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Particle Swarm Optimization for Plug-in Hybrid Electric Vehicle Control Strategy Parameter

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***Abstract*—Plug-in hybrid electric vehicles (PHEVs) differ from hybrid electric vehicles (HEVs) with their ability to use off-board electricity generation to recharge their energy storage systems. In addition to possessing charge-sustaining HEV operation capability, PHEVs use the stored electrical energy during a charge-depleting (CD) operating period to displace a significant amount of petroleum consumption. The choice of CD operating strategy directly influences the benefit derived from the PHEV technology. This paper describes the application of the particle swarm optimization (PSO) algorithm for the optimization of the control parameters in plug-in hybrid electric vehicles (HEV). In this study, based on CD operating strategy, the fitness function is defined so as to maximize the vehicle engine fuel economy (FE). The driving performance requirements are then considered as constraints. The results from the computer simulation show the effectiveness of the approach and improvement in fuel economy (FE) while ensuring that the vehicle performance is not sacrificed.**

***Keywords*—Particle swarm optimization; Plug-in Hybrid Electric Vehicles; Control Strategy; Fuel consumption; Optimization**

I. INTRODUCTION

Conventional HEVs deliver efficiency improvements through means such as enabling the engine to shut off rather than idle, recapturing a portion of normally wasted braking energy, and permitting engine downsizing to improve average in-use efficiency. While such hybridization benefits do improve the fuel economy of these vehicles, all of the available energy still comes from the fuel tank [1].

A plug-in hybrid-electric vehicle (PHEV) is a hybrid-electric vehicle (HEV) with the ability to recharge its electrochemical energy storage with electricity from an off-board source (such as the electric utility grid) [2, 3]. PHEVs can deliver performance equivalent with today's modern vehicles. Furthermore, by blending aspects of the BEV with conventional HEVs, one can gain many of the advantages of a BEV while eliminating several disadvantages. The PHEV has no range penalty and charging times are much shorter than an equivalent BEV. In. contrast to an equivalent HEV, fuel consumption is further reduced since fuel energy is supplied from both electricity and liquid fuel as opposed to just liquid fuel as is the case for conventional HEVs[4].

A PHEV has essentially two operating modes: a charge-sustaining mode and a charge-depleting mode [5]. The total consumption benefits of a PHEV are a combination of the charge-depleting and charge-sustaining mode improvements. In order to be as efficient as it is possible, proper control strategy is required, according to which, energy is produced, used, and saved. Due to the complex nature of PHEV, a control strategy based on the engineering intuition frequently fails to achieve satisfactory overall system efficiency. ADVISOR's built-in parametric study capabilities were used to evaluate the energy management strategy options [6]. However, this method obtained parameters only by analysis and couldn't simultaneously accomplish. Therefore, in order to get more suitable control strategy parameters, an optimization algorithm need to be used. Considering the highly nonlinear and non-continuous characteristic of the optimization problem, a non-gradient based evolutionary optimization method is proposed.

In this paper, application of particle swarm optimization (PSO) is described for optimization of the control strategy in plug-in HEV. The objective of the optimization is defined to maximize the fuel economy (FE) and vehicle performance requirements are also defined as constraints. However, as PSO is not directly applicable to constrained optimization problems, the constraints are handled by using penalty functions. The optimization process is then performed for two driving cycles including UDDS and HWFET. The simulation results are finally obtained to investigate the effectiveness of the approach and the effect of driving cycle on the optimization of PHEV control strategy.

II. VEHICLE PLATFORM, PERFORMANCE, AND ASSUMPTIONS

In this study, in order to compare with the method by ADVISOR's built-in parametric study capabilities, the vehicle assumptions and the performance constraints will be the same as those proposed in the paper [6]. Table I details main characteristics of the vehicle, while Table II defines the performance constraints used in this study.

TABLE I
MAIN CHARACTERISTICS OF THE VEHICLE

Name	Value	Units
Engine Peak Power	38	kW
Motor Peak Power	73.5	kW
Battery Pack Capacity	13.5	kWh
Battery Pack Power	88	kW
Transmission	TX_5SPD_CI	--
Frontal area	2.174	m^2
Aerodynamic drag coefficient	0.327	--
Coefficient of rolling resistance	0.008	--
Wheel radius	0.313	m
Vehicle glider mass	1053	kg
Average electrical accessory load	500	W
Average DC/DC converter efficiency	85	%
Vehicle Mass	1545	kg
Vehicle Test Mass	1681	kg

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TABLE II
PERFORMANCE CONSTRAINTS

Attribute	Value	Special Conditions
Gradeability		
@50 mph for 15 min	7.2%	1)initial SOC=charge sustaining SOC 2)final SOC>20%
@30 mph for 30 min	7.2%	1)initial SOC=charge sustaining SOC 2)final SOC>20%
Acceleration		
0-60mph	9.5s	Initial SOC=charge sustaining SOC
50-70mph	5.1s	
Top Speed	>90mph	
Trace miss	<2mph	
Cycle charge-sustaining SOC	>20%	

In this study, the configuration selected is a parallel hybrid, which incorporates a fuel converter (IC Engine), an electric motor, battery pack as shown in Fig.1.

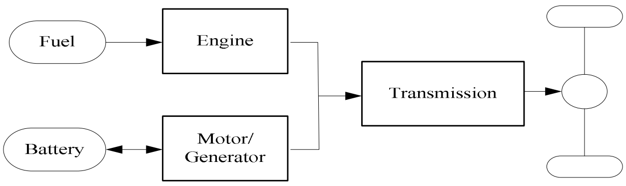

Figure 1. Parallel HEV configuration

III. CONTROL STRATEGY ALGORITHM

The control strategy will attempt to bias the energy flows towards battery pack usage while the pack exhibits a high state of charge. As the state of charge of the pack begins to fall, the strategy will bias the energy usage more towards the engine in order to maintain state of charge in the pack and to prevent pack damage and reduced cycle life. This strategy has characteristics of both charge-depleting and charge-sustaining strategy, as shown in Fig. 2. The main parameters used to implement this control logic in ADVISOR for charge-depleting hybrid electric vehicles have been detailed in Table III.

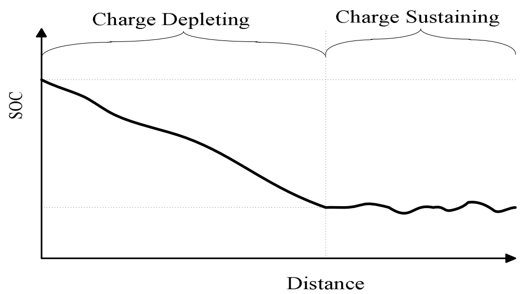

Figure 2. Control strategy schematic

TABLE III
ENERGY MANAGEMENT STRATEGY PARAMETERS

Parameter	Description
L_{SOC}	Lower limit on battery state of charge
H_{SOC}	Upper limit on battery state of charge
T_{ch}	Torque load on engine to recharge the battery pack when engine is on
$T_{\min}$	Fraction of maximum engine torque above which engine must operate if SOC< L_{SOC}
V_L	Vehicle speed below which vehicle attempts to run all electrically at low SOC
V_H	Vehicle speed below which vehicle attempts to run all electrically at high SOC

IV. OPTIMIZATION PROBLEM FORMULATION

In this work, fuel economy is selected as the optimization target. The objective function is defined as follows:

$$J(x) = \frac{FE_{st}}{\int FE(t)dt} \tag{1}$$

In addition, the vehicle performance requirements are defined as constraints

The problem can be defined as the solution for a constrained nonlinear programming problem as described by (2):

$$\begin{cases} \min J(x) \\ x \in \Omega \\ s.t.\ g_i(x) \le 0 \quad i = 1, 2, \ldots n \end{cases} \tag{2}$$

Where Ω is the solution space, $g_i(x) \le 0$ is a group of nonlinear constraint, in the case of HEV optimization, it represents the vehicle performance requirements, such as accelerate time, the grade ability, the balance of SOC, etc.; $J(x)$ is the objective function and n is the number of constraints.

V. APPLICATION OF PSO TO THE OPTIMIZATION OF PLUG-IN HEV CONTROL STRATEGY

A. *PSO Algorithm Description*

Particle Swarm Optimization (PSO) algorithm was developed by Kennedy and Eberhart in 1995 [7], which is a kind of heuristic global optimization technology and belongs to the category of swarm intelligence methods.

PSO works by 'flying' a population of co-operating potential solutions called particles through a problem's solution space, The particles in PSO consist of a D-dimensional position vector X, and a D-dimensional velocity vector V, the i-th member of a population's position is represented as $X_i = (x_{i1}, x_{i2}, ..., x_{iD})$, the best particle of the swarm, is denoted by index g. The best previous position of the i-th particle is recorded and represented as $P_i = (p_{i1}, p_{i2}, ..., p_{iD})$ and the position change (velocity) of the i-th particle is $V_i = (v_{i1},\ v_{i2},\ \ldots,\ v_{iD})$.

The particles are manipulated according to the following equations (the superscripts denote the iteration):

$$V_i^{k+1} = \chi(wV_i^k + c_1 r_{i1}^k (P_i^k - X_i^k) + c_2 r_{i2}^k (P_g^k - X_i^k)) \quad (3)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (4)$$

Where $i = 1,2,...,N$, and N is the size of the population; χ is a constriction factor which is used to control and constrict velocities; w is the inertia weight; c_1 and c_2 are two positive constants, called the cognitive and social parameter respectively; r_{i1} and r_{i2} are random numbers uniformly distributed within the range [0; 1]. Equation (3) is used to determine the i-th particle's new velocity at each generation, while (4) provides the new position of the i-th particle, adding its new velocity to its current position. The performance of each particle is measured according to a fitness function, which is problem-dependent.

B. *Fitness Function*

To apply PSO to the control strategy parameters of the PHEV, a fitness function is required to evaluate the performance of each particle. In this study, the fitness function is considered to be the objective function described in (1), the driving performance requirements are considered as constrained. However, as PSO is directly applicable only to unconstrained optimization problem, the constraints are handled by using penalty function that penalizes the infeasible solutions by adding their fitness values [8]. In this case, the fitness function will take the following form:

$$F(x) = J(x) + h(k)H(x) \quad (5)$$

Where $h(k)$ is a dynamically modified penalty value, k is the algorithm's current iteration number; $H(x)$ is a penalty factor, defined as

$$H(x) = \sum_{i=1}^{m} \theta(q_i(x)) q_i(x)^{\gamma(q_i(x))} \quad (6)$$

Where $q_i(x) = \max\{0,\ g_i(x)\}$, $i = 1,...,m$. The function $q_i(x)$ is a relative violated function of the constraints; $\theta(q_i(x))$ is a multi-stage assignment function; $\gamma(q_i(x))$ is the power of the penalty function; and $g_i(x)$ are the constraints described in (2). In this study, the values of $\gamma(q_i(x))$ and $\theta(q_i(x))$ are described as follows:

$$\gamma(q_i(x)) = \begin{cases} 1 & q_i(x) < 1 \\ 2 & \text{others} \end{cases} \quad (7)$$

$$\theta(q_i(x)) = \begin{cases} 10 & q_i(x) < 0.001 \\ 20 & 0.001 \le q_i(x) < 0.1 \\ 100 & 0.1 \le q_i(x) < 1 \\ 300 & \text{others} \end{cases} \quad (8)$$

$$h(k) = \sqrt{k}\text{ , k is current generation} \quad (9)$$

C. *Driving Cycles*

Based on the analysis of HEV model and optimization variables, we define the particles with the following coefficients:

$x = (L_{SOC}, H_{SOC}, T_{ch}, T_{\min}, V_L, V_H)$

In this optimization study, in order to evaluate the fitness function, two driving cycles have been used, the Urban Driving Dynamometer Driving Schedule (UDDS) and the highway drive cycle (HWFET). To assess the impact of distance, each cycle has been repeated 2, 4, 6 and 8 times.

The two drive cycles are shown in Fig. 3(a) and 3(b), respectively, while their parameters are displayed in Table IV.

TABLE IV
DRIVING CYCLE CHARACTERISTIC PARAMETERS

	Unit	UDDS	HWFET
Time	s	1369	765
distance	km	11.99	16.51
Max speed	Km/h	91.25	96.4
Avg speed	Km/h	31.51	77.58
Max accel	m/s^2	1.48	1.43
Max decel	m/s^2	-1.48	-1.48
Avg accel	m/s^2	0.5	0.19
Avg decel	m/s^2	-0.58	-0.22
Idle time	s	259	6

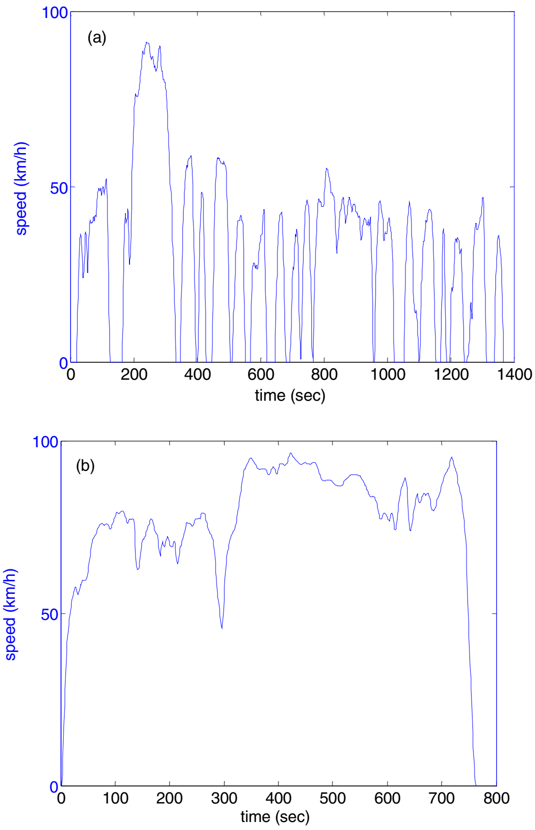

Figure 3. UDDS and HWFET driving cycles

VI. OPTIMIZATION RESULTS AND ANALYSIS

The advanced vehicle simulator (ADVISOR) [9] is used for simulation study. ADVISOR employs a combined forward/backward facing approach for the vehicle performance simulation. The optimized variables and their upper and lower limit are listed in Table V.

In this paper, the following value is used for the other parameters of algorithm: $\chi = 1$, $w = 0.8$, $c_1 = 0.5$ and $c_2 = 2.0$; $V_{\max} = X_{\max} - X_{\min}$; the population size of PSO is set to be 20 and the maximum number of generations is set to be 50.

TABLE V
RANGE OF VARIATION FOR DESIGN VARIABLES

Design variable	Lower bound	Upper bound
L_{SOC}	0.2	0.5
H_{SOC}	0.5	1.0
T_{ch}	4	35
$T_{\min}$	0	0.73
V_L	0	15
V_H	0	30

A. Parameter Control Values

Table VI shows the optimization results of the UDDS standard drive cycle.

TABLE VI
OPTIMIZED PARAMETERS FOR UDDS DRIVE CYCLE

	2UDDS	4UDDS	6UDDS	8UDDS
L_{SOC}	0.3787	0.2035	0.2103	0.2131
H_{SOC}	0.5062	0.88	0.8999	0.5805
T_{ch}	34.5893	21.7362	29.5288	31.2918
$T_{\min}$	0.4943	0.1063	0.0968	0.1966
V_L	14.2319	11.6285	0.3232	6.2494
V_H	29.5336	19.5879	16.7837	20.1501

B. Selection of the Best Single Set of Parameters

To select a single set of parameters, we considered the average as well as the spread of the fuel economy from two different points of view:

1) Same distance with parameters optimized for different ones (2, 4, 6 and 8 UDDS).

2) Different distances with parameters optimized on only one (2, 4, 6 or 8UDDS).

Fig. 4 shows the average and spread of each set of runs and optimum parameters for UDDS. As one notices, using the parameters optimized on different distance, driving a short distance will always bring the best fuel economy. In addition, if the parameters are optimized on a short distance but longer distances are driven, the fuel economy will fluctuate more and can get higher than optimizing on a long distance and driving a short one.

From above analysis, selecting a single set of parameters will depend on the average driving distance and will consequently be different from one drive to another. Considering the high sensitivity to distance of the parameters, the parameters from the 4 UDDS appear to be the best compromise if only one set can be selected.

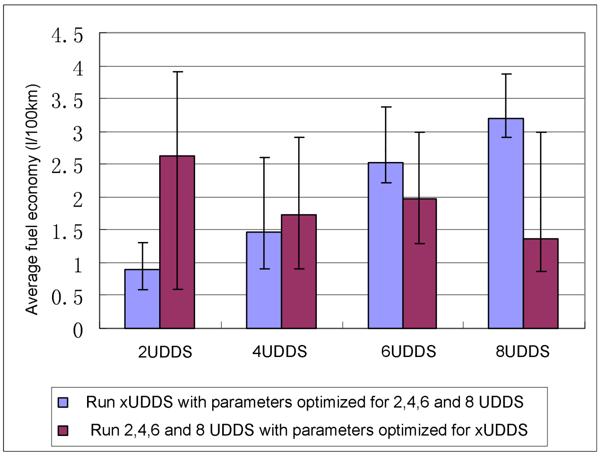

Figure 4. Average and spread of each set of runs and optimum parameters for UDDS

C. Impact of Drive Cycle Characteristic

Table VII shows the optimization results of the HWFET standard drive cycle. Compared with Table VI, it can be seen that the optimal parameters are different for the two driving cycles. It implies that an optimal control strategy for a driving pattern is not necessarily optimal for other driving cycles.

TABLE VII
OPTIMIZED PARAMETERS FOR HWFET DRIVE CYCLE

	2HWFET	4HWFET	6HWFET	8HEFET
L_{SOC}	0.2855	0.2197	0.2044	0.2009
H_{SOC}	0.5037	0.704	0.5244	0.8590
T_{ch}	12.1018	25.8672	31.0199	25.1833
$T_{\min}$	0.1685	0.4562	0.0258	0.1921
V_L	4.5264	3.4124	3.8607	3.3663
V_H	29.1288	24.4602	15.3437	24.3943

D. Comparison Analysis

To evaluate the effectiveness of the proposed approach, the original PHEV [6] is simulated over the two driving cycles (2, 4, 6, 8, 10UDDS and 2, 4, 6, 8, 10HWFET). Fig. 5 and Fig. 6 compare the fuel consumptions over different distance with original parameters and optimal parameters from 4UDDS and 4HWFET respectively. It can be seen that the optimized control strategy can improve fuel economy of the PHEV.

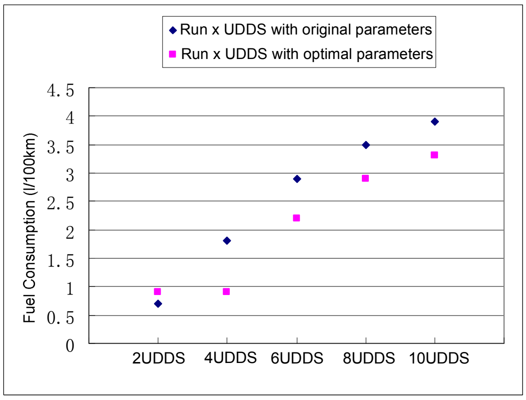

Figure 5. Fuel consumptions of PHEV over xUDDS

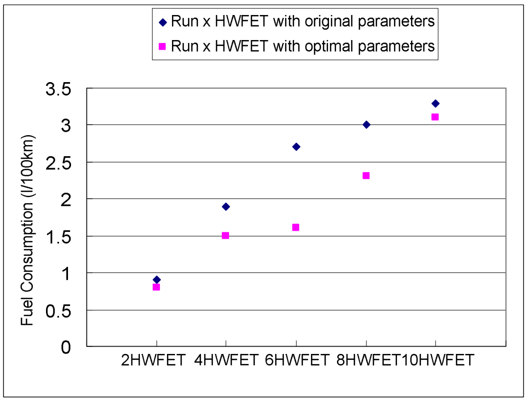

Figure 6. Fuel consumptions of PHEV over xHWFET

VII. CONCLUSIONS

Application of particle swarm optimization algorithm is described for the optimization of the control strategy in plug-in HEV. The optimization problem is formulated for a charge-depleting control strategy in order to get the high fuel economy while maintaining the vehicle performance requirements. In addition, the optimization is performed over two driving cycles, and the effect of driving pattern and different range on the optimization of control strategy is investigated. Finally, the proposed approach is compared with the method by ADVISOR's built-in parametric study capabilities so as to evaluate its effectiveness. The results show that different driving pattern and distance need different control parameters. If only one parameter is used, the parameters obtained from medium distances are selected as trade-off. On the side, the optimal parameters can reduce the fuel consumption than the original.

REFERENCES

[1] Jeffrey G, Jony M, "Energy Management Strategies for Plug-in Hybrid Electric Vehicles", SAE paper 2007-01-0290, SAE World Congress, April 2007, Detroit, Michigan.

[2] Simpson, A. "Cost-Benefit Analysis of Plug-In Hybrid Electric Vehicle Technology". 22nd International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium (EVS-22). October 2006. Yokohama, Japan.

[3] Bradley T.H, Frank A.A. Design, demonstrations and sustainability impact assessments for plug-in hybrid electric vehicles. Renew Sustain Energy Rev (2007), doi:10.1016/j.rser.2007.05.003

[4] M.P. O'Keefe and T. Markel, "Dynamic Programming Applied to Investigate Energy Management Strategies for a Plug-in HEV Presented at the 22nd International Battery", Hybrid and Fuel Cell Electric Vehicle Symposium and Exhibition (EVS-22) Yokohama, Japan October 23–28, 2006

[5] D. Karbowski, R. Aymeric, P. Sylvain, S. Phillip, "Plug-in vehicle control strategy: from golobal optimization to real-time application", the 22nd International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium & Exposition (EVS 22), Yokohama, Japan, Oct, 2006.

[6] Tony Markel and Keith Wipke, "Modeling Grid-Connected Hybrid Electric Vehicles Using ADVISOR", NREL/CP-540-30601

[7] J. Kennedy, "The particle swarm: Social adaptation of knowledge," in Proc. IEEE Int. Conf. Evol. Comput, Indianapolis, IN, 1997, pp.303–308.

[8] P. Angeline, "Evolutionary optimization versus particle swarm optimization philosophy and performance differences," in Proc. 7th Annu. Conf. Evol. Program.1998, pp. 601–610.

[9] T. Markel, A. Brooker, T. Hendricks, V. Johnson, K. Kelly, B.Kramer, M. O'Keefe, S. Sprik, K. Wipke,ADVISOR: a systems analysis tool for advanced vehicle modeling, J. Power Sources 110 (2002) 255–266.