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An Improved Energy Management Strategy for 24t Heavy-Duty Hybrid Emergency Rescue Vehicle With Dual-Motor Torque Increasing

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ABSTRACT Emergency rescue vehicles are special equipment for fire, flood, earthquake and other disasters. They need to have high efficiency and high mobility under various terrain and road conditions. The fuel economy of emergency rescue vehicles is very poor in climbing and complex terrain due to the heavy weight of vehicle chassis and upper loading. The dual-motor torque increasing hybrid power system designed in this paper greatly improves the dynamic performance and mobility of emergency rescue vehicles, and the use of dual-motor drive in steep slopes and complex terrain can avoid the engine working in low efficiency area. In order to further improve the fuel economy of vehicles under various working conditions, a fuzzy logic control strategy based on improved particle swarm optimization (PSO) is proposed in this paper. The torques of engine and dual-motor are reasonably distributed under different working conditions. A novel fuzzy parameter optimization mode is designed, which reduces the workload of optimization calculation and ensures the optimization accuracy. The off-line simulation and hardware-in-the-loop experiments are carried out for the dual-motor torque increasing hybrid power system model and the proposed improved energy control strategy. The results show that the fuzzy logic control strategy optimized by simulated annealing particle swarm optimization algorithm (SimuAPSO-FLC) has the best effect and meets the requirements of high efficiency, high mobility and stability of the emergency rescue vehicle.

INDEX TERMS Energy management strategy, SimuAPSO-FLC, 24t heavy-load hybrid emergency rescue vehicle, dual-motor torque increasing.

I. INTRODUCTION

A. LITTERATURE REVIEW

Due to the special application of emergency rescue vehicles, they need to respond quickly after disasters and accidents, to drive at high speed on flat roads, to adapt to various terrain and road conditions, and to be able to carry heavy upper loading, etc. Frequent changes in working conditions will make the engine efficiency very low, and then the fuel economy and rapid response of the vehicle are poor. The multi-power sources hybrid electric system can adapt to different driving conditions by changing the energy distribution between the several power sources, thereby it can improve the rapid response and fuel economy of the emergency rescue vehicle.

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As the core part of the hybrid electric system, energy management strategies have a direct impact on vehicle performances. Among the current energy management strategies, the torque-based parallel control strategy is the most studied, which is mainly divided into two categories: one is rule-based control strategy, and the other is strategy based on optimization algorithm [1]–[4]. The rule-based control strategy includes the static logic threshold control strategy with deterministic rules and the fuzzy logic control strategy. Early studies mainly adopted this kind of strategy. Its main idea is to determine the torque distribution and working status of the hybrid system by setting a series of established rules. The static logic threshold control strategy[5-8] has simple algorithm and strong real-time performances, which is the most widely used strategy at present. However, since the thresholds and rules are set according to experience and are static, it is impossible to ensure its optimality or follow the dynamic changes of working conditions. In comparison, the control strategy based on fuzzy rules has better robustness and adaptability [9]–[13]. However, the establishment of fuzzy rules and the determination of membership functions still rely on experience, so the simple fuzzy control is not very adaptable to different driving conditions. The combination of fuzzy control strategy and other intelligent optimization algorithms can make up for some shortcomings of fuzzy control and achieve good results [14]–[17]. The control strategy based on optimization algorithm includes real-time optimization control strategy and global optimal control strategy. The core idea of real-time optimization control strategy is to minimize energy loss as much as possible during energy flow at any time, which is generally divided into equivalent consumption minimum strategy (ECMS) [18]–[20] and the control strategy based on model prediction [21]–[23]. However, the real-time optimization control strategy can only ensure that each step is optimal, but cannot ensure the global optimization, so it is difficult to apply in practice. The global optimal control strategy can achieve the global optimization in offline states, which is widely studied at present. The most widely used intelligent optimization algorithms mainly include genetic algorithm [24]–[26], simulated annealing (SA) algorithm [27], particle swarm optimization (PSO) algorithm [14], [28]–[32], and other intelligent optimization algorithm strategies.. In addition, the neural network, working condition recognition, machine learning and other technologies are used to design energy management strategies [33]–[39]. The above algorithms have their own advantages, but there are still some spaces for improvement, including the setting of optimization parameters and optimizing strategies.

B. MAIN CONTRIBUTIONS

In this paper, a new method of fuzzy control parameter configuration is proposed considering the optimization accuracy and difficulty, and the simulated annealing algorithm is introduced into the improved PSO algorithm, which absorbs the advantages of fast convergence speed, simple algorithm, high optimization efficiency and good optimizing ability. At the same time, it can avoid the defects that PSO algorithm is prone to "premature" and fall into a local extemum and unable to jump out by itself. The experimental results verify that the SimuAPSO-FLC strategy can satisfy the dynamic requirements of the emergency rescue vehicle, and greatly reduce the fuel consumption.

II. CONTROL MODEL OF THE HYBRID ELECTRIC SYSTEM

The structure parameters and performance indicators of the emergency rescue vehicle studied in this paper are shown in Table 1. And the vehicle chassis structure designed according to the vehicle performance requirements is shown in FIGURE 1.

The vehicle is a multi-power sources hybrid system. The rear axle is driven by a single-motor, which is working at a pure electric mode. The required power of the motor is provided by the battery pack. The front axle is driven by a single-shaft parallel hybrid system, while the engine and the motor/generator can operate independently or jointly. When the required torque is very high, the motor/generator is used as a motor. When the battery power is insufficient during driving, the battery pack can be charged by the engine, which can drive the motor/generator as a generator; and the energy can also be recovered into the battery pack by the generator during braking.

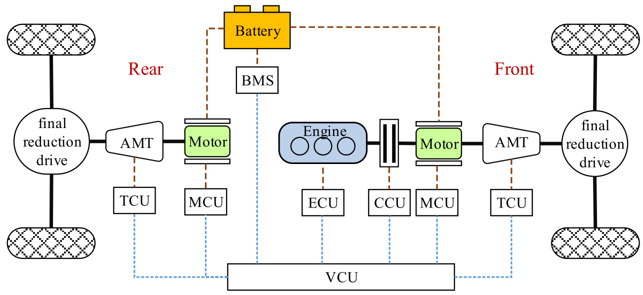

FIGURE 1. Schematic diagram of vehicle chassis structure.

TABLE 1. Parameters and performance indicators of the vehicle.

Name	Design Values
Vehicle mass	24000kg
Distance from gravity center to front wheel	3.164m
Gravity center height	1.672m
Frontal Area	7.25m^2
Drive wheel radius	0.72m
Wheelbase	5.2m
Maximum driving speed	≥100km/h
Maximum climbable gradient at 3.5km/h	≥60%

TABLE 2. Parameters of the vehicle components.

Name	Design Values
Peak power of engine	265kW
Peak torque of engine	1800N·m
Peak power of front motor/generator	130kW
Peak torque of front motor/generator	1000N·m
Peak power of rear motor	140kW
Peak torque of rear motor	1200N·m
Battery capacity	50.45kWh
Maximum charge/discharge current	2C
Automatic transmission gear	6.39/3.97/2.40/1.48/1/0.73

This vehicle chassis structure can ensure the dynamic performance of the 24t heavy-load emergency rescue vehicle. The parameters of main components in the hybrid electric system are shown in TABLE 2.

The schematic diagram of the vehicle control system is shown in FIGURE 2. The acceleration or braking of the vehicle is determined by comparing the expected speed with the actual speed. If the expected speed is greater than the actual speed, the vehicle will be accelerated; and if the expected speed is less than the actual speed, the vehicle will be braked. The driver model outputs the driving required power (or required braking force), and the energy management strategy distributes the required power (or braking force) to the engine,

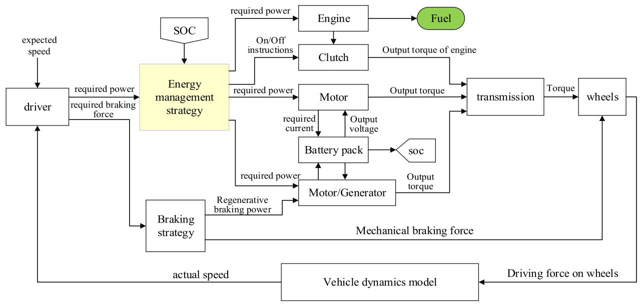

FIGURE 2. Control system diagram of the hybrid vehicle.

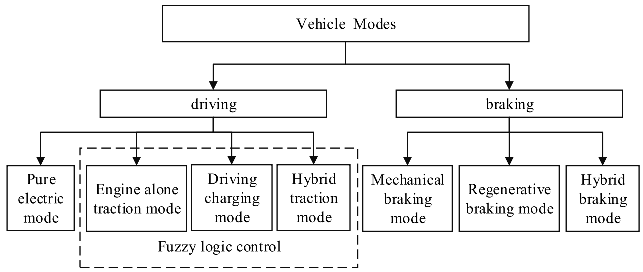

FIGURE 3. Vehicle working modes.

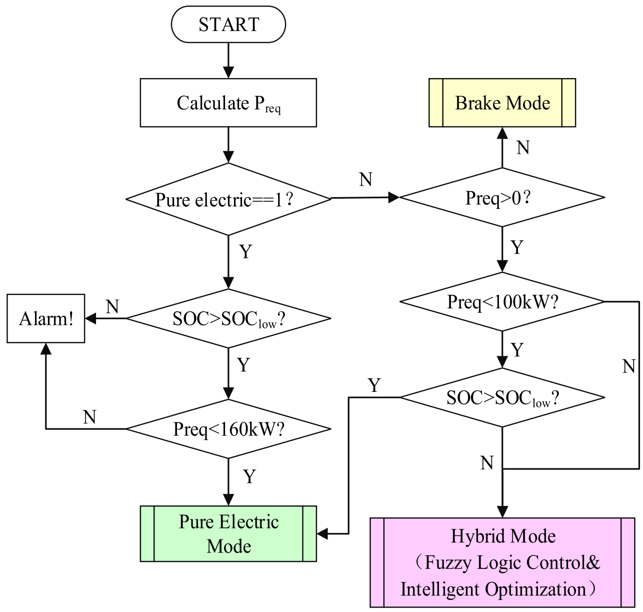

FIGURE 4. Flow chart of the energy management strategy.

the motor/generator, and the pure motor according to the set rules. Then the torque output from the three power sources is collected to the transmission system and four wheels to make the vehicle accelerate or brake. The energy management strategy in FIGURE 2 is the focus of this research, and the ''Fuel'' is the target value we most focus on.

III. DESIGN OF VEHICLE ENERGY MANAGEMENT STRATEGY

According to different working conditions, there are 5 driving modes can be used: pure electric traction mode, engine alone traction mode, engine traction and generation (driving charging) mode, engine and motor hybrid traction mode (hybrid traction mode) and braking mode. When the vehicle required power is relatively small (less than 100kW) and the state of charge (SOC) of the battery pack is greater than the minimum allowable value ($SOC > SOC_{low}$), the vehicle is driven in pure electric traction mode. In this case, the battery pack is discharged to supply the two motors to operate in electric mode, and the principle of energy distribution in this mode is shown as follows:

$$\begin{cases} P_{mf\_req} = \min(P_{req}, P_{mf\_r}) \\ P_{mr\_req} = P_{req} - P_{mf\_req} \\ P_{e\_req} = 0 \end{cases} \tag{1}$$

where, P_{req} is the total required power of the vehicle, P_{e_req} is the required power of the engine, P_{mf_req} is the required power of the front axle motor, P_{mr_req} is the required power of the rear axle motor, and P_{mf_r} is the rated output power of the front axle motor.

When the required power of the vehicle is large (greater than 100kW) or the discharge condition of the battery pack is not satisfied ($SOC < SOC_{low}$), the fuzzy logic control strategy is used to determine the working mode, as shown in FIGURE 3.

When the pure electric switch of the vehicle is turned on, the vehicle will run in the pure electric mode if the battery pack SOC is in the dischargeable range and the vehicle required power is less than 160kW. If not, the system alarms. When the pure electric switch of the vehicle is turned off, and if the required power is positive, the vehicle will run in the driving mode. Otherwise, it will run in the braking mode. If the power is less than 100kW and the SOC is in the dischargeable range, the vehicle will also run in the pure electric mode, otherwise the vehicle control mode is determined by the fuzzy logic control strategy. The control strategy flowchart is shown in FIGURE 4.

The purpose of the fuzzy logic control strategy is to reasonably allocate the required power to the engine, the battery pack and two motors through certain rules, so that they all work in their respective high-efficiency areas (FIGURE 5), so as to achieve the purpose of reducing fuel consumption and improving the economy on the premise of matching the dynamic requirement. The principle of the fuzzy logic control strategy is shown in FIGURE 6.

A. DETERMINATION OF FUZZY VARIABLES

Appropriate fuzzy variables have a great influence on the control performance of the system. The input variables that can be used in this system include vehicle required torque, required power, vehicle speed, pedal angle and battery pack SOC, etc. The output variables include required power of engine, required power of two motors and required power of battery pack, etc.

In order to simplify the fuzzy logic control system and reduce the amount of fuzzy calculation, the engine load factor $\lambda(\lambda = P_{req}/P_{e\_\max})$ and battery pack SOC are selected as the inputs of the fuzzy controller, and the engine power

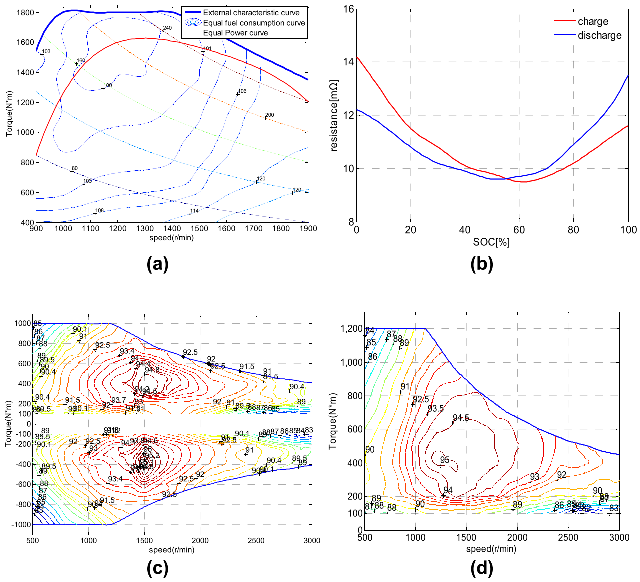

FIGURE 5. *(a)* **Engine fuel consumption characteristics map;** *(b)* **SOC-Rint Curve of the battery pack;** *(c)* **motor/Generator (front axle) efficiency MAP;** *(d)* **Motor (rear axle) efficiency MAP.**

distribution coefficient $k_e (k_e = P_{e\_req}/P_{req})$ is selected as the output of the fuzzy controller.

Here, P_{req} is the total required power of the vehicle, $P_{e\_\max}$ is the maximum power that the engine can provide at the current speed, and P_{e_req} is the target required power of the engine.

According to the working principle of the system, the required power of the engine is $P_{e\_req} = k_e \cdot P_{req}$, the required power of the battery pack is $P_{bat\_req} = (1 - k_e) \cdot P_{req}$, and the required power of the two motors is shown as follows:

$$\begin{cases} P_{mf\_req} = P_{mr\_req} = \frac{1}{2} P_{bat\_req}, & P_{bat\_req} > 0 \\ P_{mf\_req} = P_{bat\_req}, P_{mr\_req} = 0, & P_{bat\_req} < 0 \end{cases} \tag{2}$$

B. VARIABLE FUZZIFICATION

When the vehicle is under light-load, the required power is less than the maximum power of the engine ($\lambda < 1$), and the vehicle can be operated in the engine alone traction mode or in the driving charging mode; when the vehicle is under heavy-load, the required power is greater than the maximum power of the engine ($\lambda > 1$), in this case the electric motor is required to supplement the power and the vehicle runs in the hybrid traction mode. According to the performance parameters of the engine, the electric motors and the battery pack, the actual universe of the engine load factor is taken as $\lambda \in [0.3, 2.0]$, and the fuzzy subset is set to be $= \{$Very Small, Medium Small, Medium, Medium Big, Very Big$\} = \{$VS, MS, M, MB, VB$\}$.

It can be seen from the SOC-Rint curve of the battery pack (FIGURE 5(b)) that when the SOC value is between 0.4 and 0.8, the internal resistance of the battery is small and the working efficiency is relatively high. Therefore, the battery SOC should be controlled within this range as far as possible

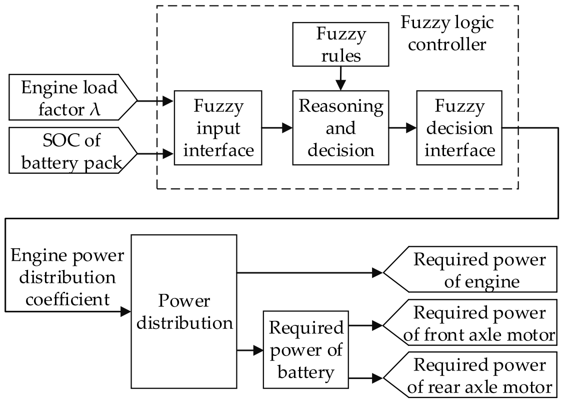

FIGURE 6. Working principle of fuzzy logic control for vehicle energy distribution.

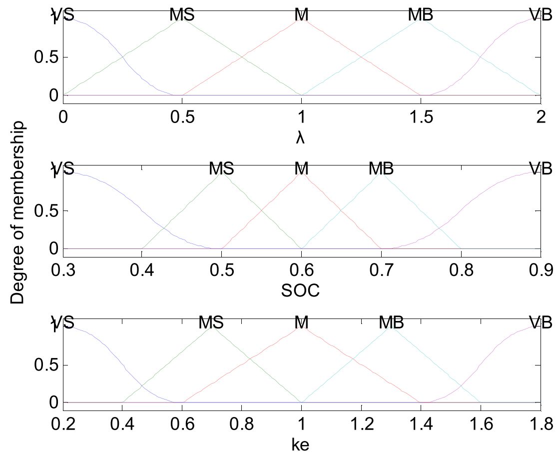

FIGURE 7. Fuzzy control input/output membership functions.

during the vehicle driving. When the SOC is lower than 0.4, the battery pack is no longer discharged and the vehicle will run in the driving charging mode. When the SOC is higher than 0.8, the battery pack is no longer charged, and the vehicle will be driven by motors first. Thus, the value range of SOC is $SOC \in [0.3, 0.9]$, and the fuzzy subset is set to be SOC $= \{$Very Small, Medium Small, Medium, Medium Big, Very Big$\} = \{$VS, MS, M, MB, VB$\}$.

According to theoretical calculations and experimental tests, the actual universe range of the fuzzy controller's output k_e is set to $k_e \in [0.2, 1.8]$, and its fuzzy subset is set to be $k_e = \{$Very Small, Medium Small, Medium, Medium Big, Very Big$\} = \{$VS, MS, M, MB, VB$\}$. The fuzzy control input/output membership function is shown in FIGURE 7.

C. BOUNDING BOX SCALE DEFINITION

1. The engine should work in the best range of fuel consumption. It can be seen from the universal characteristic curve of the engine that when the engine power is above the medium level, the fuel consumption is relatively less. Therefore, if the vehicle required power is below medium, the engine power distribution coefficient can be appropriately increased. Now the engine is working in the

TABLE 3. Fuzzy logic control rules.

k_e		λ				
		VS	**MS**	**M**	**MB**	**VB**
SOC	**VS**	VB	MB	M	MS	MS
	MS	VB	MB	M	MS	MS
	M	VB	MB	MS	MS	MS
	MB	VS	VS	MS	MS	MS
	VB	VS	VS	MS	MS	MS

high-efficiency area, and the output power of the engine is greater than the power required by the vehicle, then the excess power is used to charge the battery pack;

2. If the required power of the vehicle is too large, which is much more greater than the maximum power that can be provided by the engine, the power distribution coefficient of the engine should be appropriately decreased to make the engine work in the optimal fuel consumption range as much as possible, and the insufficient required power is supplemented by two electric motors.
3. The battery pack SOC should work in the high-efficiency area. When the SOC is higher than 0.8, the engine power distribution coefficient should be decreased, and the vehicle should first be driven by the two motors. When the SOC is small, the engine power distribution coefficient should be increased, to charge the battery pack in time to avoid excessive discharge. The fuzzy rules designed based on the above principles are shown in TABLE 3.

Since the formulation of fuzzy rules relies on the designer's experience, and the determination of the parameters of the fuzzy subset also relies on the knowledge and reasoning of experts, which cannot ensure the optimization of the system. Therefore, it is necessary to optimize the system through intelligent algorithms to achieve the lowest fuel consumption of the vehicle.

The complexity and accuracy of the parameters to be optimized are also important factors that can affect the control strategy. Too many parameters will make the system optimization process be much difficult and the amount of calculation be increased exponentially, while too few parameters or too small setting range will make the system not be optimal.

If there are no constraints on the parameters, each input/output variable will require 11 parameters to determine the five fuzzy sets, such as FIGURE 8(a), and the entire system will require 33 parameters (that is, 33 dimensional variables need to be optimized). Thus, the amount of calculation is too large, and it is difficult to obtain very accurate optimization results.

The hybrid vehicle model is very complicated. In order to reduce the calculation time and calculation amount, the number of optimization parameters should not be too large. Therefore, the parameters of fuzzy sets should be reduced as much as possible under the condition of considering the difficulty and accuracy of optimization. The method is as follow: set the fuzzy control range and the median value unchanged,

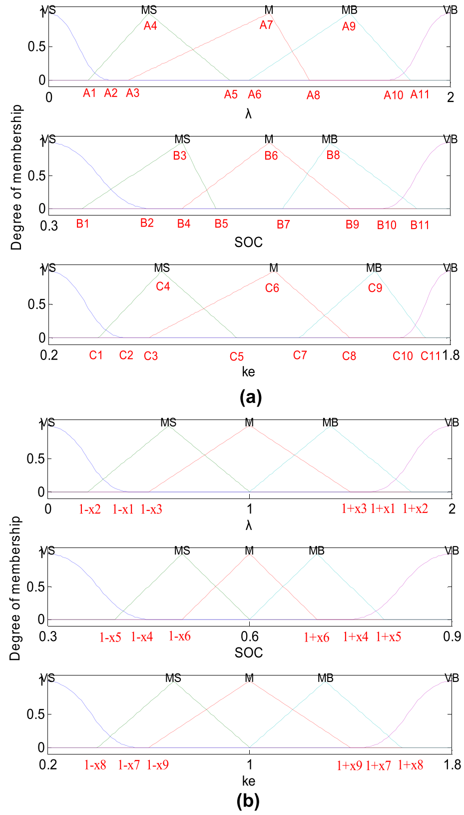

FIGURE 8. Membership functions of fuzzy rules. (a) rules without constraints, (b) rules with constraints.

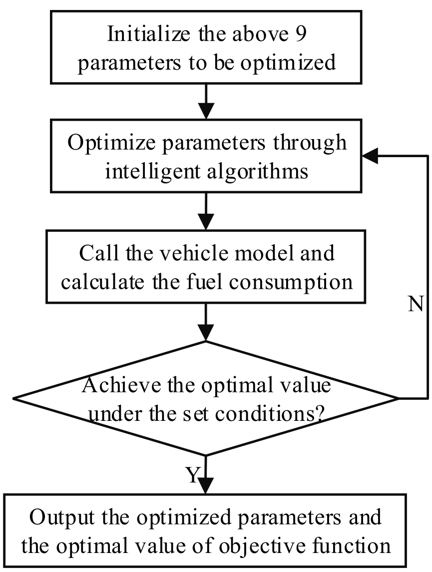

FIGURE 9. Parameters optimization process.

each fuzzy subset is symmetrically distributed, MS and MB are symmetrically distributed about the median value, and VS and VB are symmetrically distributed about the median value too. In this way, the optimization parameters of each input/output variable can be set as 3, and the total optimization parameters of the system are set as 9, which are shown in FIGURE 8(b). The boundary conditions of each parameter

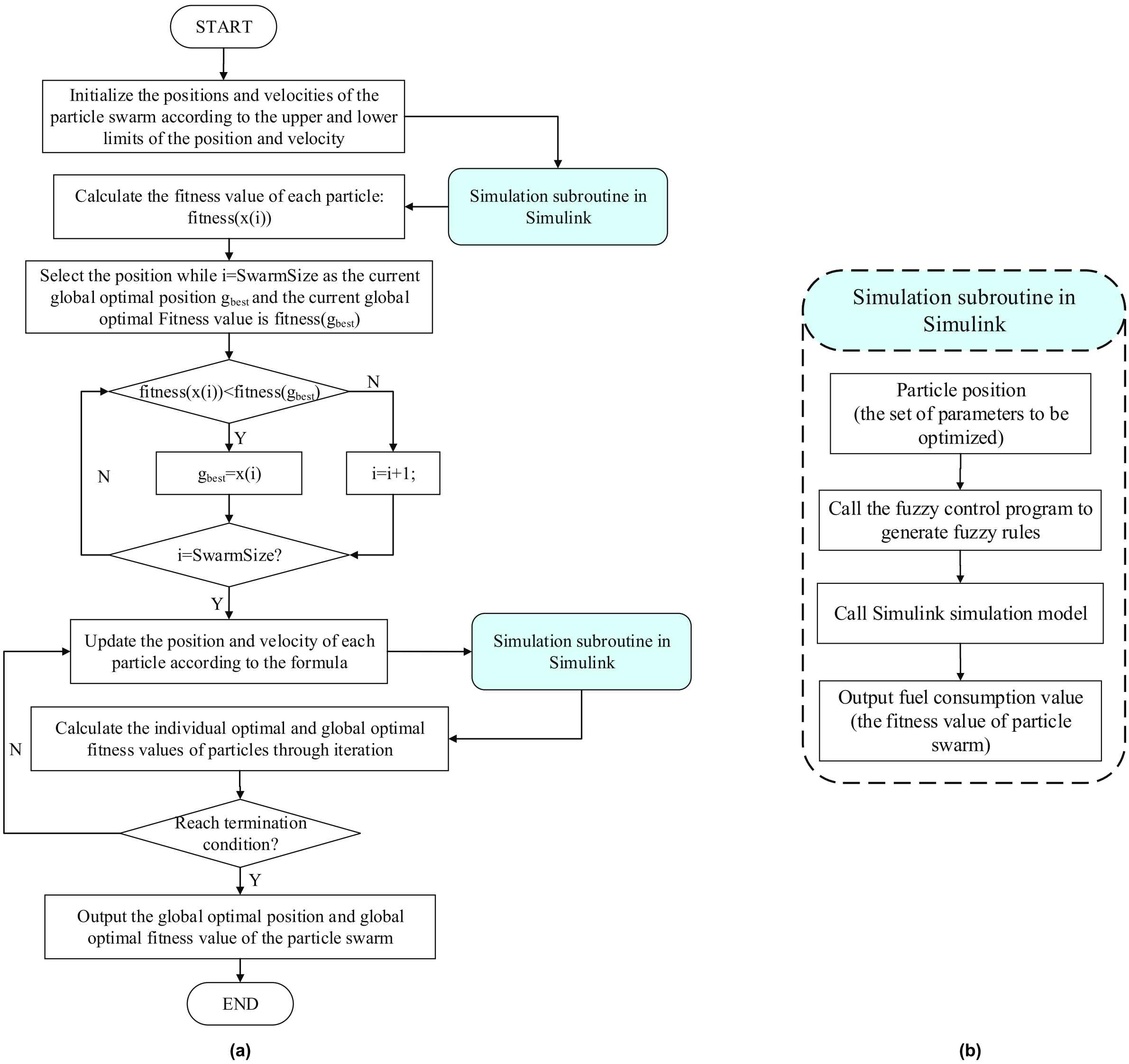

FIGURE 10. **(a) Design process of particle swarm optimization algorithm; (b) The subroutine calling vehicle model and calculating fuel consumption process in Simulink.**

are set as follows:

$$\begin{cases} 0 \leq x_1, x_2, x_3 \leq 1 \\ 0 \leq x_4, x_5, x_6 \leq 0.3 \\ 0 \leq x_7, x_8, x_9 \leq 0.8 \end{cases} \quad (3)$$

Then, 9 parameters are optimized through intelligent optimization algorithm to achieve the purpose of reducing the overall fuel consumption of the vehicle as much as possible. The PSO algorithm and its improved algorithms are used to optimize the fuzzy parameters. The optimization process is shown in FIGURE 9.

IV. FUZZY PARAMETERS OPTIMIZATION BASED ON IMPROVED PSO ALGORITHMS

The PSO algorithm is a simple and effective global optimization algorithm, which realizes the search of the optimal solution in a complex space through cooperation and competition among individuals. Its advantage is that it not only retains the global search strategy based on the population, but also avoids the complexity genetic manipulation. In this paper, PSO algorithm is selected as the basic optimization algorithm, the nine parameters x1-x9 are taken as the spatial dimensions of the particle swarm, and the fuel consumption of the vehicle is taken as the optimization objective (fitness value).

However, the basic PSO algorithm is easy to fall into premature, so that the optimal value of the system cannot be obtained. In order to improve this problem, inertia weight is added to the basic PSO algorithm. The algorithm is described as follows:

In a 9-dimensional search space, a population $X = \{X_1, X_2 \cdots X_N\}$ is composed of N particles, where the position of the i-th particle is represented as $X_i = \{X_{i1}, X_{i2} \cdots X_{i9}\}$, and each X_i represents a solution of the optimization problem. Each particle has a velocity $V_i = \{V_{i1}, V_{i2} \cdots V_{i9}\}$, and the particle adjusts its position through flying, and searches for the individual and global optimal solution through iteration. The particle velocity and position update formula are as formula (4) and (5):

$$v_{i,j}(k+1) = \omega \cdot v_{i,j}(k) + c_1 r_1[p_{i,j}(k) - x_{i,j}(k)] + c_2 r_2[p_{g,j}(k) - x_{i,j}(k)] \tag{4}$$

$$x_{i,j}(k+1) = x_{i,j}(k) + v_{i,j}(k+1) \tag{5}$$

where: $i = 1, 2, \cdots N$, $j = 1, 2, \cdots 9$, $k = 1, 2, \cdots M$, ω is the inertia weight, N is the number of particles, M is the maximum number of iterations.

The inertia weight can affect the particle's local and global optimal search capability. A larger ω is conducive to make particles jump out of the local minimum and improve the algorithm's global search capability, while a smaller one can enhance the algorithm's local search capability and is conducive to the rapid convergence of the algorithm. In this paper, the variable weight method is used. During the iteration, the inertia weight is gradually decreased. At the beginning of the iteration, larger inertia weight can enhance the global search capability, and in the later stage of iteration, small inertia weight can improve the accuracy of local search capability, thereby improving the optimization performance of the system. The fitness value (vehicle fuel consumption) of the objective function is obtained by calling the model built in Simulink. The specific implementation process of the algorithm is shown in FIGURE 10.

In order to further optimize the objective function, PSO algorithm with shrinkage factor (YSPSO) and SimuAPSO algorithm are used to optimize the objective function.

A. YSPSO ALGORITHM

The shrinkage factor is introduced on basis of the basic PSO algorithm formula (formula 6) to constrain the flying speed of particles (formula 7), and the particle position is still updated by formula (5). The YSPSO can ensure the convergence of the algorithm, and achieve a balance between global detection and local search.

$$v_{i,j}(k+1) = v_{i,j}(k) + c_1 r_1[p_{i,j}(k) - x_{i,j}(k)] + c_2 r_2[p_{g,j}(k) - x_{i,j}(k)] \tag{6}$$

$$v_{i,j}(k+1) = \phi \cdot v_{i,j}(k+1)$$
$$\phi = \frac{2}{\left|2 - C - \sqrt{C^2 - 4C}\right|}, \quad C = c_1 + c_2, C > 4 \tag{7}$$

B. SimuAPSO ALGORITHM

$P_{g,j}(k)$ in the velocity update formula (6) is the optimal position of the group. According to the velocity update algorithm, all particles will fly to the optimal position of the group after enough iterations. However, if the optimal position of the group is just at the local minimum point, all particles will fly to the optimal position of the group. All particles will tend to the local minimum, which will lead to the weakening of the global search ability, and the particle swarm algorithm will fall into premature and cannot automatically jump out of the local extreme point. Therefore, the simulated annealing algorithm is introduced, in which the energy of the system is regarded as the objective function of the optimization problem, and the annealing temperature is used to control the solution process to the optimal value optimization direction. At the same time, it receives inferior solutions with a certain probability, so it can jump out of the local extreme point, as the initial temperature is high enough and the annealing process is slow enough, the system can converge to the global optimal solution. Therefore, SimuAPSO is a global optimal algorithm.

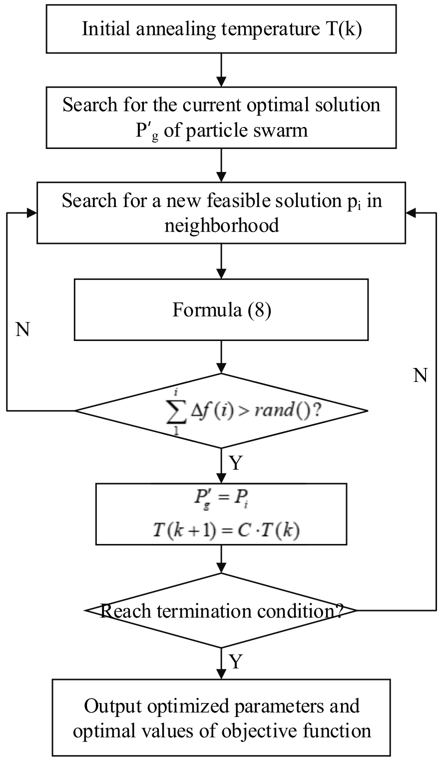

FIGURE 11. Optimization process of SimuAPSO algorithm.

Select the solution P_i that is slightly worse than the global optimal solution P_g in its neighborhood, and the sudden jump probability Δf that P_i relative to P_g when the temperature is set to T is calculated according to formula (8).

$$\Delta f = \frac{e^{-(f(p_i) - f(p_g))/T}}{\sum_{j=1}^{SwarmSize} e^{-(f(p_i) - f(p_g))/T}} \tag{8}$$

Then when $\sum_1^i \Delta f(i)$ is greater than the random number in [0, 1], the solution P_i is accepted and is introduced into the speed update formula as the global optimal solution. That is, replace $P_{g,j}(k)$ in formula (6) with $P'_{g,j}(k)$, as shown in formula (9).

$$v_{i,j}(k+1) = \phi\{v_{i,j}(k) + c_1 r_1[p_{i,j}(k) - x_{i,j}(k)] + c_2 r_2[p'_{g,j}(k) - x_{i,j}(k)]\} \tag{9}$$

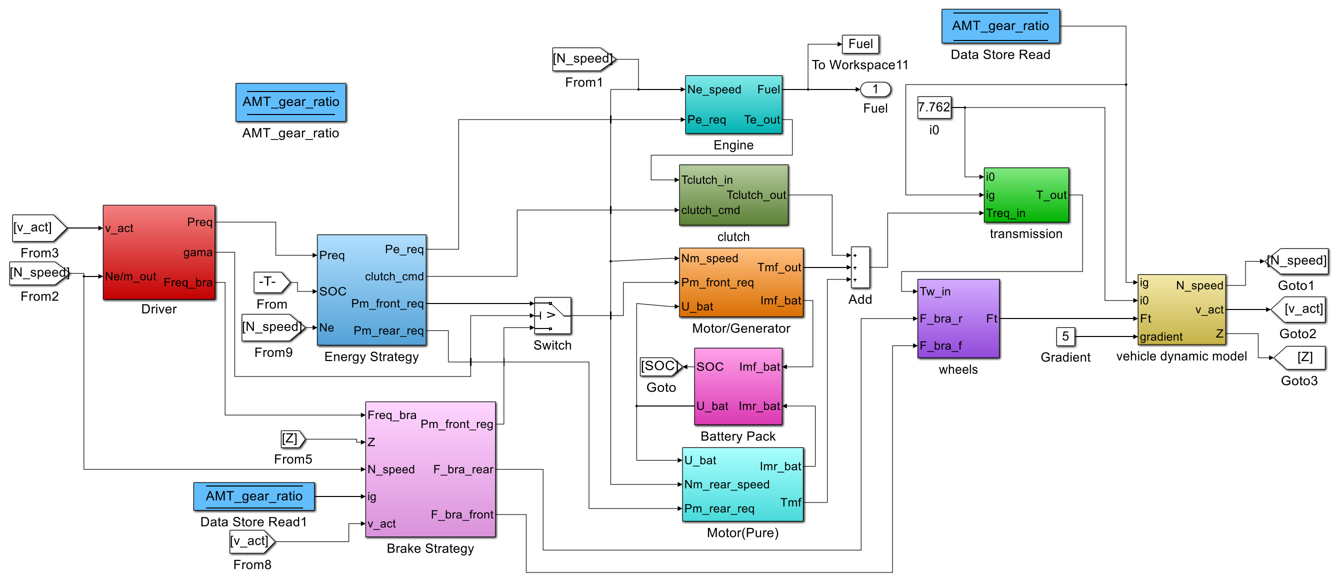

FIGURE 12. Simulation model of hybrid emergency rescue vehicle.

In this way, the algorithm can jump out of the local minimum value and enhance the global search ability of the algorithm. The solution process of the algorithm is shown in FIGURE 11.

V. SIMULATION AND EXPERIMENT

In order to verify the correctness and practicability of the fuzzy control strategy and optimization algorithm designed in this study, the emergency rescue hybrid power simulation model is first built on the Simulink platform, and offline simulation was performed; then the hardware in the loop simulation system of driver-vehicle controller is built on dSPACE platform, and the real-time performance and effectiveness of the optimized control strategy are verified by the experiment.

A. OFFLINE SIMULATION

The simulation model of the emergency rescue vehicle is shown in FIGURE 12. The front axle adopts parallel hybrid power mode, and the rear axle adopts pure electric mode. The entire model includes driver model, vehicle energy management strategy model, brake control strategy model, engine model, clutch model, hybrid motor/generator model, pure electric motor model, power battery pack model, transmission model, wheels model, and vehicle dynamics model etc.

The driver model adopts fuzzy PID control. In the simulation model, the angle of the accelerator pedal and the brake pedal of the vehicle are simulated by controlling the deviation between the expected speed and actual speed of the vehicle. The angle of the pedal (in simulation, the accelerator pedal and the brake pedal can be integrated into one pedal.) can be calculated according to formula (10). When the expected speed is greater than the actual speed, the angle of the pedal is positive (corresponding to the accelerator pedal), and the greater the speed deviation, the greater the pedal angle value; when the expected speed is less than the actual speed, the angle of the pedal is negative (corresponding to the brake pedal), and the greater the speed deviation (absolute value), the greater the pedal angle (absolute value).

$$\begin{aligned}\gamma_{driver} &= k_p[(v^* - v) + \frac{1}{T_i}\int_0^t (v^* - v)dt + T_d\frac{d(v^* - v)}{dt}] \\ &= k_p e + K_i\int_0^t edt + K_d\frac{de}{dt} = \begin{cases}\gamma_{acc} & e \geq 0 \\ \gamma_{bra} & e < 0\end{cases} \qquad (10)\end{aligned}$$

The angle of the pedal is converted into the actual required power (or braking force) of the vehicle, then the required power (or braking force) is allocated to the engine and the two motors through the energy management strategy. In hardware-in-the-loop experiments and actual vehicles, the experiments can be carried out by replacing the driver model with actual pedals.

In order to reflect the effectiveness of the control strategy under multiple operating conditions, the simulation conditions used in this research are a mixture of urban condition UDDS and high-speed condition HWFET. The speed following curve under mixed operating conditions is shown in FIGURE 13.

Under the fuzzy control membership function designed according to experience, the fuel consumption of the vehicle by simulation is 7.1045L per 100 km. The 9 parameters of the fuzzy control membership function are optimized by APSO, YSPSO and SimuAPSO respectively.

In order to avoid the occurrence of a minimum value, that can cause the fuzzy rule to fail to run, the upper and lower

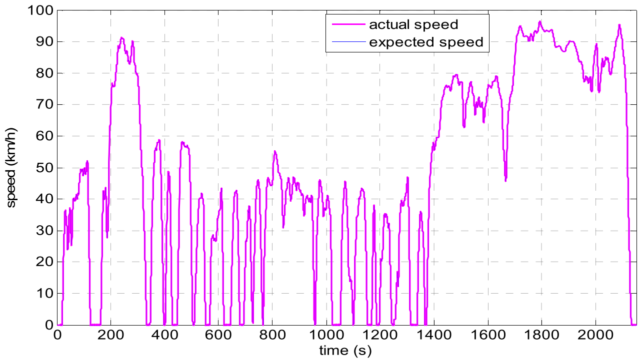

FIGURE 13. Velocity following curve under mixed conditions.

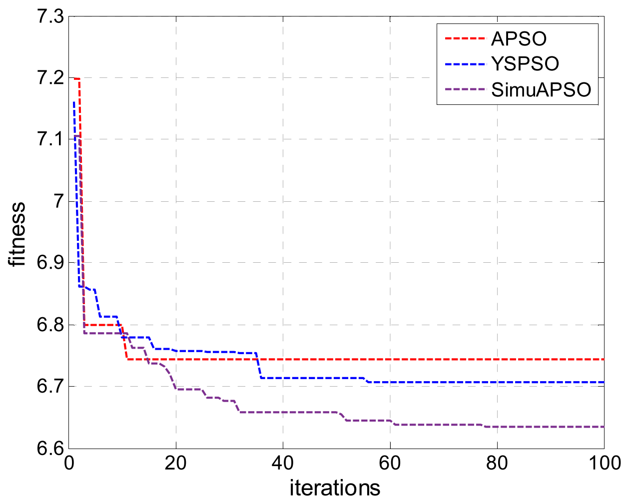

FIGURE 14. Fitness curves of the three optimization algorithms.

limits of the particle position are set as follows:

$$x_U = [0.9, 0.9, 0.8, 0.25, 0.25, 0.2, 0.75, 0.75, 0.6];$$
$$x_L = [0.1, 0.1, 0.1, 0.05, 0.05, 0.05, 0.1, 0.1, 0.1].$$

The upper and lower limit of the flying speed of particles is set to $v \in [-0.05, 0.05]$, the number of particle groups is set to $N = 100$, and the maximum number of iterations is set to $M = 100$.

The fitness curves of the three optimization algorithms are shown in FIGURE 14. It can be seen from the figure that the optimization effect of the SimuAPSO algorithm is the best, and the iteration speed is the fastest. After 32 iterations, the fitness value is optimized to 6.6572. And after 78 iterations, the fitness value is optimized to 6.6346. The optimization results of the three algorithms are shown in TABLE 4. The fuel consumption curve of 100km of the vehicle without optimization and after optimization by the three algorithms is shown in FIGURE 15.

The battery pack SOC curve after optimizing by the three optimization algorithms is shown in FIGURE 16. It can be seen the YSPSO algorithm and the SimuAPSO algorithm can better maintain the battery pack SOC value within the interval of the minimum internal resistance, which can reduce fuel consumption and improve vehicle economy. The distribution

TABLE 4. Comparison of fuel consumption before and after optimization.

Optimization algorithm	Fuel consumption (Fitness)	Higher rate than fuzzy controller
Fuzzy (without optimization)	7.1045	/
APSO	6.7442	5.07%
YSPSO	6.7062	5.61%
SimuAPSO	6.6346	6.61%

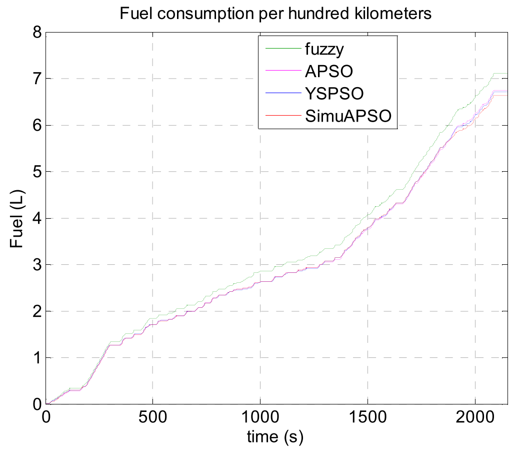

FIGURE 15. Fuel consumption curve without optimization and after three algorithms optimization.

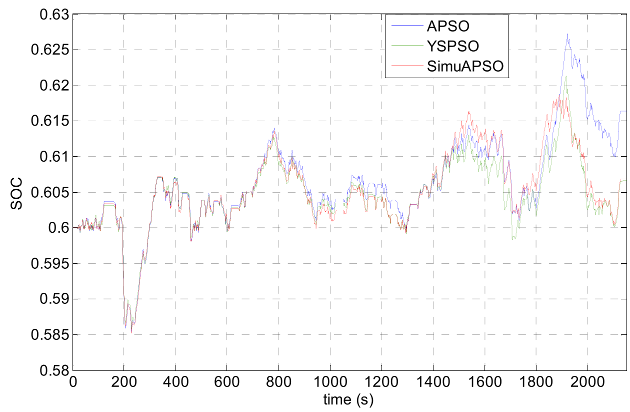

FIGURE 16. SOC curve after three algorithms optimization.

of engine operating points without optimization and after optimization by SimuAPSO is shown in FIGURE 17. It can be seen from the figure that the engine after SimuAPSO optimization works more in the high-efficiency area, which can save the fuel energy.

B. HARDWARE-IN-THE-LOOP EXPERIMENT

In the offline simulation, a driver model is used to simulate the vehicle driver. However, the operation habits of real drivers and pedal angle conversion errors are not considered in the model. Meanwhile, in order to better test the real-time and effectiveness of the vehicle energy management strategy, the hardware-in-the-loop simulation experiment based on dSPACE is carried out. The experimental principle is shown in FIGURE 18, and the experimental platform is as

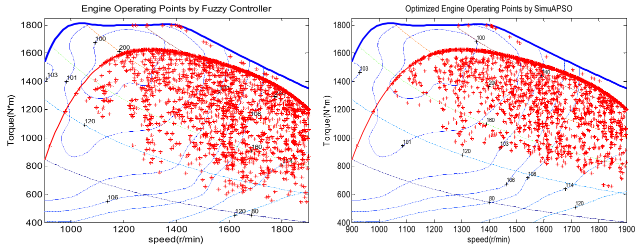

FIGURE 17. Distribution of engine operating points before and after SimuAPSO optimization.

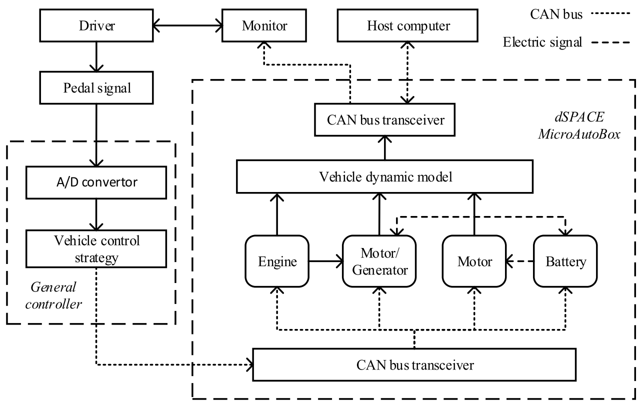

FIGURE 18. Hardware-in-the-loop experiment principle.

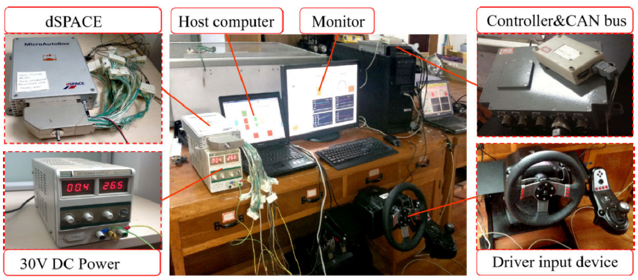

FIGURE 19. Hardware-in-the-loop simulation experiment platform.

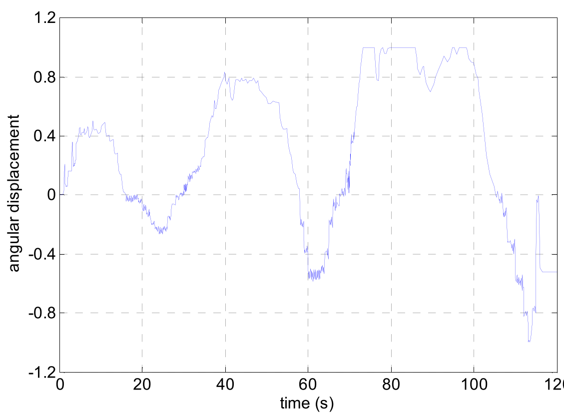

FIGURE 20. Vehicle pedal angular displacement signal.

FIGURE 19. In this platform, the dSPACE uses MicroAutoBox 1401/1504. The equipped 4M memory is specially used for high-speed communication between the Monitor

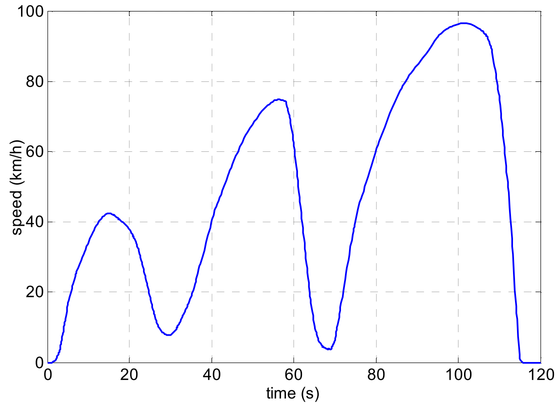

FIGURE 21. Vehicle speed curve measured by experiment.

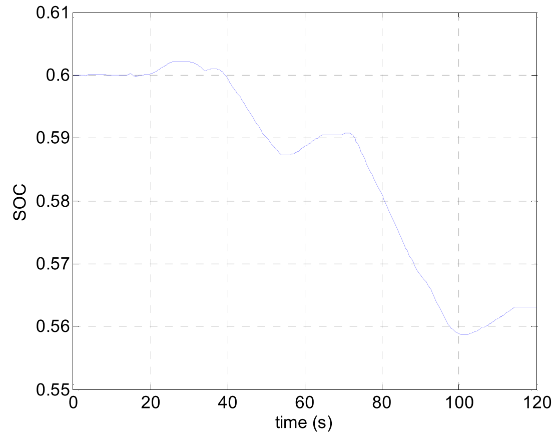

FIGURE 22. SOC variation curve of battery pac.

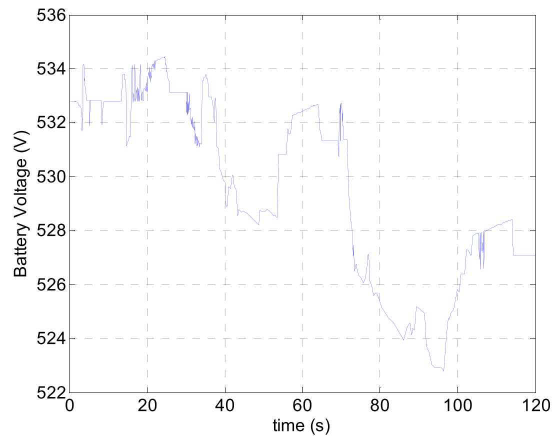

FIGURE 23. Voltage variation curve of battery.

computer and the Host computer, and the 16M flash memory is used to store the algorithm code and flight recorder. Moreover, 4-Way CAN bus is equipped for data communication.

Firstly, write the vehicle model (optimized) established in Simulink into dSPACE through the host computer, dSPACE can automatically convert to machine-recognizable C code for operation. Then the driver operates the accelerator/brake pedal (handle) to achieve vehicle acceleration and braking, the pedal (handle) angle signal (analog) collected by the

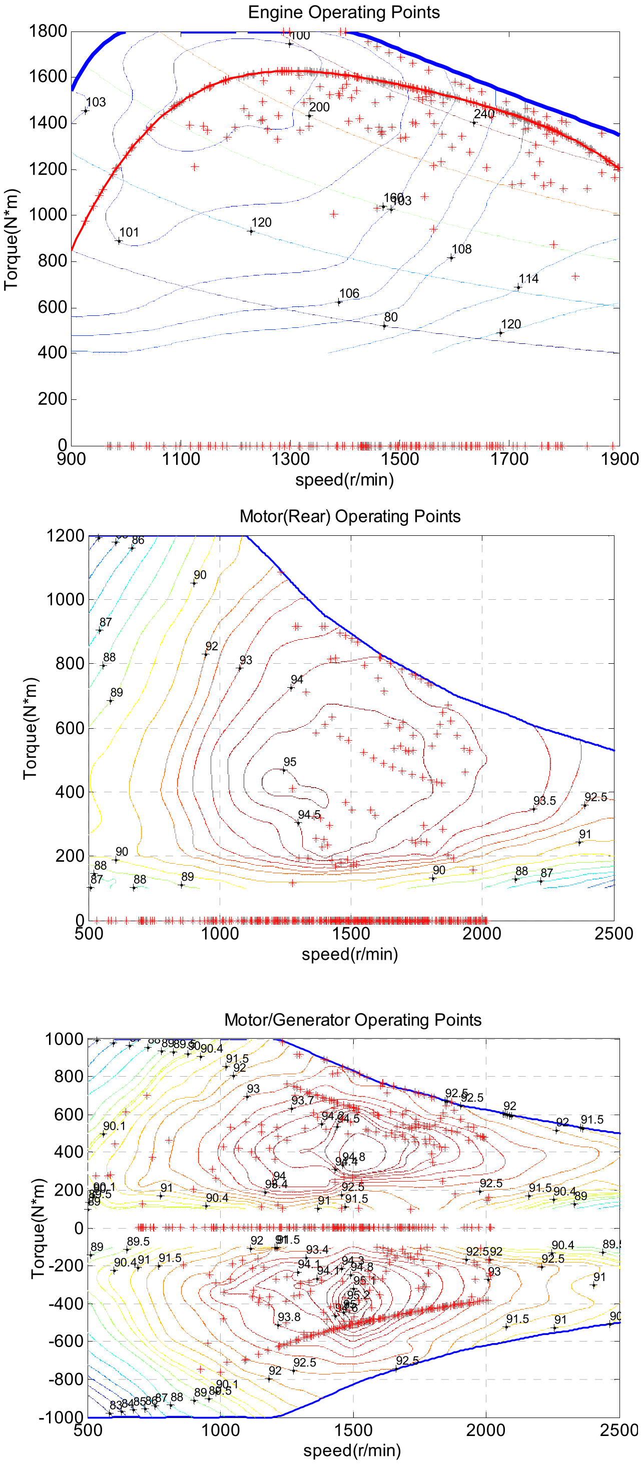

FIGURE 24. Working points distribution of the three power sources.

sensor is transmitted to the vehicle controller. The angle signal is converted into the vehicle control strategy after A/D conversion for energy distribution, in the vehicle controller the torque or power required by the engine, front-axle motor/generator, rear-axle motor and power battery pack is calculated and transmitted to dSPACE through CAN bus. The real-time control is completed in dSPACE and the relevant parameters are output through CAN bus.

In order to verify the accuracy and effectiveness of the vehicle model and the optimization algorithm more comprehensively, the "low speed-medium speed-high speed" mode is adopted in this experiment, and the test steps are as follows:

First, step on the pedal lightly to turn a small angle, then release the accelerator pedal and step on the brake pedal lightly to turn a small angle.

Second, increase the accelerator pedal angle, roughly step on the 2/3 position, and then release the accelerator pedal, depress the brake pedal to the 2/3 position.

Third, release the brake pedal and quickly depress the accelerator pedal to the maximum position, after staying for a few seconds, release the accelerator pedal and quickly depress the brake pedal to the maximum position, then release.

The pedal signal collected during the whole process is shown in FIGURE 20, and the measured vehicle speed is shown in FIGURE 21. The speed curve obtained is consistent with the predicted speed curve, which proves that the vehicle model established in this study is accurate.

The measured SOC curve and voltage curve of battery pack are shown in FIGURE 22 and FIGURE 23.

The operating points of engine and two motors are shown in FIGURE 24. It can be seen that the operating points of the engine are basically in the high-efficiency area. When the vehicle is running in the low efficiency area of the engine, the engine is shut down and the torque is provided by the two motors, and the battery pack can be charged by the front axle motor according to the vehicle load and SOC conditions. The working points of the two motors are mostly concentrated in the high efficiency areas too, which proves the effectiveness of the optimization algorithms.

VI. CONCLUSION

In this study, a dual-axle and dual-motor torque increasing hybrid vehicle model is established for a heavy-duty emergency rescue vehicle, and the improved energy management strategy based on SimuAPSO-FLC is designed. Then three improved PSO algorithms are used to optimize the fuzzy parameters. After that, the model and the designed vehicle energy management strategy are verified by off-line simulation and hardware-in-the-loop experiments. The conclusions are as follows:

1. The dual-motor torque increasing vehicle system greatly improves the dynamic performance and mobility of emergency rescue vehicle. Especially, the low efficiency of engine can be avoided by using dual motor drive in steep slope and complex terrain.
2. The setting of fuzzy rule parameters for optimization is a key issue that affects the optimization results. The 9 parameters designed in this research can meet the requirements of fuzzy logic control accuracy, while reducing the difficulty of intelligent algorithm optimization and improving optimization efficiency.
3. The three optimization algorithms of APSO, YSPSO and SimuAPSO have good optimization effects on fuzzy logic

control. The simulation experiment results verify that the optimization effect of the SimuAPSO algorithm is the best, which is consistent with the theoretical analysis results. The improved SimuAPSO-FLC strategy has strong robustness, strong adaptability and high efficiency, which is very suitable for the energy management strategy of the heavy-duty emergency rescue vehicles studied in this paper.

4. The hardware-in-the-loop simulation experiments verify that the hybrid vehicle model and energy management strategy designed in this study are accurate and effective. The optimized energy management strategy can meet the requirements of vehicle real-time performance, and the engine and electric motor work in their respective high-efficiency areas, which can reduce the fuel consumption of the vehicle. The experiment proves that the energy management strategy in this paper can be used in the next real vehicle experiment.

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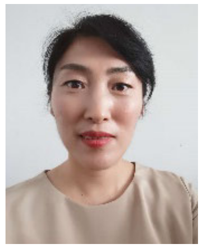

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