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Multi-objective parameter optimization for a single-shaft series-parallel plug-in hybrid electric bus using genetic algorithm

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Recently, the single-shaft series-parallel powertrain of Plug-in Hybrid Electric Bus (PHEB) has become one of the most popular powertrains due to its alterable operating modes, excellent fuel economy and strong adaptability for driving cycles. Nevertheless, for configuring the PHEB with single-shaft series-parallel powertrain in the development stage, it still faces greater challenge than other configurations when choosing and matching the main component parameters. Motivated by this issue, a comprehensive multi-objectives optimization strategy based on Genetic Algorithm (GA) is developed for the PHEB with the typical powertrain. First, considering repeatability and regularity of bus route, the methods of off-line data processing and mathematical statistics are adopted, to obtain a representative driving cycle, which could well reflect the general characteristic of the real-world bus route. Then, the economical optimization objective is defined, which is consist of manufacturing costs of the key components and energy consumption, and combined with the dynamical optimization objective, a multi-objective optimization function is put forward. Meanwhile, GA algorithm is used to optimize the parameters, for the optimal components combination of the novel series-parallel powertrain. Finally, a comparison with the prototype is carried out to verify the performance of the optimized powertrain along driving cycles. Simulation results indicate that the parameters of powertrain components obtained by the proposed comprehensive multi-objectives optimization strategy might get better fuel economy, meanwhile ensure the dynamic performance of PHEB. In contrast to the original, the costs declined by 18%. Hence, the strategy would provide a theoretical guidance on parameter selection for PHEB manufacturers.

multi-objective parameter optimization, single-shaft series-parallel powertrain, plug-in hybrid electric bus (PHEB), genetic algorithm (GA), driving cycle, city bus route

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1 Introduction

The decline in fossil fuel reserves and the rise in fuel prices have motivated the search of alternative technology to reduce fuel dependence [1,2]. Recently, plug-in hybrid electric bus (PHEB) has appealed more attentions, due to its better overall fuel economy than the conventional hybrid electric vehicles (HEVs) by partly utilizing the cheaper electric grid energy [3,4]. HEVs are a complex combination of various components, which involve a large number of design parameters that could be optimally selected to get optimum performance [5]. In practice, component parameters of the PHEB powertrain significantly impact the fuel economy, components costs, and dynamic performance.

The powertrain configuration plays a very important role, and different configurations might lead to the difference in

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overall efficiency of PHEB. Whereas, PHEB is a complex electro-mechanical system and the interaction between the various components makes it difficult to size specific component manually or analytically. In recent years, a large amount of approaches have been adopted in solving the component sizing problem, which commonly described as static optimization algorithms including genetic algorithm [6,7] and Particle Swarm Optimization (PSO) [8,9] in the research works. A multi-objective genetic algorithm is developed for parameter optimization of a series hybrid electric vehicle and the advantages are validated compared with single-objective genetic algorithm [9]. A genetic algorithm, based on the optimization procedure, is proposed and applied to optimize the parameters for the key components of a parallel HEV to ensure emission reduction and fuel economy [10]. PSO is applied to optimize the main component size of parallel HEV powertrain to reduce fuel consumption and exhausted emissions of the HEV more efficiently [11]. In addition, other approaches, such as parallel chaos optimization algorithm (PCOA) [12], harmony search algorithm (HAS) [13] and convex optimization [14], are used to solve the component sizing problems.

All above researches have provided wonderful cases for this paper to study the component sizing of this novel architecture. The economy is directly related to energy consumptions and component costs. Moreover, the parameters of key components would determine the final economy, especially the component cost. Compared with the other optimization algorithms, GA has the advantages of global optimization character, and it is suitable for solving the non-linear problem of PHEB parameters optimization. However, the special but complex structural characteristic of this configuration makes it difficult to obtain the appropriate parameters match by using the original algorithm without improvement. Considering the structural characteristics of the novel powertrain, the two motors' output power should be limited by the battery, and the peak power of EM2 would satisfy the driving force as shifting. Some new constraints or requirements should be taken into account during the optimization process of the algorithm, to ensure a more suitable result. Moreover, a representative driving cycle, where the optimization is evaluated, is established from a large number of bus route data by off-line data dealing method and mathematical statistics. And the new driving cycle is closer to the real-world situation.

The paper is organized as follows. Models and preparative optimization parameters of PHEB are described in Section 2. The component sizing optimization of PHEB including driving cycle, optimization variables, problem constraints, problem formulation, and GA optimization, is proposed in Section 3. The simulation including optimization results and analysis, validation and comparison, is given in Section 4. Finally, Section 5 presents the conclusion .

2 Models and optimization parameters of PHEB

2.1 Single-shaft series-parallel models of PHEB

2.1.1 Vehicle models

In this paper, a novel single-shaft series-parallel powertrain is studied and the configuration is sketched in Figure 1. The main components include the internal combustion engine (ICE), the electric motor (EM), the energy storage system, the automated mechanical transmission (AMT), and final drive. An extra motor is added to the output-shaft of AMT of the single-shaft parallel powertrain, as shown in [15,16]. And due to this characteristic of distribution, the power interruption of transmission, which is caused by the discontinue characteristic of AMT and would reduce the vehicle comfort performance, could be avoided by the torque compensation of EM2 during the gear shifting process. In this process, the EM2 would supply the power to drive the vehicle. And the EM1 would coordinate the rotation speed of the AMT input shaft to shift the gear. While in other situations, the EM1 would play the role of the auxiliary equipment to supply the power for the bus. In addition, both of the EMs, could work as generators simultaneously, so they may charge the battery by either regenerative braking or absorbing the excess power from the ICE. Therefore, one of the advantages of the system is to recover the energy more sufficiently. And a quick-charge plug-in hybrid electric bus is treated as the original. The basic parameters of the powertrain are listed in Table 1.

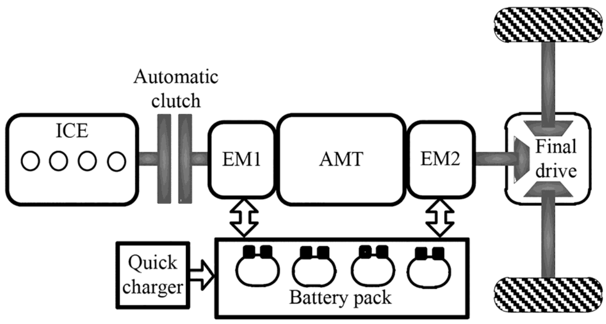

Figure 1 Single-shaft series-parallel configuration of the PHEB structure.

Table 1 Basic parameters of the original

Component	Description
Engine	YC6G230N, CNG, 6.454 L, nominal power: 170 kW
EM1	Permanent magnet, max torque: 600 Nm, nominal power: 60 kW, peak power: 121 kW
EM2	Permanent magnet, max torque: 850 Nm, nominal power: 100 kW, peak power: 130 kW
Battery	Lithium titanate, capacity: 60 Ah, nominal voltage: 346 V
Gearbox	4-speed AMT, gear ratios: 2.92, 1.63, 1.00, 0.73
Final drive	5.571

A forward simulation model of PHEB is adopted in this paper. According to the vehicle longitudinal dynamics equation and combining with the configuration simultaneously, the torque on the wheel could be expressed as follows:

$$T_w = \eta_T [i_g \cdot i_0 (T_e + T_{m1}) + i_0 \cdot T_{m2}] + T_b, \tag{1}$$

where η_T is the transmission efficiency. i_g and i_0 represent the gear ratio of the AMT and the final drive ratio, respectively. T_e, T_{m1}, and T_{m2} are the engine torque, the EM1 torque, and the EM2 torque, respectively. And the driving torque is composed of the three different parts. T_b is the braking torque acting on the wheel. And T_w is the torque of wheel which can be expressed as follows:

$$T_w = \left(mgf_r \cos\theta + \frac{1}{2} C_D \rho_d A V^2 + mg \sin\theta + \delta m \frac{\mathrm{d}V}{\mathrm{d}t} \right) r, \tag{2}$$

where m is the sum of vehicle mass m_v and passenger mass m_p, is the gravity acceleration, and θ is the road slope angle. C_D, ρ_d , and A represent the air drag coefficient, air density, and frontal area of the bus, respectively. V, δ, and r are the vehicle speed, the correction coefficient of rotating mass, and wheel radius, respectively. f_r is the rolling resistance coefficient which can be represented as follows:

$$f_r = f_1 + f_2 \cdot V. \tag{3}$$

In the equation, f_1 and f_2 are constants. The relationship between the rotating speed of wheel and that of the three power sources are described as follows:

$$\omega_w = \frac{\omega_e}{i_g \cdot i_0} = \frac{\omega_{m1}}{i_g \cdot i_0} = \frac{\omega_{m2}}{i_0}, \tag{4}$$

where ω_w, ω_e, ω_{m1}, and ω_{m2} are the rotational speed of wheel, of the output shafts of the engine, EM1, and EM2, respectively. And we can see it clearly that the rotational speed of EM2 is the lowest among the three speeds of the power sources, when the vehicle maintain a constant speed.

2.1.2 Key component model related to fuel economy

With the fuel economy as one of the evaluations, the compressed natural gas (CNG) consumption rate $Q_g(t)$ of a CNG engine can be described as follows.

$$Q_g(t) = \frac{P_e(t) b}{367.1 \rho_g g}, \tag{5}$$

where $P_e(t)$ is the engine power calculated through the equation: $P_e(t)$=$T_e(t)\cdot\omega_e(t)$. b is the compressed natural gas consumption rate corresponding to the current engine torque and rotational speed. ρ_g is the density of CNG.

The two motors might work at the same time or only one is in working condition. The motors power can be written as follows.

$$P_{EM1}(t) = \begin{cases} T_{m1}(t)\omega_{m1}(t) \big/ \eta_{EM1}, & \text{motor}, \\ T_{m1}(t)\omega_{m1}(t)\eta_{EM1}, & \text{generator}, \end{cases} \tag{6}$$

$$P_{EM2}(t) = \begin{cases} T_{m2}(t)\omega_{m2}(t) \big/ \eta_{EM2}, & \text{motor}, \\ T_{m2}(t)\omega_{m2}(t)\eta_{EM2}, & \text{generator}. \end{cases} \tag{7}$$

According to the expression of EMs power, the equation of the sum of electricity power consumption can be described as follows.

$$P_{EM}(t) = P_{EM1}(t) + P_{EM2}(t). \tag{8}$$

In the discrete-time format, the battery SOC can be calculated as follows:

$$\mathrm{SOC}(t) = \mathrm{SOC}(t-1) - \frac{U_{oc}(t) - \sqrt{U_{oc}^2(t) - 4R_{\mathrm{int}}(t) P_{EM}(t)}}{2R_{\mathrm{int}}(t)}. \tag{9}$$

The equation is an iteration and t represents the sequence number of sampling point. U_{oc} and $R_{\mathrm{int}}(t)$ are the open circuit voltage and internal resistance of the battery, respectively.

The energy consumption includes CNG and electricity consumption. So the cost per hundred kilometers, M_{egy} (yuan/100 km), can be calculated as follows.

$$M_{\mathrm{egy}} = (P_{\mathrm{CNG}} \cdot C_{\mathrm{CNG}} + P_e \cdot C_e) / D \times 100, \tag{10}$$

where P_{CNG} (yuan/m^3) and P_e (yuan/kWh) represent the market price of CNG and electricity. D(km) is the driving cycle mileage. C_{CNG} (m^3) and C_e (kWh) are the gas consumption and electricity consumption which described as follows:

$$C_{\mathrm{CNG}} = \int_1^N Q_g(t) \mathrm{d}t, \tag{11}$$

$$C_e = \sum_{t=1}^{N} \left\{ [\mathrm{SOC}(t) - \mathrm{SOC}(t-1)] \cdot \frac{U_{oc}}{1000} \cdot \Delta t \right\}, \tag{12}$$

where N and Δt are the number of sampling points and sampling time, respectively. The aforementioned parameters are listed in Table 2.

Table 2 Basic Parameters for PHEB models

Parameter	Value
Vehicle mass m_v (kg)	12500
Gravity acceleration g (m/s^2)	9.8
Vehicle speed V (m/s)	–
Rolling resistance coefficient f_r	f_r=0.0076+0.0002016 V
Road slope angle θ (rad)	–
Air drag coefficient C_D	0.51
air density ρ_d (kg/m^3)	1.2258
Frontal area A (m^2)	8.25
Wheel radius r (m)	0.48
Correction coefficient of rotating mass δ	1.1

2.2 Cost of key components

The optimization objective of components parameters is to enhance the economy of PHEB in the condition of ensuring the dynamic performance. And the cost of components is an important part to influence the economy. Furthermore, in order to simplify this optimization problem, the drivetrain cost only includes the component cost of the engine, two motors, and battery. Other components are assumed to be the same for all types of PHEB. So, the costs of some components, like charger, AMT, and final drive, are ignored. To unify the evaluation criterion, the key hybrid driving components wear cost per hundred kilometers M_{WC} (yuat/100 km) can be given as follows.

$$M_{WC}=(M_{\mathrm{ICE}}+M_{EM1}+M_{EM2}+M_{BT})\times 100, \tag{13}$$

where M_{ICE}, M_{EM1}, M_{EM2}, M_{BT} are the wear cost per hundred kilometers of ICE, EM1, EM2, and battery described as follows.

$$M_{\mathrm{ICE}}=\mathrm{COST}_{\mathrm{ICE}}/LM_{\mathrm{ICE}}, \tag{14}$$

$$M_{EM1}=\mathrm{COST}_{EM1}/LM_{EM1}, \tag{15}$$

$$M_{EM2}=\mathrm{COST}_{EM2}/LM_{EM2}, \tag{16}$$

$$M_{BT}=\mathrm{COST}_{BT}/LC_{BT}/D, \tag{17}$$

where $\mathrm{COST}_{\mathrm{ICE}}$, COST_{EM1}, COST_{EM2}, COST_{BT} represent ICE cost, EM1 cost, EM2 cost, and battery cost, which are deduced with the statistical analysis of Chinese market of PHEB. They can be described as follows:

$$\mathrm{COST}_{\mathrm{ICE}}=400P_{\mathrm{ICE}}+12000, \tag{18}$$

$$\mathrm{COST}_{EM1}=450P_{EM1}+8000, \tag{19}$$

$$\mathrm{COST}_{EM2}=450P_{EM2}+8000, \tag{20}$$

$$\mathrm{COST}_{BT}=216(N_{BP}\cdot N_{BS})+3000, \tag{21}$$

where P_{ICE} is the nominal power of ICE in kW, P_{EM1} and P_{EM2} are the peak power of EM1 and EM2, respectively. N_{BP} and N_{BS} are the numbers of parallel and series cells, respectively.

In eqs. (14) to (17), LM_{ICE}, LM_{EM1}, LM_{EM2}, and LC_{BT} are the ICE life mileage, the EM1 life mileage, the EM2 life mileage, the battery life charge-discharge cycle times, respectively. The above are constants, with the lifetime, daily mileage, every-year running-days, and lifecycle is taken into account.

3 PHEB component sizing optimization

In this section, a multi-objective GA is adopted to solve the component sizing optimization problem of PHEB, with the consideration of the properties of the single-shaft series-parallel powertrain. The schematic diagram of the proposed methodology is shown in Figure 2. The scheme is a flow of GA optimization combined with driving cycle and the powertrain.

3.1 Driving cycles

Driving cycles are defined as test cycles to standardize the evaluation of vehicle economy or dynamic performance. To achieve reasonable values of the design variables, selecting

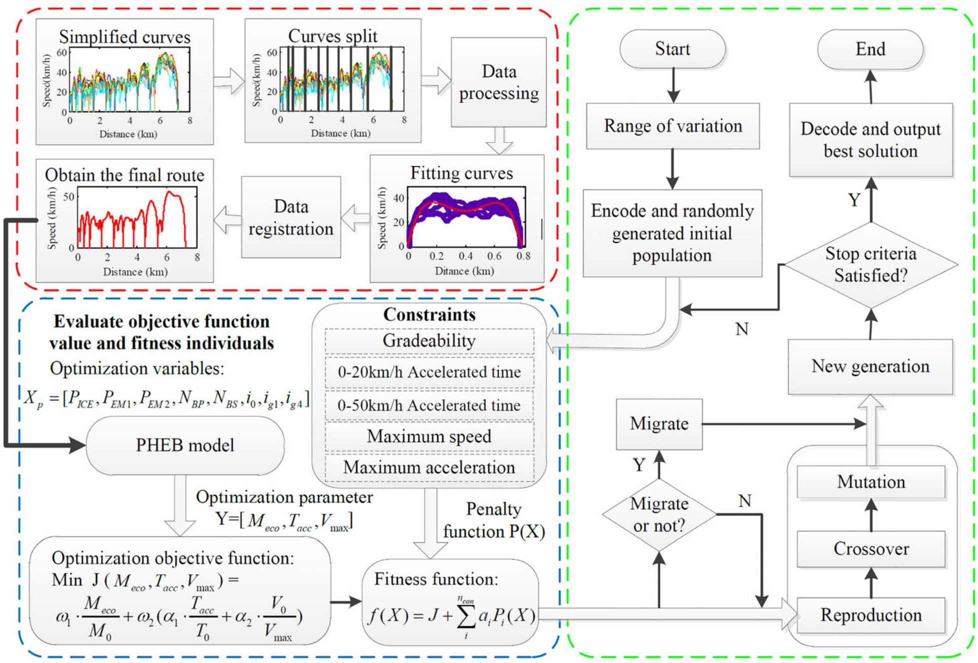

Figure 2 (Color online) Flow chart of optimization.

an appropriate driving cycle is essential [17,18]. Bus driving cycles are more repeatable and regular due to the fixed routes, but differences still exist due to the random change during various driving periods. Therefore, in this paper, a representative driving cycle is developed based on a large number of trips traffic data through the off-line dealing method.

First, a large number data collected from the bus route 88 in Jinan, China, are selected. The bus route has a one-way distance of 20.1 km and 26 stations including the initial one. To simplify the driving cycle, a part of the bus route, which has a distance of 7.8 km with 10 stations, is selected to construct the represented cycle. Each trip traffic data is the relation between speed and time. In order to analyze the properties of the bus route, the speed-time curve is converted to a distance-speed curve. And all the curves of trips are plotted in a coordinate system which is shown in Figure 3.

The bus stations and traffic lights information are obtained by GPS. When the driving cycles are drawn together, it can be found that the curves show regularity. Then, the curves are cut up into 9 segments at the locations which represent the stations, shown in Figure 4. Next, for each segment, the large number of data is fitted into a single curve, and then the fitted curve is smoothed. For example, one segment route data is shown in Figure 5. After fitting and smoothing, the final curve is obtained, and the curve is shown in Figure 5. In this way, for each segment, a processed curve could be obtained. Finally, all of the processed curve segments would be spliced together, and then, a completed cycle curve is obtained which is shown in Figure 6. Moreover, to evaluate the dynamical performance of PHEB, a special linear peed-increasing driving cycle is defined. Contrast to a typical driving cycle, the new curve can represent the certain bus route and is more suitable for the following optimization. This section corresponds to the red dashed box in Figure 2.

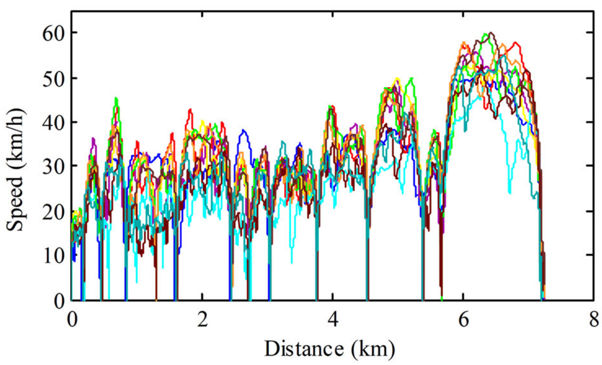

Figure 3 (Color online) The simplified driving cycles curves.

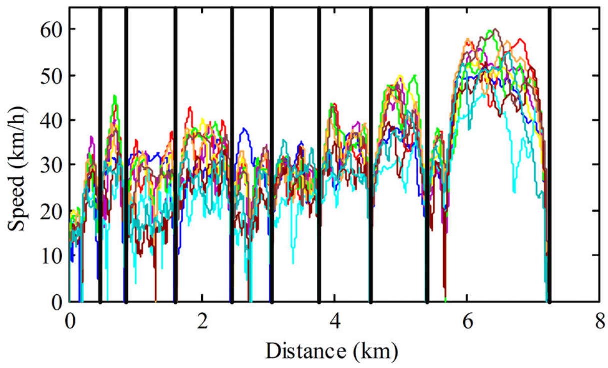

Figure 4 (Color online) The segments after cutting up.

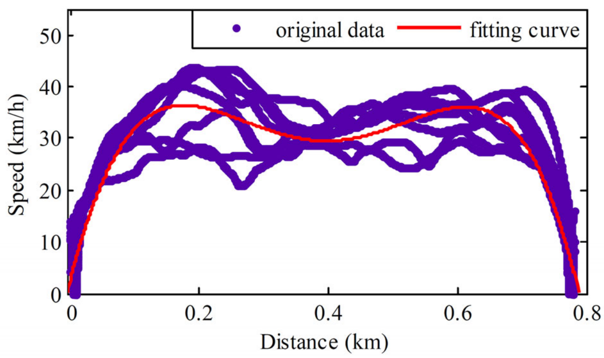

Figure 5 (Color online) An example of obtaining the fitting curve.

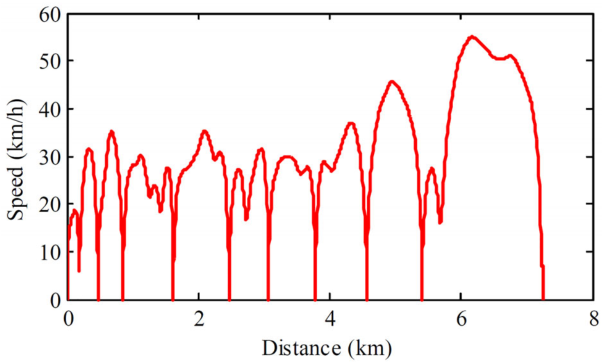

Figure 6 (Color online) The final speed-distance curve.

3.2 Optimization variables

As we can see from Figure 1, the key components of the single-shaft series-parallel configuration are the ICE, two EMs, the AMT, the final drive and a Lithium titanate battery. So it is significant to match the parameters of all these key components suitably. The parameters related to the hybrid powertrain optimization are listed in Table 3. In the system, a 4-speed AMT is adopted and its ratios are approximately considered as a geometric sequence. Then ratios of the lowest and highest gears might be selected as the optimization parameters of AMT. The relationship between the costs of key hybrid driving components and their parameters can be expressed as follows.

So according to the design requirement, the optimization variables can be expressed as X_p, then

$$X_p = [P_{\mathrm{ICE}}, P_{EM1}, P_{EM2}, N_{BP}, N_{BS}, i_0, i_{g1}, i_{g4}]. \tag{22}$$

Table 3 Preparative parameters for powertrain optimization

Parameter	Description
P_{ICE}	The nominal power of ICE (kW)
P_{EM1}	The peak power of EM1 (kW)
P_{EM2}	The peak power of EM2 (kW)
N_{BP}	The number of battery modules in parallel
N_{BS}	The number of battery cells in series
i_0	Final drive ratio
i_{g1}	Ratio of the lowest gear (1st gear)
i_{g4}	Ratio of the highest gear (4th gear)

3.3 Optimization problem constraints

For the optimization problem, the dynamic performance requirements, such as gradeability, acceleration time, maximum speed and maximum acceleration, are defined as constrains. According to the unique characteristic of the single-shaft series-parallel powertrain, one of the advantages is that the powertrain may avoid interruption during the gearshift. As a result, a higher requirement of the EM2 would be proposed in order to realize this function. That is to say, the EM2 would provide enough power to drive the bus alone and ensure the acceleration keeping still in the shifting process. So the constraints of electric motors' peak-power might be taken into consideration. In summary, the bus requires to meet kinds of dynamic performance constrains and physical constraints, which are shown in Table 4.

3.4 Optimization problem formulation

As mentioned previously, the PHEB design in this paper aims to minimize components cost and energy consumption without impairing dynamic performance. The components wear cost per hundred kilometers M_{WC} and the energy consumption cost per hundred kilometers M_{egy}, are defined as economy objectives, that is proposed in Part 2. Due to the costs unified with the dimension of yuan, a new optimization objective of the economy M_{eco} would be described as follows:

$$M_{\mathrm{eco}} = M_{\mathrm{egy}} + M_{WC}. \tag{23}$$

In addition, another two optimization objectives, 0–50 km/h acceleration time T_{acc} and maximum speed $V_{\max}$ are defined as the dynamic optimization objectives. The problem is a highly constrained nonlinear multi-objective optimization problem described by the following equations:

$$\begin{cases} \underset{X\in\Omega}{\text{Minimize}}\,[M_{\mathrm{eco}}(X), T_{\mathrm{acc}}(X), V_{\max}(X)], \\ s.t. \quad h_i(X) \leqslant 0, \quad i = 1, 2, \cdots, n_{\mathrm{con}}, \end{cases} \tag{24}$$

where X is the vector of decision variable and Ω is the feasible solution space, n_{con} is the quantity of constraints, $h_i(X) \leq 0$ represents a group of nonlinear inequality constraints.

For the multi-objective optimization problem, the critical step is to define an objective function including the economy and dynamic optimization objectives. And to balance the value of the function, M_0, T_0, and V_0 are obtained from the prototype, which represent the economy index, acceleration time, and maximum speed, respectively.

The objective function equation is described as follows:

$$J(M_{\mathrm{eco}}, T_{\mathrm{acc}}, V_{\max}) = \omega_1 \cdot \frac{M_{\mathrm{eco}}}{M_0} + \omega_2 \left(\alpha_1 \cdot \frac{T_{\mathrm{acc}}}{T_0} + \alpha_2 \cdot \frac{V_0}{V_{\max}} \right), \tag{25}$$

where ω_1, ω_2, α_1, and α_2 are defined as the weighting factors to investigate the effect of different objectives on the optimization result. And the above three parts are shown in the blue dashed box in Figure 2.

Table 4 PHEB performance constraints

Constraint	Description
Grade ability	>20%, at 10 km/h
0–20 km/h Acceleration time	≤9 s
0–50 km/h Acceleration time	≤25 s
Maximum speed	≥80 km/h
Maximum acceleration	≥0.1 g
P_{EM2}	at least keep the acceleration unchanged when shifting

3.5 GA optimization

Genetic algorithm (GA) is a kind of heuristic searching algorithm based on the mechanics of natural selection and natural genetics [19,20]. The main process of GA optimization is illustrated in the green dashed box in Figure 2. The global solution could be found for both linear and nonlinear formulations [21]. The optimal solution searching process is independent of the form of the objective function, and will not be trapped in the rapid descending direction introduced by local minima.

3.5.1 Range of variation for decision variables

In order to enhance the performance of the GA for optimization of powertrain, the upper bound and lower bound of variables should be specified in advance. They are determined according to the real vehicle calibrations test, and the performance constraints. And the characteristics of components are illustrated in Table 5.

3.5.2 Fitness function

In the genetic algorithm optimization process, a fitness function, which related to the objective function and the performance constraints above mentioned, is established. And the constraints are implemented by using penalty functions that indicate the inferior individuals by decreasing their fitness values. Here, the fitness function is finally defined as follows.

Table 5 Range of variation for decision variables

Parameter	Lower bound	Upper bound
P_{ICE}	50	200
P_{EM1}	55	105
P_{EM2}	120	200
N_{BP}	4	8
N_{BS}	120	150
i_0	5	6
i_{g1}	0.7	1
i_{g4}	2.5	3

$$f(X) = J(X) + \sum_{i=1}^{n_{\mathrm{con}}} \alpha_i P_i(X), \tag{26}$$

where $f(X)$ and $J(X)$ are the fitness function value and the objective function value, respectively. $P_i(X)$ is the penalty function corresponding to the ith constraint and α_i is a penalty factor. Here, $P_i(X)$ $P_i(X)$ and α_i corresponding to the performance constraints listed in Table 4, are simply defined as follows.

$$P_i(X) = \begin{cases} 0, & \text{the } i\text{th constraint is satisfied,} \\ 1, & \text{otherwise,} \end{cases} \tag{27}$$
$$\alpha_{\mathrm{i}} = -0.2, \qquad i = 1, 2, 3, 4, 5, 6.$$

3.5.3 Multi-objective GA process

As seen in Figure 3, the flow of GA methodology for the optimization of powertrain component sizes could be generalized as follows.

Encode and randomly generated initial population according to the range of variation for decision variables. Evaluate objective function value and fitness individuals over the driving cycle.

If the range of sequence several generation fitness values satisfies the condition of migrate, migrate to generate new generation and jump to the step 5, if not, do the next step.

The process of natural biological evolution includes selection, crossover and mutation. After the series of operation, a new generation is produced.

The optimization process is checked against termination criteria. The criteria might be a fixed number of iterations or a stable fitness function value.

If the optimization termination criterion is not met, the new generations are used to repeat the step 2) to 5) until the optimization termination criterion is achieved.

If the optimization termination criterion is satisfied, the optimum component parameters are obtained and decoded.

4 Simulation

4.1 Optimization result and analysis

After introducing the series-parallel model and the genetic algorithm in the previous sections, the optimization based on GA is evaluated by using the proposed driving cycle. The initial population is 30, and individuals of the design parameters are selected randomly according to the solution space shown in Table 5. The generations are set to 50. The terminating conditions are set to the generations 50 or the change of objective function value less than 0.0000001 for 10 generations. And the process of fitness function values based on multi-objective GA is presented in Figure 7. Table 6 shows the optimization result of design components for 3 times and the average one.

As seen in Table 6, the optimized parameters are reference values. Taking into account the actual bus speed may be higher than the fitting curve of bus speed at the same time point, it will lead to a smaller parameter optimization results. In order to ensure optimized parameters can provide enough power, a domain coefficient is proposed to adjust the power of engine and motors. According to the results of engineering experience and numerous optimization, the domain coefficient is set to 1.1, which means the parameters after the correction are 1.1 times the optimized ones,shown in Table 6.

As shown in Figure 7, with the increase of generation, the objective function value declining until the 40th generation. That is to say, the GA optimization is effective to the multi-objective components. And the result can ensure to improve the economy without sacrificing dynamic performance. In contrast to the basic parameters of the original, the optimization parameters are more reasonable.

Table 6 Result of optimization component parameters

Parameter	Value1	Value2	Value3	AV	CV
P_{ICE}	118.8	121.4	120.5	120	132
P_{EM1}	55	55	55	55	60
P_{EM2}	120	120	120	120	132
N_{BP}	4	4	4	4	4
N_{BS}	150	150	149	150	150
i_0	5.857	5.332	5.798	5.6	5.6
i_{g1}	0.7	0.7	0.7	0.7	0.7
i_{g4}	3.0	3.0	3.0	3.0	3.0

Note: AV, average value; CV, correction value.

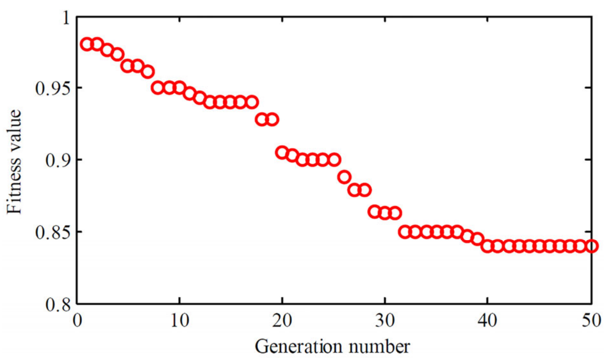

Figure 7 (Color online) Optimization result of fitness value.

4.2 Validation and comparison

In order to test and verify the effectiveness of the optimization result, a trip of bus route 88 in Jinan, Shandong Province, China is selected as the driving cycle. And the bus routine obtained from Baidu Maps is shown in Figure 8. The driving cycle starts from Kuangshan Community station (point A in Figure 8) to North of Liberation Bridge station (point B in Figure 8). And it has a one-way distance of 14.06 km and 22 stations. The road grade information is not considered in this paper due to the flat terrain of the area. And the average number of the passengers along the routine was adopted for simulation. And the corresponding velocity-time curve of the test cycle was shown in Figure 9. And the simulation results about the optimization parameters and the original parameters were shown in Figures 10 and 11, respectively.

As seen from Table 7, which shows the dynamical performance of original and optimal parameters, the dynamic requirement is satisfied. To measure the fuel economy of the proposed method, another four actual driving cycles along the same routine were selected and simulated separately. And the final simulation results about the economy costs, which are composed of energy consumption costs and component costs, are listed in Table 8. Comparing the simulation results with that of the original, the costs declined by 18% and the effective of optimization is validated.

5 Conclusion

In this paper, a novel single-shaft series-parallel architecture was first studied. Due to the specified structure, it has variable working modes, excellent fuel economy, and good adaptive capacity for driving cycles. Based on large number trips of datas from a certain bus route, a representative driving cycle, which could well reflect the real-world general regular pattern, is developed. Then, a multi-objective optimization strategy based on GA is presented to solve the parameter selection problems for the powertrain.

In this way, the best component combination of the powertrain is achieved by evaluating the objective function value in the condition of considering dynamic performance

Table 7 The dynamical performance of original vs. optimal parameters

Parameters	0–20 km/h accelerated time	0–50 km/h accelerated time	Maximum speed	Maximum acceleration	Grade ability
Original parameters	7.3 s	23.7 s	133.0 km/h	2.27 m/s^2	32%
Optimal parameters	7.3 s	24.1 s	121.7 km/h	1.95 m/s^2	25%
Reference value	9 s	25 s	80 km/h	0.98 m/s^2	20%

Table 8 The economy perform ance of original vs. optimal parameters

Cycle	Original parameters				Optimal parameters				Improvement (%)
	FC (m^3)	EC (kWh)	CC (RMB)	TC (RMB/100 km)	FC (m^3)	EC (kWh)	CC (RMB)	TC (RMB/100 km)	
1	26.26	29.33	84.47	231.97	19.22	35.40	66.28	188.17	18.88
2	24.92	32.37	84.47	228.98	18.93	36.13	66.28	187.60	18.07
3	28.32	30.89	84.47	242.80	20.01	35.69	66.28	192.02	20.91
4	22.19	36.44	84.47	220.77	17.58	39.60	66.28	184.99	16.21
5	25.77	31.10	84.47	231.54	20.03	34.18	66.28	190.60	17.68
Average	25.49	32.03	84.47	231.21	19.15	36.20	66.28	188.66	18.40

Note: FC, fuel consumption per 100 km of the engine in m^3; EC, electricity consumption per 100 km motors in kWh; CC, cost per 100 km of the main component in RMB; TC, total cost per 100 km of FC, EC and CC in RMB.

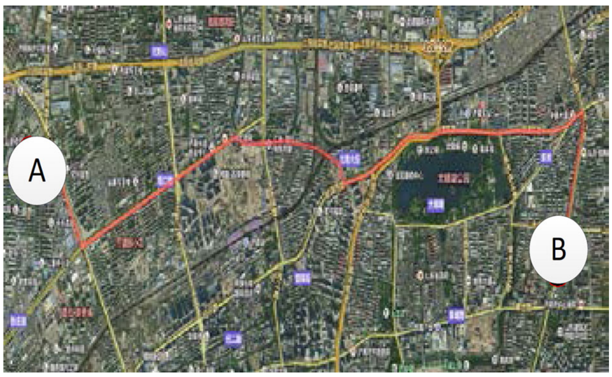

Figure 8 (Color online) The bus routine of the test cycle.

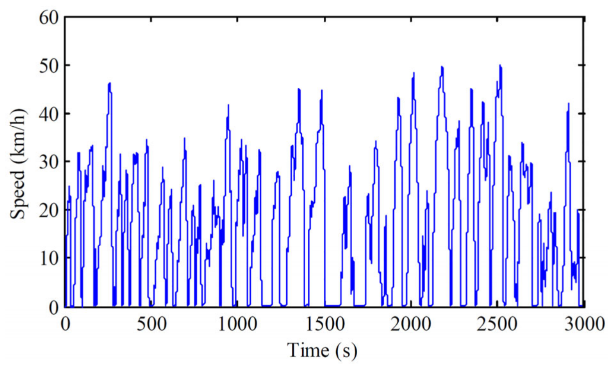

Figure 9 (Color online) The velocity-time curve.

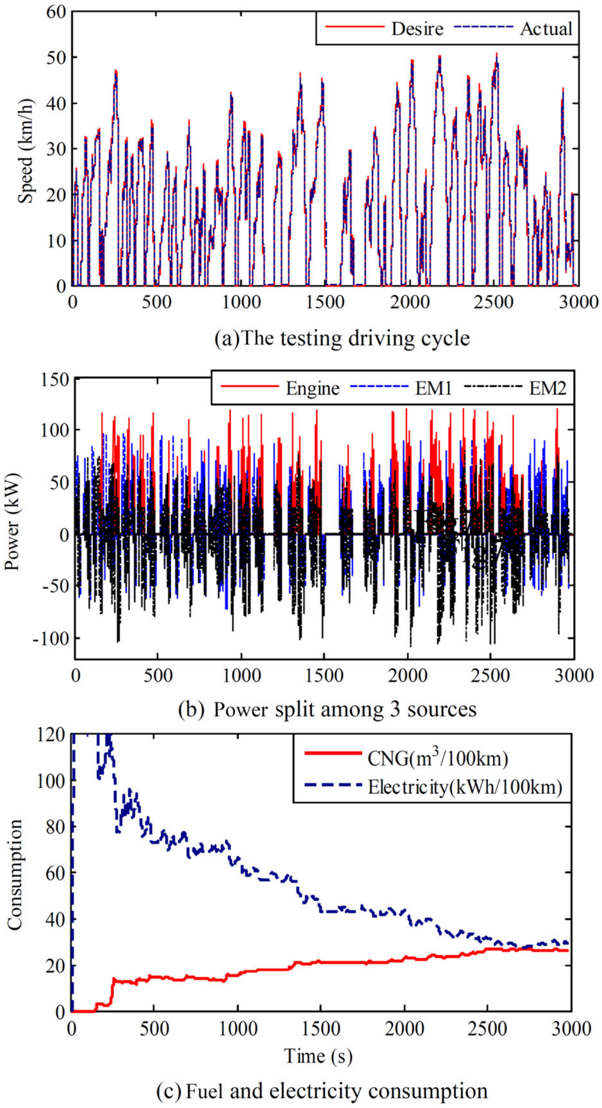

Figure 10 (Color online) The original parameter results.

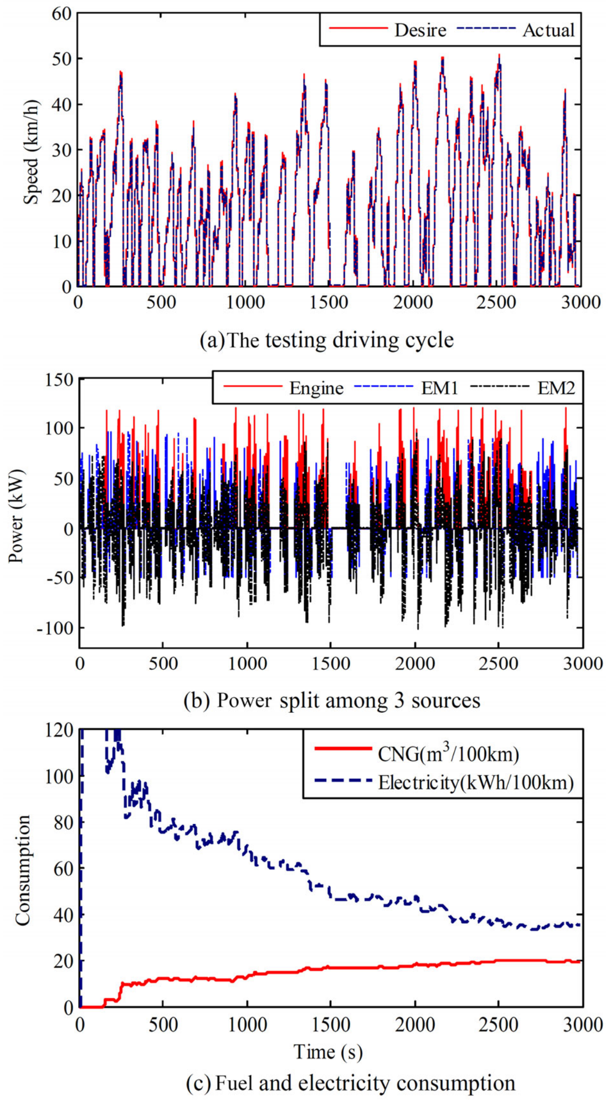

Figure 11 (Color online) The optimization parameter results.

constraints. At last, a certain driving cycle is selected to validate the effectiveness of the optimization. The results show that, the preferable parameters for the powertrain components could be obtained by the proposed strategy. And the economical costs, including energy consumption and components costs, are minimized effectively without sacrificing dynamical performance.

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