

Article

Multi-Objective Optimization and Matching of Power Source for PHEV Based on Genetic Algorithm

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Abstract: Power system parameter matching is one of the key technologies in the development of hybrid electric vehicles. The power source is the key component of the power system which composed of engine, motor, and battery. Reasonable power source parameters are conducive to improve the power, fuel economy, and emission performance of vehicles. In this paper, regarding the problem that the plug-in hybrid electric vehicle (PHEV) parameter matching needs to weigh different design objectives, a multi-objective optimization and matching method based on a genetic algorithm is proposed. The vehicle dynamic model is established based on MATLAB/Simulink (Mathworks in Natick, Massachusetts, USA), and the feasibility of the model is verified by simulation. The main performance parameters of the power source are matched by theoretical analysis, and the PHEV integrated optimization simulation platform is established based on Isight(Dassault Systemes in Paris, France) and MALTAB/Simulink. Power source components are optimized considering fuel economy and lightweight objectives under the performance constraints. Firstly, the optimal matching results under different weights are obtained by transforming different objectives into single objective, and the multi-island genetic algorithm is used to obtain the optimal matching results in which the equivalent fuel consumption of 100km is reduced by 1%. Then the Pareto solution is obtained using the NSGA-II algorithm. The optimal matching results can be found after determining the weights of different design objectives, which proves the effectiveness and superiority of the multi-objective optimization matching method. The optimization results show that compared with the original vehicle, the fuel economy effect is increased by 2.26% and the lightweight effect is increased by 8.26%.

Keywords: optimization; matching; PHEV; genetic algorithm; fuel economy; lightweight

1. Introduction

Nowadays, the number and annual production of internal combustion engine vehicles are increasing rapidly, resulting in energy crisis, urban air pollution, and other issues that are becoming increasingly serious [1]. Pure electric vehicles are subject to current power battery technology and current infrastructure imperfections, and driving ranges and charging times bring great troubles to consumers [2]. Plug-in hybrid electric vehicle (PHEV) takes into account the advantages of traditional hybrid vehicles and pure electric vehicles. Compared with traditional hybrid vehicles, PHEV power battery packs have a larger capacity, a longer driving range, and can be charged by an external power grid, as well as better fuel economy and emission performance; it is a research hotspot in the field of new energy vehicles [3–5]. As the PHEV is equipped with two power source components: A traditional internal combustion engine and a driving motor, reasonable power source parameters matching is very necessary [6].

The parameter matching of hybrid electric vehicle's power system has the characteristics of non-linearity, multi-parameter and multi-degree of freedom. The whole matching process is complicated and cumbersome. It has been one of the hot topics in the research of hybrid electric vehicles [7].

Zeng et al. [8] presents the design method of a hybrid degree for parallel hybrid electric vehicles. The design of total power of power source satisfies the dynamic constraints. Then the design of hybrid degree is simplified by total power matching. Finally, the design variables are exhausted within the reasonable range of hybrid degree from 12.5% to 37.5%. The relationship between fuel economy improvement and hybrid degree is obtained by least square curve fitting. The optimum mixing design scheme is selected based on the lowest fuel consumption per kilometer. In Reference [9], combined with the development process of fuel cell bus power system, the simulation is carried out by adding the driving cycles of NYCC (New York City Cycle), ECE (Economic Commission for Europe), and New York BUS in the ADVISOR library. Under the condition of constant total power, the exhaustive mixing degree variable is used to select the optimal power system matching scheme with the objective of minimum fuel consumption. Exhaustion method is the simplest and most feasible method to optimize the matching problem, but it wastes time and computer costs. When the number of optimization variables increases, the number of optimization times increases exponentially, and the degree of optimization results depends on the minimum increment of variables. Wang et al. [10] used the basic orthogonal test method and comprehensive orthogonal test method to optimize the power system with orthogonal factors such as mixing degree, battery voltage, battery capacity, and main deceleration ratio. The results showed that the fuel economy of the optimized power system improved by 4.1% in urban conditions of China and 8.7% in urban conditions of Wuhan. Orthogonal test method can effectively reduce the number of optimization times and improve the optimization efficiency under the same number of optimization variables, but the overall optimization time is still long, and the optimization accuracy is not high.

In Reference [11], a constrained non-linear optimization model for the fuel cell hybrid power system is established. The design variables are the rated power of fuel cell, the number of power accumulator units, the initial and objective values of SOC (state of charge), and the transmission ratio of the gearbox and main reducer. Sequential quadratic programming (SQP) is applied to optimize the hybrid power system with the lowest hydrogen consumption being the objective, and the influence of design variables on the fuel economy of the vehicle is analyzed. Zhao et al. [12] also uses SQP to match the power system parameters of four-wheel drive fuel cell hybrid electric vehicle, but the objective function is the size of power transmission system components. By optimization of the design, the battery power is increased, the driving time and starting frequency of fuel cell are reduced, and the size of each component is optimized. Hu et al. [13] discusses the optimal matching problem of hybrid energy storage system (HESS) for fuel cell hybrid buses, a convex programming method is proposed to optimize HESS parameters and energy management strategy parameters synchronously. A dynamic battery life state (SOH) model is integrated to quantitatively evaluate the impact of battery replacement strategy on HESS parameters and fuel economy. The impact is based on the total cost of life cycle, and the battery SOH is the constraint to obtain the optimal HESS system and energy management strategy. Gao et al. [14] compares the matching effect of the DIRECT algorithm, simulated annealing algorithm, genetic algorithm and particle swarm optimization algorithm on the hybrid power system. The results show that DIRECT algorithm and simulated annealing algorithm are the most effective, but also the most time-consuming, and needs to spend 100 hours on PAST. It is suggested to combine the characteristics of the non-gradient algorithm and gradient algorithm to establish a hybrid algorithm for optimal matching, which can achieve global optimization and fast convergence. In Reference [15], the fuel consumption, CO, HC and NO_x indicators are weighted. And the four indicators are standardized since the units and magnitudes are different. On the basis of Reference [15], Wu et al. [16] increases the cost of replacing batteries in the future of the objective function. Omar et al. [17,18] selected the fuel cell and supercapacitor cost of fuel cell electric vehicles as well as battery weight and volume factors as the objective function to establish a detailed cost model.

In Reference [19], aimed at the shortcomings of genetic algorithm, which is characterized by premature convergence and low search efficiency in the later evolution stage, the simulated annealing principle with strong local search ability is introduced into genetic algorithm to obtain adaptive genetic algorithm. The power system parameters and control parameters are optimized simultaneously. Compared with a conventional genetic algorithm, the comprehensive performance of fuel consumption and emission can be improved by 4%.

As mentioned above, optimal matching method is widely used in power system parameter matching because of its high efficiency and high precision. However, most studies focus on single-objective optimization with optimum fuel economy or minimum cost, and few studies focus on multi-objective optimization with both fuel economy and lightweight. The lightweight of power system component is to reduce the power system total power so that to reduce the component size, reduce the weight of power system and balance the cost of the whole vehicle. In this paper, a PHEV integrated optimization simulation platform is established based on Isight and MATLAB/Simulink software for plug-in hybrid electric bus. The power system components are optimized by weight method and non-normalization method (Pareto mechanism) respectively considering fuel economy and lightweight, and the corresponding optimal matching results are obtained.

2. Powertrain Model of PHEV

In this paper, a single-shaft parallel plug-in hybrid electric bus is selected as the research object to study the matching and optimization of the power source of the hybrid power system. The powertrain of the system is shown in Figure 1. The single-shaft parallel hybrid power system consists of an engine, a clutch, a motor, a power battery, a gearbox, a final drive, and associated controllers. A hybrid electric bus with this configuration can achieve a variety of working modes (as shown in Figure 2), including pure electric mode, engine driving mode, hybrid driving mode, charging mode and braking energy recovery mode, which can effectively improve the fuel economy.

The vehicle type equipped with this hybrid system is a low-floor bus, and Table 1 shows the basic parameters and performance indexes of the vehicle, which is also the design goal of matching and optimization in this paper.

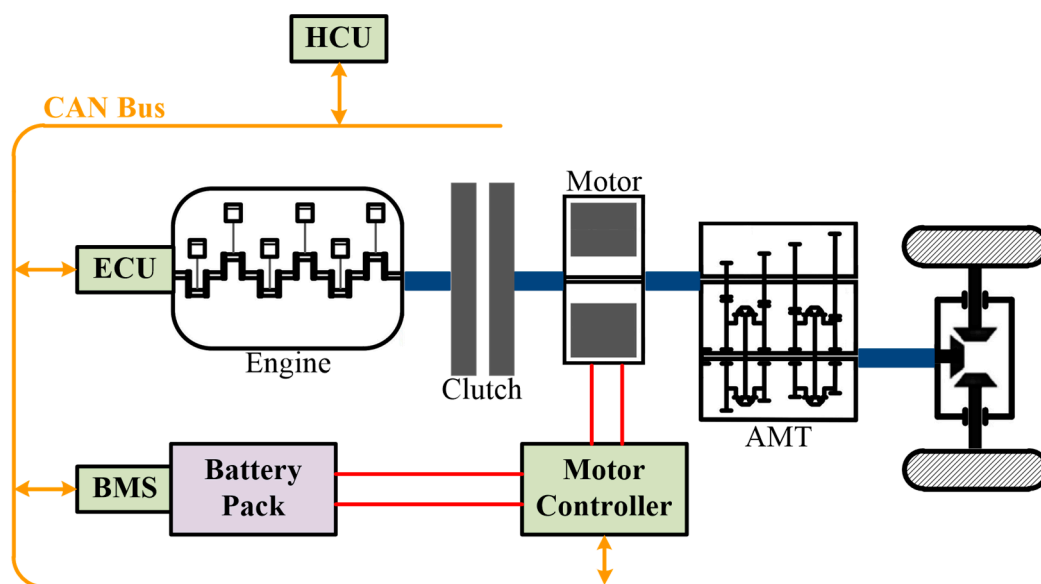


Figure 1. Configuration of the studied hybrid powertrain.

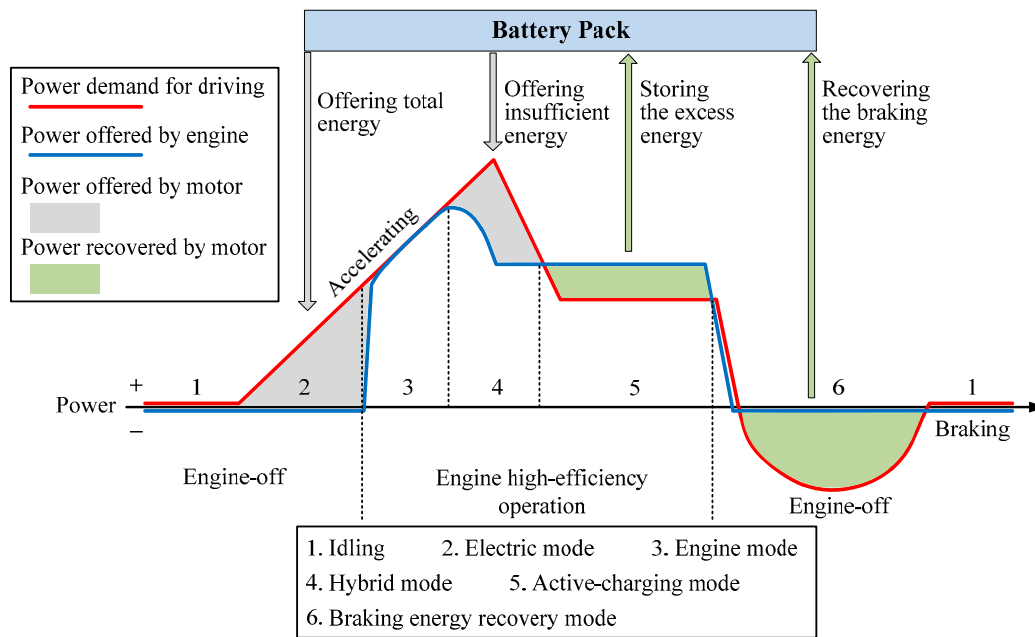


Figure 2. Working modes of the plug-in hybrid electric vehicle (PHEV).

Table 1. Main parameters of PHEV.

Vehicle Parameter	
Full mass	18,000 kg
Curb mass	12,000 kg
Aerodynamic resistance coefficient	0.55
Windward area	6.6 m ²
Wheel radius	0.473 m
Performance Index	
Maximum speed	80 km/h
Maximum gradeability	20%
0–50 km/h Accelerating time (HEV)	20 s
0–50 km/h Accelerating time (EV)	25 s
Engine	
Maximum power	120 kW (2500 rpm)
Maximum torque	704 Nm (1200–1800rpm)
Driving Motor	
Rated power/Maximum power	76 kW/150 kW
Rated torque/Maximum torque	535 Nm/1584 Nm
Power Battery	
Voltage class	576 V
Battery capacity	60 Ah

2.1. Engine Model

It is very complex and inefficient to establish a non-linear model which can characterize the internal dynamic characteristics of the engine. In this paper, the experimental modeling method is adopted, which focuses only on the input and output characteristics of the engine, ignores the fuel consumption caused by the dynamic migration of the engine working point, and uses the steady-state test data of the bench test to establish the engine’s model [20].

The engine torque T_e is expressed as Equation (1):

$$T_e = f(\text{Throttle}, n_e) \quad (1)$$

The fuel consumption per unit time \dot{m}_f is expressed as Equation (2):

$$\dot{m}_f = \frac{T_e \omega_e b_e}{367.1 \rho g} \quad (2)$$

$\omega_e = 2\pi n_e$, b_e is fuel consumption rate [g/(kWh)], ρ is fuel density (kg/L), and g is acceleration of gravity (m/s^2).

The engine fuel consumption m_f is expressed as Equation (3):

$$m_f = \int_0^t \dot{m}_f dt \quad (3)$$

2.2. Driving Motor Model

The establishment of driving motor's model is similar to that of the engine. It pays no attention to the electromagnetic and thermodynamic characteristics of the motor body, but only to the dynamic characteristics of the motor [2]. The external characteristics and working efficiency of the motor are measured by bench test.

The working efficiency η_m of the motor is expressed as Equation (4):

$$\eta_m = f(T_{m_req}, n_m) \quad (4)$$

T_{m_req} is the demand torque of the motor (Nm), and n_m is the current speed of the motor (rpm).

The actual output torque of the motor T_m is expressed as Equation (5):

$$T_m = \begin{cases} \min(T_{m_req}, T_{m_dis_max}(n_m)) & T_{m_req} > 0 \\ \max(T_{m_req}, T_{m_chg_max}(n_m)) & T_{m_req} < 0 \end{cases} \quad (5)$$

$T_{m_dis_max}$ and $T_{m_chg_max}$ are respectively the maximum driving torque and braking torque of the motor, which are related to the current motor speed.

The output power of the motor P_m is expressed as Equation (6):

$$P_m = \begin{cases} \frac{T_m n_m}{9550 \eta_m} & T_m > 0 \\ \frac{T_m n_m \eta_m}{9550} & T_m < 0 \end{cases} \quad (6)$$

2.3. Power Battery Model

The power battery system is one of the sources of energy for hybrid electric vehicles, and its performance directly affects the power performance and fuel economy of the vehicle. The lithium-ion battery is used in the researched PHEV for its superior high specific energy and specific power performance [21]. In this paper, the equivalent circuit model is used to establish the battery model (as shown in Figure 3), V_{oc} is the open circuit voltage, R_{int} is the equivalent internal resistance, V_0 is the load voltage, and I_0 is the charge-discharge current.

According to Ohm's law, the battery load voltage V_0 and load power P_{bat} are expressed as Equation (7):

$$\begin{cases} V_0 = V_{oc} - I_0 R_{int} \\ P_{bat} = V_0 I_0 = V_{oc} I_0 - I_0^2 R_{int} \end{cases} \quad (7)$$

The battery charge–discharge current I_0 is expressed as Equation (8):

$$I_0 = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_{int}P_{bat}}}{2R_{int}} \quad (8)$$

The SOC in the battery model is calculated by the ampere–time integral method, as shown in Equation (9):

$$SOC(k+1) = SOC(k) + \frac{\int_k^{k+1} I_0(SOC, P_{bat})dt}{3600 \cdot Q_0} \quad (9)$$

$SOC(k)$ is the SOC of the battery at k time, and Q_0 is the battery capacity (Ah).

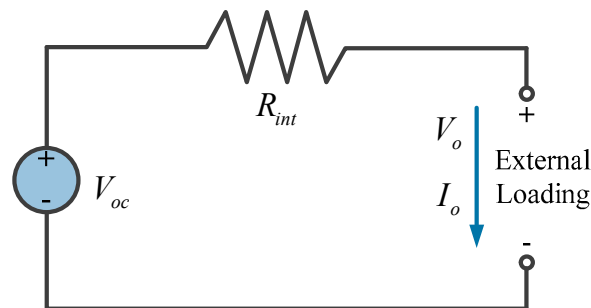


Figure 3. Equivalent circuit diagram of power battery model.

2.4. Longitudinal Dynamic Model

This paper mainly studies the longitudinal dynamic model of vehicle driving process, ignoring the influence of lateral dynamics on vehicle. The driving torque and braking torque acting on the drive shaft accelerate or decelerate the vehicle.

According to the automobile theory [22], when the vehicle is driving:

$$F_t = \frac{T_t i_g i_0 \eta_T}{R_{wh}} = F_f + F_w + F_i + F_j \quad (10)$$

$$\begin{cases} F_f = fmg \cos \theta \\ F_w = \frac{1}{2} C_D A \rho_a v_r^2 \\ F_i = mg \sin \theta \\ F_j = \delta m \frac{du_a}{3.6dt} \end{cases} \quad (11)$$

when the vehicle is braking:

$$F_b = F_{b_motor} + F_{b_mech} = F_f + F_w + F_i + F_j \quad (12)$$

F_t is the vehicle driving force (N), T_t is the power source driving torque (Nm), i_g is the gear ratio of the transmission, i_0 is the gear ratio of the main reducer, η_T is the powertrain efficiency, R_{wh} is the wheel rolling radius (m), and F_b is the vehicle braking force (N), which is the sum of the electric braking force F_{b_motor} and the mechanical braking force F_{b_mech} . F_f is the rolling resistance (N), f is the rolling resistance coefficient, and the specific value can be expressed as a function of vehicle speed, which is $f = 0.0076 + 0.000056u_a$, u_a is the vehicle speed (km/h), m is the vehicle mass (kg), θ is the ramp angle of the road (rad), F_w is the air resistance (N), C_D is the air resistance coefficient, A is the windward area (m^2), ρ_a is the air density (kg/m^3), v_r is the relative vehicle speed (m/s), F_i is the gradient resistance (N), F_j is the acceleration resistance (N), and δ is the vehicle rotation mass conversion factor, which is calculated as Equation (13):

$$\delta = \begin{cases} 1 + \frac{\sum J_w}{mR_{wh}^2} + \frac{(J_e + J_m)i_g^2 i_0^2 \eta_T}{mR_{wh}^2} & \text{Clutch engaged} \\ 1 + \frac{\sum J_w}{mR_{wh}^2} + \frac{(J_m)i_g^2 i_0^2 \eta_T}{mR_{wh}^2} & \text{Clutch disengaged} \end{cases} \quad (13)$$

J_w is the vehicle rotational inertia ($\text{kg}\cdot\text{m}^2$), J_e is the engine rotational inertia ($\text{kg}\cdot\text{m}^2$), and J_m is the driving motor rotational inertia ($\text{kg}\cdot\text{m}^2$).

The research object of this paper is a plug-in hybrid electric bus, which mainly runs in city driving cycle, so the simulation is based on Chinese Bus Driving Cycle (CBDC). The simulation result is shown in Figure 4. The difference between the actual speed and the expected speed is within 1 km/h, which can track the speed of driving cycle well and meet the accuracy requirements.

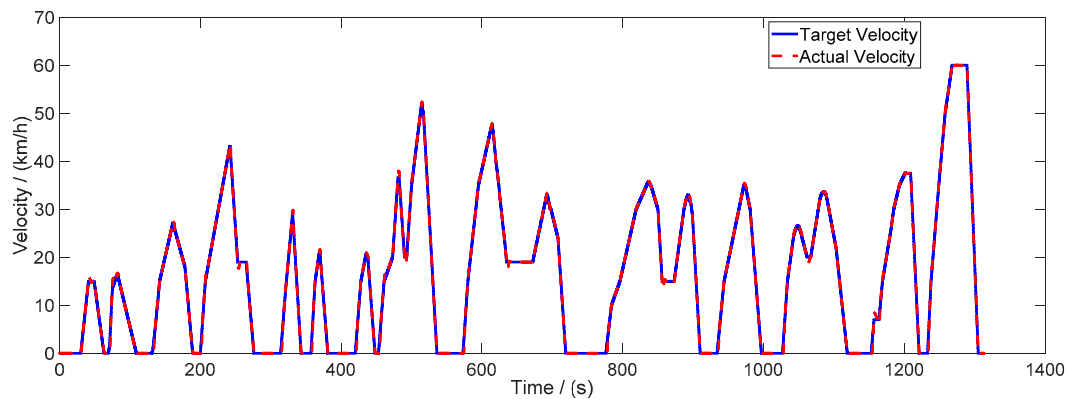


Figure 4. Simulation result of vehicle speed in Chinese Bus Driving Cycle (CBDC).

3. Optimization and Matching Design Method of PHEV

According to the performance constraints of PHEV, the fuel economy and lightweight optimization targets are selected to optimize and determine the design parameters of the PHEV main power components, including engine power P_e , motor power P_m and battery capacity Q_0 . The optimization and matching process of PHEV power sources is shown in Figure 5.

3.1. Analysis of Power Unit Parameters

The parameter selection of the plug-in hybrid system is related to the power performance, the fuel economy, the manufacturing cost and the use cost. In the initial stage of vehicle design, it is necessary to select the main performance parameters of the power system from the performance requirements of the vehicle, so as to provide a basis for establishing a more accurate simulation model and optimization analysis.

3.1.1. Determination of Power Source Total Power

PHEV has two power sources: Engine and motor. It is not necessary to use engine alone to improve peak power when considering vehicle power performance requirements. Therefore, compared with traditional internal combustion engine vehicles, PHEV mainly considers power performance requirements of power sources under hybrid driving mode, including maximum vehicle speed, maximum climbing degree, acceleration power demand and driving cycle demand.

(1) Power demand of maximum vehicle speed:

$$P_{total1} = \frac{u_{a_max}}{3600\eta_T} \left(mgf + \frac{C_D A u_{a_max}^2}{21.15} \right) \quad (14)$$

where u_{a_max} is the maximum vehicle speed under hybrid driving mode.

(2) Power demand of maximum climbing degree:

$$P_{total2} = \frac{u_a}{3600\eta_T} (mgf \cos \alpha_{max} + mg \sin \alpha_{max} + \frac{C_D A u_a^2}{21.15}) \tag{15}$$

where α_{max} is the vehicle maximum climbing degree.

(3) Power demand of acceleration under hybrid driving mode:

$$P_{total3} = \frac{u_{a_end}}{3600\eta_T} (mgf + \frac{C_D A u_{a_end}^2}{21.15} + \frac{m\delta u_{a_end}}{3.6\Delta t} [1 - (\frac{t_m - \Delta t}{\Delta t})^{0.5}]) \tag{16}$$

where u_{a_end} is the final vehicle speed during acceleration under hybrid driving mode (km/h), t_m is the acceleration time (s), and Δt is the iteration step, usually 0.1s.

(4) Power demand of driving cycle:

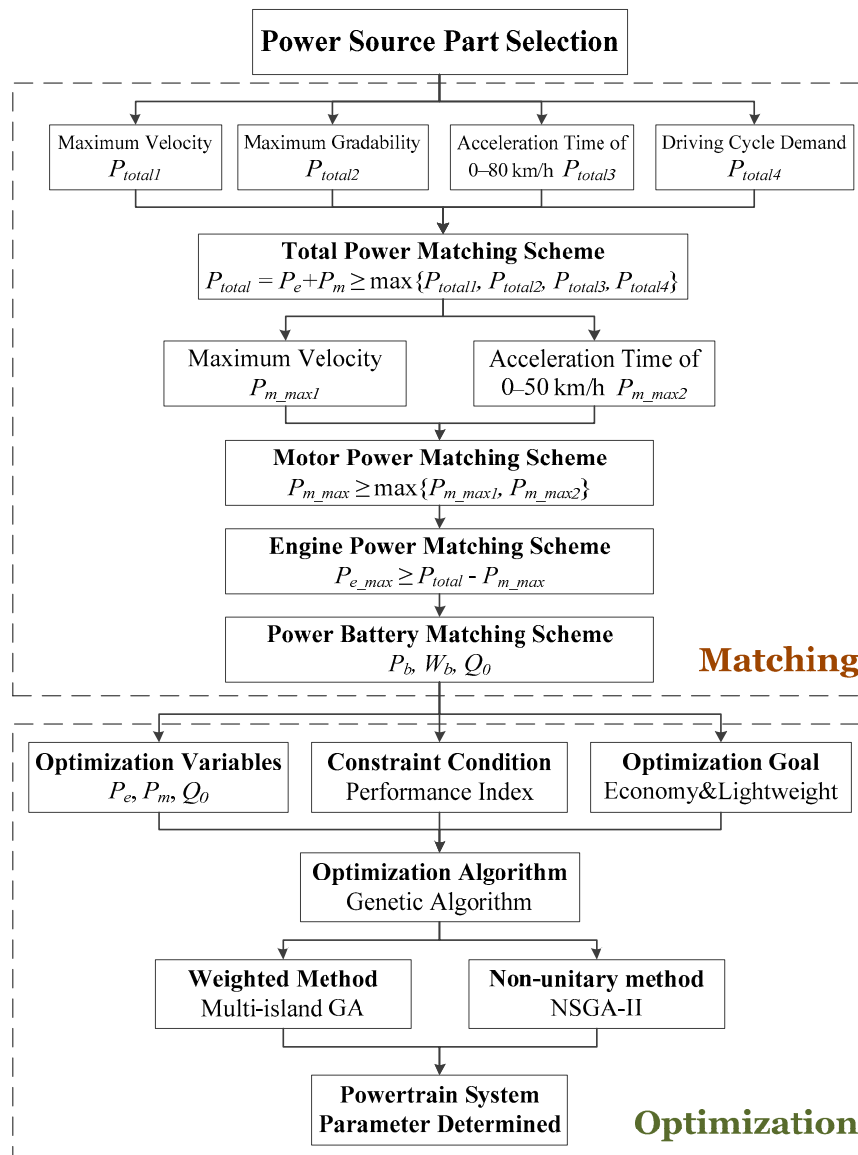


Figure 5. Optimization and matching design process of PHEV power sources.

The instantaneous driving power demand of the vehicle for the power system at t time of the target driving cycle is:

$$P_{cyc_t} = \frac{u_{a_t}}{3600\eta_T} \left(mgf + \frac{C_D A u_{a_t}^2}{21.15} + m\delta \frac{u_{a_t} - u_{a_t-1}}{3.6 \cdot dt} \right) \quad (17)$$

where u_{a_t} and u_{a_t-1} are respectively the instantaneous vehicle speed in target driving cycle at t and $t-1$ time, the power demand of driving cycle is shown as Equation (18):

$$P_{total4} = \max(P_{cyc_t}) \quad (18)$$

The total power should be greater than the maximum power of the four indicators mentioned above:

$$P_{total} \geq \max\{P_{total1}, P_{total2}, P_{total3}, P_{total4}\} \quad (19)$$

3.1.2. Determination of Motor and Engine Power

For the traditional hybrid electric vehicles, the motor mainly provides the required peak power to the electric drive system. The acceleration performance of the vehicle and the peak power of the load in the driving cycle are its main concerns. However, in the driving process of PHEV, due to the existence of pure electric driving mode, the power of the motor needs to meet the power demand of the driving cycle when the motor drives the vehicle separately, including the power demand of maximum vehicle speed and acceleration under pure electric driving mode.

(1) Power demand of maximum vehicle speed under pure electric driving mode:

$$P_{m_max1} = \frac{u_{m_max}}{3600\eta_T} \left(mgf + \frac{C_D A u_{m_max}^2}{21.15} \right) \quad (20)$$

where u_{m_max} is the maximum vehicle speed under pure electric driving mode.

(2) Power demand of acceleration under pure electric driving mode:

$$P_{m_max2} = \frac{u_{m_end}}{3600\eta_T} \left(mgf + \frac{C_D A u_{m_end}^2}{21.15} + \frac{m\delta u_{m_end}}{3.6\Delta t} \left[1 - \left(\frac{t_m - \Delta t}{\Delta t} \right)^{0.5} \right] \right) \quad (21)$$

where u_{m_end} is the final vehicle speed during acceleration under pure electric driving mode (km/h).

According to the maximum power calculated by the dynamic indexes mentioned above, the driving motor power must satisfy the following requirements:

$$P_{m_max} \geq \max\{P_{m_max1}, P_{m_max2}\} \quad (22)$$

Meanwhile, the sum of motor and engine power must meet the design requirements described in Section 3.1.1:

$$P_{total} = P_e + P_m \geq \max\{P_{total1}, P_{total2}, P_{total3}, P_{total4}\} \quad (23)$$

Therefore, the engine power must satisfy:

$$P_{e_max} \geq P_{total} - P_{m_max} \quad (24)$$

3.1.3. Determination of Power Battery Parameters

As the power source of motor, the performance parameters of power battery mainly consider two factors: Power demand and energy demand. The battery pack should ensure that the peak discharge power of the battery is higher than the maximum power of the motor, and the total energy of the battery can meet the driving range requirements.

(1) Power demand of the power battery:

$$P_{b_max} \geq \frac{P_{m_max}}{\eta_b \eta_m} \quad (25)$$

η_b is the discharging efficiency of the power battery, η_m is the motor efficiency.

(2) Energy demand of the power battery:

$$W_b = \frac{P_v L}{(SOC_1 - SOC_0) \eta_b \eta_m v} \quad (26)$$

P_v is the power of the vehicle running at constant speed v (km/h); L is the driving range under pure electric driving mode (km); SOC_1 and SOC_0 are respectively the maximum and minimum values of battery SOC applicable range.

Therefore, the rated capacity of the power battery pack must satisfy:

$$Q_0 \geq \frac{W_b}{V_{oc}} \quad (27)$$

3.2. Construction of Optimization Model

For PHEV, it is hoped that fossil fuels will be replaced as much as possible by grid power. At the same time, the hybrid electric city bus is usually focused on the optimization of vehicle fuel economy. Therefore, the optimization problem of PHEV power system is to find the best fuel economy power system scheme [23] on the premise of satisfying the dynamic index constraints. Its mathematical model is described as Equation (28):

$$\begin{cases} \min & f(X) \\ \text{s.t.} & g_j(X) \geq 0 \quad j = 1, 2, \dots, m \\ & x_i^{low} \leq x_i \leq x_i^{up} \quad i = 1, 2, \dots, n \end{cases} \quad (28)$$

$f(X)$ is the objective function, X is the optimization variables; $g_i(X)$ is the constraint conditions, m is the number of constraints; x_i is the parameter to be optimized, x_i^{low} and x_i^{up} are respectively the lower and upper limits of i^{th} parameter to be optimized, n is the number of optimization variables.

3.2.1. Optimization Variables

In the optimization problem, the selection of design variables is the basis of the optimization design. The design variables should not only represent the power components, but also update the characteristic curve of the power components when the design variables are updated. For engines and motors, the power parameter is often selected as the design variable [24]; for batteries, battery capacity is proportional to the charge-discharge power and the number of batteries, therefore battery capacity is chosen as the design variable.

Consequently, the maximum engine power P_{e_max} , the maximum motor power P_{m_max} , and the battery capacity Q_0 are selected as design variables, as shown in Equation (29).

$$X = [P_{e_max}, P_{m_max}, Q_0] \quad (29)$$

In the process of parameter optimization, it is necessary to update the design variables continuously through the optimization algorithm, and then evaluate the objective function value under the design variables. Therefore, the component model should be extensible, that is, when the design variables are updated, the component model should be updated accordingly so that the corresponding component optimization can be performed. Linear extended model is widely used in commercial software because of its simplicity and convenience. The nonlinear extended model is complex and computationally

intensive, and the results obtained by linear extended method are not much different from those obtained by non-linear extended method [25]. Therefore, the linear extended model is adopted for all parts of power system in this paper, and the component model established in Chapter 2 is used for reference model.

3.2.2. Constraint Conditions

The optimization and matching of PHEV power sources must satisfy the system development objectives, the system development objectives and other component constraints constitute the constraints of the optimization. This paper does not discuss vehicle emissions, so there are three main dynamic indicators: Maximum vehicle speed, acceleration time, and maximum climbing degree, and one economic indicator: Equivalent fuel consumption per hundred kilometers. Meanwhile, the design variables of reference models should be adjusted by the analysis in Section 3.1, as shown in Table 2.

Table 2. Constraint conditions of optimization and matching.

Constraint Conditions	Lower Boundary	Upper Boundary
Maximum velocity (EV)	50 km/h	-
Maximum velocity (Hybrid)	80 km/h	-
0-50km/h Accelerating time (EV)	-	25 s
0-50km/h Accelerating time (Hybrid)	-	20 s
Maximum gradeability	20%	-
Fuel consumption of 100 km	-	32.6 L
Engine power	68 kW	150 kW
Driving motor power	120 kW	225 kW
Power battery capacity	50 Ah	100 Ah

3.2.3. Selection of Energy Management Strategy

PHEV mainly has the following several energy management modes: Charge-depleting mode, charge-sustaining mode, pure engine mode, and pure electric mode. In this paper, the energy management strategy in reference [26] is adopted. The control strategy consists of three parts: Pure electric mode (EV), charge-depleting mode (CD), and charge-sustaining (CS). In EV mode, the motor drives the vehicle separately, and all the driving power comes from the power battery pack. In CD mode, the SOC of the power battery pack decreases gradually when the motor and the engine drive the vehicle together, and because the engine participates in the power output, the speed of SOC decreases slower than that of EV mode. In CS mode, the engine provides most of the power output required for driving the vehicle, and SOC is maintained in a suitable range until parking. The switching control rules of PHEV working modes are shown in Figure 6. SOC_{CD} is the SOC threshold from EV mode to CD mode, and SOC_{CS} is the SOC threshold from CD mode to CS mode.

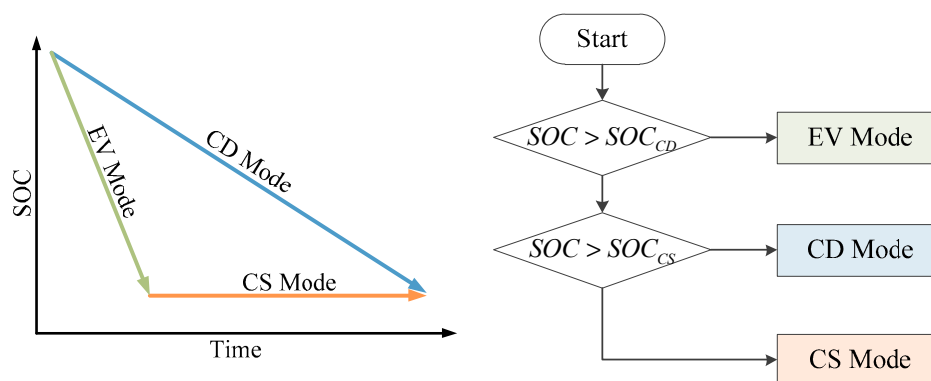


Figure 6. Switching control rules of PHEV working modes.

3.2.4. Optimization Platform

The structure of the PHEV integrated optimization platform based on Matlab/Simulink and Isight is shown in Figure 7. The PHEV model in the MATLAB/Simulink environment is invoked through the interface module of Isight, and the parameters of PHEV to be optimized in the model are modified. Then, under the Isight environment, the global optimization algorithm program and PHEV model are simulated to solve the power performance and fuel economy, and the results are fed back to Isight, so that the iteration steps are repeated until the preset iteration steps are completed or the preset accuracy is achieved.

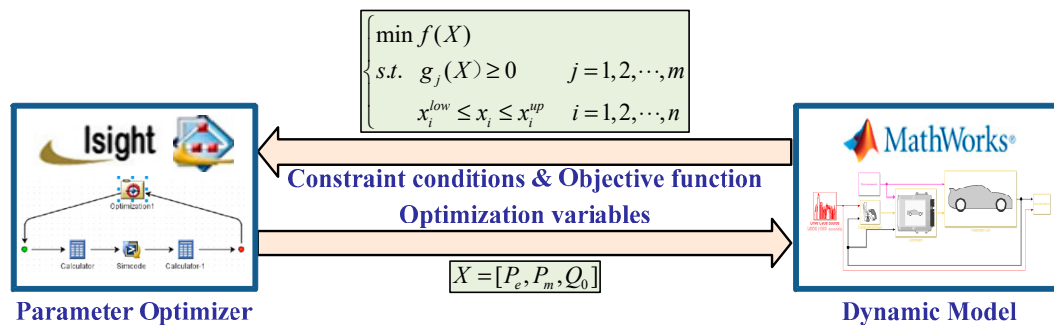


Figure 7. Integrated optimization platform based on Isight.

4. Multi-Objective Optimization Considering Fuel Economy and Lightweight

Aiming at the problem that parameter matching needs to weigh different design objectives, a multi-objective optimization matching method is proposed. When matching power sources, factors of lightweight, fuel economy, power performance, emission and cost are usually considered. This paper does not consider emission performance, the cost is achieved through lightweight. When the engine, motor and battery are lightweight, the mass is smaller, and the cost is lower. Therefore, this paper adopts weight method and non-normalization method respectively, and considers fuel economy and lightweight as the objectives to optimize PHEV power source components.

The fuel economy of vehicle is usually measured by the fuel consumption of 100 kilometers under certain operating conditions. However, PHEV can provide power either from fuel or from battery, the equivalent fuel consumption of 100 kilometers is used to measure the fuel economy of PHEV. Electricity equivalent fuel consumption is converted into fuel consumption through Equation (30) [27]:

$$FC_e = \frac{E_{\Delta SOC}}{q_g \eta_e \eta_m} = \frac{\Delta SOC \cdot Q_0 \cdot 3600 \cdot \int V_{oc} d(1 - SOC)}{q_g \eta_e \eta_m} \quad (30)$$

q_g is fuel btu (J/kg), η_e is engine efficiency, η_m is engine efficiency, ΔSOC is variation of SOC, and $E_{\Delta SOC}$ is the energy converted for electricity consumption.

Equivalent fuel consumption of electricity consumption plus actual fuel consumption is equivalent fuel consumption of vehicles. Equivalent fuel consumption of 100 km is shown as Equation (31):

$$FC = \frac{FC_g + FC_e}{10^{-5} \rho_g d_{cyc}} \quad (31)$$

FC is the equivalent fuel consumption of 100 kilometers (L/100 km), FC_g is fuel consumption (g), ρ_g is fuel density (kg/L), and d_{cyc} is the distance of driving cycle (m).

Hybrid electric system consists of engine, motor, battery pack, and other components. The mass variations of vehicle can be estimated by the following mass model. The vehicle power system mass [28] can be described as Equation (32):

$$\begin{cases} M_{pt} = M_e + M_m + M_b \\ M_e = a \times P_{e_max} + b \\ M_m = c \times P_{m_max} + d \\ M_b = \frac{Q_0 \times V_t}{h} \end{cases} \quad (32)$$

a, b, c, d, h are fit coefficients, which are obtained by linear fitting of the mass, power and energy relationships of engine, motor and power battery; M_{pt} is power system mass of PHEV (kg), M_e is the engine mass (kg), M_m is the motor mass (kg), and M_b is the power battery mass (kg). Through Equation (32), it can be seen that the mass of the vehicle power system has a linear relationship with the power of the power system, that is to say, reducing the system power can reduce the mass of the vehicle power system and achieve lightweight.

4.1. Weighted Method

Weighted method is a commonly used method to deal with multi-objective problems, which can transform multi-objective problem into single-objective problem. The optimization objectives considering fuel economy and lightweight can be expressed as Equation (33):

$$\min f(X) = [P_{e_max}, P_{m_max}, Q_0, FC] \quad (33)$$

By weighting and normalizing, the objective function is shown as:

$$f(X) = w_1 \frac{P_{e_max}}{120} + w_2 \frac{P_{m_max}}{150} + w_3 \frac{Q_0}{60} + w_4 \frac{FC}{32.6} \quad (34)$$

The objective function value of the original vehicle is 1.0, which facilitates the comparison between the matching results and the original vehicle parameters. Four different weight combinations (as shown in Table 3) are selected. Among them, combination 1 gives priority to engine lightweight, combination 2 gives priority to motor lightweight, combination 3 gives priority to battery lightweight, and combination 4 balances the lightweight and economy of power components.

Table 3. Values of weight coefficients.

	1 st Set	2 nd Set	3 rd Set	4 th Set
w_1	0.7	0.1	0.1	0.25
w_2	0.1	0.7	0.1	0.25
w_3	0.1	0.1	0.7	0.25
w_4	0.1	0.1	0.1	0.25

The multi-island genetic algorithm (MIGA) is used to optimize the power system parameters in the optimization platform established in Section 3.2.4. The MIGA is developed on the basis of traditional genetic algorithm (GA). It inherits the basic ideas of GA. The biggest difference between them is that MIGA divides many populations into several sub-populations, performs GA selection, crossover, and mutation operations in sub-populations, and periodically performs targeted immigration operations among different populations [29]. The evolutionary process of its two adjacent generations is shown in Figure 8.

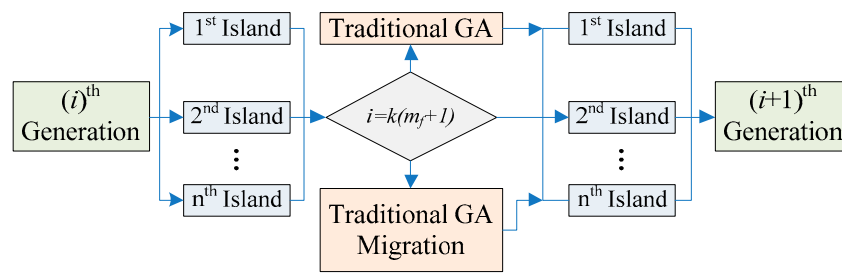


Figure 8. Evolutionary process of the multi-island genetic algorithm (MIGA).

Considering the optimization time and the accuracy of the results, the parameters of the multi-island genetic algorithm are set as follows: the total population size is 50, the number of evolutionary generations is 500, the crossover probability is 0.9, and the mutation probability is 0.01.

The results of different weight combination optimizations are listed in Table 4. Combination 1 indicates that the engine of the original vehicle has much room for lightweight. Combination 2 and 3 show that the motor and battery parameters of the original vehicle are close to the minimum value of the constraints. Because of the power constraint between the motor and battery capacity, the maximum power of the motor or the battery capacity will be reduced while the value of another parameter is reduced, so the optimal matching results of combination 2 and 3 are close.

Table 4. Optimal matching results using weight method.

Title Design Variables	1 st Set	2 nd Set	3 rd Set	4 th Set	Original
P_e (kW)	72.4	102.3	97.8	80.5	120
Variation (%)	-39.67	-14.75	-18.5	-32.92	0
P_m (kW)	165.5	136.4	143.9	141.2	150
Variation (%)	10.33	-9.06	-4.07	-5.87	0
Q_0 (Ah)	67.3	54.3	56.1	57.7	60
Variation (%)	12.17	-9.5	-6.5	-3.83	0
FC (L/100 km)	32.92	32.8	32.73	32.15	32.6
Variation (%)	0.98	0.61	0.4	-0.99	0

The optimal matching result of combination 1 is that the maximum engine power is 72.4 kW, the maximum motor power is 165.5 kW, and the battery capacity is 67.3 Ah. When the priority is given to the lightweight of the engine, the maximum power of the engine is determined by the lowest speed of the engine driving mode, and the maximum power of the engine is 39.67% lower than that of the original vehicle. Meanwhile, other dynamic and fuel economy indexes are satisfied by increasing motor power and battery capacity. The maximum power of motor increases by 10.33% and battery capacity increases by 12.17%. The optimal matching result of combination 2 is that the maximum engine power is 102.3 kW, the maximum motor power is 136.4 kW, and the battery capacity is 54.3 Ah. When the priority is given to the lightweight of the motor, the power of the motor is determined by the requirement of pure electric driving mode acceleration time for motor power. The engine power decreases compared with the original vehicle. The optimal matching result of combination 3 is that the maximum engine power is 97.8 kW, the maximum motor power is 143.9 kW, and the battery capacity is 56.1 Ah. When the priority is given to the lightweight of the power battery, the matching result is determined by the requirement of motor power for battery power, so the matching result is not much different from that of combination 2. The optimal matching result of combination 4 is that the maximum engine power is 80.5 kW, the maximum motor power is 141.2 kW, and the battery capacity is 57.7 Ah. When considering lightweight and economy, all design objectives are improved, and better matching results can be obtained in all aspects of indicators. The equivalent fuel consumption of 100 km is decreased by about 1%.

4.2. Non-Normalized Method

The non-normalized method is used to solve multi-objective optimal problem, without setting the weight of each target in advance, and the Pareto mechanism is adopted. Pareto frontier and optimal solution set can be obtained by the non-dominated sorting genetic algorithms with elite strategy (NSGA-II), and the optimal solution [30] can be obtained under any preference for the optimal objective.

Since the multi-objective algorithm has lower accuracy for solving problems with more than four design goals and above, the solution speed is slow, and it is difficult to process the optimization results, the design goal of Section 3.2.1. needs to be reduced. The maximum discharge power of the battery is equal to the maximum power of the motor, and the design variables are only engine power and motor power. Then, the goal of lightweight is unified into the total power of engine and motor. The transformed multi-objective problem can be expressed as:

$$\min f(X) = [P_{(e+m)\text{max}}, FC] \quad (35)$$

$P_{(e+m)\text{max}} = P_{e\text{max}} + P_{m\text{max}}$ represents the total power of the power system.

In this section, the multi-objective optimization algorithm NSGA-II based on Pareto mechanism is adopted. The implementation step is shown as Figure 9.

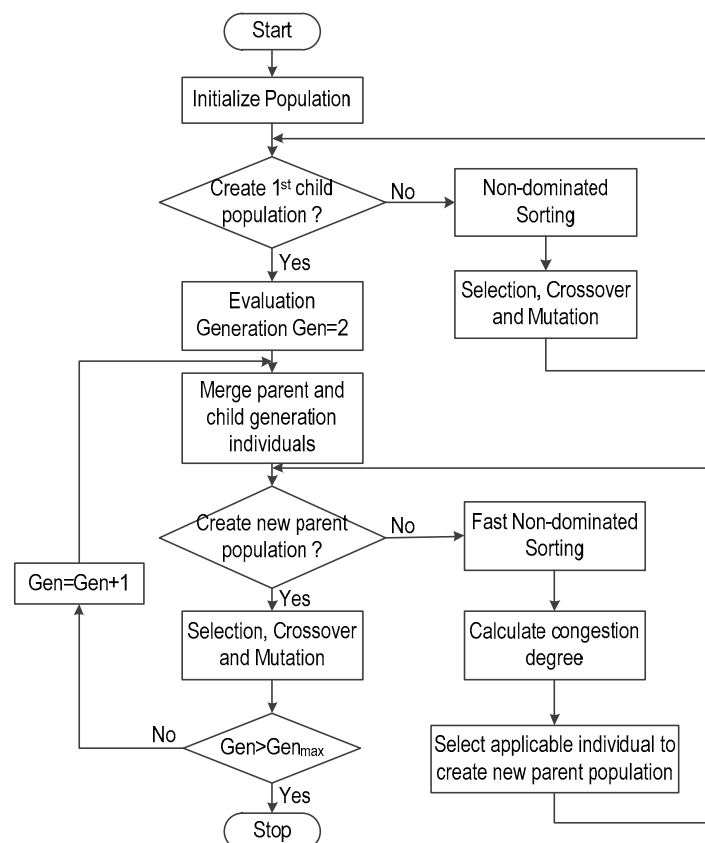


Figure 9. The non-dominated sorting genetic algorithms with elite strategy (NSGA-II) algorithm optimization step.

Then multi-objective optimization is performed by the NSGA-II algorithm, and the number of individuals per generation is 72, the number of evolutionary generations is 300, the crossover probability is 0.9, and the mutation probability is 0.01. Figure 10 shows the results of multi-objective optimization matching considering fuel economy and lightweight. The smaller the total power value of power system, the better the lightweight, and the smaller the equivalent 100 km fuel consumption,

the better the fuel economy. It can be seen from Figure 10 that the lightweight and fuel economy of the power components are conflicting, and the lightweight will inevitably lead to an increase in fuel consumption. So, how to balance lightweight and fuel economy is very important. As can be seen from Figure 10, the design point of the original vehicle is not at the Pareto frontier, and there is much room for improvement in both lightweight and fuel economy.

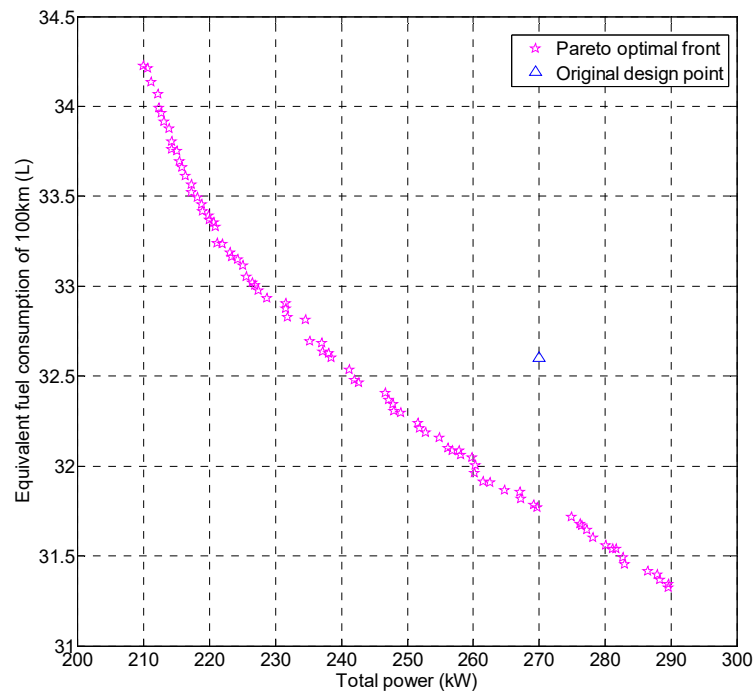


Figure 10. Multi-objective optimization results considering lightweight and fuel economy.

Considering the lightweight and fuel economy of power system components, the points on Pareto frontier should be selected to obtain better results than other matching combinations. The Pareto frontier in Figure 10 is extracted and 3rd order polynomial fitting is carried out to obtain cubic curve with higher fitting accuracy, as shown in Figure 11. The fitting curve equation is as follows:

$$FC = -7.257 \times 10^{-6} \times P_{(e+m)\text{max}}^3 + 0.0057 \times P_{(e+m)\text{max}}^2 - 1.532 \times P_{(e+m)\text{max}} + 170.1 \quad (36)$$

According to the Pareto frontier fitting curve, the optimal relationship between the total power of the power system and the equivalent fuel consumption of 100 km is estimated. If the economy of the equivalent fuel consumption of 100 kilometers is 32.5 L, the minimum total power of the power system is 243.2 kW. Figure 11 shows that increasing the total system power can reduce fuel consumption, but reducing the fuel consumption of 1L requires more power increasing. Since the curve of fuel consumption and total power per 100 km is convex, the power cost of reducing fuel consumption is also increasing. Moreover, when the total power of the system exceeds 290 kW, the equivalent fuel consumption per 100 km is almost no longer reduced and the optimal fuel economy is achieved.

Figure 12 shows the distribution points of the design variables in the multi-objective optimization matching results considering fuel economy and lightweight. It can be seen that the maximum power of motor selected in the range of 140 kW to 215 kW can satisfy all constraints and obtain feasible solutions; and the maximum power of engine selected in the design range can obtain feasible solutions. But in order to get the best matching result, the maximum power of engine and motor can only be selected in limited space. The Pareto solution set of Figure 12 is divided into two sections and respectively fitted

to obtain the relationship between the maximum power of the motor and the maximum power of the engine as shown in Equation (37):

$$P_{m_max} = \begin{cases} -7.7881 \times P_{e_max} + 783.11 & P_{e_max} \in [75, 85] \\ 140 & P_{e_max} \in [70, 85] \end{cases} \quad (37)$$

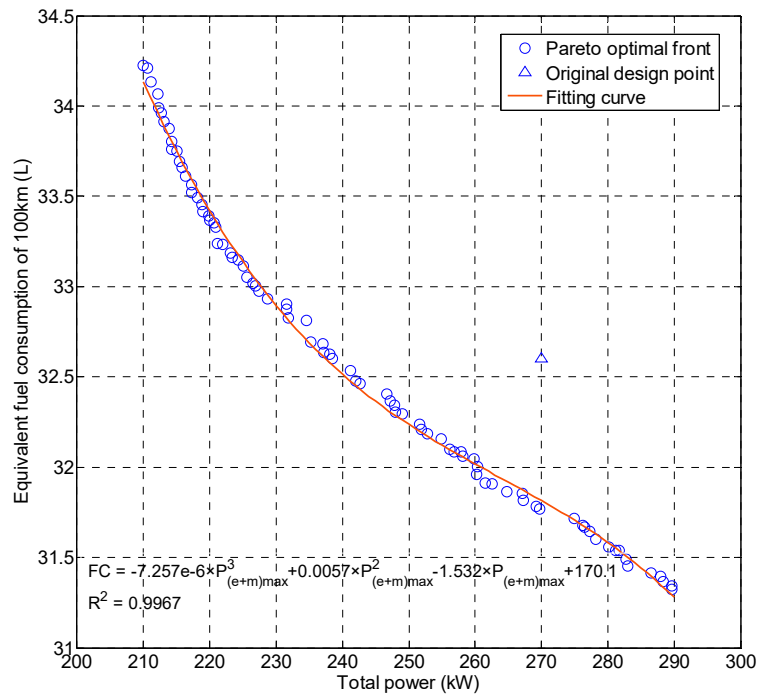


Figure 11. Fitting curve of the Pareto frontier.

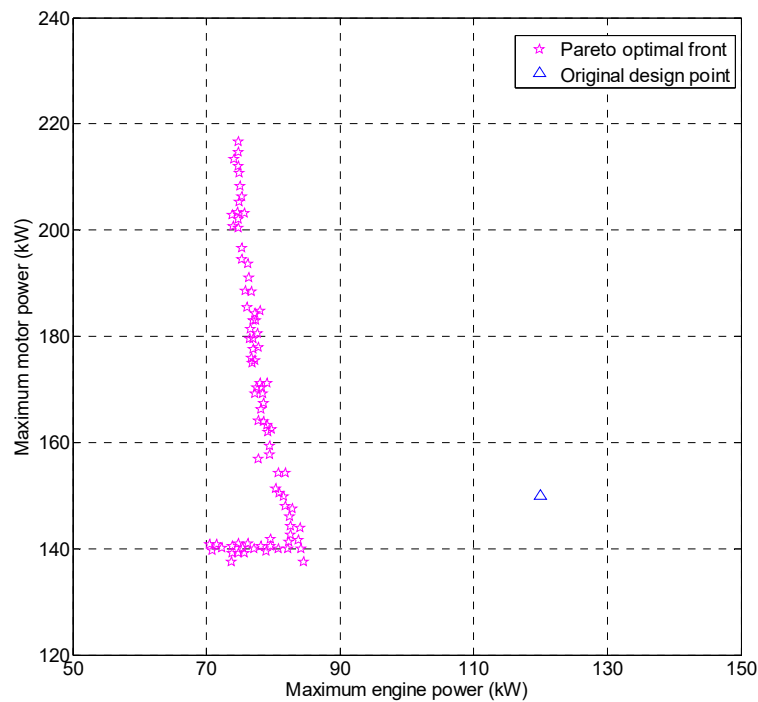


Figure 12. Design variable distribution of multi-objective optimization results.

Figure 13 is a three-dimensional point map of multi-objective optimization results considering fuel economy and lightweight. The optimal lightweight and economy can be obtained by selecting the power system assembly according to Equation (37).

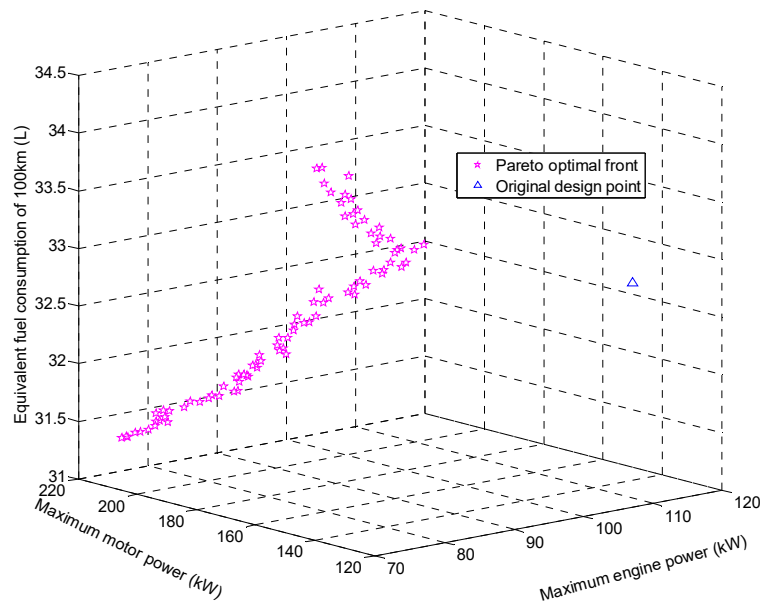


Figure 13. 3D point of multi-objective optimization results.

20 sets of Pareto solutions superior to the original vehicle in terms of lightweight and fuel economy are selected, as shown in Table 5. The choice of the power system can be determined by the designer's different preferences for the two objectives. If the largest lightweight effect and the smallest volume are to be achieved, the first group of matching results should be chosen, where the lightweight effect is increased by 8.26%; if the best fuel economy is to be achieved, the 20th group of matching results should be chosen, where the fuel economy effect is increased by 2.26%.

Table 5. Optimal matching results using NSGA-II algorithm.

Parameters	Design Variables			Design Target	
	P_{e_max} (kW)	P_{m_max} (kW)	Q_0 (Ah)	$P_{(e+m)_max}$ (kW)	FC (L/100 km)
Original	120	150	60	270	32.6
1 st Set	78.48	169.23	67.69	247.71 (−8.26%)	32.46 (−0.41%)
2 nd Set	77.50	170.30	68.12	247.80 (−8.22%)	32.40 (−0.60%)
3 rd Set	78.36	170.30	68.12	248.66 (−7.90%)	32.37 (−0.71%)
4 th Set	78.11	171.11	68.44	249.22 (−7.69%)	32.34 (−0.78%)
5 th Set	79.10	171.11	68.44	250.21 (−7.33%)	32.30 (−0.93%)
6 th Set	76.89	174.87	69.95	251.76 (−6.75%)	32.28 (−0.98%)
7 th Set	77.26	175.41	70.16	252.67 (−6.42%)	32.24 (−1.11%)
8 th Set	76.77	175.95	70.38	252.72 (−6.40%)	32.21 (−1.21%)
9 th Set	77.02	177.56	71.02	254.58 (−5.71%)	32.18 (−1.28%)
10 th Set	77.75	177.83	71.13	255.58 (−5.34%)	32.16 (−1.35%)
11 th Set	76.53	179.45	71.78	255.97 (−5.20%)	32.10 (−1.54%)
12 th Set	77.02	179.45	71.78	256.46 (−5.01%)	32.09 (−1.57%)
13 th Set	76.65	181.33	72.53	257.98 (−4.45%)	32.07 (−1.63%)
14 th Set	77.63	180.52	72.21	258.15 (−4.39%)	32.06 (−1.65%)
15 th Set	77.02	182.94	73.18	259.96 (−3.72%)	32.04 (−1.70%)
16 th Set	77.39	182.94	73.18	260.33 (−3.58%)	32.00 (−1.83%)
17 th Set	76.16	185.36	74.14	261.52 (−3.14%)	31.96 (−1.96%)
18 th Set	77.27	184.29	73.72	261.55 (−3.13%)	31.91 (−2.11%)
19 th Set	78.00	184.82	73.93	262.83 (−2.66%)	31.90 (−2.15%)
20 th Set	75.80	188.59	75.44	264.38 (−2.08%)	31.86 (−2.26%)

5. Conclusions

In this paper, regarding the problem that PHEV parameter matching needs to weigh different design objectives, a multi-objective optimization matching method based on genetic algorithm is proposed. This method is not only suitable for plug-in hybrid electric buses, but also for other types of hybrid electric vehicles, traditional vehicles, and pure electric vehicles. The vehicle dynamic model is established based on MATLAB/Simulink, and the feasibility of the model is verified by simulation. The main performance parameters of the power system are matched by theoretical analysis, and the PHEV integrated optimization simulation platform is established based on Isight. Power source components are optimized considering fuel economy and lightweight objectives under the constraints of dynamic indicators. The weight method is adopted by transforming multi-objective problems into single-objective problems, and the multi-island genetic algorithm is used to obtain the optimal matching results. The results show that the weight method can obtain optimal matching results, and the equivalent fuel consumption of 100 km is reduced by 1%. Then, the four design objectives are reduced to two design objectives by removing the constraints, and the Pareto optimal solution set is obtained by using the NSGA-II algorithm. The optimization results show that compared with the original vehicle, the lightweight effect is increased by 8.26% and the fuel economy effect is increased by 2.26%.

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