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Parameter Optimization and Control Strategy of Hybrid Electric Vehicle Transmission System based on Improved GA Algorithm

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Abstract: Most of the traditional hybrid electric vehicles (HEVs) choose to optimize the transmission ratio parameters, and the parameter changes of the whole vehicle and other components are only calculated as fixed values. It is difficult to give consideration to the optimization of the economy and power of hybrid vehicles. Therefore, the research proposes to build the transmission ratio, the required power of the vehicle's working mode, and other models through the dynamic analysis. The parameters of the whole vehicle are optimized on the basis of parameter matching. At the same time, this paper chooses to adopt a hybrid optimization algorithm, combining particle swarm optimization (PSO) and genetic algorithm (GA). The weighted average method and constraint method are used to design the fitness function. The simulation experiment is carried out by Cruise software and MATLAB. Compare the iterative fitness of the PSO-GA algorithm with the traditional PSO and GA algorithm. It can be concluded that PSO-GA converges at the 12th iteration, with an average optimal fitness of 0.5239, which is higher than the traditional algorithm. At the same time, the parameter optimization of PSO-GA and the simulated annealing algorithm is compared. It is found that in the same task, the gasoline consumption after SA algorithm optimization is 0.561 L, while the fuel consumption under PSO-GA algorithm optimization is 0.475 L. The method proposed in this study has improved the power and economy of the HEV model and is effective.

Keywords: HEV; transmission parameters; PSO-GA; multi-objective optimization

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1. Introduction

Technology has driven the rapid development of the automobile industry. The increasingly serious ecological and environmental problems and energy crises have determined that new energy vehicles have become the development trend of the automobile industry. To meet the urgent requirements of energy conservation and emission reduction, many countries around the world are competing to phase out gasoline and diesel vehicles [1–3]. Both the market and the environment, as well as people's demand for comfort, power, and economy of vehicles, have put forward higher requirements for the development and progress of new energy vehicle technology. The energy management strategy of HEV and the key parameters of the powertrain directly determine its energy consumption and power performance. Research on parameter matching and parameter optimization of HEV is conducive to reducing vehicle emissions and energy consumption and improving vehicle power performance. It is of great significance not only for the sustainable development goal of energy conservation and emission reduction but also for the vehicle market [4,5]. The research on the energy management strategy of parallel and series HEVs with simple structures has been relatively mature. However, for multi-mode HEVs, more modes often mean more serious computational load problems. The computational complexity of these strategies cannot be ignored in the process of method optimization [6–9]. In this study, the parameter-matching problem of the HEV transmission system is analyzed through a dynamic model, and the parameters of the overall vehicle power, engine, motor, and battery are coupled. Additionally, the mixed PSO and GA are used in the optimization algorithm to optimize the parameters. The purpose of this study is to propose a new, reliable, and efficient HEV parameter optimization method without increasing the amount of real-time calculation. Finally, this study aims to improve the economy and power performance of HEV in the market.

2. Related Works

In automobile transmission, Yan Zhengfeng et al. built the powertrain model of traditional automobiles by the bond-graph method. The vibration and noise in the running process are reduced, and the driving comfort is improved through the optimization method of vehicle state variables. Simulation experiments show that the method verifies the effective performance of the optimized parameters and provides a reference for DMF simulation [10]. Rajan et al. took HEV as the research object and designed the optimized hybrid transmission to control the cost of the vehicle. In different simulation experiments, the optimization effect of this method in CO_2 emission reduction and shift times have been verified [11]. Bansal et al. used the iterative hierarchical model to supplement the control in the traditional diesel vehicle powertrain control. In the test, this method shows good computational performance, but it is not outstanding in economic performance optimization [12]. Shaoyou Shi et al. proposed an optimized V model for the mass production of electric vehicles to optimize the design of the transmission system. Iterative completion verifies the effectiveness of this method, and its design based on the advantages of mission purpose and power demand purpose can better complete the parameter optimization research [13]. Lewis Geoffrey et al. talked about the necessity of vehicle power efficiency and vehicle quality optimization in terms of environmental safety. Starting from the energy efficiency of lightweight vehicles, the author has put forward 10 principles of influencing factors of key parameters of vehicle environmental performance based on the life cycle perspective [14]. Due to the influence of hydraulic oil temperature, the torque control accuracy of a traditional wet clutch is not high. To improve the control accuracy of a vehicle's clutch torque, Park J and others proposed an adaptive control method. Additionally, the author has proved the effectiveness of this method through the simulation model of parallel power vehicles [15]. Dario Mangoni et al. also proposed to optimize the vehicle powertrain based on the lightweight model. They analyze the efficiency of the vehicle transmission system by evaluating the battery status of the electric vehicle. This method can be effectively applied to electric vehicles at this stage [16]. Liu Huanlong et al. proposed a coupling model of an electro-hydraulic hybrid power system applied to automobiles, which has optimization effects on power and economy. Additionally, this method has better energy-saving characteristics when applied to the vehicle starting and acceleration [17].

In the application of PSO and GA swarm intelligent optimization algorithms in the field of mechanical engineering, Stojanovic Blaza et al. applied the intelligent optimization algorithm to the stability control of a multi-machine power system. Through comparative experiments of simulation results, the stability of this method in system dynamic stability control is proved [18]. Anwar Jarndal et al. applied PSO and GA swarm intelligence optimization algorithms to the efficient electrothermal large signal GaN HEMT modeling. The model also shows the accurate simulation of a nonlinear power amplifier with very good calculation speed and convergence [19]. Song Ji-Hun et al. coupled the temperature and structure of the brake system through the finite element method and adopted GA parameter optimization and sensitivity analysis. This method can optimize the thermal stress and deformation of the fan mouth under a high-temperature environment [20].

To sum up, although the parameter optimization of new energy vehicles has been greatly developed, the complexity of the calculation and solution of these strategies cannot be ignored. Especially for multi-mode HEVs, more modes often mean more serious calculation load problems. The optimization method in this study adopts a PSO-GA hybrid algorithm, and the optimization idea and calculation are relatively simple. Therefore, it has reference significance for the research of HEV transmission system parameter optimization and control in the market.

3. HEV Transmission System Control Optimization Method Based on Improved GA Algorithm

3.1. Construction of HEV Parameter Matching Model

Parameter optimization of HEV involves many factors, such as transmission system parameter matching, vehicle layout, etc. In this study, the parameters of the vehicle are optimized. On the basis of meeting the power demand, the economic objective is taken as the optimization design objective as far as possible. Therefore, the quality of traditional system parameters largely determines the dynamic economic performance of HEV [21]. Therefore, this study will build the HEV transmission parameter matching optimization model and use the improved GA algorithm. In HEV, the parameter matching of the motor, battery, and engine, as well as the power matching of the whole vehicle. determine the performance of the traditional vehicle system. The transmission system of HEV is shown in Figure 1.

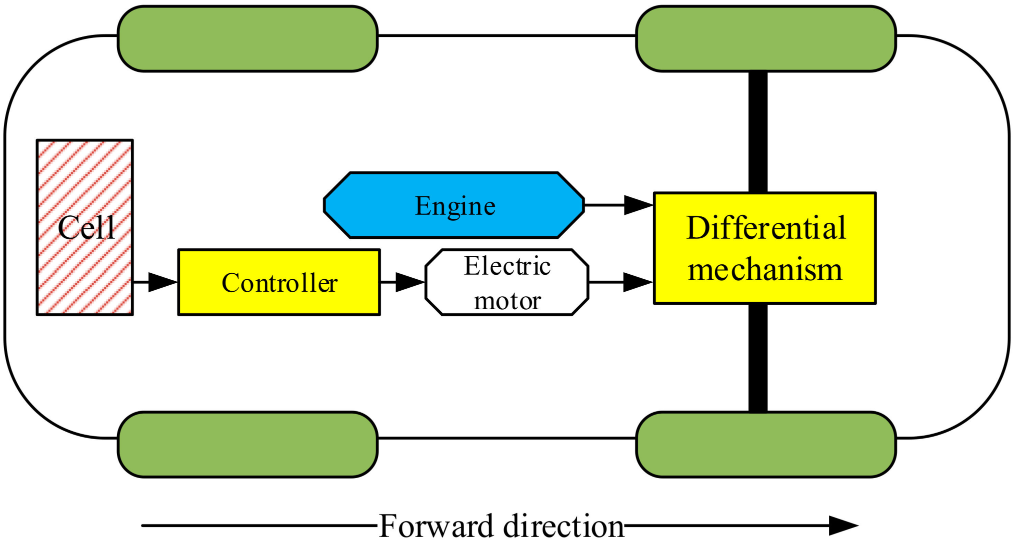


Figure 1. Transmission system structure of HEV.

First of all, the overall power of HEV needs to meet the maximum speed, climbing requirements, and acceleration performance at the same time. At the best speed, the HEV power demand calculation formula is shown in Formula (1).

$$P_{\max1} = \frac{V_{\max}(m_1 g f + (C_d A V_{\max}^2 / 21.15))}{3600\eta_t} \tag{1}$$

$P_{\max1}$ refers to the power demand of the hybrid vehicle at the maximum speed in Formula (1). $V_{\max}$ represents the maximum speed of the vehicle. m_1 is the half-load mass. g is the acceleration of gravity. f stands for the overall rolling resistance coefficient of the vehicle. C_d means the overall wind resistance coefficient of the vehicle. A is the windward area of the car. η_t represents the total efficiency of the transmission system. The force exerted by the car when climbing is shown in Figure 2.

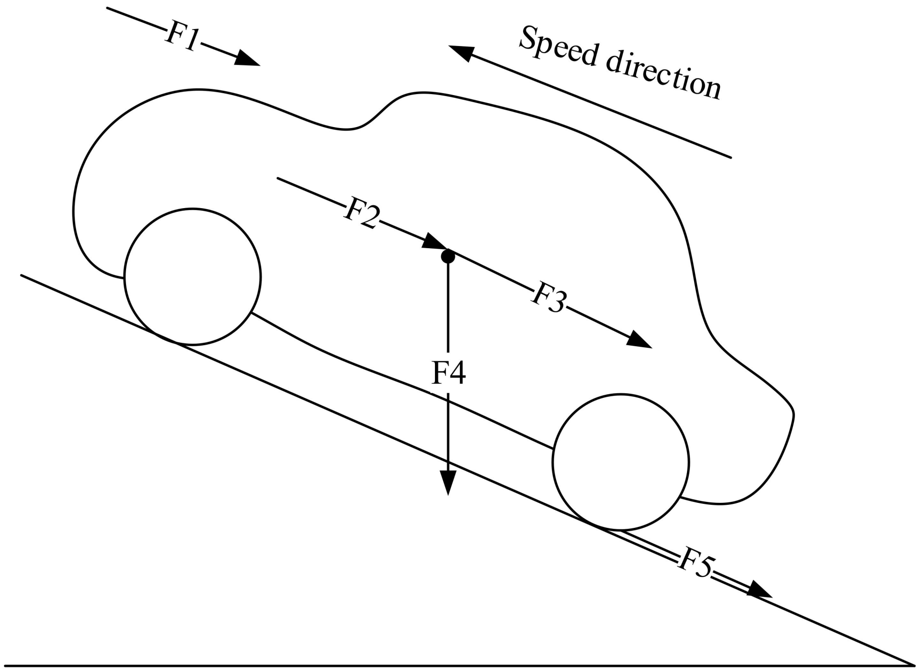


Figure 2. Analysis of wind resistance, acceleration resistance, uphill resistance, gravity, and rolling resistance when the car is uphill.

In Figure 2, F1–F5 represents the wind resistance, acceleration resistance, uphill resistance, gravity, and rolling resistance of the car when it is uphill. Therefore, the power demand for car climbing is shown in Formula (2).

$$P_{\max 2} = \frac{V_i(m_2 g f \cos\alpha + m_2 g \sin\alpha + (C_d A V_i^2/21.15))}{3600\eta_t} \tag{2}$$

$P_{\max 2}$ represents the power demand of the hybrid vehicle when climbing in Formula (2). V_i represents the speed of car climbing. m_2 is the full load mass. $\alpha = \tan^{-1}(i_{\max}/100)$. $i_{\max}$ indicates the maximum climbing slope. Finally, the formula for calculating the power demand when the vehicle accelerates is Formula (3).

$$\begin{aligned} P_{\max 3} &= \frac{[\delta m_3 v(dv/dt) + m_3 g f v + (C_d A V^2/21.15)]}{3600\eta_t} \\ &= \frac{[\delta m_3 v_{m2}^2/7.2 + m_3 g f \int_0^{t_{m1}} v_{m1}(t^{0.5}/{t_{m1}}^{0.5})dt + (C_d A/21.15)\int_0^{t_{m1}} v_{m1}^3 (t^{1.5}/{t_{m1}}^{1.5})dt]}{3600 t_{m1}\eta_t} \end{aligned} \tag{3}$$

m_3 represents the light load mass in Formula (3). t_{m1} and v_{m1} represent the acceleration time and the speed after acceleration of the hybrid vehicle, respectively. δ is the moment of inertia coefficient. After obtaining the above maximum speed, power demand when climbing and accelerating, the transmission optimization target of HEV is $P_{total} = \max(P_{\max 1}, P_{\max 2}, P_{\max 3})$. In addition to the power of the whole vehicle, the total power of the vehicle also needs to be matched with the power of the engine, motor, and battery [22]. First of all, when calculating the engine's climbing power, because it is easy to drain the battery during the climbing process, we require the motor not to work when climbing, and the whole process is driven by the engine alone. When cruising at high speed and cruising at high speed, the climbing and acceleration of the whole vehicle are not considered at this time. Therefore, the engine power is expressed as Formula (4).

$$\begin{cases} P_{e1} = \frac{V_i(m_2 g f \cos\alpha + m_2 \sin\alpha + (C_d A V_i^2/21.15))}{3600\eta_t} \\ P_{e2} = \frac{V_e(m_1 g f + (C_d A V_e^2/21.15))}{3600\eta_t} \end{cases} \tag{4}$$

P_{e1} and P_{e2} represent the required power of HEV when climbing and cruising in Formula (4). V_e refers to the vehicle speed when the vehicle is running. In the power matching calculation of the motor, the total power of the motor shall meet the requirements of starting the whole vehicle independently to reach the specified speed within the specified time. Therefore, the formula for calculating the total power of the motor is shown in Formula (5).

$$\begin{cases} P_{\mathrm{m1}} = \frac{[\delta m_3 v_{m2}^2/7.2 + m_3 g f \int_0^{t_{m2}} v_{m2}(t^{0.5}/{t_{m2}}^{0.5})dt + (C_d A/21.15)\int_0^{t_{m2}} v_{m2}^3 (t^{1.5}/{t_{m2}}^{1.5})dt]}{3600 t_{m2} \eta_t} \\ P_{m2} = \frac{v_i(m_2 g f \cos\alpha + m_2 \sin\alpha + C_d A V_i^2/21.15)}{3600\eta_t} \end{cases} \quad (5)$$

t_{m2} and v_{m2} represent the pure electric acceleration time and the speed after pure electric acceleration of the hybrid vehicle, respectively, in Formula (5). P_{m1} and P_{m2} represent the required power of the automobile motor when climbing and accelerating in pure electric mode. Finally, the battery parameter matching includes battery power matching and energy verification, and the battery power is calculated according to the motor power demand. Under extreme working conditions, the battery provides the power of the motor when it is fully loaded, and the whole vehicle is accelerating. At this time, the maximum current of the battery is expressed as Formula (6).

$$I_{\max} = \frac{P_m}{\eta_c \eta_m U} \quad (6)$$

P_m is the total power of the motor, η_c represents the efficiency of the inverter, η_m is the efficiency of the motor, and U represents the voltage level in Formula (6). The purpose of the optimization of the transmission system of HEV is to make the vehicle in the efficient area where the motor and engine work as much as possible. The minimum transmission ratio of the transmission system can be calculated according to the maximum vehicle speed when the engine is driven separately. The calculation formula of the minimum transmission ratio is shown in Formula (7).

$$i_{\min} \leq 0.377 n_{\max} r_w / v_{\max} \quad (7)$$

$n_{\max}$ is the maximum engine speed, r_w is the effective rolling radius of the wheel, and $v_{\max}$ is the maximum vehicle speed in Formula (7). The maximum transmission ratio is the product of the first gear ratio and the final reduction ratio of the transmission. Therefore, it is necessary to meet the requirements of maximum climbing slope and adhesion conditions. Therefore, its calculation formula is shown in Formula (8).

$$m_2 g(f\cos\alpha + \sin\alpha) r_w / T_{e-\max}\eta \leq i_{\max} \leq m_v g \varphi r_w / T_e \eta \quad (8)$$

$T_{e-\max}$ is the total torque of the motor, m_v is the mass of the drive axle, φ is the coefficient of adhesion, and T_e is the maximum torque of the engine in Formula (8).

3.2. HEV Transmission System Parameter Optimization Method based on PSO-GA Algorithm

From the HEV parameter model in the previous section, the total power and additional power requirements are optimized by the transmission system parameters. Therefore, parameter optimization is a MOO problem. When there are multiple evaluation indicators for a problem, and the evaluation indicators conflict with each other, it is easy to sacrifice other indicators to improve one indicator. Therefore, it is difficult to determine the optimal solution to the MOO problem. The general method to solve the MOO problem is to coordinate the optimization objectives and conduct global optimization to achieve the desired results. The initial application of MOO was in the field of economics, and after promotion, it was widely used in the field of applied mathematics and engineering [23]. The key parameters of the traditional algorithm to solve the MOO problem need to be determined manually based on experience. Therefore, it is difficult to accurately judge the advantages and disadvantages of the solution, and it is difficult to obtain the optimal solution. With the continuous optimization of programming logic, more and more intelligent optimization algorithms have emerged, and they have also achieved good results in the field of MOO. Intelligent optimization algorithm refers to the fact that human beings integrate its principles into the algorithm logic based on their own cognition of relevant behaviors, rules, experience, and mechanisms in biological, physical, chemical, and other fields. Then extract the feature model according to the specific problem, and finally, design an intelligent iterative search optimization algorithm. The method commonly used in MOO is shown in Figure 3.

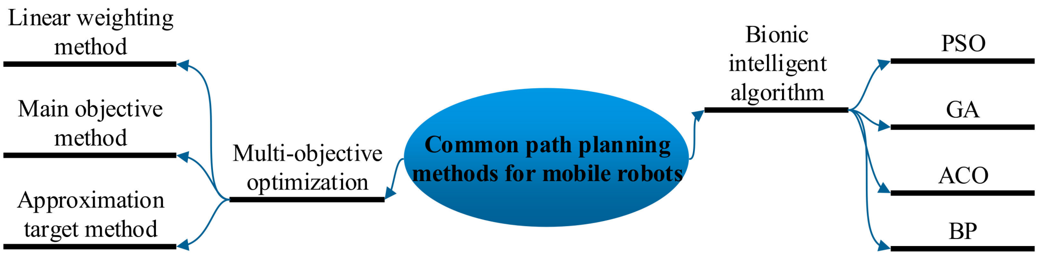


Figure 3. Methods for multi-objective optimization problems.

PSO is based on the simulation of the cognition of the foraging behavior rules of birds so as to achieve optimal search. On the other hand, GA optimizes the search through chromosome genetic simulation based on the understanding of the evolution rules of natural organisms. The two optimization algorithms are aimed at a population composed of several individuals, so this study is to design a hybrid optimization algorithm. Firstly, the fitness function of parameter optimization in this study is determined, and the required power of HEV has been determined in the parameter matching model. Genetic PSO is used to optimize the transmission system parameters of pure electric vehicles. The goal is to meet the requirements of power and economy at the same time. The fitness function is designed based on the principle of linear weighting. The acceleration time and endurance mileage are selected as two evaluation indicators, and they are weighted average as the fitness function of genetic PSO. The acceleration of the motor and the cruise mode of the vehicle are selected from the parameter construction model to measure. The fitness function formula is expressed as the following Formula (9).

$$F = w_1 \frac{P_{m1}}{t_{ref}} + w_2 \frac{L_{ref}}{P_{e2}} \tag{9}$$

F is the fitness function of PSO-GAMOO in Formula (9). P_{m1} and P_{e2} are the power requirements of HEV under acceleration and endurance, respectively. w_1 is the acceleration power demand weight. w_2 is the weight of cruise power demand. t_{ref} represents the acceleration time required by the design. L_{ref} refers to the range required by the design. Combining the fitness function and HEV parameter model Formulas (4) and (5), the value of the fitness function is related to vehicle mass and transmission efficiency. With the acceleration and endurance as the objective functions, the power demand for climbing and the maximum speed of the vehicle is studied and constructed in the parameter model. Therefore, in order to optimize the parameter design of the power system as a whole, the climbing power demand and the maximum speed power demand are taken as constraint functions. Formula (10) is a specific calculation.

$$\begin{cases} CF_1 = \arcsin \frac{T - C_d A V_i^2 / 21.15}{mg\sqrt{f^2+1}} - \arctan(f) \geq i_{\max} \\ CF_2 = \frac{0.377 \cdot r_w \cdot n_{\max}}{v_{\max}} \geq u_{\max} \end{cases} \tag{10}$$

CF_1 indicates that the power of the hybrid vehicle is greater than or equal to the design requirements in Formula (10). CF_2 indicates that the power of the hybrid vehicle at the maximum speed is greater than the design requirements. $u_{\max}$ represents the design requirement of maximum speed. After obtaining the objective function and constraint function, the search range of parameters is determined according to the traditional calculation results of the pure electric vehicle transmission system. Additionally, the rand function is used to assign initial values to the particle position and velocity. The particle attribute is substituted into the fitness function to calculate the fitness value, and the individual optimal fitness value and the group optimal fitness value are obtained by comparison. The particles will adjust their position and speed according to the different weights and move closer to the optimal position. Each movement will update the particle speed, position, and fitness values, and continue to iterate until the optimal solution is found. The velocity iteration formula for each time is as follows.

$$v_{id}^{k} = \omega v_{id}^{k-1} + c_1 r_1 (p_b - x_{id}^{k-1}) + c_2 r_2 (g_b - x_{id}^{k-1}) \tag{11}$$

In Formula (11), ω represents inertia weight. c_1 and c_2 are acceleration constants, respectively. r_1 and r_2 are random functions within the range of [0, 1]. p_b and g_b represent individual optimal position and group optimal position, respectively. x_{id}^{k} is the position parameter. Formula (12) is for each position iteration.

$$x_{id}^{k} = x_{id}^{k-1} + v_{id}^{k-1} \tag{12}$$

According to Formulas (11) and (12), the properties of particles are updated to obtain the next generation of particles and repeat the new particles to obtain the new particle swarm. The selection operation of GA is used to select several individuals randomly from the particle swarm each time, and the optimal individuals are selected according to the fitness size to enter the next generation of the population, and the above operation is repeated until a new population is formed. In this work, the fitness value will be calculated based on the selection operation, and the crossover probability will be determined by adaptive operation. The individual will be selected as the parent, and the neighboring individual will be selected as the parent, and the pair-wise crossover operation will be carried out, as shown in Formula (13).

$$p_c = \begin{cases} k_1(\hat{f} - f_{\min})/(\overline{f} - f_{\min}), \hat{f} < \overline{f} \\ k_2, \hat{f} \geq \overline{f} \end{cases} \tag{13}$$

k_1 and k_2 represent fixed parameters in Formula (13). $f_{\min}$ represents the optimal fitness. $\hat{f}$ is the smaller value of the fitness of the two individuals to be crossed. $\overline{f}$ is the average value of fitness. Additionally, mutation operation is carried out on the basis of particle swarm formed by cross operation. First, the fitness value of all individuals in the particle swarm is calculated, and adaptive mutation operation is adopted. That is, the mutation probability of individuals with high fitness is 0. Additionally, the mutation probability of individuals with low fitness is calculated according to the corresponding formula. Formula (14) is the specific expression.

$$p_m = \begin{cases} k_3(f - f_{\min})/(\overline{f} - f_{\min}), f < \overline{f} \\ k_4, f \geq \overline{f} \end{cases} \tag{14}$$

In Formula (14), k_3 and k_4 represent fixed parameters. f is the individual fitness value. Finally, the workflow of this study is shown in Figure 4.

In Figure 4, this study builds a dynamic parameter model of HEV based on the optimization of vehicle economy and power. The dynamic model of acceleration and cruise state is selected as the fitness function of the PSO-GA optimization algorithm, and the maximum speed and climbing performance are taken as the constraint functions. Through the iterative optimization of intelligent hybrid algorithm optimization, the optimal design value of parameters is obtained.

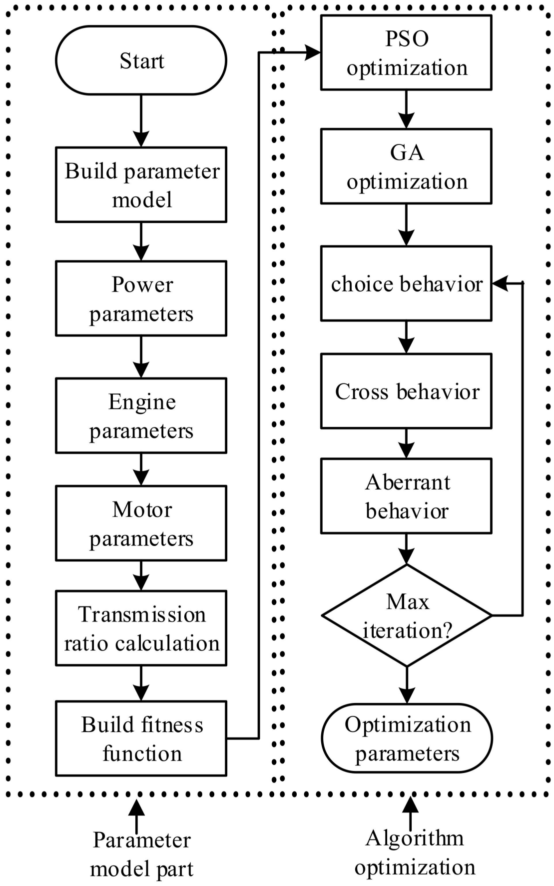


Figure 4. Parameter optimization process of HEV.

4. Application Analysis of PSO-GA in HEV Transmission System Parameter Optimization

4.1. Simulation Experiment Analysis of HEV Model

A domestic pure electric vehicle model is taken as a reference. The transmission system structure is a single-motor rear drive structure without a reducer. According to the CRUISE platform, the car simulation model is first built in this experiment. According to the power transmission direction and energy flow direction of HEV, the whole vehicle module, battery module, drive motor module, engine module, main reducer module, differential module, brake module, and tire module are selected from the module library. The parameters of the HEV model based on the research model and parameter optimization are shown in Table 1.

Table 1. Parameters of HEV Model.

Parameter Name	Character	Value and Value Range
Light weight	m_3	1140 kg
Drag coefficient	C_d	0.312
Windward area	A	2.05 m^2
Coefficient of rolling resistance	f	0.0125
Drive system efficiency	η_t	0.915
Coefficient of moment of inertia	δ	1.08
Maximum speed	$V_{\max}$	≥150 km/h
0–100 km/h Acceleration time	/	≤15
10 km/h Climbing performance	/	≥20
60 km/h Operating range	/	≥200 km
Tyre specification	/	215/70 R16

This study first compares the traditional PSO algorithm and GA algorithm with the PSO-GA hybrid optimization algorithm in this study. Through programming with MAT-

LAB software, set the population number to 500 and the maximum number of iterations to 100. PSO learning factors are all 2. The inertia weight is 0.8. The final result is shown in Figure 5.

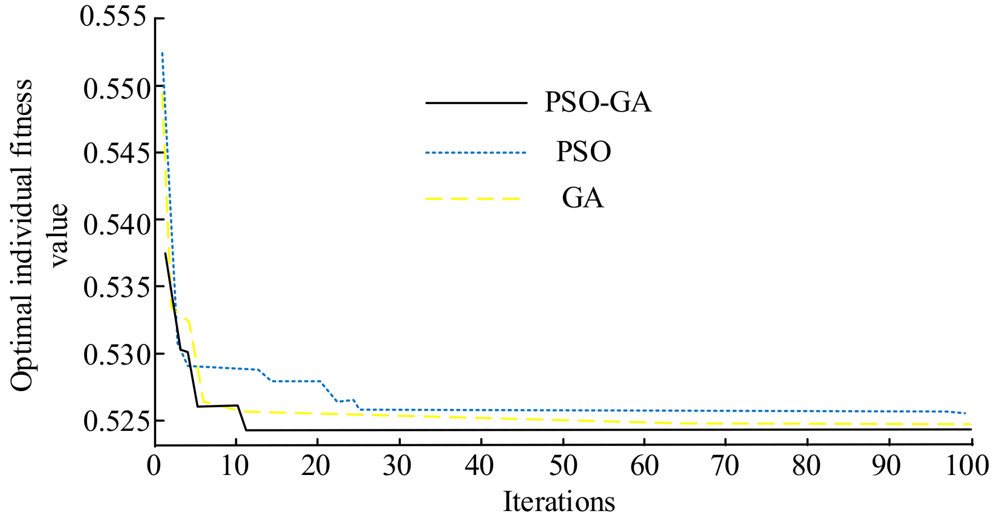


Figure 5. The best fitness value of different algorithms in the iterative process.

In Figure 5, the PSO-GA optimization algorithm is superior to the traditional algorithm in terms of convergence speed and stability. Reply: Based on your feedback, an explanation of Figure 5 has been added. The maximum number of iterations set for this PSO-GA algorithm is 100, but the actual maximum number of iterations is 38. After the 12th iteration, the fitness value of the algorithm tends to be flat, so 0.5239 is the average fitness value of 12–38 tests. The traditional PSO algorithm and GA algorithm converge at 22 and 18 times, respectively, with the average optimal fitness of 0.5267 and 0.5256, respectively. Experiments show that the PSO-GA hybrid optimization algorithm adopted in this paper is faster than the traditional GA algorithm and PSO algorithm. Additionally, the optimization efficiency and stability have been effectively improved.

The corresponding arrival time of all levels of speed is checked through the simulation result file. In Table 2, the acceleration time of the optimized simulation vehicle model from 0 to 100 km/h is 8.4 s, which meets the design requirements of less than 15 s. Additionally, the initial value of power battery discharge is set at 90%, and the end state is set at 5% to evaluate the vehicle's endurance performance. It is concluded that the endurance mileage at 60 km/h constant speed is 320 km, which is greater than the design requirement of 200 km.

Table 2. Simulation of acceleration performance of hybrid vehicle.

Velocity (km/h)	Time (s)	Distance (m)	Speed (1/min)
10	0.8	1.11	568.41
20	0.6	4.44	1136.82
30	2.4	9.92	1705.23
40	3.2	17.79	2273.64
50	4.01	27.68	2842.05
60	4.83	40.37	3410.46
70	5.63	55.69	3978.87
80	6.55	73.90	4547.28
90	7.45	95.05	5115.69
100	8.4	120.3	5684.11
110	9.49	151.69	6252.52
120	10.72	191.33	6820.93
130	12.11	239.85	7389.34
140	13.74	299.76	7957.75

Table 2. *Cont.*

Velocity (km/h)	Time (s)	Distance (m)	Speed (1/min)
150	15.54	373.71	8526.16
160	17.67	465.54	9094.57
170	20.19	581.09	9662.98
180	23.24	729.38	10,231.39
190	27.06	925.79	10,799.8
200	32.12	1200.15	11,369.21
210	39.54	1623.54	11,936.62
220	53.45	2456.82	12,505.03

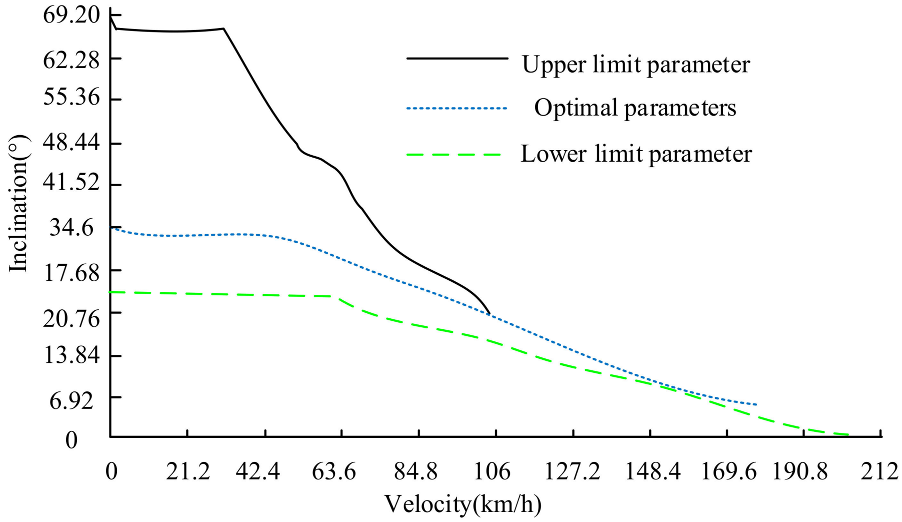
The climbing performance of the parameter optimization simulation vehicle model can be analyzed in Table 3. When the speed in the table is 10 km/h, the gradient is 35.73%, which meets the design requirement that the gradient is not less than 20% when the vehicle is 10 km/h. The maximum speed of the vehicle is 204 km/h, meeting the design index that the maximum speed is not less than 150 km/h.

Table 3. Simulation of climbing performance of hybrid vehicles.

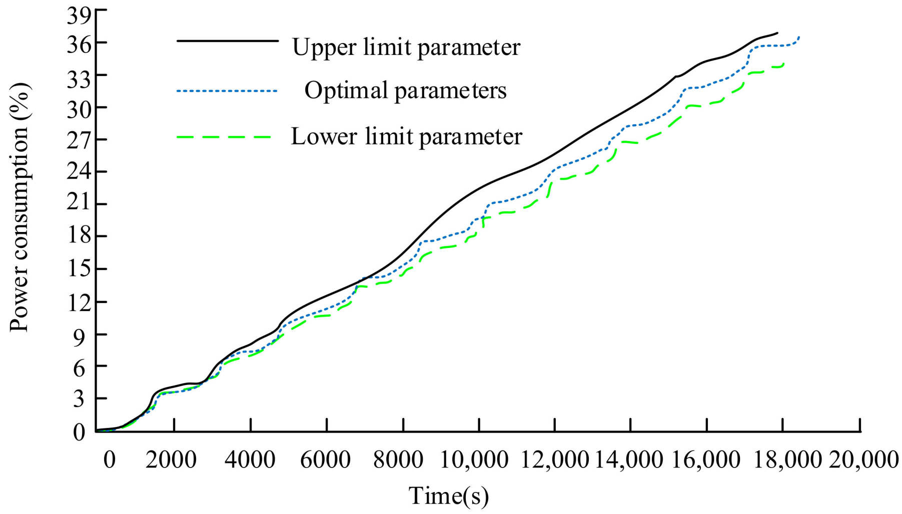
	Maximum Climbing Capacity	
Max inclination (°)	Velocity (km/h)	Speed (1/min)
35.73	10	398.87
	Measuring points speed	
Speed (1/min)	Velocity (km/h)	Max inclination (°)
0.00	0.00	36.54
866.67	15.25	35.73
5200	91.48	31.75
10,000	175.93	10.53

This experiment compares the parameter value range in Table 1 with the optimal value after an iteration and compares the upper and lower limit values of the parameter, the climbing ability, and the energy consumption of the optimal value. From Figure 6a, in the upper limit parameters, the maximum gradient of the simulated vehicle is 67.4. In the lower limit parameter value, the climbing slope is 23 degrees. After PSO-GA iterative optimization, the maximum gradient of the car is 35.1 degrees under the optimal parameter value. In Figure 6b, after completing the 18,000 s cruise, the power consumption of the upper limit parameter is 37.41%, and the power consumption of the lower limit parameter is 32.57%. The power consumption of the best parameter is 33.48%. The lower limit parameter has better energy economy, but the climbing ability is insufficient, while the upper limit parameter has defects in endurance. Under the optimal parameter value optimized by the PSO-GA algorithm proposed in this study, the maximum gradient is 52% higher than the lower limit parameter, so the method optimizes the energy consumption while retaining the power.

The upper limit and lower limit values of the parameters as well as the acceleration and speed of the best value are also compared. As shown in Figure 7a, the acceleration time of the upper limit parameter HEV 0–100 km/h is 6.98 s, the acceleration time of the lower limit parameter vehicle is 13.88, and the acceleration time of the best optimization parameter is 8.4 s. In Figure 7b, the maximum speed of the upper limit parameter HEV is 197 km/h, the maximum speed of the lower limit parameter vehicle is 188 km/h, and the maximum speed of the optimal parameter is 202 km/h. Compared with the lower limit parameters, after PSO-GA optimization, the maximum speed had an increase of 7%, and the acceleration time from 0 to 100 km/h had a decrease of 17%.

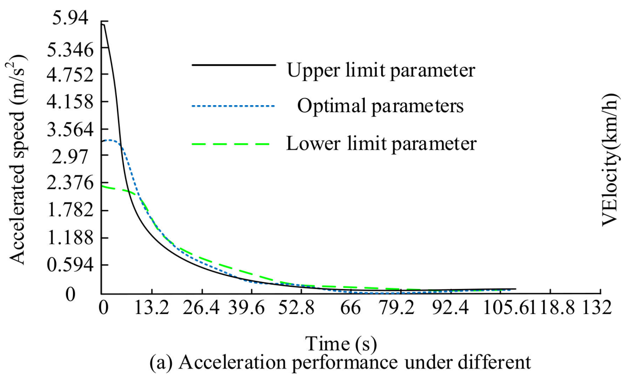


(a) Climbing ability of different parameter values

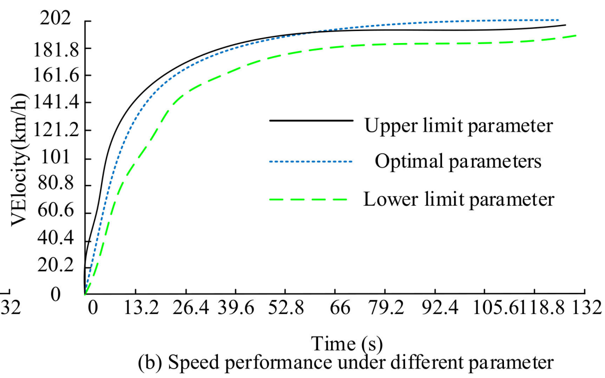


(b) Energy consumption with different parameter values

Figure 6. Analysis of vehicle climbing ability (**a**) and economy (**b**) under different parameter values.



(a) Acceleration performance under different parameter values



(b) Speed performance under different parameter values

Figure 7. Performance analysis of vehicle acceleration (**a**) and vehicle speed (**b**) under different parameter values.

4.2. Performance Comparison and Analysis of Hybrid Power Parameter Optimization Algorithms

After passing the parameter optimization simulation model test of HEV, this study will compare different transmission system parameter optimization methods. The object of this experiment is the simulation vehicle model in Table 1. In addition to the parameters in the table, the optimal transmission ratio of HEV is 9.2, and the maximum torque and power of the transmission system are 270 Nm and 147 kW, respectively.

This experiment first compares the energy consumption of the simulated annealing algorithm (SA) and the PSO-GA algorithm proposed in the study in HEV parameter optimization. From Figure 8a, the comparison of gasoline consumption between the two algorithms shows that, on the whole, the fuel consumption of the SA algorithm is higher than that of the PSO-GA algorithm. In the same 20,000 s task, the gasoline consumption after SA algorithm optimization is 0.561 L, while the fuel consumption of the hybrid power under PSO-GA algorithm optimization and completing the 2000 s task is 0.475 L. From Figure 8b, under the charging of planetary gear mode, the variation of battery state of charge of the simulated annealing algorithm is more obvious. After SA optimization, the battery SOC of the HEV fluctuates between 30.2% and 31%. After PSO-GA optimization, the SOC of the HEV battery fluctuates between 30.2% and 30.6%. After the optimization of PSO-GA algorithm parameters, the HEV consumes less energy, and the remaining state of battery power remains more stable.

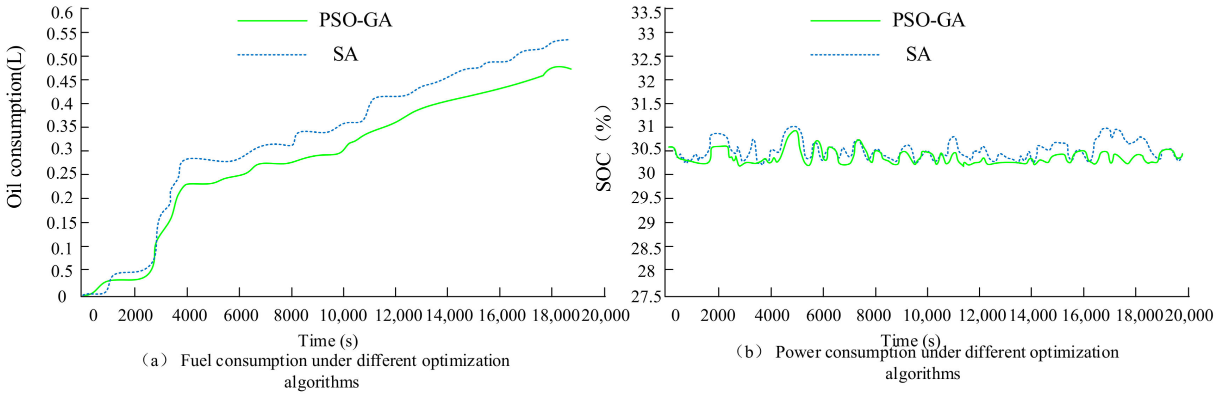


Figure 8. Analysis of automobile energy consumption under the optimization of simulated annealing algorithm and PSO-GA algorithm.

After comparing the energy consumption of the SA algorithm and PSO-GA algorithm, this experiment will compare the economy of the two algorithms after optimizing parameters. From Figure 9, after SA optimization, the HEV is about 0.34 yuan per kilometer within 6 km. After PSO-GA optimization, the HEV is about 0.31 yuan per kilometer within 6 km.

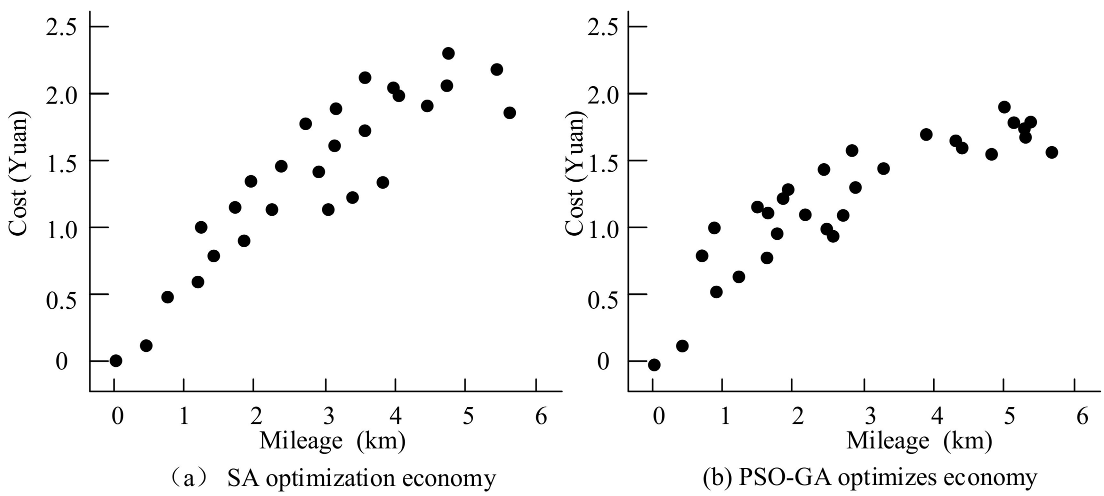


Figure 9. Analysis of automobile economy under the optimization of simulated annealing algorithm and PSO-GA algorithm.

5. Conclusions

This paper analyzes the structure and parameter coupling of the power train of HEV and builds the whole vehicle model of HEV based on CRUISE software. On this basis, the power train parameters are optimized by the PSO-GA algorithm. PSO-GA reached convergence at the 12th iteration, with an average optimal fitness of 0.5239, and its convergence speed and stability are higher than those of traditional algorithms. In the vehicle model simulation, the acceleration time of the optimized simulation vehicle model from 0 to 100 km/h is 8.4 s, which meets the design requirements of less than 15 s. The endurance mileage under a constant speed of 60 km/h is 320 km, which is greater than the design requirement of 200 km. Finally, the performance of PSO-GA and the simulated annealing algorithm under parameter optimization is analyzed. In the same 20,000 s task, the gasoline consumption after SA algorithm optimization is 0.561 L, while the fuel consumption of the hybrid power under PSO-GA algorithm optimization and completing the 2000 s task is 0.475 L. After PSO-GA optimization, the battery SOC of HEV fluctuates between 30.2% and 30.6%. After SA optimization, the HEV is about 0.34 yuan per kilometer within 6 km. After PSO-GA optimization, the HEV is about 0.31 yuan per kilometer within 6 km. The PSO-GA algorithm proposed in this study is effective in parameter optimization and meets the design requirements. It is superior to other algorithms in performance comparison. This experiment's inadequacy is that only one HEV simulation model has been used for effectiveness and performance analysis experiments, and there are few experimental objects. This study did not consider the thermal model of the engine and motor battery, and also insufficient consideration was given to exhaust emissions. Therefore, the future research direction of the model is to coordinate exhaust emissions as the optimization goal, and the model can be further included in the economic optimization goals.

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