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HYBRID ELECTRIC VEHICLE ENERGY MANAGEMENT STRATEGY BASED ON GENETIC ALGORITHM

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Abstract. A genetically optimized fuzzy control algorithm is used to realize the parallel hybrid system's real-time energy distribution between the engine and the electric motor. This paper first adopts fuzzy control to improve the robustness and real-time performance of the entire system. Then, a membership function optimization method based on a genetic algorithm is proposed by simulating the working state of CYCUDDS. Simulation experiments show that compared with unoptimized fuzzy control, the improved fuzzy controller can improve the vehicle's fuel economy and prevent continuous battery discharge, thereby improving battery endurance.

Key words: Genetic Algorithm; Hybrid electric vehicle; Battery optimization; Energy management; Fuzzy control

1. Introduction. Hybrid vehicles use a design that combines an internal combustion engine with an electric transmission, making the structure of the entire vehicle more complex. As the core of new energy vehicle control, its energy management method is the focus of its research. Adjusting and operating the motor within the effective range can save energy and reduce emissions. Literature [1] studies the operation mode of hybrid drive military hybrid vehicles. Improve vehicle fuel economy by building logical connections and state transitions between operating modes. However, its theoretical basis is based on experience. Literature [2] established a regular energy consumption control model for HEV and used algorithms such as genetic algorithm and quadratic programming to optimize the model's threshold value to improve the vehicle's fuel economy. However, the author only optimized it under local working conditions. Literature [3] uses wavelet analysis to separate high-frequency and low-frequency signals in load forecasting. Use wavelet transform to establish load forecasting model. using neural networks to train and predict high-frequency and low-frequency signals. The project achieved a 2.37% reduction in fuel consumption. Literature [4] combines variable prediction area RBF network and Q-learning to construct a battery state-of-charge energy management strategy under dynamic operating conditions. The project results achieved improvements in fuel economy. Therefore, this project plans to take the single-row star hybrid vehicle system as the research object and use the working condition information obtained from the actual vehicle test. Working condition information trains, the vehicle speed prediction model [5]. Genetic algorithm fuzzy control and other methods are used to establish the optimal optimization control problem in the short-term forecast area. A hybrid power system's energy consumption management method is studied using working condition speed prediction and differential evolution methods. The hybrid vehicle system's energy-saving and emission-reduction goals can be achieved.

2. Vehicle parameter matching and modeling. The main parameters of the vehicle in the hybrid system are directly related to the working status of the system, so how to select appropriate parameters is a critical link in the development of the entire system.

2.1. Maximum speed is used as the basis to calculate the total power of the system. When half the vehicle's weight is $m_a = 1750$ kg, the maximum speed $V_{\max}$ of the vehicle is expected to reach 200 km/h, and the total electric power $P_{v\max}$ with speed as the target can be determined by formula (2.1).

$$P_{v\max} = \frac{1}{\zeta_T}\left(\frac{m_a chV_{\max}}{3600} + \frac{Z_\beta AV_{\max}^3}{76140}\right)$$

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ζ_T is the overall efficiency of the entire power system, and 0.9 is selected as the calculation parameter. c represents the gravitational factor, $N/\text{kg}.h$ is the rolling resistance factor. Z_β is the drag factor. A is the headwind side of the car, m^2.

2.2. Determine the total power based on the maximum gradient. The obstacle-crossing performance of a car is the maximum slope it can climb on a good road. Due to the total weight $m_h = 2000$ kg, its maximum climbing slope can reach $\theta_{\max} = 35\%$ when the speed is $V_\delta = 30$ km/h, and the total power $P_{\delta\max}$ taking the slope as the target is determined by the formula (2.2).

$$P_{\delta\max} = \frac{1}{\zeta_T}\left(\frac{m_a chV_\delta}{3600} + \frac{Z_\beta AV_\delta^3}{76140} + \frac{m_a c\theta_{\max}V_\delta}{3600}\right)$$

The total power $P_{\delta\max} = 67$ kW with the slope as the target can be calculated from formula (2.2). The maximum power of the power supply must meet the following dynamic index:

$$P_{\max} > \max\left(P_{v\max}, P_{\delta\max}\right)$$

3. Battery model. A lithium-ion battery energy storage system is proposed using the constant rate method. If it is driven at a constant speed at a speed of $V_e = 60$ km/h in a pure electric state, it is expected to cover 60 kilometers. In this process, the electric motor supplies all the power required by the vehicle [6]. The total capacity required by the battery at this time is obtained through formula (2.4).

$$\begin{cases} W_\varphi\zeta_\varphi = \int_0^T P_m dT \\ P_m = \frac{V_e}{3600\zeta_T}\left(m_a ch + \frac{Z_\beta AV_e^2}{21.15}\right) \\ T = 3600\frac{S}{V_e} \\ Z = \frac{1000W_\varphi}{U} \end{cases}$$

ζ_φ is the battery discharge efficiency. T is the driving time. P_m is the motor working power, kW.W_φ is the total energy required by the battery, kW $\cdot$ h.Z is the battery capacity. U is the voltage level, V.

3.1. Transmission system model. The maximum power point also corresponds to the maximum rotational speed, so when the maximum vehicle speed $V_{\max} = 200$ km/h, the rotational speed n is 6000 .

$$V_{\max} = 0.377\frac{nd}{\theta_c\theta_0}$$

d is the radius of the wheel rotation. θ_c is the speed of the transmission system. θ_0 is the transmission ratio of the main reduction gear transmission. The maximum reduction ratio calculation formula is based on the maximum climbing slope.

$$\frac{T_{\max}\theta_c\theta_0\zeta_T}{d} = m_h ch\cos\delta + m_h c\sin\delta$$

4. Calculation of vehicle torque. The torque required by the vehicle is calculated based on the vehicle operating equilibrium equation of the vehicle power system [7]. This provides a basis for the formulation of energy control plans.

$$T_{tq} = \frac{d}{\theta_c\theta_0\zeta_T}\left(Gh + \frac{Z_d AV_e^2}{21.15} + Gi + \delta m\frac{du}{dt}\right)$$

T_{tq} is the torque required by the entire vehicle. θ_c is the transmission ratio. θ_0 is the primary reducer speed ratio. ζ_T is the drive train efficiency. G is the gravity of the vehicle. h is the rolling resistance coefficient. Z_d is the air resistance coefficient. A is the windward area of the vehicle. u is the vehicle speed. θ is the slope. δ is the car rotation mass conversion coefficient. m is the vehicle mass.

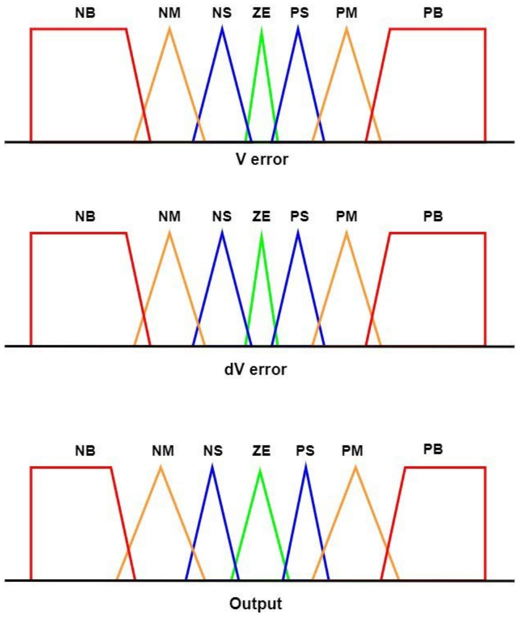


Fig. 5.1: *Input variable membership function.*

5. Fuzzy control algorithm. The energy flow distribution rules of internal combustion engines and electric motors under different working conditions are studied to achieve adequate control of energy saving and emission reduction [8]. Therefore, this paper proposes a method based on fuzzy control.

5.1. Input and output of variables. The fuzzy control method can ensure that the engine operates within the efficient range and the balance of the battery charge state [9]. This paper uses the torque S_d required by the car and the battery charging status as input quantities and carries out fuzzy control based on this. Take the engine torque S_a as the output variable.

5.2. Membership function. In designing the fuzzy controller, we must first determine its degree of belonging and, secondly, determine the segmentation point appropriately and try to select the appropriate fuzzy subset [10]. The membership degrees of input and output are partitioned based on the actual working conditions of parallel hybrid vehicles. The demand torque S_d is divided into five fuzzy subgroups $\{\alpha, \beta, \gamma, \delta, \varepsilon\}$, whose domains are [-6o,6o], respectively. The adaptive battery state of charge of the battery pack is divided into five fuzzy subsets $\{\zeta, \eta, \theta, l, \kappa\}$, whose domains are [o,1], respectively. The engine's range output depends on its accurate output torque, and its range is $\{40, 43, 45, 48, 51, 53, 56, 58,$ 6o$\}$. According to the characteristics of the fuzzy sub-region, the ladder-like membership function is selected to obtain accurate control output. Figure 3.1 shows the input variable membership function.

5.3. Fuzzy control rules. It is necessary to fully use the control system's actual work experience and fully consider the input and output characteristics of the controlled system. One is that the engine drives the car independently while the battery is charging. When the required torque exceeds the maximum torque the engine can carry, the motor will assist the engine in driving the car. Second, when the battery charge is small, and the power characteristics of the electric vehicle are maintained, the engine distributes appropriate torque to the battery for charging. When the maximum torque equals the required torque, the engine's power characteristics should first be considered [11]. Third, the engine will automatically stop when the speed is low. In this case, the engine runs independently, reducing fuel consumption. Fourth, the engine and motor drive the car together to achieve high-load operation. An input/output relationship mapping diagram (Figure 3.2) was developed for the abovementioned situation.

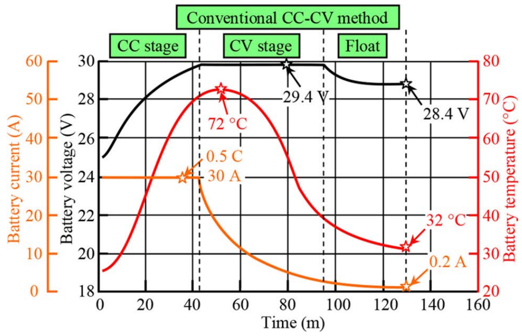


Fig. 5.2: *Input/output relationship map diagram.*

6. Membership function optimization based on fuzzy control. Due to the traditional manual judgment method, selecting member weights in fuzzy control systems is often subjective, and it isn't easy to achieve the overall optimal. Therefore, it must be optimized to achieve the system's optimal control effect [12]. It is often difficult to obtain optimal results using classical optimization methods for more complex problems, such as parameter optimization of membership functions. This paper proposes a multi-objective optimization method based on genetic algorithms at this time.

6.1. Initialize the overall. This paper proposes a fuzzy controller design method based on a genetic algorithm. Since the decimal chromosome has a short length, high accuracy, fast operation speed, and good stability to the population of mutation operations, we use the decimal encoding method. As can be seen from Figure 4.1, X1, X2, X3, and X4 each represent subdivisions corresponding to their respective functions. Since all lines of input and output need to be encoded, a one-dimensional decimal matrix with a length of 49 is finally generated [13]. In this matrix, X1-X20 is the code of the required torque membership function, and X21-X40 is the membership of the battery. Degree function codes, X41X49, are engine output torque membership function codes.

6.2. Selection of fitness function. Optimum fuel consumption and minimum exhaust emissions conflict with each other in most operating ranges and are consistent in only a few. The engine must be kept within this range as much as possible to achieve optimal control [14]. For this purpose, the exhaust gas, fuel consumption and other indicators under actual working conditions are selected, and the optimized objective function is obtained by weighting each indicator.

$$G(x) = \frac{1}{\psi_1 + \psi_2 + \psi_3 + \psi_4} \times$$
$$\left(\psi_1 \int_0^s \frac{Q}{Q} dt + \psi_2 \frac{HC}{HC} dt + \psi_3 \int_0^s \frac{NO_x}{NO_x} dt + \psi_4 \int_0^s \frac{CO}{CO} dt \right)$$

x represents a marker that corresponds to the chromosome number. $\psi_1, \psi_2, \psi_3, \psi_4$ represents the corresponding weighted value. Q is fuel consumption. HC stands for hydrocarbon emissions. NO_x stands for the release of nitrogen oxides. CO stands for the release of carbon monoxide. $\bar{Q}, \overline{HC}, \overline{NO_x CO}$ is the optimal reference value corresponding to each parameter. $\psi_1 = 0.7, \psi_2 = \psi_3 = \psi_4 = 0.1$ is used to determine the weight of each optimization index when performing optimization.

6.3. Operation parameter setting. The group size is directly related to species diversity and production efficiency. If it is too small, the species diversity of the species will decrease, and if it is too large, it will be detrimental to production. The roulette method is used for personal selection. When performing crosses, two cut-point crosses were selected, and the probability of crosses was 0.9; because the mutation rate of this variety is relatively low, it was set at 0.01; the maximum number of gene generations was set at 50.

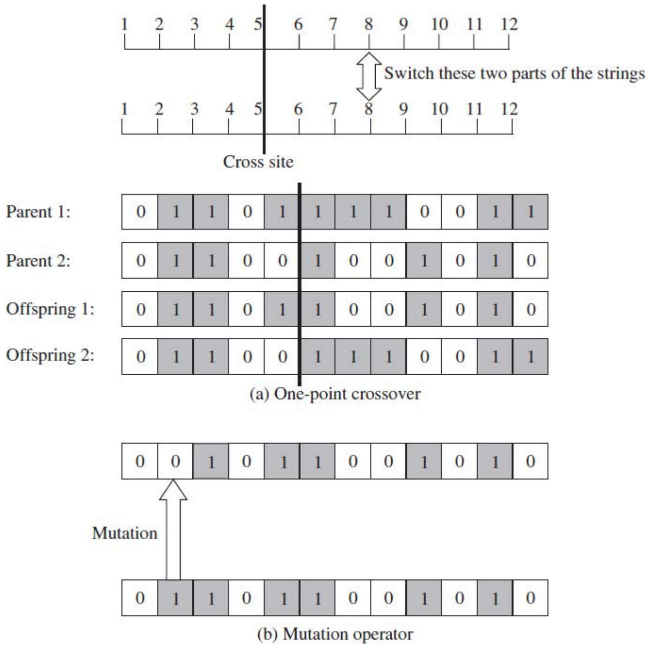


Fig. 6.1: *Decimal encoding method.*

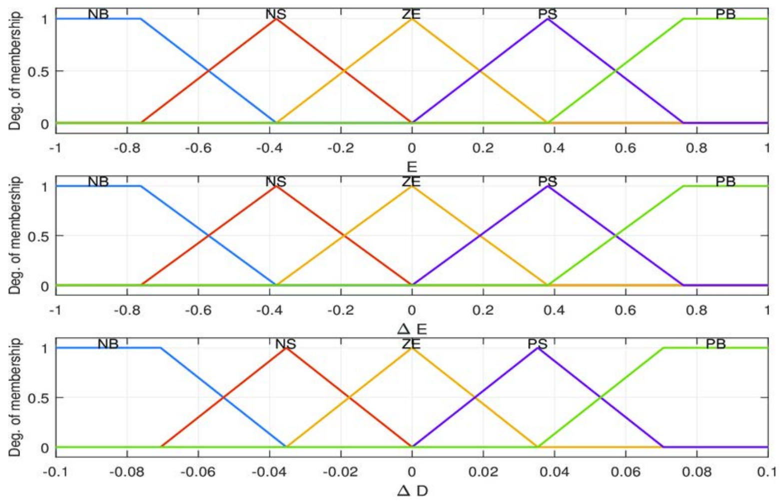


Fig. 6.2: *Optimized input variable membership function.*

6.4. Optimization results. Genetic algorithms optimize and adjust it continuously, taking parallel hybrid power as the object. Finally, the optimal membership function is given, as shown in Figure 4.2.

7. Simulation analysis. This project plans to use Intel(R) Core (TM) i7-9700CPU@3.00GHz computer, use Python language to implement the rate prediction of GRU-NN and implement rapid prediction of the model through Python programming [15]. Call the data of the genetic algorithm speed prediction model for simulation. The primary performance indicators of the car and the relevant parameters of the differential evolution algorithm are shown in Table 5.1 and Table 5.2.

This project plans to use a combination of genetic and differential evolution algorithms to compare fuel

Table 7.1: *Vehicle parameters.*

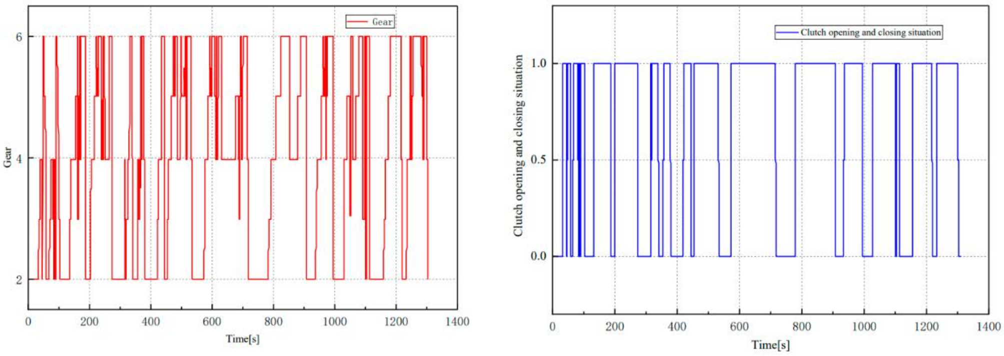
Part	**Parameter**	**Numerical value**
	Vehicle mass/kg	1425
Vehicle parameters	Windward area/m^2 rolling resistance coefficient drag coefficient Tire radius/m Main reducer transmission ratio Maximum speed/$(r \cdot min^{-1})$	1.819 0.014 0.313 0.299 4.094 6250
Engine	Maximum output power/kW Maximum speed/$(r \cdot min^{-1})$	58 6250
Motor MG1 Motor MG2	Maximum torque/$(N \cdot m)$ Maximum speed/$(r \cdot min^{-1})$	318 5729
	Maximum torque/$(N \cdot m)$ Capacity/$(A \cdot h)$	57 6.8
Power Battery	SOC Sun gear teeth	0.45 0.75 31
Planetary gear	Number of teeth of the ring gear	81

Table 7.2: *A-DE algorithm parameters.*

Parameter	**Numerical value**
Initial population size	21
Number of iterations	100
Intrinsic coefficient of variation	0.52
Crossover probability	0.31

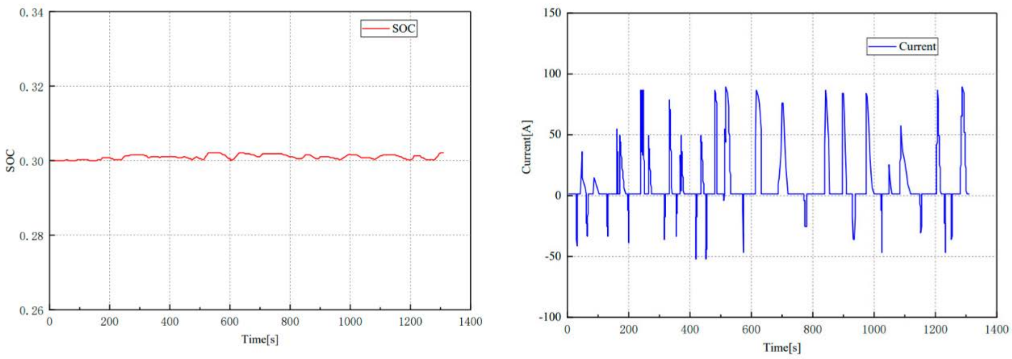
consumption with three optimization methods: optimal system dynamics optimization and minimum equivalent fuel consumption, in which the adaptive battery state of charge is taken as 0.55. This project plans to use a reverse algorithm to analyze the optimal driving parameters of each stage and the minimum fuel consumption value of each stage from the final state. A forward iteration method obtains the optimal driving mode under each operating condition. And optimize each operating condition of this mode to achieve the optimal configuration of the best operating mode for each working condition [16]. This enables effective control of the startup MG1 and MG2 operating modes. Fuel consumption is shown in Table 5.1. The power distribution of the engine, motor MG1 and motor MG2 is shown in Figure 5.1, and the motion trajectory of the adaptive battery state of charge is shown in Figure 5.2.

The final value of the adaptive battery state of charge controlled by the genetic algorithm fuzzy control is 0.5448, the fuel consumption is 3.4510 L/100 km, and the fuel economy is 93.04%, which is 4.55% lower than the differential evolution and dynamics planning (Table 5.3). Figure 5.1 shows that the starting power of the differential evolution and dynamic planning strategies is maximum in the first 300 seconds, while the genetic algorithm fuzzy control maintains the engine power's stability, and power planning reduces the engine starting time. The MG1 motor using differential evolution produces large oscillations during operation, but using genetic algorithm fuzzy control can keep the output of MG1 stable. Therefore, the adaptive battery state of charge under fuzzy control in Figure 5.2 will experience more excellent attenuation in the early stages, and the power planning will undergo more significant changes. At the same time, the differential evolution algorithm maintains a stable, highly adaptive battery charge—electrical state. In the subsequent high-speed range, the genetic algorithm fuzzy control is used to maintain a more stable number of starts and a more appropriate engine power. At the same time, differential evolution has problems with the high number of starts, high starting power consumption, and adaptive battery state-of-charge changes during working conditions—big questions. During the entire driving process, the output power of the engine when starting and stopping the dynamic planning



(**a**) (**b**)

Fig. 7.1: *Power distribution under different methods and strategies.*



(**a**) (**b**)

Fig. 7.2: *SOC trajectory.*

Table 7.3: *Experimental results.*

Method strategy	**Final value SOC (T)**	**Fuel consumption/ [L · (100km)$^{-1}$]**	**Fuel economy/%**
Dynamic programming	0.573	3.361	100
Genetic Algorithm Fuzzy Control	0.568	3.595	96.917
Differential Evolution Algorithm	0.563	3.766	88.490

strategy is greater than the other three control methods, resulting in high fuel consumption, while the genetic algorithm fuzzy control always maintains a small adaptive battery state-of-charge change interval, thereby preventing the harm to the battery caused by changes in the adaptive battery state of charge.

8. Conclusion. It was found that all three solutions can keep the battery's state of charge at equilibrium. Before and after optimization, the SOC value decreased by 0.0427 and 0.0063. By improving this method, the battery's state of charge changes significantly, thereby improving the battery's endurance. In addition, the battery's state of charge before optimization was finally 0.6865. After optimization, the battery state of charge showed a trend from low to high over time and finally stabilized around 0.7260, indicating that the optimized electric vehicle braking system performs better. The working condition distribution of the optimized engine is relatively scattered, making it difficult to always be in an efficient working range when facing various working conditions. Each working point can work in a relatively dense area, and most of the working points are located in the high-efficiency area using this method.

REFERENCES

[1] Guzs, D., Utans, A., Sauhats, A., Junghans, G., & Silinevics, J. (2022). Resilience of the Baltic power system when operating in island mode. IEEE Transactions on Industry Applications, 58(3), 3175-3183.

[2] Ding, N., Prasad, K., & Lie, T. T. (2021). Design of a hybrid energy management system using designed rule-based control strategy and genetic algorithm for the series-parallel plug-in hybrid electric vehicle. International Journal of Energy Research, 45(2), 1627-1644.

[3] Sidharthan Panaparambil, V., Kashyap, Y., & Vijay Castelino, R. (2021). A review on hybrid source energy management strategies for electric vehicle. International Journal of Energy Research, 45(14), 19819-19850.

[4] Li, J., Zhou, Q., Williams, H., Xu, H., & Du, C. (2021). Cyber-physical data fusion in surrogate-assisted strength pareto evolutionary algorithm for PHEV energy management optimization. IEEE Transactions on Industrial Informatics, 18(6), 4107-4117.

[5] Wang, L., Li, M., Wang, Y., & Chen, Z. (2021). Energy management strategy and optimal sizing for hybrid energy storage systems using an evolutionary algorithm. IEEE Transactions on Intelligent Transportation Systems, 23(9), 14283-14293.

[6] Yuan, H. B., Zou, W. J., Jung, S., & Kim, Y. B. (2022). Optimized rule-based energy management for a polymer electrolyte membrane fuel cell/battery hybrid power system using a genetic algorithm. International Journal of Hydrogen Energy, 47(12), 7932-7948.

[7] Raboaca, M. S., Bizon, N., & Grosu, O. V. (2021). Optimal energy management strategies for the electric vehicles compiling bibliometric maps. International Journal of Energy Research, 45(7), 10129-10172.

[8] Zhang, J., Roumeliotis, I., & Zolotas, A. (2021). Nonlinear model predictive control-based optimal energy management for hybrid electric aircraft considering aerodynamics-propulsion coupling effects. IEEE Transactions on Transportation Electrification, 8(2), 2640-2653.

[9] Ray, P., Bhattacharjee, C., & Dhenuvakonda, K. R. (2022). Swarm intelligence-based energy management of electric vehicle charging station integrated with renewable energy sources. International Journal of Energy Research, 46(15), 21598-21618.

[10] Kandidayeni, M., Trovão, J. P., Soleymani, M., & Boulon, L. (2022). Towards health-aware energy management strategies in fuel cell hybrid electric vehicles: A review. International Journal of Hydrogen Energy, 47(17), 10021-10043.

[11] Gharibeh, H. F., Yazdankhah, A. S., Azizian, M. R., & Farrokhifar, M. (2021). Online energy management strategy for fuel cell hybrid electric vehicles with installed PV on roof. IEEE Transactions on Industry Applications, 57(3), 2859-2869.

[12] Król, A., & Sierpiński, G. (2021). Application of a genetic algorithm with a fuzzy objective function for optimized siting of electric vehicle charging devices in urban road networks. IEEE Transactions on Intelligent Transportation Systems, 23(7), 8680-8691.

[13] Wang, X., Wang, R., Shu, G., Tian, H., & Zhang, X. (2022). Energy management strategy for hybrid electric vehicle integrated with waste heat recovery system based on deep reinforcement learning. Science China Technological Sciences, 65(3), 713-725.

[14] Boukoberine, M. N., Donateo, T., & Benbouzid, M. (2022). Optimized energy management strategy for hybrid fuel cell powered drones in persistent missions using real flight test data. IEEE Transactions on Energy Conversion, 37(3), 2080-2091.

[15] Liu, Q., Lanfermann, F., Rodemann, T., Olhofer, M., & Jin, Y. (2023). Surrogate-assisted many-objective optimization of building energy management. IEEE Computational Intelligence Magazine, 18(4), 14-28.

[16] Yang, C., Zha, M., Wang, W., Yang, L., You, S., & Xiang, C. (2021). Motor-temperature-aware predictive energy management strategy for plug-in hybrid electric vehicles using rolling game optimization. IEEE Transactions on Transportation Electrification, 7(4), 2209-2223.

[17] Hou, Z., Guo, J., Xing, J., Guo, C., & Zhang, Y. (2021). Machine learning and whale optimization algorithm based design of energy management strategy for plug-in hybrid electric vehicle. IET Intelligent Transport Systems, 15(8), 1076-1091.

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