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Series Hybrid Electric Vehicle Power System Optimization Based on Genetic Algorithm

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Abstract. Hybrid electric vehicles (HEV), compared with conventional vehicles, have complex structures and more component parameters. If variables optimization designs are carried on all these parameters, it will increase the difficulty and the convergence of algorithm program, so this paper chooses the parameters which has a major influence on the vehicle fuel consumption to make it all work at maximum efficiency. First, HEV powertrain components modelling are built. Second, taking a tandem hybrid structure as an example, genetic algorithm is used in this paper to optimize fuel consumption and emissions. Simulation results in ADVISOR verify the feasibility of the proposed genetic optimization algorithm.

1. Introduction

Hybrid electric vehicles can save fuel and reduce environmental pollution [1, 2]. Compared with conventional vehicles, HEV have a huge advantage and market prospect. However, because of the complicated hybrid structure, the relationships among some vehicle components are not clear. Although a variety of control strategies and energy management systems have been developed and applied to HEV, there are still much work to do for further reducing the fuel consumption and emissions of vehicles. The interactions among different vehicle components need to be further investigated to provide theoretical foundations for a more practical HEV powertrain controller design.

In recent years, many studies from academy and industry have been carried out on how to reduce emissions and save fuel using HEV with various control algorithms and strategies. The intelligent control algorithm, such as genetic algorithm (GA), particle swarm optimization (PSO) algorithm, dynamic programming algorithm and artificial neural network, have gained much attention [3]. For example, Yan [4], without sacrificing the premise of vehicle dynamic performance, employed genetic algorithm to optimize the HEV parameters configuration with improved fuel economy and reduced emissions.

This paper aims to optimize the component size to make it work in a more efficient manner so as to reduce fuel consumption and emissions. Taking the series hybrid electric vehicle as example, based on the modelling of the most important parts, the relationship between components and their optimal working range can be found, particularly the ratio between the generator speed and gear in "optimization" zone of the engine. The organization of the rest of this paper is as follows. First, the basic vehicle configuration and parameters are given.; then the genetic algorithm and Control Strategy Optimization part of ADVISOR are used to set the parameter range; Furthermore, simulation are conducted to find out the most reasonable size of components and parameters; Finally, compared with the original size, the optimized components size are verified to achieve the better vehicle performance.

2. HEV powertrain system

2.1. Hybrid electric vehicle components

Series hybrid electric vehicle components are shown in the Figure 1.

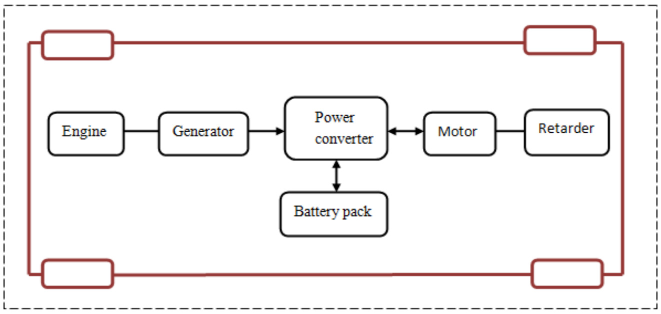

Figure 1. The hybrid powertrain system components

Series hybrid electric vehicle parameters in detail are shown in the Table 1.

Table 1. Parameters of series hybrid electric vehicle.

Component	Parameter	Value	Component	parameter	standard	name	parameter	standard
	CC	1.6L		mold	lithium battery		maximum power	75Kw
Engine	maximum power	41Kw		The battery block	45～50	generator	maximum speed	8000r/min
	Maximum torque	160Nm		single marker	26Ah		Maximum torque	120Nm
	maximum power	80Kw	lithium battery	energy density	105W h/kg		vehicle weight	1136kg
	maximum speed	10000r/min		power density	1000w/kg		windward area	2.0m^2
Motor	Maximum torque	273Nm		total voltage	360～420v	vehicle parameter	drag coefficient	0.335
	Mold	asynchronous motor					wheel base	2.6m

3. Optimization of series hybrid electric vehicle components

3.1. Optimization objective

The goals of HEV optimization are to reduce fuel consumption and emissions such as HC, NOx, CO, etc as much as possible under the premise of guaranteeing the vehicle dynamic performance [5]. These three kinds of pollutants: HC, NOx, and CO with the same unit of measurement, are considered as the terms of optimization goals. According to the requirements, equivalent fuel consumption per hundred kilometres is taken as another term of optimization goals. Using ADVISOR software is used in this paper for car simulation and optimization process. The optimization goal in this study is defined as follows:

$$\begin{cases} \min\ f(x) = 0.7Fuel(X) + 0.1CO(X) + 0.1HC(X) + 0.1NO_X(X) \\ X \in \Omega \\ \quad st \quad g_i(x) \geq 0 \qquad j = 1,2...m \\ \qquad x_i^{\min} \leq x_i \leq x_i^{\max} \quad i = 1,2...m \end{cases} \tag{1}$$

where X is the vector of parameters to be optimized; Ω is the feasible solution space; x_i is the parameter to be optimized； n is the number of parameters； $g_i(x) \geq 0$ is constraint conditions which describe the vehicle's performance requirements such as maximum speed, acceleration time and climbing capacity. $[Fuel(X), O(X), HC(X), NO_X, COST(X)]$ are multiple objective functions, followed by fuel consumption per hundred kilometres and carbon tariff. It is refined as follows:

The design variables: $X^T = \{x_1, x_2.x_3, x_4\}^T$ = ｛Engine power, generator power, motor power, battery power｝ The objective function： $f(x) = \{f_1(x), f_2(x), f_3(x)\}$= ｛Fuel economy, emissions, car costs｝

The constraint condition: $g(x) = \{g_1(x), g_2(x), g_3(x)\}$= ｛Top speed, climbing, acceleration｝ The Boundary constraints： $x_{min} \leq x_i \leq x_{max}$

Table 2. The optimization target and weight coefficient

Measurement	Target	Unit	Weight coefficient
Fuel	6	L/100km	0.7
HC	0.6	g/km	0.1
CO	1	g/km	0.1
NO_x	0.27	g/km	0.1

Table 2 show the optimization targets and the weight coefficients in the optimization objective function.Using genetic algorithm, it sets the evolutionary population size as 100, biggest evolution algebra as 50, the mutation probability as 0.1, crossover probability as 0.9, and other relevant genetic parameters use the default values. The optimization algorithm is based on simulation results generated in ADVISOR software to analyse the evaluation of the vehicle performance. Figure 2 shows the running condition for simulations, which is composed of three types of working conditions. Table 3 shows the optimized design variables and control variables including three component parameters and four control strategies, and the constraint condition is the original vehicle dynamic performance requirements. The following are the design variables, using the control strategy optimization of ADVISOR as simulation tools [6].Table 3 shows the minimum motor power and maximum battery capacity. The most economic mode is when it is in pure electricity mode and the dominant factor is the determination of upper and lower limits of power elements. Based on the simulation result to figure out target function and constraint and then collect the data of fuel consumption and emission.

Table 3. Mixed power system optimization parameters

Design variable	Engine power	Motor power	Battery capacity	Highest SOC	Lower SOC	Max power command	Min power command
default	41kW	80 kW	26A ħ	0.8	0.2	30Kw	20kw
lower limit	25 kW	38 kW	13A ħ	0.7	0.2	25 kW	5 kW
upper limit	53kW	110Kw	39A ħ	0.9	0.5	41Kw	20kW

3.2. Driving cycles

As road traffic environment is complicated and variable, some research only chose single road condition as the selection of driving cycles. Although some good results have been obtained, single driving cycle cannot cover the real driving patterns. The complicated working conditions are selected in the simulation. As the simulation target, to be exact, the working condition is a combination of urban roads and highways about 64 kilometres [7].

3.3. Simulation and results analysis

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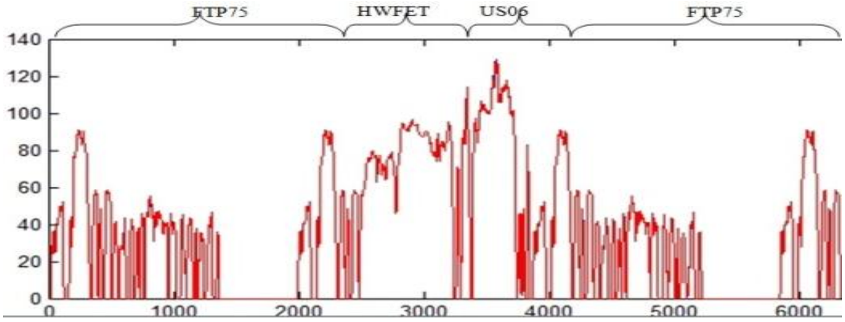
In this part, three driving cycles are combined into a single loop combination as the mixed operating mode, as shown in Figure 2.

Speed (km/h)



Time(s)

Figure 2. Combined city and highway driving cycles

Before optimization, the vehicle model is built to meet the requirements of standard dynamic performance [8].

1) 0-96.6km/h: 10.5s; 2) 64.6-96.6km/h: 5.6s; 3) 0-137km/h: 24.6s; 4) At 96.6 km/h speed climbed the slope of 25%. Figure 3-Figure 5 respectively shows that the values of three emssions HC, NO_x, CO with the change of the number of iterations.

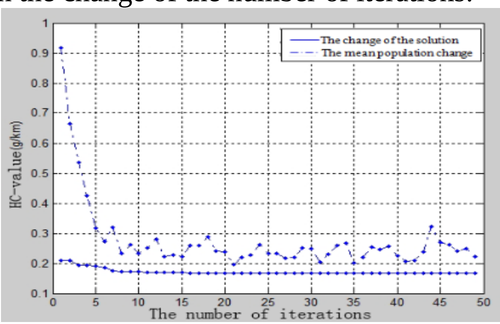


Figure 3. *HC* Emission changing curve

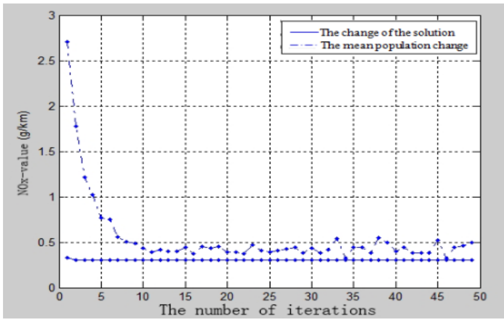


Figure 4. NO_x Emission changing cur

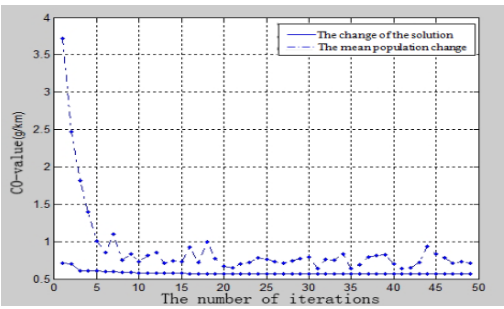


Figure 5. *CO* Emission changing curve

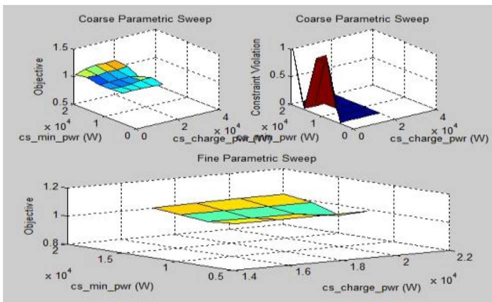


Figure 6. *CO* Emission changing curve

From Figures 3-5, it can be seen that the initial values of *HC*, NO_X, *CO* are 0.21 g/km, 0.35 g/km and 0.70 g/km, respectively. With the increase of the number of iterations, the optimal values of three kinds of emissions decrease gradually and finally tend to be stable with optimal values 0.17 g/km, 0.30 g/km and 0.60 g/km or so. In terms of pollutant emissions, *CO* emissions obtain the largest decline, followed by HC. Although NO_x increases slightly, the overall emissions decrease, which is beneficial to the environment. The sum of the three kinds of pollutants emissions is shown in Figure 6. From the results of Figure 6, for coarse parametric sweep which is rough scanning parameters, the sum of the three pollutants are between 1 g/km and 1.5 g/km, tending to be 1 g/km, while for fine parametric sweep which is precise scanning parameters, the result is more accurate than before, and the interval narrows down to 1 g/km ~ 1.2 g/km. Based on the simulation results for 5 groups from ADVISOR, the fuel consumption and emission values before and after optimization are listed in Table 4. The simulation results demonstrate that fuel consumption and the emission have been significantly reduced with the proposed genetic algorithm. The optimal simulation is also helpful in optimizing the vehicle components. The simulation solutions for the following 5 groups are shown as the Table 5.

Table 4. The optimization results

No.	*Fuel*/（L/100km）	*HC*/(g/km)	CO/(g/km)	NO_X /(g/km)
1	5.6	0.145	0.698	0.280
2	5.8	0.138	0.592	0.275
3	5.8	0.145	0.680	0.292
4	5.7	0.148	0.715	0.299
5	5.9	0.168	0.827	0.315

Table 5. Optimal design variables and performance values

Sol.	Engine power	Motor power	Battery capacity	Highest SOC	Lower SOC	Max power command	Min power command	0～96 km/h	40～96 km/h	0～137 km/h	Climbing ability of 96.6 km/h
1	31 kW	88kW	30.2A h	0.79	0.30	33.1 kW	13.7 kW	7.7s	3.6s	16.4 s	26.0%
2	28 kW	92kW	29.8A h	0.81	0.35	36.6kW	13.3kW	7.3s	3.3s	15s	27.6%
3	29.2kW	96kW	28.9A h	0.82	0.32	32.2 kW	9.8 kW	7.7s	3.6 s	16.5s	25.9%
4	30 kW	90kW	27.2A h	0.8	0.30	33 kW	5.6 kW	7.2s	3.3s	15s	27.2%
5	40 kW	94kW	26.5A h	0.84	0.30	32kW	12.4 kW	7.5s	3.5 s	16s	27.8%

According to Table 4, the emissions obtained by genetic algorithm and the ADVISOR simulation are in the same order of magnitude despite of somewhat gap. And this shows that the proposed optimization algorithm for component parameters and fuel consumption is feasible. And Table 5 shows the optimized design variables and performance values. For example, comparing Solution 1 with Solution 2, although the engine power is reduced, vehicle's acceleration and climbing ability are improved by increasing the motor power and the capacity of the battery. Solution 4 shows that the emission is not as satisfactory as the solution 3 even when the number of batteries and the power of the motor are increased and thereby the cost is increased by 5%From the optimization results, it is clear that the good matching of components could have positive effect on the vehicle performance and emission of hybrid vehicle.

4. Conclusions

In this paper, genetic algorithm is used to optimize the components and fuel consumption of series hybrid vehicle. Simulation results show that fuel economy and emissions can be optimized simultaneously. By comparing the selection of appropriate component parameters through analyzing the five values obtained by optimization, this research narrows the optimization area of the region to maximum optimization value.Due to the inadequate number of iterations of algorithm and the selection of fitness function, there are some difference between the results and that of the ADVISOR. The further research will focus on increasing the number of iterations and adjustment of the corresponding algorithm parameters, such as the number of lithium batteries, the engine unit transmission ratio, and the motor with high rotating speed and smaller peak power, in order to improve efficiency and reduce the weight of the motor.

In general, the genetic algorithm can make an easier and more effective search to the optimal solution of hybrid cars system parameters, and call to optimize parameters can improve the matching of components and fuel economy, thus improving the overall performance of the vehicle, genetic which also verified the effectiveness of the hybrid system optimization problems.

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