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PSO ALGORITHM-BASED PARAMETER OPTIMIZATION FOR HEV POWERTRAIN AND ITS CONTROL STRATEGY

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ABSTRACT−The coordination between the powertrain and control strategy has significant impacts on the operating performance of hybrid electric vehicles (HEVs). A comprehensive methodology based on Particle Swarm Optimization (PSO) is presented in this paper to achieve parameter optimization for both the powertrain and the control strategy, with the aim of reducing fuel consumption, exhaust emissions, and manufacturing costs of the HEV. The original multi-objective optimization problem is converted into a single-objective problem with a goal-attainment method, and the principal parameters of powertrain and control strategy are set as the optimized variables by PSO, with the dynamic performance index of HEVs being defined as the constraint condition. Computer simulations were carried out, which showed that the PSO scheme gives preferable results in comparison to the ADVISOR method. Therefore, fuel consumption and exhaust emissions of HEVs can be effectively reduced without sacrificing dynamic performance of HEVs.

KEY WORDS : Parallel hybrid electric vehicle, Particle swarm optimization, Goal-attainment method, Powertrain, Control strategy

1. INTRODUCTION

As energy security and environmental issues intensify in the world, the development of clean vehicles with high fuel economy and low exhaust emissions has become a leading research area in the automotive industry. Among these new clean vehicles, hybrid electric vehicles (HEVs) have attracted most of the research attention in the last few years due to unnecessary external battery charging and new infrastructure.In addition, HEVs had superior fuel economy as well as lower emissions without compromising dynamic performance.

The HEV powertrain, consisting of an internal combustion engine, electric motor, power battery and transmission, etc., is a complicated driving system with integrated mechanical, electrical, chemical and thermodynamic devices. Hence, the coordination and control strategy for the components of a powertrain have a significant influence on dynamic performance, fuel economy, emissions, among other things. To counteract this issue, many researchers have strived to find optimal solutions with various schemes. A number of studies have paid attention to optimizing powertrain size according to dynamic performance (Ehsani *et al.*, 1997; Chu *et al.*, 2000). However, they did not take fuel consumption and exhaust emissions into full consideration for optimal design. To account for this, some researchers have applied traditional optimization methods to optimize powertrain size (Wipke *et al.*, 2001), but these methods require too many assumptions in the objective function including continuity, differentiability, satisfaction of the Lipshitz condition, etc. Therefore, a genetic algorithm was used to optimize the component size of the HEV powertrain (Galdi *et al.*, 2001; Zhu *et al.*, 2005), and the results showed the suitability and effectiveness of a genetic algorithm for this nonlinear optimization problem. However, the effect of control strategy parameters on vehicle performance was also ignored. This is not so important, though, as many researchers concentrate their research on optimization of the control strategy parameters. Delprat *et al.* (2001) and Antonio *et al.* (2001) used optimal control theory and genetic algorithms respectively, to optimize the parameters of the control strategy. Unfortunately, in their work the vehicle powertrain was fixed during the optimization of the control strategy.

Similar to genetic algorithms, particle swarm optimization (PSO) (Kennedy and Eberhart, 1995) is a stochastic global optimization approach. The method's strength lies in its simplicity, being easily coded and requiring very few algorithm parameters to define convergence behavior. In this paper, PSO is applied to optimize both the main component size of a parallel HEV powertrain and the parameters of control strategy, so as to reduce fuel consumption and exhaust emissions of the HEV more effectively. The parallel HEV as well as an electric assist control strategy are employed as the targets to formulate the optimization problem. A multi-objective function, i.e. the minimization of fuel consumption, exhaust emissions, and manufacturing cost is established, and thereafter the function is converted

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into a single-objective function by a goal-attainment method. The optimized variables include the power capacity of the engine and the electric motor, the number of the power battery and six parameters of the control strategy. PNGV performance requirements including acceleration and gradeability characteristics are considered as constraints to ensure that vehicle dynamic performance is not sacrificed during the optimization. The simulation results show that the PSO approach for simultaneous optimization of HEV powertrain size and control strategy is effective to bring about a substantial reduction of fuel consumption and exhaust emissions.

2. PARALLEL HEV CONTROL STRATEGY

A parallel style powertrain is used in this study for a hybrid electric vehicle, and the configuration is schematically shown in Figure 1 (Pu *et al.*, 2005). The internal combustion engine and electric motor are combined together through a torque combination device. Both the engine and the motor can supply driving torque to propel the vehicle. In addition, the motor can also act in reverse as a generator for braking and to charge the batteries. Thus, in a parallel HEV the size of the engine and motor is small. The engine can operate at a high efficiency range during most of driving time, and the battery capacity may be small depending on concrete requirements.

The control strategy of a parallel hybrid electric vehicle (PHEV) determines the optimum combination of the torque values from both the engine and the motor, while battery charging is being maintained. The PHEV adopts an electric assist control strategy based on logic threshold methods (Johnson *et al.*, 2000), which are widely used in commercial hybrid electric vehicles such as INSIGHT. The electric assist control strategy adopts a set of control parameters to define operating windows for each power component in accordance with fixed control logic. The main parameters of the electric assist control strategy are shown in Table 1.

The details of the control strategy are descried as follows:

(1) If the battery state of charge (SOC) is higher than SOC_{low}, the motor will supply all the driving torque when the vehicle speed is below a certain minimum value V_e or the required torque is smaller than T_{off}.

(2) When the engine runs efficiently with the required driving torque at a given speed, the engine will produce the required torque to drive the vehicle alone.

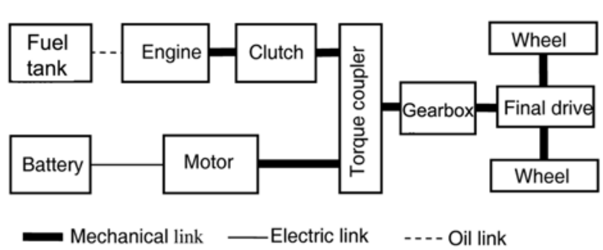

Figure 1. Parallel vehicle configuration.

Table 1. Control strategy parameters description.

Name	Description
SOC_{high}	Highest desired battery state of charge (SOC)
SOC_{low}	Lowest desired battery state of charge
V_e	Vehicle speed below which vehicle operates as a zero emissions vehicle
F_{off}	Factor of the off torque envelope when SOC> SOC_{low} $T_{off} = T_{max} \times F_{off}$; T_{max} is maximum torque of engine
F_{min}	Factor of the minimum torque envelope when SOC<SOC_{low} $T_{min} = T_{max} \times F_{min}$
T_{chg}	Torque loading on engine to recharge the power battery

(3) The motor is used for assistance torque if the required torque is greater than the maximum that can be produced by the engine at the engine's operating speed.

(4) When the battery SOC is lower than SOC_{low}, the engine will provide additional torque, which will be used by the motor to replenish the battery.

(5) The motor charges the batteries by regenerative braking if the battery SOC is lower than SOC_{high}.

The employment of this control strategy requires suitable tuning of the aforementioned parameters, since they will present outstanding impacts on the vehicle performance in terms of fuel consumption, exhaust emissions and dynamic performance.

3. PROBLEM FORMULATION

The principal aim of designing hybrid electric vehicles is to reduce fuel consumption, exhaust emissions and manufacturing costs without sacrificing HEV performance such as vehicle maximum speed, expected acceleration and gradeability. As mentioned above, the size of the powertrain and the parameters of control strategy have remarkable influence on the vehicle performance, hence the problem of HEV optimization is defined as a constrained nonlinear programming problem, whose optimization objective is to minimize fuel consumption, exhaust emissions and manufacturing cost. The size of powertrain and the control strategy parameters are taken as the variables to be optimized. In addition, the vehicle dynamic performance requirements are defined as the constraints. The objective function is defined as follows:

$$\min(f_{FC}(X), f_{HC}(X), f_{CO}(X) f_{NO_x}(X), f_{COST}(X))$$
$$\text{s.t. } g_j(X) \geq 0 \quad j = 1,2, \ldots \text{m} \tag{1}$$

Where, $X=[P_e, P_m, N_b, V_e, F_{off}, F_{min}, T_{chg}, SOC_{high}, SOC_{low}]$, Ω is the solution space, $g_j(X)$ is a set of nonlinear functions describing the design constraints such as vehicle maximum

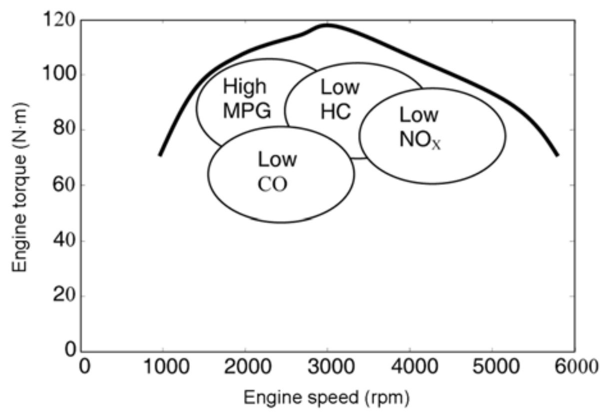

Figure 2. Fuel economy and exhaust emissions trade-off for an SI engine.

speed, expected acceleration, and the specified road grade. $f_{\mathrm{FC}}(X)$, $f_{\mathrm{HC}}(X)$, $f_{\mathrm{CO}}(X)$, $f_{\mathrm{NOx}}(X)$ and $f_{\mathrm{COST}}(X)$ represent the fuel consumption, HC, CO, NO_X emissions and the manufacturing cost of the vehicle.

For a spark ignition (SI) engine, the desired operating levels for fuel and exhaust emissions may be different, as shown in Figure 2. Hence the fuel economy and the exhaust emissions are not necessarily compatible with each other, and on the contrary, they always conflict with each other. The manufacturing cost of the vehicle is also in conflict with the minimization of fuel economy and exhaust emissions.

A suitable tradeoff solution among the objectives should be identified, to counteract which multi-objective problem is transferred into a single-objective problem with the goal-attainment method (Gembicki and Haimes, 1975) as follows.

$$\text{s.t.}\begin{cases} f_{\mathrm{FC}}(X)-\lambda\omega_1\le \mathrm{FC} \\ f_{\mathrm{HC}}(X)-\lambda\omega_2\le \mathrm{HC} \\ f_{\mathrm{CO}}(X)-\lambda\omega_3\le \mathrm{CO} \\ f_{\mathrm{NO_x}}(X)-\lambda\omega_4\le \mathrm{NO_x} \\ f_{\mathrm{COST}}(X)-\lambda\omega_5\le \mathrm{COST} \end{cases} \tag{2}$$

where, ω_i (i=1~5) is the set of degrees either under or over achievement of the goals, $\omega_i \in R^n$ $s.t.$ $\omega_i \ge \varepsilon$, $\Sigma_{i=1}^{5}\omega_i=1$ and $\varepsilon \ge 0$, The value of ω_i is set high when its correlative goal function is more important than others; FC, HC, CO and NO_X express the objectives of fuel consumption and exhaust emissions in a driven cycle; COST is the objective of manufacturing cost.

For this kind of optimization problem, multiple local minima may exist due to the complexity of the interaction among HEV powertrain components. Therefore, classical optimization methods, such as sequential quadratic programming (SQP), are local rather than global by nature and thereby can be sensitive to the initial conditions. Compared with classical optimization methods, PSO is an attractive tool for the constrained nonlinear problem described above. PSO can deal with non-smooth, non-continuous and non-differentiable functions simply with objective function information. Thus, PSO is chosen for optimization of the powertrain size and the control strategy parameters to enhance vehicle performance.

4. PARTICLE SWARM OPTIMIZATION FOR OPTIMAL PHEV POWERRAIN AND CONTROL STRATEGY

4.1. Particle Swarm Optimization

Particle swarm optimization is a stochastic global optimization approach first introduced by Kennedy and Eberhart in 1995. It was developed through a simulation of a simplified social system. In PSO, a population of particles is flown in multidimensional space to arrive at a position that can give an optimum solution. Each particle flies in the solution space with a velocity dynamically adjusted according to the flying experiences of its own and those of its peers. The following gives a brief introduction to the operation principle of the PSO algorithm.

Consider a swarm of N particles, each particle i ($i\in\{1,2,\ldots, N\}$) is associated with a position vector $x_i=\{x_1^i, x_2^i,\ldots,x_D^i\}$ (D is the number of decision parameters of an optimal problem) and a velocity vector $v_i=\{v_1^i, v_2^i,\ldots,v_D^i\}$. In each iteration step $k+1$, all particles' positions and velocities are updated in the following formulas:

$$v_d^i(k+1)=wv_d^i(k)+c_1\cdot r_1\cdot(pBest_i(k)-x_d^i(k)) \\ +c_2\cdot r_2\cdot(gBest_i(k)-x_d^i(k)) \tag{3}$$

$$\begin{cases} v_d^i(k+1)=v_d^{\max}, & if\ v_d^i(k+1)>v_d^{\max} \\ v_d^i(k+1)=-v_d^{\max}, & if\ v_d^i(k+1)<-v_d^{\max} \end{cases} \tag{4}$$

$$x_d^i(k+1)=x_d^i(k)+v_d^i(k+1) \tag{5}$$

where, $pBest_i(k)$ is the best-found cost location by particle i up to time step k, which represents the cognitive contribution to the search vector $v_d^i(k+1)$; $gBest(k)$ is the global best-found position among all particles in the swarm up to time step k and forms the social contribution to the velocity vector; c_1 and c_2 are two positive constants, while r_1 and r_2 are two random parameters which are chosen uniformly within the interval [0, 1]; w is called the inertia weight and provides a balance between global and local explorations, and $v_d^{\max}$ is a parameter that limits the velocity of the particle in the dth coordinate direction. This iterative process will continue swarm by swarm until a convergence criterion is satisfied, and this forms the basic iterative process of a PSO algorithm.

4.2. Calculation for Scope of Particle

In order to enhance the performance of the PSO algorithm for optimization of the powertrain and the control strategy, the maximum and minimum limit values of a particle must be specified in advance. The parameter scopes of the control strategy may be defined based on experience. The maximum and minimum limit values of the powertrain components may be calculated according to the control strategy and the dynamic performance of the vehicle.

4.2.1. Scope of engine power

As described in the control strategy, the engine is assigned to play a primary role in providing average power for the vehicle operation, whereas the motor is arranged to produce peak power at certain circumstances. So the output power of ideal engine operation points can be calculated as follows:

$$P_e = P_f + P_{acc} + P_{chr} \tag{6}$$

where P_{acc} is the accessory power, P_{chr} is the charge power, P_f is the load power in steady driving and can be calculated by the following equation in terms of mean cruise speed v (km/h).

$$P_f = \frac{1}{\eta_T} \cdot \left(\frac{m \cdot g \cdot f \cdot v}{3600} + \frac{C_D \cdot A \cdot v^3}{76410} \right) \tag{7}$$

where η_T represents the powertrain efficiency, m is the vehicle mass in kg, g is the constant of gravity, f is the coefficient of rolling resistance, C_D is the coefficient of aerodynamic resistance, and A is front area of the vehicle in m^2.

As the optimal operating region of the engine is 60%~80% of the maximum power, the minimum power that the engine needs may be determined by the following equation:

$$P_{e\_min} = P_e / 0.7 \tag{8}$$

The maximum power that the engine requires for driving at the maximum speed v_{max}(km/h) may be determined by the following formula:

$$P_{e\_max} = \frac{1}{\eta_T} \cdot \left(\frac{m \cdot g \cdot f \cdot v}{3600} + \frac{C_D \cdot A \cdot v_{max}^3}{76410} \right) \tag{9}$$

4.2.2. Scope of motor power

According to the control strategy, the vehicle is driven by the motor at a constant low speed on a road with a slope of a specified degree. So the minimum power of the motor can be defined by the following equation:

$$P_{m\_max} = \frac{1}{\eta_T} \cdot \left(\frac{m \cdot g \cdot f \cdot \cos\alpha + m \cdot g \cdot \sin\alpha}{3600} \right) \cdot v_1 + \frac{1}{\eta_T} \cdot \frac{C_D \cdot A \cdot v_1^3}{76410} \tag{10}$$

where v_1 is the constant low speed in km/h and α is the slope degree of the road.

The maximum power of the motor is defined to meet the acceleration constraint, the peak power of which can be obtained by the following formula (Ehsani *et al.*, 1999):

$$P_{m\_max} = \frac{30 \cdot m \cdot \delta}{9549 \pi \cdot t_f} \cdot \left(\frac{v_b^2 + v_f^2}{2} \right) \tag{11}$$

where t_f is the acceleration time in seconds, δ is the correction coefficient of the rotating mass, v_f is the final high speed in m/s, to which the vehicle is accelerated from zero in t_f, and v_b(m/s) is the vehicle speed corresponding to the base speed of motor n_{mb}, which is represented by:

$$v_b = \frac{\pi n_{mb} r}{30 i_o} \tag{12}$$

where r is the wheel radius in m and i_o is the gear ratio of transmission.

4.2.3. Scope of battery number

The number of batteries is determined by two factors, one is the voltage, and the other is the power requirement. The minimum number of the power battery modules connected in series for the motor at its minimum voltage is obtained by the equation:

$$V_{b\_min} = \text{roung}\left(\frac{V_{m\_min}}{V_{b\_min}} \right) \tag{13}$$

where V_{m_min} and V_{b_min} are respectively the minimum voltage of the motor and that of the power battery module; round() is the function that gives a superior integer of the argument.

For the peak power demand of the motor, the maximum number of battery modules is calculated by the following equation:

$$N_{b\_max} = \frac{P_{m\_max} \cdot 4 R_{b\_dis}}{V_{b\_oc}^2} \tag{14}$$

where, R_{b_dis} is the discharge resistance of the battery, and V_{b_oc} is the open circuit voltage of the battery.

4.3. Fitness Function Evaluation

For evaluation of an individual in the swarm, a fitness function should be defined accordingly. The fitness of each particle may be evaluated as the following goal function:

$$\begin{aligned} \lambda = \max\{ & (f_{FC}(X) - \mathrm{FC})/\omega_1, (f_{HC}(X) - \mathrm{HC})/\omega_2, \\ & (f_{CO}(X) - \mathrm{CO})/\omega_3, (f_{NO_x}(X) - \mathrm{NO_x})/\omega_4, \\ & (f_{COST}(X) - \mathrm{COST})/\omega_5 \} \end{aligned} \tag{15}$$

In Equation (15), the manufacturing cost of vehicle is mainly affected by the sizes of the engine, motor and battery. Thus, the manufacturing cost of the vehicle can be calculated by the costs of these components. The fuel consumption and exhaust emissions of the vehicle can be obtained with the ADVISOR software. As shown in Figure 3, the PSO algorithm modifies some parameters of a specified base PHEV, i.e. the optimized variables, and calls for some ADVISOR simulation runs such as a drive cycle test, and then obtains the evaluations of the objective values including fuel consumption and exhaust emissions.

In order to eliminate the influence of energy from the battery on fuel consumption, it is wise to run the simulation several times starting with different initial SOC values until the delta SOC (the variance between the initial SOC and the end SOC) becomes negligible (within [–0.5%, +0.5%]) in ADVISOR.

Similar to objectives of fuel consumption and exhaust emissions, the dynamic performance of the vehicle is evaluated in the ADVISOR acceleration test and the grade test so as to evaluate the constraints shown in Equation (1). For the sake of saving simulation time, if the particle can't satisfy any one of the constraints, the simulation for objective functions is cancelled and the fitness of this particle is evaluated directly with a big value.

4.4. Optimization Course

In summary, the optimization process of the PSO algorithm for PHEV can be stated as follows:

Step 1: Initialize positions and associated velocities of all particles in the population randomly in the *D*-dimensional search space. The particle position represents optimization variable *X* in Equation (1) and is encoded in float form. The lower and upper boundaries of each particle are specified according to Equations (6)~(14).

Step 2: Evaluate the objective functions and constraint functions of each particle of the population by combining the PSO algorithm and the ADVISOR software.

Step 3: Calculate the fitness values of all particles according to Equation (15) and determine the *pBest* and g*Best* of the current generation.

Step 4: Update new velocities and positions of each particle using Equations (3) and (5) respectively.

Step 5: Stop the program if the convergence criteria is satisfied, otherwise go to step 2. The convergence criteria are that the fitness of *gBest* does not change for *N* iterations. Output the *gBest* with the minimum fitness value in the last generation. P_e, P_m and N_b are rounded to their superior integers.

5. SIMULATION STUDY

The methodology described in the previous sections is applied to a PHEV model established in ADVISOR, whose

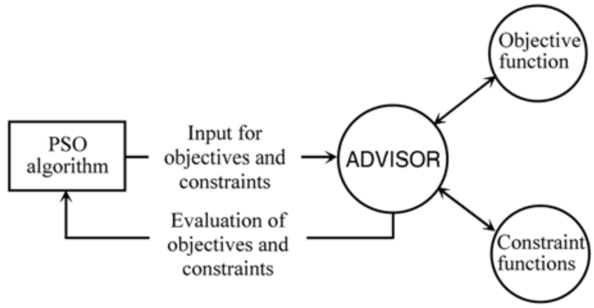

Figure 3. ADVISOR linkage with PSO.

Table 2. Vehicle assumptions.

Parameter/unit	Value
HEV glider mass/kg	592
Frontal area/m^2	2
Tire radius/m	0.304
Aero-dynamic drag coefficient	0.335
Tire rolling resistance coefficient	0.009

configuration is shown in Figure 1. ADVISOR has been reported to be one of the most famous pieces of software for electric vehicle simulation. The parameters of original PHEV model are listed in Table 2. The main components of the powertrain are selected as follows: Spark Ignition engine, AC induction motor, NiMH power battery, and five-speed manual gearbox.

The PSO algorithm is developed in Matlab programming language. The NEDC driving cycle (as shown in Figure 4 is used to evaluate the fuel consumption and exhaust emissions of the optimized parallel hybrid vehicle. Dynamic performance requirements are taken from those set out by the U.S. Consortium for Automotive Research for the PNGV effort. These targets are defined in Table 3.

As shown in Figure 5, the best fitness of a swarm appears to evolve with time, and as long as the evolutions take place over 120 generations, the fitness value will gradually approach the minimum 4.2931 with little later change. Therefore, the *gBest* at 120 generations is considered as the optimal solution for optimization of the HEV powertrain and the control strategy. The elapsed time for the algorithm is approximately 62 hours on a PC with CPU of 3.2 GHz frequency.

In order to evaluate effectiveness of the PSO algorithm for HEV optimization, a comparison is made with the

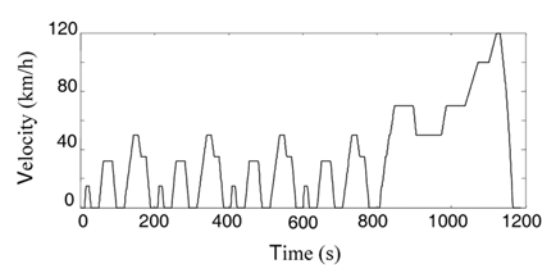

Figure 4. NEDC driving cycle.

Table 3. Vehicle dynamic performance constraints.

Type	Description
Acceleration	0-96.6 km/h in 12 s
	64.4-96.6 km/h in 5.3 s
	0-136.8 km/h in 23.4 s
Gradeability	6.5% grade ability at 88.5 km/h and 272 kg additional weight for 20 min
Maximum speed	over 144 km/h

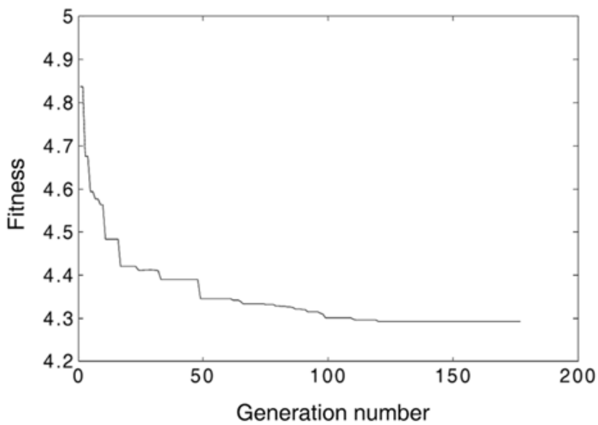

Figure 5. Optimization process for NEDC driving cycle.

Table 4. Comparison of optimization results between PSO and ADVISOR method.

Parameters/unit	PSO approach	ADVISOR approach
P_e/kw	34	58
P_m/kw	14	7
N_b	23	17
V_e/(km/h)	15	10
F_{off}	0.08	0.02
F_{min}	0.3	0.23
T_{chg}/(N·m)	24	30
SOC_{high}	0.75	0.81
SOC_{low}	0.32	0.25

results obtained through the ADVISOR optimization method, which is listed in Table 4. In the ADVISOR software, the SQP is adopted as the optimization method. The powertrain components are optimized first to minimize the mass of vehicle using a control strategy with fixed parameters, then another optimization process is performed to find the optimal control strategy parameters based on the obtained powertrain components.

The dynamic performances of the two HEV optimizations, whose parameters are shown in Table 4, are summarized in Table 5. As it can be seen, the total power of the HEV optimized by PSO is smaller than that optimized by ADVISOR, but the results of PSO can satisfy the dynamic performance defined by PNGV. In addition, the PSO results are better than ADVISOR results in acceleration performance.

With respect to PSO and ADVISOR respectively, simulations are also done on the HEV model for different driving cycles so as to evaluate its relative performance in terms of fuel consumption and exhaust emission. The obtained results are summarized in Table 6. The simulation results indicate that, compared with the ADVISOR method, the PSO algorithm can minimize the overall objectives rather than a single objective. In addition, the PSO optimization exhibits better performance not only for the NEDC but also for other driving cycles.

Table 5. Dynamic performance of the two methods.

Parameters/unit	PSO approach	ADVISOR approach
Max speed/(km/h)	178	176
Grade/%	6.5	11.4
0-96.6 km/h/s	10.4	11.3
64.4-96.6 km/h/s	5.3	5.3
0-136.8 km/h/s	22.7	23.4

Table 6. Comparison of fuel consumption and exhaust emissions for various driving cycles.

Test cycle	Parameters/unit	PSO approach	ADVISOR approach
NEDC	FC/(L·100 km^{-1})	5.6	6
	CO/(g·km^{-1})	0.331	0.428
	NOx/(g·km^{-1})	1.393	1.879
	HC/(g·km^{-1})	0.19	0.21
	λ	4.2931	4.7561
FTP	FC/(L·100 km^{-1})	5.1	5.9
	CO/(g·km^{-1})	0.2489	0.315
	NOx/(g·km^{-1})	1.028	1.29
	HC/(g·km^{-1})	0.18	0.185
	λ	4.7862	4.9753
UDDS	FC/(L·100 km^{-1})	5.3	6.1
	CO/(g·km^{-1})	0.31	0.416
	NOx/(g·km^{-1})	1.348	1.745
	HC/(g·km^{-1})	0.213	0.227
	λ	4.9023	5.124

6. CONCLUSION

The paper presents an optimization methodology for a parallel hybrid electric vehicle to enhance vehicle performance based on particle swarm optimization, in which the principal component parameters of both the powertrain and the control strategy are taken as the optimized variables simultaneously. Fuel consumption, exhaust emissions and the manufacturing cost of PHEV are set as the optimized objectives and are converted into a single-objective optimization problem by the goal-attainment method.

Comparative simulations are performed between the proposed approach and the ADVISOR approach. The results show that, the PSO approach can give preferable parameters for the powertrain components and the control strategy. The parallel hybrid electric vehicle with optimized parameters can minimize fuel consumption and exhaust emissions effectively without sacrificing dynamic performance.

As for the slow convergence speed of the PSO algorithm, future research will be performed with an emphasis on the possible combinations of the PSO algorithm with other optimizers, such as gradient-based optimizers to speed up the convergence process for optimal solutions.

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