Optimization of Control Parameters in Parallel Hybrid Electric Vehicles Using a Hybrid Genetic Algorithm

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Abstract—**This paper describes the application of a hybrid genetic algorithm for the optimization of the parameters of the control strategy in parallel hybrid electric vehicles (HEV). Considering the shortage of genetic algorithm (GA), a simulated annealing, adaptive based hybrid genetic algorithm (SAAHGA) is developed and applied to the optimization, and then based on an electric assist control strategy, an HEV optimal method combining optimization algorithm and HEV simulation tool is introduced. ADVISOR2002 is used as the vehicle simulator. The results show the effectiveness of the hybrid genetic algorithm.**

Key words: hybrid genetic algorithm; optimization; hybrid electric vehicle

1. INTRODUCTION

Hybrid electric vehicle (HEV) is projected as one of the solutions to the world's need for cleaner and more fuel-efficient vehicles. Optimization of the parameters of the control strategy is a key element for the success of a HEV.

Recently, Genetic Algorithm (GA) is widely applied in the optimization of HEV [1-4]. Since it has conquered the deficiencies of the gradient-based optimization algorithms that require calculating the derivative of the objective function, GA is suitable for this non-linear optimization problem. However, the shortcoming of GA is that it is prone to be premature convergence, which means that it can easily find the local optima but not the global optima. Therefore, in this paper, two measures are taken to overcome the shortcoming of GA. First, the adaptive crossover fraction is adopted to create crossover children and mutation children. Second, the ideology of simulated annealing algorithm (SA) is integrated with GA. The new algorithm is called SAAHGA (Simulated annealing, adaptive based hybrid genetic algorithm). In this paper, ADVISOR (ADvanced VehIcle Simulator) version 2002 is used as the simulation tool to study the optimization of control parameters in parallel hybrid electric vehicles (PHEV).

II. PARALLEL HEV CONFIGURATION AND CONTROL STRATEGY

A. Parallel HEV configuration

In parallel HEV, both electric motor and fuel converter (IC Engine) may deliver power to the vehicle wheels as shown in Fig. 1. The electric motor may also be used as a generator to charge the battery by either the regenerative braking or absorbing the excess power from the engine when its output is greater than that required to drive the wheels.

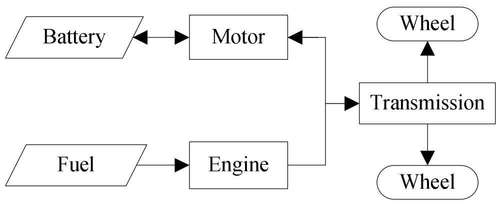

Fig. 1. Parallel HEV configuration

B. Control strategy

The electric assist control strategy determines how the torques from the engine and motor will combine to produce the required torque while maintaining

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charge in the battery. As shown in Figs. 2 and 3[5], when the battery SOC is below cs_lo_soc, additional torque is required from the engine to charge the battery. This additional charging torque is proportional to the difference between SOC and the average of cs_lo_soc and cs_hi_soc. This engine torque is prevented from being below a certain fraction, cs_min_trq_frac, of the maximum engine torque at the current operating speed. This is intended to prevent the engine from operating at an inefficiently low torque. Engine torque is only requested when the engine is on. If the speed required is less than the electric launch speed, cs_electric_launch_spd, the engine could turn off. If the SOC is higher than its low limit, the engine could turn off. If both the requested speed is less than the launch speed and the SOC is higher than the low limit, the engine will turn off. If the torque required is less than a cutoff torque, cs_off_trq_frac fraction of the maximum torque, the engine could turn off. If both the requested torque is lower than this cutoff and the SOC is higher than the low limit, the engine will turn off.

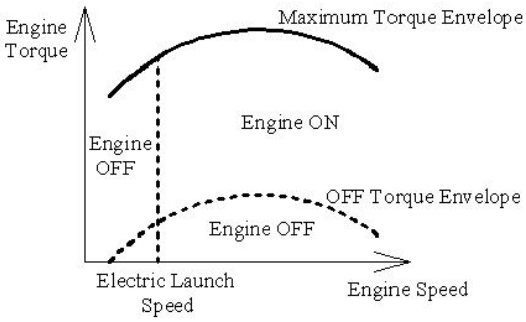

Fig. 2. Electric assist control strategy, for SOC>cs_lo_soc

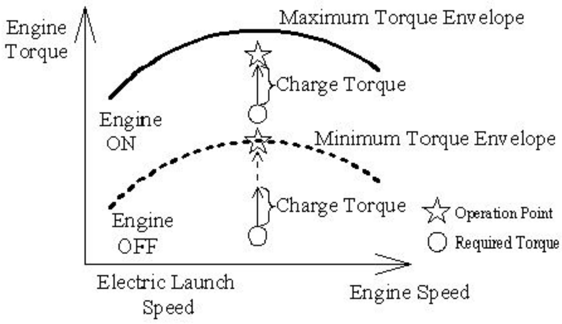

Fig. 3. Electric assist control strategy, for SOC<cs_lo_soc

III. Simulated Annealing, Adaptive Based Hybrid Genetic Algorithm

The flowchart of simulated annealing, adaptive based hybrid genetic algorithm (SAAHGA) is shown in Fig. 4. The SAAHGA is composed by an iterative procedure through the following five main steps:

1. Code and create an initial population.
2. Evaluate of the performance of each individual of the population, by means of a fitness function.
3. If the stopping criteria is met, the best individuals are attained by decoding and the algorithm stops; otherwise, go to step 4.
4. Select the individuals to generate the next population, including elite children, crossover children and mutation children. The elite children will be preserved and the crossover children and the mutation children are produced with an adaptive crossover fraction.
5. Every individual of crossover children and mutation children produced in step 4 is the start point of the simulated annealing (SA) algorithm. The best points found by SA and the elite children make up of the new population of GA. Then return to step 2.

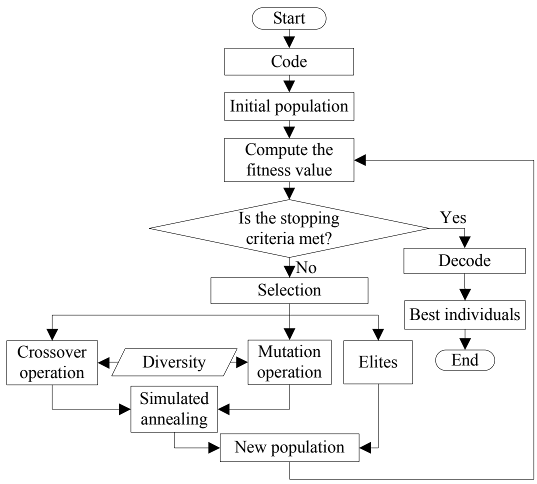

Fig. 4. SAAHGA flowchart

A. Adaptive crossover fraction

Both crossover and mutation are essential to the genetic algorithm. Crossover enables the algorithm to extract the best genes from different individuals and recombine them into potentially superior children.

Mutation adds to the diversity of a population and thereby increases the likelihood that the algorithm will generate individuals with better fitness values.

Crossover fraction specifies the fraction of the population, other than elite children, that are crossover children [6]. For example, if the population size is 20, the elite count is 2, and the crossover fraction is 0.8, the numbers of each type of children in the next generation are as follows:

- There are two elite children.
- There are 18 individuals other than elite children, so the algorithm rounds 0.8×18 = 14.4 to 14 to get the number of crossover children.
- The remaining four individuals, other than elite children, are mutation children.

A crossover fraction of 1 means that all children other than elite individuals are crossover children, while a crossover fraction of 0 means that all children are mutation children. So crossover fraction must be a suitable value to produce suitable number of crossover children and mutation children. However, in the conventional GA, crossover fraction is set to be a fixed value and it cannot change during the optimization [6].

The shortcoming of GA is that it is prone to be premature convergence, which means that the diversity of the population is so low that the algorithm cannot find the global optima. Diversity refers to the average distance between individuals in a population and is essential to the genetic algorithm because it enables the algorithm to search a larger region of the space [6]. A population has high diversity if the average distance is large; otherwise it has low diversity. On the other hand, mutation adds to the diversity of a population. Therefore, in SAAHGA, the crossover fraction varies adaptively in response to the average distance between individuals in a population and is calculated by (1). When the average distance between individuals is small, which means the diversity of the population is low, the crossover fraction is low so that more mutation children can be produced to enhance the diversity of the population.

$$cf=\begin{cases} cf\_max, & ad>ad\_up \\ cf\_min+\dfrac{cf\_max-cf\_min}{ad\_up-ad\_low}(ad-ad\_low), & ad\_low<ad<ad\_up \\ cf\_min, & ad<ad\_low \end{cases} \quad (1)$$

Where, cf is the crossover fraction; cf_max is the maximum of the crossover fraction; cf_min is the minimum of the crossover fraction; ad is the average distance between individuals in a population; ad_up is the upper limit of the average distance; ad_low is the lower limit of the average distance.

B. Combining with SA

Simulated annealing (SA) models the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimizing the system energy. At each iteration of the simulated annealing algorithm, a new point is randomly generated. The distance of the new point from the current point, or the extent of the search, is based on a probability distribution with a scale proportional to the temperature. The algorithm accepts all new points that lower the objective, but also, with a certain probability, points that raise the objective. By accepting points that raise the objective, the algorithm avoids being trapped in local minima, and is able to explore globally for more possible solutions. Therefore, the character of SA can be used to avoid the premature convergence of GA.

SA accepts new point with the following probability:

$$p=\begin{cases} 1, & (E(x_{new})<E(x_{old})) \\ \exp[-\dfrac{E(x_{new})-E(x_{old})}{T}], & (E(x_{new})>E(x_{old})) \end{cases} \quad (2)$$

Where, p is the probability that SA accepts new point; x_{new} is the new point; x_{old} is the current point; E(•) is the objective function; T is the current temperature.

The temperature decreases as follows:

$$T=0.95^{i}T_0 \quad (3)$$

Where, T_0 is the initial temperature; T is the current temperature; i denotes the iteration number.

The start point of SA is each individual of crossover children and mutation children produced by the crossover operation and mutation operation of GA. The best points found by SA and the elite children of GA make up of the new population. In this way, SA and GA are integrated.

C. Link SAAHGA with ADVISOR

In this study the SAAHGA is written in MATLAB, whereas the fitness function evaluation is performed in ADVISOR. Since ADVISOR can run without GUI [5], it is possible to link SAAHGA with ADVISOR. Fig. 5 illustrates the linkage between SAAHGA and ADVISOR.

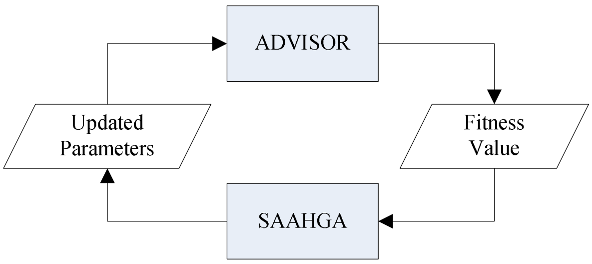

Fig. 5. Linkage between SAAHGA and ADVISOR

IV. CASE STUDY

A. Problem definition

The vehicle we simulated is the default parallel HEV given by ADVISOR, with specifications in Table I. In this case, seven parameters of the electric assist control strategy are optimized, listed in Table II. The optimization of HEV control strategy is aimed at minimization of the fuel consumption and exhaust emissions (HC, CO and NOx), and maintaining driving performance. The following equation shows the mathematical model of the optimization problem:

$$\text{minimize } J = \frac{FC_{default}}{FC(X)} + \frac{HC(X)}{HC_{default}} + \frac{CO(X)}{CO_{default}} + \frac{NOx(X)}{NOx_{default}} \tag{4}$$

$$\text{subject to } \begin{cases} LB \le X \le UB \\ G(X) \le 0 \end{cases}$$

Where, FC(X) indicates the fuel consumption (mi/gal); HC(X),CO (X) and NOx(X) are emissions of HC,CO and NOx (grams/mile); $FC_{default}$, $HC_{default}$, $CO_{default}$, $NOx_{default}$ are the fuel consumption and emissions of the default control strategy in ADVISOR; X is a solution to the problem including a vector of control strategy parameters whose bounds are listed in Table II and G(X) is the constraints to ensure the vehicle performance requirements. In this study, PNGV passenger car constraints [7] are used given in Table IV. The UDDS drive cycle is used to evaluate the fuel economy and the parameters of SAAHGA are given in Table III.

Generally speaking, the tolerance of SOC between the beginning and the end of a drive cycle should be transmitted into the fuel consumption. The Zero-Delta SOC correction routine adjusts the initial SOC until the simulation run yields a zero change in SOC +/- a tolerance band. It can be used to avoid the influence of SOC when calculating the fuel consumption. In this case, the tolerance is set to be 0.5%.

Table I - Specification of Simulated Vehicle

Parameters	Specifications
Engine	1.0L SI engine, 41kW/5700rpm
Motor	AC induction motor, 75kW
Battery	12V26Ah10EP sealed VRLA
Battery Module	25 Modules
Transmission	Manual 5-speed

Table II - Parameters of the Control Strategy

Parameters	Lower bound	Upper bound
cs_hi_soc	0.6	0.9
cs_lo_soc	0.1	0.6
cs_electric_launch_spd_hi (m/s)	5	30
cs_electric_launch_spd_lo (m/s)	0	5
cs_off_trq_frac	0.1	1
cs_min_trq_frac	0.1	1
cs_charge_trq (N·m)	1	30

Table III - Parameters of Applied SAAHGA

Parameter	Specifications
Population type	Double Vector
Population size	20
Initial population	Random
Fitness scaling	Rank
Selection function	Stochastic uniform
Elite count	2

Crossover fraction	Adaptive
cf_max	0.8
cf_min	0.6
ad_up	1
ad_low	0.5
Crossover function	Scattered
Mutation function	adaptfeasible
Initial temperature	80
Maximal iterations of SA	10
Maximal Generations	30

B. Results

The optimization procedure is presented in Fig. 6 and it indicates that the fitness value decreased as the generation evolved forwards.

The optimization results are listed in Table IV. The analysis of the results evidences that with respect to the SAAHGA based approach the optimization procedure achieves a strongly reduction of the fuel consumption, the HC, CO and NO_X emissions, while the vehicle performance constraints are satisfied.

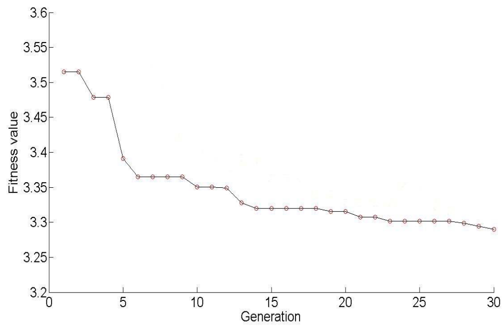

Fig. 6. Trace of optimization over generations

Table IV - Optimization Results

Items		**Before optimization**	**After optimization**	**Target/ Improvement**
Parameters	cs_hi_soc	0.7	0.8969	/
	cs_lo_soc	0.6	0.5514	/
	cs_electric_launch_spd_hi (m/s)	0	13.4476	/
	cs_electric_launch_spd_lo (m/s)	0	0.8831	/
	cs_off_trq_frac	0	0.2011	/
	cs_min_trq_frac	0.4	0.2744	/
	cs_charge_trq (N·m)	15.25	27.1361	/
Constraints	Acceleration time for 0~60mph (t_1)	9 s	9.1	≤12s
	Acceleration time for 40~50mph (t_2)	4.5 s	4.5 s	≤5.3s
	Acceleration time for 0~85mphkm/h (t_3)	18.3 s	18.4 s	≤23.4s
	Gradeability at 55 km/h for 20min (Grad)	6.8%	6.8%	≥6.5%
FC and Emissions	Fuel Consumption (mi/gal)	31.4881	35.8376	13.81%
	HC (grams/mile)	0.6457	0.5879	8.95%
	CO (grams/mile)	4.1866	2.8520	31.88%
	NOx (grams/mile)	0.5753	0.4718	17.99%

V. CONCLUSION

This paper has studied the optimization of parameters of electric assist control strategy for a PHEV. A simulated annealing, adaptive based hybrid genetic algorithm is developed as the optimization algorithm. The new algorithm uses adaptive crossover fraction which may vary in response to the average distance between individuals to maintain the diversity of the population. Then the new hybrid algorithm has been applied to the optimization of the control parameters. The results have proved the effectiveness of the hybrid genetic algorithm and the PHEV after optimization has better fuel economy and lower emissions than that of the original one while the vehicle performance constraints are satisfied. As part of future work, the performance of the vehicle will be analyzed using a multi-objective optimization.

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