multienergy management control based on the hybrid model, to ensure the overall power performance and economy of the vehicle, and to optimize the total energy generated during the driving process with efficiency as the optimization target. The experimental results show that the power performance of the hybrid vehicle based on the fuzzy control of small variables meets the requirements of the vehicle, and the economy is improved. But the battery life has not been extended [4].

3. Dynamic System Model Building Based on Distributed Parameter Model

3.1. Hybrid Power Structure. The power system is made simpler by using a distributed parameter model to analyse the multienergy management of hybrid automobiles. The simplified structure of the hybrid vehicle is shown in Figure 1. Figure 1 contains fuel cells, batteries, unidirectional DC/DC converters, DC loads, controllers, etc., [5, 6].

In Figure 1, p_{lr} represents the power required by the vehicle's load, i_{lr} represents the current required by the load, i_{fcr} represents the output current of the fuel cell, v_{bus} represents the bus voltage of the vehicle, and *soc* represents the charging state of the accumulator battery.

3.2. Fuel Cell Model. To represent the fuel cell, a distributed parameter model is employed. Gas flow rate, pressure, and temperature influences on the dynamic properties of the fuel cell are not taken into account. To improve the suggested multienergy management method, the relevant fuzzy controller parameters were determined based on the fuzzy control technique through extensive research. The fuel cell model is shown in Figure 2.

In Figure 2, the mathematical model of a fuel cell is represented by formulas (1) and (2).

$$v_{fc} = E_{oc} - E_{act} - E_{ohm}, \tag{1}$$

$$v_{fc} = E_{oc} - NA1n\left(\frac{i_{fc}}{i_0}\right)\bullet\frac{1}{sT_d/3+1} - i_{fc}R_{ohm}. \tag{2}$$

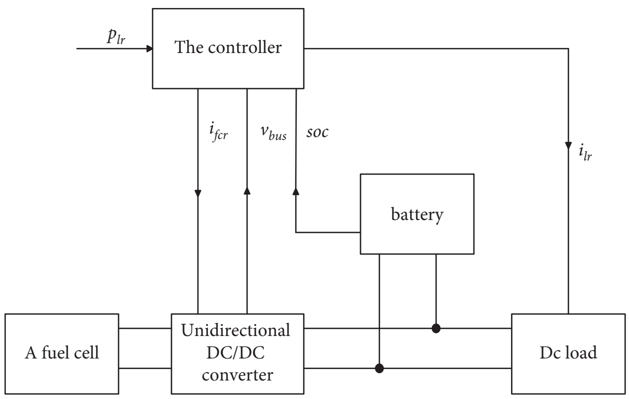

Figure 1: Simplified structure of power system.

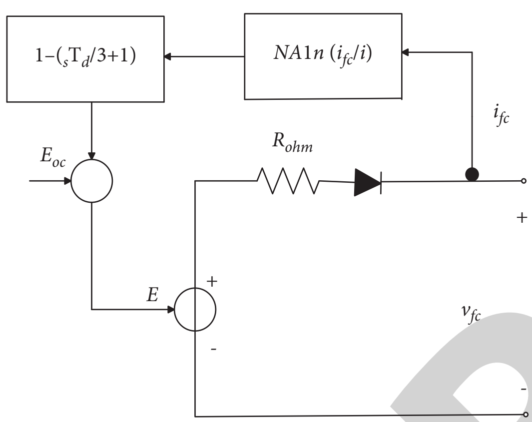

Figure 2: Fuel cell model.

In formulas (1) and (2), v_{fc} represents the output voltage, E_{oc} represents the open-circuit voltage, E_{act} represents the voltage of activation polarization, E_{ohm} represents the voltage of Ohm polarization, N represents the number of batteries, A represents the slope of Tafi, i_{fc} represents the output current, i represents the exchange current, T_d represents the response time, and R_{ohm} represents the equivalent internal resistance.

The instantaneous hydrogen consumption of a fuel cell is expressed by the following formula fd3:

$$m_{fc} = \frac{N_{cell} i_{fc} M_{H2}}{2F}. \quad (3)$$

Fuel cells have not only stacks but also air compressors, solenoids, and cooling devices. Fuel cells must resource energy for additional devices, so the net power of a fuel cell is represented by the following formula fd4:

$$P_{fc} = v_{fc} i_{fc} - P_{aux}. \quad (4)$$

In formula (4), P_{aux} represents the power consumption of the additional unit.

According to formulas (3) and (4), the efficiency of the fuel cell system is calculated by the following formula fd5:

$$\eta_{fc} = \frac{v_{fc} i_{fc} - P_{aux}}{m_{fc} H_{LHV}}. \quad (5)$$

In formula (5), H_{LHV} represents the low heat value of hydrogen.

The fuel cell parameters selected in this paper are represented by Table 1, and the voltage-ampere characteristic curves of the fuel cell are obtained by MATLAB simulation from Figure 3 [7, 8].

3.3. One-Way DC/DC Converter. In order to device the power output of the fuel cell while matching the output voltage of the fuel cell with the bus voltage, a one-way DC/DC converter must be connected between the fuel cell and the bus component [9, 10].

3.4. Accumulator Model. The battery model is shown in Figure 4. The mathematical model of the accumulator is represented by formulas (6) and (7):

$$C\frac{dv_c(t)}{dt} = i_b(t) - \frac{v_c(t)}{R_2}, \quad (6)$$

$$v_{bus}(t) = v_{oc}(t) - v_c(t) - i_b(t)R_1. \quad (7)$$

In formulas (6) and (7), C represents the equivalent capacitance, R_1 and R_2 represent the equivalent internal resistance, $v_c(t)$ represents the short voltage of the equivalent capacitance, c represents the output current, and $v_{oc}(t)$ represents the open voltage.

4. Multienergy Management Strategy Based on Improved Deep Q-Learning

In combination with the above dynamic system model based on distributed parameter model, the deep Q-learning algorithm is used to train multienergy management strategies in the training phase using related data-driven methods [11, 12]. The vehicle demand strategy is modelled as a density function random variable with known probability using a Markov chain, and the probability of transfer is computed using the nearest neighbour method and maximum likelihood estimation method. The status data of hybrid vehicles are gathered using the platform of vehicle electronic control tests. The probability matrix of demand power transfer is established based on current and next moment power and the transfer probability is expressed by the following formula fd8:

$$p_{k,ij} = \frac{N_{k,ij}}{N_{k,i}}, \text{ if } \quad N_{k,i} \neq 0. \quad (8)$$

In formula (8), when $N_{k,ij}$ represents the average speed of a vehicle is v_{ave}^k, the probability of the occurrence of the conversion from P_{demand}^i to P_{demand}^j is calculated, while $N_{k,i}$ represents the average speed of a vehicle is v_{ave}^k, and the total number of the probability of the conversion from P_{demand}^i to the occurrence of the demand power is calculated. Using sanitized data to create a matrix of transfer probabilities at various speeds [13, 14].

To prevent the multiobjective optimization from complicating the calculation, an evaluation mechanism based on the minimum strategy reward of equivalent consumption is proposed. The reward function is established with the

Table 1: Fuel cell parameters.

Parameter	Rated power (kW)	Maximum power (kW)	Number of batteries per battery
The numerical	15	30	200

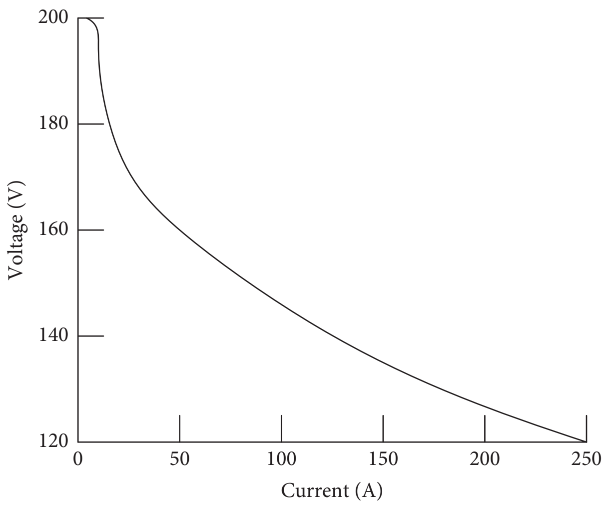

Figure 3: Voltammetric characteristic curve of the fuel cell.

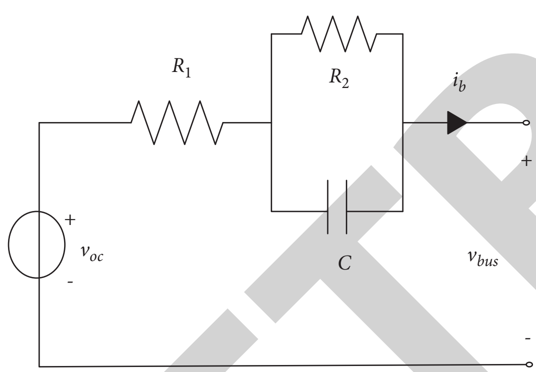

Figure 4: Battery model.

minimum equivalent hydrogen consumption as the optimization objective. The minimum strategy of equivalent consumption is to use the equivalent instantaneous energy consumption of lithium batteries and supercapacitors as the energy consumption of fuel cell chemistry expressed by the following formula fd9:

$$\min C_{\text{total}}(t) = k_{FC}(t) + k_{BAT}C_{BAT}(t) + k_{UC}C_{UC}(T). \tag{9}$$

In formula (9), $\min C_{\text{total}}(t)$ represents the total instantaneous minimum hydrogen consumption of the vehicle, including the direct hydrogen consumption $C_{FC}(t)$ of the fuel cell, k_{FC} represents the penalty coefficient for the high-efficiency horizontal operation of the fuel cell, k_{BAT} and k_{UC} are the parameters of the actual energy source of the hybrid vehicle based on the equivalent factors calculated by the lithium battery and supercapacitor SoC of the hybrid vehicle, The specific constraint of the minimum strategy of equivalent consumption is expressed by the following formula fd10:

$$\begin{cases} SoC(t) - SoC_{ref} \quad SoC(t) < SoC_{ref}; \\ 0, \quad SoC(t) \geq SoC_{ref} \\ 0.4 \leq SoC_{BAT}(t) \leq 0.8 \\ SoC_{BAT,ch} \leq 2C \\ SoC_{BAT}.disch \leq 4C \\ P_{FC,\min} \leq P_{FC}(t) \leq P_{FC,\max} \\ -P_{\text{demend}} \leq P_{BAT}(t) \leq P_{\text{demend}} \end{cases}. \tag{10}$$

In formula (10), SoC_{ref} represents the reference SoC of lithium battery of the hybrid electric vehicle, $SoC_{BAT,ch}$ and $SoC_{BAT,disch}$ represent the charging and discharging efficiency of lithium battery of the hybrid electric vehicle, $P_{FC,\min}$ represents the minimum output power of fuel cell, $P_{FC,\max}$ represents the maximum output power of fuel cell, $-P_{BAT}$ and P_{BAT} represent the range of output power of lithium battery of the hybrid electric vehicle, and all constraint boundaries are obtained from the platform of hybrid electric vehicle test of fuel cell [15, 16].

Taking the fuel economy and battery life cycle of fuel cell hybrid vehicles as the optimization objectives, the reward value r of deep Q learning is proposed, which is expressed by the following formula fd11:

$$r = C_{\text{total}}(t) + \kappa \times (\Delta SoC)^2. \tag{11}$$

In formula (11), $C_{\text{total}}(t)$ represents the instantaneous hydrogen consumption of the hybrid electric vehicle, ΔSoC represents the deviation between the current lithium battery SoC and the reference SoC, and κ represents the adjusted coefficient so that $C_{\text{total}}(t)$ and $(\Delta SoC)^2$ are at the same level [17, 18].

Deep Q-learning is an off-line training and online decision-making method. The off-line training process of the proposed hybrid vehicle multi-energy management strategy is as follows.

Using the potential hybrid vehicle s, it specifically includes the required power P_{demand}, vehicle speed, lithium battery, and supercapacitor SoC, and the output power of the supercapacitor. The $\varepsilon -$ greedy strategy green is used to select the distribution of energy source power of the hybrid electric vehicle, the minimum strategy of equivalent consumption is used as the reward value r in the corresponding state obtained in the main reward matrix, and the probability transfer matrix is used to predict the next state of a hybrid electric vehicle.

The way of Q value updating in deep Q learning is expressed as follows:

$$Q(s_t,a;\theta)\leftarrow Q(s_t,a;\theta)+\alpha[TargetQ_t-Q(s_t,a;\theta)];$$
$$TargetQ_t=r+\gamma\max_a Q(s_t,a;\theta),\tag{12}$$
$$L(\theta)=E\Big[\big(TargetQ_t-Q(s_t,a,\theta)\big)^2\Big].$$

In formula (12) and (13), θ represents the parameters of the deep Q-learning network, and $Q(s_t,a;\theta)$ represents the use of the neural network to approach the current Q value; α represents the learning rate, $\gamma\in[0,1]$ represents the discount factor, the estimated network structure is consistent with the target network structure, and the initialized weight is the same, $L(\theta)$ a function representing the mean square error. After off-line training, the decision set can be generated to complete the real-time energy management of fuel cell hybrid vehicles.

A more effective experience extraction approach is used, and the experience playback mechanism of summation tree structure priority is introduced in light of the deep Q-learning experience playback method's huge sampling randomness and low learning efficiency. The leaf node of the tree is the level value of experience priority, the two nodes are combined into a group and overlaid upward, and the tree root value is the total of all level values of experience priority [19, 20]. When sampling, divide the interval of batch size, take samples randomly from each interval, search the sampling experience value of each node, and clarify the final sampled hybrid vehicle data. This sampling method can extract high priority data samples without traversing the experience pool, reduce the consumption of computing hybrid vehicle resources, and improve the speed of model training. The priority value of experience sample (s_t,a,r,s_{t+1}) of a hybrid electric vehicle is expressed by $TD-$ error and the extraction probability p_i of $TD-$ error and experience sample is expressed by formulas (13) and (14):

$$TD-reeor=r_t+\gamma Q_T\left(s_t+1,a,\widetilde{\theta}\right)-Q(s,a,\theta),\tag{13}$$

$$P(i)=\frac{p_i}{\sum p_i}.\tag{14}$$

When the value of $|TD-\text{error}|$ is relatively large, it indicates that the current Q function is far from the optimization objective function and needs to be updated many times. And, the probability method is adopted to extract the experience of hybrid electric vehicles, so as to ensure that the experience can be extracted even if the $TD-$ error value is 0, so as to prevent the fitting phenomenon of the network. The above process completes the multienergy management of fuel cell hybrid vehicle based on distributed parameter model.

5. Experimental Result

In order to prove the effectiveness of the multienergy management strategy of fuel cell hybrid electric vehicle based on distributed parameter model proposed in this paper. Table 2 shows the parameters of fuel cell hybrid vehicles.

Table 2: Parameters of fuel cell hybrid vehicles.

Parameter	Value
Coefficient of rolling resistance	0.015
Windward resistance coefficient	0.33
Windward area (m^2)	2.9
Full load mass (kg)	1960
Battery capacity (Ah)	20
Rated battery voltage (V)	384
Maximum power of fuel cell (kW)	35
Fuel cell rated power (kW)	25

Figure 5 shows the comparison of SOC values between the multienergy management strategy of hybrid vehicles with improved deep Q-learning and the multienergy management strategy of hybrid vehicles based on efficiency tracking.

Through the analysis of Figure 5, it can be seen that the SOC value of the multienergy management strategy of hybrid electric vehicle based on efficiency tracking is relatively lower than that of the method proposed in this paper at the beginning of the experiment, but with the increase of time, the SOC value of this method increases linearly and decreases sharply when the time is 200s. Although the difference between the multienergy management strategy of hybrid electric vehicle based on improved deep Q learning and the SOC value based on the efficiency tracking method is small; the SOC values of the proposed method and the efficiency tracking method float up and down within 60%, but the method proposed in this paper is still lower, which can effectively reduce the battery power consumption of hybrid electric vehicles and prolong the service cycle of vehicle batteries. The above-given simulation results show that the multienergy management strategy proposed in this paper can effectively complete the multienergy management of fuel cell hybrid vehicles, improve the working efficiency of fuel cells, and reduce the consumption of battery power. In this paper, the management strategy of deep Q-learning is compared with the multienergy management strategy based on improved deep Q-learning proposed in this paper, and the equivalent hydrogen consumption is analyzed by using four classical cycle conditions, Fuel economy is shown in Table 3.

Through the analysis of Table 3, it can be seen that under the working conditions of typical wltp, the multienergy management strategy of hybrid electric vehicles based on improved deep Q-learning proposed in this paper improves the fuel economy by 3.6% compared with the multienergy management strategy of hybrid electric vehicles based on traditional deep Q-learning. Under the working conditions of typical UDDS, the fuel economy of this strategy is improved by 3.8% compared with the traditional deep Q-learning strategy, under the working condition of wvu-sub, the fuel economy is improved by 3.1%. Under the four typical working conditions, the fuel economy under NEDC working condition is the highest, which can reach 8.3%. This shows that the management strategy proposed in this paper has very good adaptability in different working conditions. Figures 6 and 7 show the efficiency curve of the management

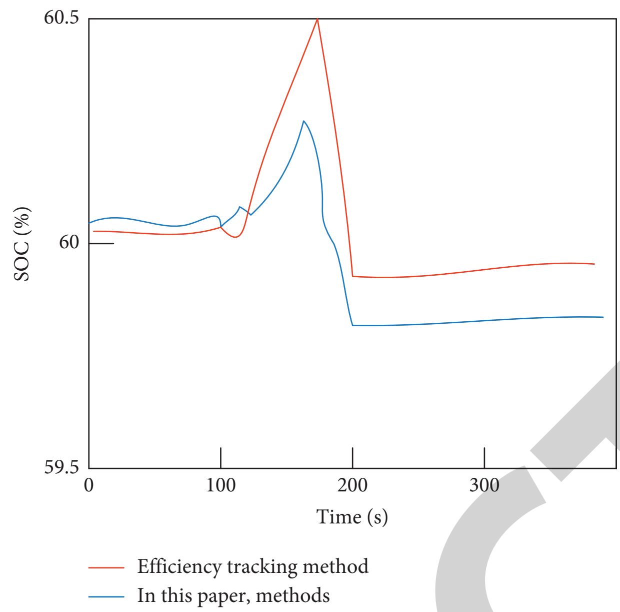

Figure 5: Comparison of SOC change curves under different methods.

Table 3: Fuel economy.

Working condition	Equivalent fuel consumption (L/100 km)		Promote (%)
	Traditional deep Q-learning	Improvement strategy of this paper	
WLTP	2.81	2.70	3.60
UDDS	2.62	2.55	3.82
NEDC	3.61	3.33	8.33
WVUSUB	3.22	3.11	3.11

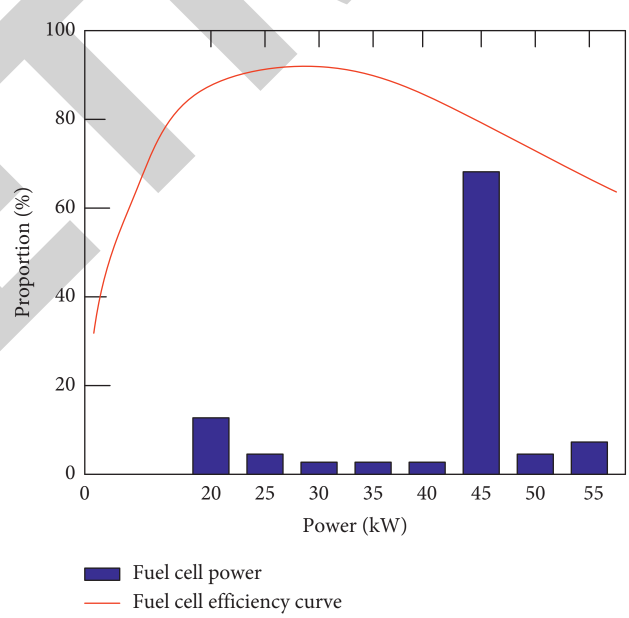

Figure 6: Method proposed in this paper.

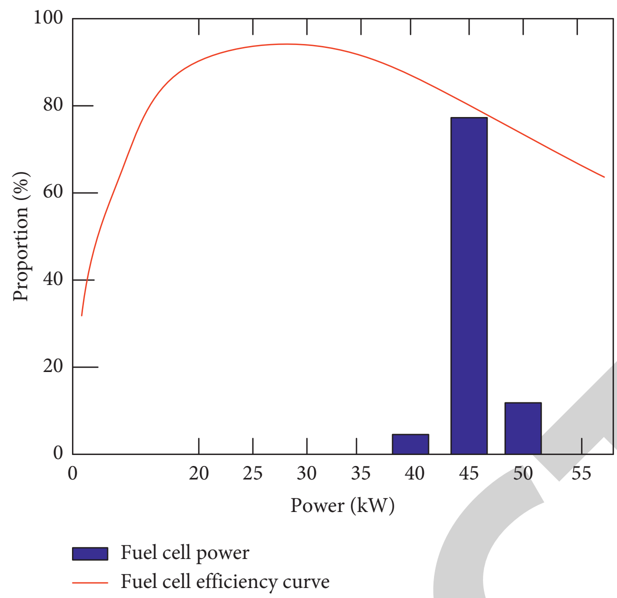

FIGURE 7: Efficiency tracking method.

strategy based on the distributed parameter model proposed in this paper and the management strategy based on efficiency tracking, as well as the comparison of the power distribution of the fuel cell.

Through the analysis of Figures 6 and 7, it can be seen that the distribution of fuel cell output power of the multienergy management strategy based on the distributed parameter model proposed in this paper is relatively wide. When the proportion is 20%, it is distributed in the areas with high efficiency, while almost all the areas of the multienergy management strategy based on efficiency tracking are distributed in the areas with low efficiency. It can be concluded that the multienergy management strategy of hybrid electric vehicle based on distributed parameter model adjusts the output power of fuel cell, makes the multienergy management strategy of fuel cell work in a more efficient range, and improves the fuel economy of the hybrid electric vehicle. Figure 8 shows the curve comparison of fuel consumption between the management strategy based on distributed parameter model proposed in this paper and the management strategy based on efficiency tracking.

As can be seen from Figure 8, when the hybrid vehicle runs for 400s, the management strategy proposed in this paper is significantly lower than that based on the efficiency tracking management strategy. Although the hybrid vehicle multienergy management strategy based on distributed parameter model and the multienergy management strategy based on efficiency tracking proposed in this paper can meet the driving needs of hybrid vehicles, and the difference is small at the beginning of the experiment, but at the end of the experiment, obviously, the multienergy management method of hybrid electric vehicles based on distributed parameter model proposed in this paper has good overall performance and good fuel economy.

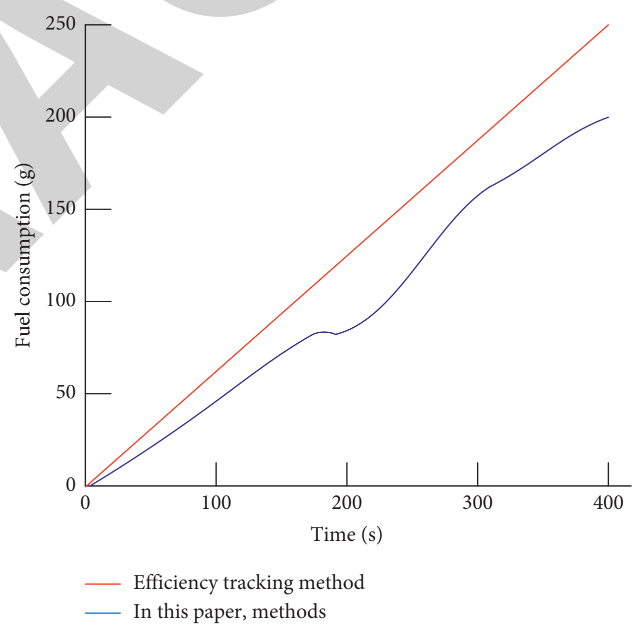

FIGURE 8: Comparison of fuel consumption curves of different management strategies.

6. Conclusions

(1) The mathematical model of the various parts of a hybrid electric car is created by utilizing a distributed parameter model, taking into account all of the characteristics of multienergy work of fuel cell, lithium battery, and supercapacitor. Through multienergy management based on reconstruction depth Q-learning mode, the minimum strategy of equivalent consumption is used as the basis to establish a multiobjective optimization function, The empirical playback mechanism of the summation tree

structure is introduced to improve the learning efficiency and convergence of deep Q-learning.

(2) Compared with the traditional deep Q-learning multienergy management and efficiency tracking established multienergy management, the method proposed in this paper can effectively improve the overall power performance of fuel cell hybrid vehicles, prolong the service cycle of batteries, and improve the fuel economy, which has a certain application value.

Data Availability

The data used to support the study are included in the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References

[1] Z. Hong, Q. Li, and R. Chen, "An energy management strategy based on PMP for the fuel cell hybrid system of locomotive," *Microcomputer Applications*, vol. 39, no. 13, pp. 3867–3878, 2019.

[2] Y. Zhao, J. Xie, and J. Shi, "Energy management strategy of fuel cell hybrid electric vehicle based on gentic algorithm-support vector machine condition recognition," *Science Technology and En gineering*, vol. 20, no. 14, pp. 5820–5827, 2020.

[3] X. Liu, Q. Li, and X. Zheng, "Energy management strategy of fuel cell vehicle based on multi-objective optimization," *Electronic Measurement Technology*, vol. 44, no. 6, pp. 81–89, 2021.

[4] Q. Wang, D. Li, and H. Miao, "Research on energy management strategy of fuel cell vehicle based on fuzzy logic control," *Automotive Engineering*, vol. 41, no. 12, pp. 1347–1355, 2019.

[5] Y. Wang, R. Dong, and Z. Wu, "Fuel cell vehicle energy management strategy based on fuzzy theory," *Science Technology and Industry*, vol. 21, no. 6, pp. 255–258, 2021.

[6] J. Li, "Research on Optimizing Energy Management Strategy of Fuel Cell Vehiclehttps://oss.wanfangdata.com.cn/file/download/perio_zgnyzyyqh201812019.aspx," *Agricultural Equipment & Vehicle Engineering*, vol. 58, no. 8, pp. 127–132, 2020.

[7] M. Zhang, Y. Yang, and Y. Luo, "Fuel cell vehicle energy management strategy based on fuzzy logic," *Electrical Automation*, vol. 42, no. 1, pp. 50–53, 2020.

[8] C. Ding, Y. Zhang, and Y. Shen, "Study on improved state machine energy management strategy for fuel cell vehicles," *Machine Building & Automation*, vol. 50, no. 2, pp. 181–184, 2021.

[9] W. Li, C. Zheng, and D. Xu, "Research on energy management strategy of fuel cell hybrid vehicles based on deep reinforcement learning," *Journal of Integration Technology*, vol. 10, no. 3, pp. 47–60, 2021.

[10] Q. Liu, Y. Zhan, and R. Li, "Research on a multi-objective optimization energy management strategy for fuel cell electric vehicles," *Electronic Measurement Technology*, vol. 43, no. 20, pp. 31–36, 2020.

[11] F. Naggar and A. Elgammal, "Multi-objective optimal predictive energy management control of grid-connected residential wind-pv-fc-battery powered charging station for plug-in electric vehicle," *Journal of Electrical Engineering &Technology*, vol. 13, no. 2, pp. 742–751, 2018.

[12] M. Gharibi and A. Askarzadeh, "Size and power exchange optimization of a grid-connected diesel generator-photovoltaic-fuel cell hybrid energy system considering reliability, cost and renewability," *International Journal of Hydrogen Energy*, vol. 44, no. 47, pp. 25428–25441, 2019.

[13] P. Nagaleshmi, "Solution for optimal power flow problem in wind energy system using hybrid multi objective artificial physical optimization algorithm," *International Journal of Power Electronics and Drive Systems*, vol. 10, no. 1, pp. 486–503, 2018.

[14] Y. Kim, V. Raghunathan, and A. Raghunathan, "Design and management of battery-supercapacitor hybrid electrical energy storage systems for regulation services," *IEEE Transactions on Multi-Scale Computing Systems*, vol. 3, no. 1, pp. 12–24, 2017.

[15] M. Zangeneh, E. Aghajari, and M. ForouzaNfAr, "Design and implementation of an intelligent multi-input multi-output Sugeno fuzzy logic controller for managing energy resources in a hybrid renewable energy power system based on Arduino boards," *Soft Computing*, vol. 26, no. 3, pp. 1459–1473, 2021.

[16] A. Rajendran and K. Narayanan, "A novel multi-objective hybrid WIPSO-GSA algorithm-based optimal DG and capacitor planning for techno-economic benefits in radial distribution system," *International Journal of Energy Sector Management*, vol. 13, no. 1, pp. 98–127, 2019.

[17] P. Annapandi, R. Banumathi, N. Pratheeba, and A. A. Manuela, "Power flow management scheme of hybrid renewable energy source to maximize power transfer capability using I2HOSOA approach," *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 3, pp. 4159–4181, 2020.

[18] B. N. Alhasnawi and B. H. J. Jasim, "A novel hierarchical energy management system based on optimization for multi-microgrid," *International Journal on Electrical Engineering and Informatics*, vol. 12, no. 3, pp. 586–606, 2020.

[19] A. Agrawal and R. Gupta, "Power management and operational planning of multiport HPCS for residential applications," *IET Generation, Transmission & Distribution*, vol. 12, no. 18, pp. 4194–4205, 2018.

[20] A. Elgammal and D. Ali, "Self-regulating active power filter compensation scheme for hybrid photovoltaic-fuel cell renewable energy system for smart grid applications," *International Journal of Renewable Energy Resources*, vol. 7, no. 2, pp. 513–524, 2017.