Using the Pareto Set Pursuing Multiobjective Optimization Approach for Hybridization of a Plug-In Hybrid Electric Vehicle

Shashi K. Shahi
Product Design and Optimization Laboratory,
Simon Fraser University,
Surrey, BC, Canada
e-mail: shashi_k_shahi@yahoo.ca

G. Gary Wang[1]
Product Design and Optimization Laboratory,
Simon Fraser University,
Surrey, BC, Canada
e-mail: gary_wang@sfu.ca

Liqiang An
Mechanical Engineering Department,
North China Electric Power University,
Baoding, China
e-mail: anliqiang@gmail.com

Eric Bibeau
Department of Mechanical and Manufacturing Engineering,
University of Manitoba,
Winnipeg, MB, Canada
e-mail: bibeauel@cc.umanitoba.ca

Zhila Pirmoradi
Product Design and Optimization Laboratory,
Simon Fraser University,
Surrey, BC, Canada
e-mail: zpirmora@sfu.ca

A plug-in hybrid electric vehicle (PHEV) can improve fuel economy and emission reduction significantly compared to hybrid electric vehicles and conventional internal combustion engine (ICE) vehicles. Currently there lacks an efficient and effective approach to identify the optimal combination of the battery pack size, electric motor, and engine for PHEVs in the presence of multiple design objectives such as fuel economy, operating cost, and emission. This work proposes a design approach for optimal PHEV hybridization. Through integrating the Pareto set pursuing (PSP) multiobjective optimization algorithm and powertrain system analysis toolkit (PSAT) simulator on a Toyota Prius PHEV platform, 4480 possible combinations of design parameters (20 batteries, 14 motors, and 16 engines) were explored for PHEV20 and PHEV40 powertrain configurations. The proposed approach yielded the optimal solution in a small fraction of computational time, as compared to an exhaustive search. This confirms the efficiency and applicability of PSP to problems with discrete variables. In the design context we have found that battery, motor, and engine collectively define the optimal hybridization scheme, which also varies with the drive cycle and all electric range (AER). The proposed method and software platform could be applied to optimize other powertrain designs. [DOI: 10.1115/1.4007149]

Keywords: multiobjective optimization, Pareto set pursuing, hybridization, PHEV, powertrain system analysis toolkit

1 Introduction

Developed by Shan and Wang [1], the Pareto set pursuing (PSP) method is a multiobjective optimization method, especially suitable for design problems that involve expensive black-box functions [1]. This approach provides a set of Pareto set for choices without any prior knowledge of the objective functions or preferences, and it can be of high efficiency for solving optimization problems that are coupled with black-box simulations. PSP captures the Pareto optimal frontier automatically without calling any formal optimization process. Approximation is used in order to guide only the sampling process, and does not demand an accurate approximation model. Through tests and applications, PSP is found robust and efficient and the Pareto set points found by PSP are actual or close-to-actual Pareto set points and spread closely and evenly over the entire Pareto optimal frontier. PSP can solve problems with continuous, discrete, or mixed type variables [2]. In this study, the applicability and computational efficiency of this approach for solving the hybridization optimization of the PHEV powertrain system components is studied. The hybridization problem for HEV/PHEVs [3] is a computationally expensive problem, which requires simulation runs in order to obtain objective function values for each set of design variables. The characteristics of these vehicles and the hybridization optimization problem will be presented first. Then the PSP method will be explained and the application of this approach for design optimization of PHEVs will be discussed.

A plug-in hybrid electric vehicle (PHEV) is a newer generation of electrified vehicles which are powered by a combination of an internal combustion engine and an electric motor with a battery pack. The battery pack can be charged through plugging the vehicle into the grid and from using excess engine power. A PHEV allows for all electric operation for limited distances, and has significant potential to reduce oil consumption and greenhouse gas (GHG) emissions [4]. The design considerations for PHEVs normally include vehicle architecture, drivetrain component selection including internal combustion engine (ICE) and electric motor, energy management systems, energy storage tradeoffs, and grid connection [5,6]. It is a critical step in PHEV design to choose the proper combination of ICE, electric motor, and battery pack. The degree of hybridization, defined as the ratio of electric motor power to the sum of electric motor and ICE power, affects the optimality of the drivetrain components performance [7]. In general, it is believed that greater degree of hybridization allows for using a smaller ICE, which operates at near its optimum efficiency for a larger proportion of time. This work addresses the hybridization by using optimization, considering simultaneously the fuel economy, operating cost, and GHG emissions for PHEVs with two drive cycles. Toyota Prius PHEV20 and PHEV40 (with 20 and 40 miles of all electric range, respectively) are chosen as the vehicle platform in this study. This work aims at demonstrating the optimal hybridization methodology rather than achieving new practical vehicle designs. Practitioners, however, can apply the proposed methodology for their actual vehicle design by changing the assumptions and vehicle platform.

2 PHEV Design Studies

There have been many research works on PHEV design. Reynolds and Kandlikar [8] found that the weight penalty for fuel consumption in HEVs was significantly lower than in equivalent conventional ICE vehicles. The performance of PHEVs has also been found to be dependent on the energy management mode and the vehicle architecture [9–11]. PHEVs can operate in four energy

[1]Corresponding author.

Contributed by the Design Automation Committee of ASME for publication in the Journal of Mechanical Design. Manuscript received November 14, 2011; final manuscript received May 24, 2012; published online August 7, 2012. Assoc. Editor: Shinji Nishiwaki.

management modes: charge sustaining (CS) mode, charge depleting (CD) mode, electric vehicle (EV) mode, and engine only mode [12–14].

There is no standard solution for the optimal size or ratio of the ICE and the electric power system. The optimum choice includes tradeoffs between the engine and electric propulsion system on one hand, and cost, fuel economy, and performance on the other. A review of the automotive industry literature shows that each company has developed its own solution for the relative size of the ICE to the electric motor, the hybridization factor. The optimal level of hybridization ranges for HEVs have been found to be between 0.3 and 0.5, depending on the total vehicle power [13]. Further increase of the hybridization factor beyond an optimum value could lead to lower energy conversion efficiency of the powertrain and higher fuel consumption [12].

The past studies in PHEV design have focused on prototyping and testing hundreds of design parameters for improving the performance of PHEVs. However, multiple testing procedures are cumbersome and time consuming. Therefore, the emphasis of research shifted to simulation-based optimization algorithms that work together in a loop with a computer simulation model to reach optimal design solution [15]. One such simulation-based algorithm for modeling the performance of HEVs and PHEVs is PSAT, developed by Argonne National Laboratory [16].

In this work, PSAT and the PSP optimization algorithm are integrated in order to search for the best hybridization of battery, engine, and motor. Such a hybridization optimization however faces a few challenges: (1) the variables are types of battery, engine, and motor and thus discrete in nature, (2) each vehicle simulation takes a relatively long time, and (3) for each combination of these components, a vehicle design needs to satisfy certain performance constraints, which requires a prior selection of the components to meet the desired performance before optimization toward the desired objective functions. In addition, this work also considers multiple objectives. The optimization is in essence an expensive simulation-based optimization problem with discrete variables. Therefore, the Pareto set pursuing (PSP) method has the potential to be used as a practical tool for this problem.

3 Methodology

Our proposed design approach is to integrate the PSP method with PSAT to optimize the components of PHEV MY04: Toyota Prius model year 2004 vehicle [16]. The drivetrain hybridization is optimized for the minimum fuel consumption, operating cost, and GHG emissions on two different drive cycles: urban dynamometer driving schedule (UDDS) [17,18] and Winnipeg weekday duty cycle (WWDC) [19,20] with two AER specifications.

3.1 Toyota Prius MY04 Vehicle Model. The Prius has two electrical machines: an electric motor and a generator. The Toyota hybrid transmission system incorporates a system of planetary gears, called a power split device, which directs power between the ICE, electric motor, generator, and wheels, in all directions. The planetary gear set is both a power summing device and a gear ratio device. Details of its configurations can be found in [7].

3.2 Vehicle Modeling and Simulation. Toyota Prius MY-04 is modeled by PSAT simulator, which can simulate the driver as a control system that attempts to follow a target driving cycle through obtaining a specific speed at every moment by actuating the accelerator and brake pedals. For the simulations in our study, we used the Prius as a baseline vehicle platform, and changed the battery, motor, and engine as driven by the optimization process. Battery capacity is designed to achieve the desired 20 or 40 miles AER; simultaneously electric motor and engine are scaled to achieve 0 to 60 mph within the required acceleration time specification of $10.5+0.0/-0.5$ s, which is approximately the acceleration performance of Toyota Prius. The PSAT split hybrid control strategy is modified so that the vehicle operates as an electric vehicle in CD mode without engaging the engine until the battery reaches a 35% SOC value, after which time the vehicle switches to the CS mode and operates like a normal hybrid Prius.

The list of drivetrain components for modeling the vehicle includes the following, whose detailed parameters can be found in the PSAT software tool.

- 14 different permanent magnet electric ac motors,
- 20 different batteries (including one lithium-ion battery, one nickel cadmium battery, nine nickel metal hydride batteries, one nickel zinc battery, and nine lead acid batteries), and
- 16 different spark ignition gasoline engines.

Other vehicle parameters remain constant, including vehicle body mass (except for battery mass, which varies with the number of battery modules), width of the vehicle, frontal area of the vehicle, length of the vehicle, height of the vehicle, distance between two front axles, mass of the vehicle cargo, and vehicle center of gravity height. For simplicity, the chosen generator is one of the available models for the Toyota Prius, and it is neither varied during the powertrain components selection phase nor during the optimization procedure. It is a permanent magnet motor with continuous power of 25 kW and peak power of 50 kW.

A comparison of key characteristics of the two drive cycles, UDDS and WWDC, is shown in Table 1. As one can see that WWDC, as compared with UDDS, has more aggressive acceleration and deceleration, and more stops and longer stop duration.

3.3 Optimization of PHEVs. For a given set of types of battery, engine, and motor, their sizes should be dynamically determined. In each PHEV battery simulation, the number of battery modules needed to reach the desired 20 or 40 miles AER is first determined in the electric only CD mode when the battery is assumed to start with 80% SOC until reaching a 35% SOC value. Then, the vehicle is operated in the CS mode to complete the 22.35 miles for PHEV 20 and 44.70 miles for PHEV40. In the CS mode, both the battery and engine work together to support the necessary driving power. The motor and engine sizes are scaled to achieve a 0–60 miles per hour acceleration within 10.5 $0.0/-0.5$ s, which is approximately the acceleration performance of a Toyota Prius [21]. This procedure is repeated iteratively for each battery type until convergence to a vehicle profile that both AER and acceleration specification is achieved for the desired drive cycle (UDDS and WWDC in our study). Finally, the electric efficiency in CD mode (kW h/mile) and the fuel efficiency in CS mode (miles/gallon) are calculated.

Figure 1 shows the optimization process for battery sizing and Eq. (1) defines the mathematical form of the optimization problem:

Table 1 Comparison of UDDS and WWDC drive cycles

Simulation parameters	Units	UDDS drive cycle	WWDC drive cycle
Cycle time	s	1369	3386
Distance	miles	7.45	19.61
Maximum speed	miles/h	56.70	61.91
Average speed	miles/h	19.58	20.85
Standard deviation speed	miles/h	14.70	16.91
Maximum acceleration	m/s^2	1.48	2.78
Average acceleration	m/s^2	0.50	0.55
Standard deviation acceleration	m/s^2	0.45	0.50
Maximum deceleration	m/s^2	−1.47	−6.48
Average deceleration	m/s^2	−0.58	−0.59
Standard deviation deceleration	m/s^2	0.52	0.57
Number of stops		17	33
Stop frequency	stop/mile	0.0014	0.0010
Stop duration	s	259	595
Stop percent of cycle	%	18.92	17.57

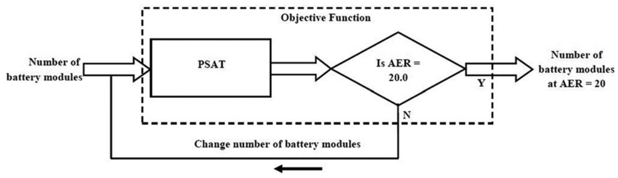

Fig. 1 Optimal battery sizing

$$\begin{aligned}&\text{Min}|\text{Simulation AER} - \text{Ideal AER}|\\&\text{w.r.t. } x = \text{number of battery modules}\end{aligned} \tag{1}$$

The optimization problem for motor and engine sizing is similar to the procedure of battery sizing as illustrated in Fig. 1, and Eq. (2) defines the mathematical form of the optimization problem, where ACC stands for "acceleration":

$$\begin{aligned}&\text{Min } |\text{Simulation ACC} - \text{Ideal ACC}|\\&\text{w.r.t. } x = \{x_1, x_2\},\ x_1 = \text{motor power, and } x_2 = \text{engine power}\end{aligned} \tag{2}$$

The optimization model uses a 1D optimization method (i.e., Matlab function *FZERO*) for battery sizing, and an nD search method (i.e., Matlab function *FMINSEARCH*) for motor and engine sizing. Theoretically, one ought to combine the two problems as defined in Eqs. (1) and (2), to define a three-variable optimization problem. It is found, however, that the problem could be decomposed into two subproblems as defined above since the battery size affects mostly the AER while the engine, and motor sizes are the key parameters determining the acceleration performance. Such a decomposition strategy also helps to reduce the total computational time for optimization.

The optimal hybridization of PHEVs is achieved by combinations of the three drivetrain components: battery storage, electric motor, and gasoline engine that provide maximum fuel economy (miles/gallon), minimum operating cost ($/mile), and operation GHG emissions (kg/mile) on UDDS and WWDC drive cycles. The optimization model includes a total of 4480 combinations of batteries, electric motors, and gasoline engines. Since for PHEV20 design it takes about 3 h on a desktop computer [Dell Optiplex 755 Intel(R) Core(TM) 2QuadCPU Q6700 @2.66 GHz, 3.25 GB of RAM] for designing one vehicle, i.e., to solve the optimization problems defined in Eqs. (1) and (2), the exhaustive search method to run all 4480 combinations will take 560 days. The time for each PHEV40 design takes more than 5 h on the same computer due to the longer drive cycle, and thus the total time for exhaustive search would be unacceptable. Therefore, we used PSP multiobjective optimization approach to select the most optimum hybridization combination from these 4480 vehicle combinations [1]. PSP has been found to be among the most efficient methods when the total of function evaluations is limited, as compared to state-of-the-art evolutionary algorithms for multiobjective design problems [2].

The PSP multiobjective optimization method builds a sampling guidance function by providing efficient and uniformly distributed set of Pareto optimal points based on approximation models [1]. The PSP approximates the entire Pareto frontier directly by sampling Pareto points for the multiobjective optimization problem of minimizing the operating costs and GHG emissions, and maximizing the fuel economy with the PSAT black-box function. It starts with a random sample in the first iteration, but moves closer to the Pareto frontier with successive iterations. Two types of sampling guidance functions are developed in the process. The first function is for the sampling of *cheap* points from the approximation model of each objective function, and the second function is for the sampling towards the Pareto frontier [1]. Figure 2 shows the flow chart of the Pareto set pursuing identification approach.

For the PHEV design in this work, as shown in Fig. 3, the input is the combination of battery, motor, and engine types. PSP algorithm selects the combination of component types, and performs

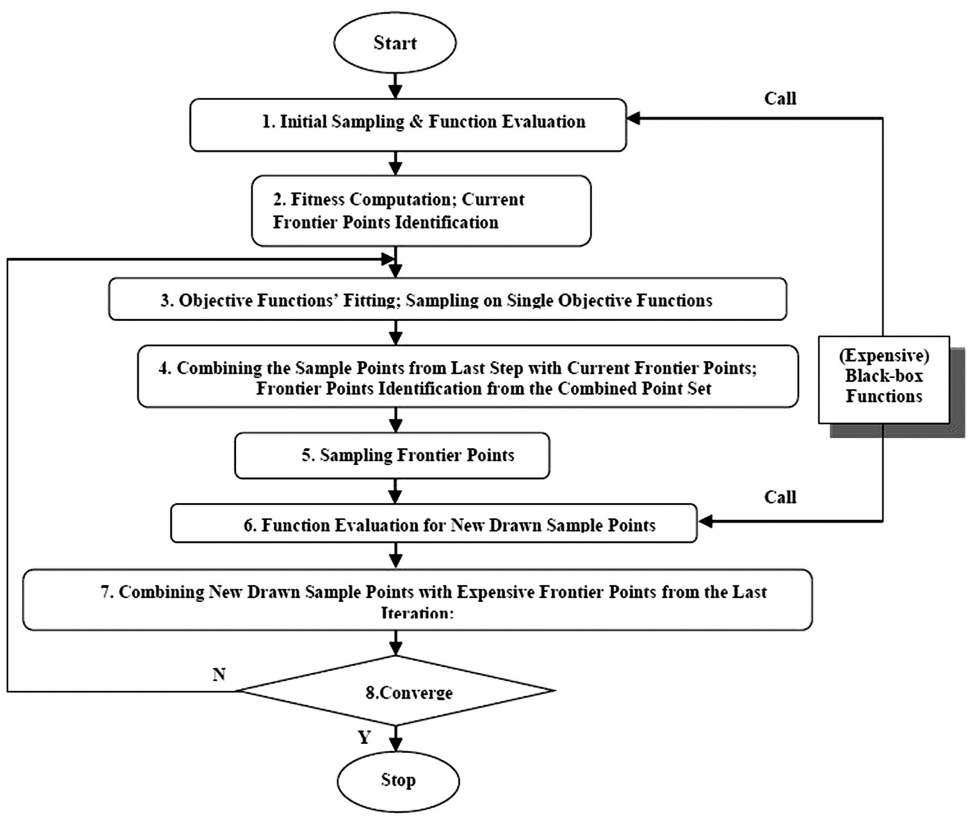

Fig. 2 Flow chart of the Pareto set pursuing approach

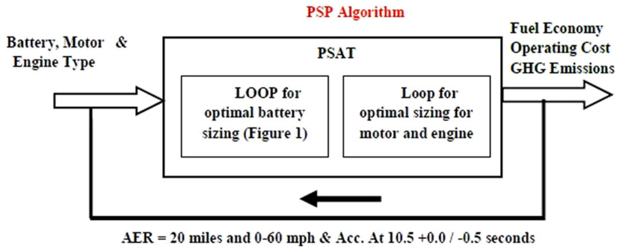

Fig. 3 PSP multiobjective optimization algorithm with PSAT as a black box

the optimal sizing for battery, as well as motor and engine by calling the PSAT as a black box. PSP algorithm finds the most efficient points based on the performance values.

Mathematically, for PHEV design, the multiobjective optimization problem is defined as

$$\text{Minimize}: F(x) = \{f_1(x), f_2(x), f_3(x)\} \tag{3}$$

$f_1(x) = -$ fuel economy, $f_2(x) =$ operating cost, c_{OP}, $f_3(x) =$ operation GHG emission, v_{OP}.

The average operating cost c_{OP} (not including the battery purchasing cost) is given by [21]

$$c_{\text{OP}} = \frac{1}{d}\left(\frac{d_{\text{CD}}}{\eta_{\text{CD}}}\frac{c_{\text{ELEC}}}{\eta_C} + \frac{d_{\text{CS}}}{\eta_{\text{CS}}}c_{\text{GAS}}\right) \tag{4}$$

where η_{CD} is CD mode vehicle electrical efficiency; η_{CS} is CS mode vehicle fuel efficiency; η_C is the charging efficiency; c_{ELEC} is the cost of electricity; c_{GAS} is gasoline cost assuming $c_{\text{ELEC}} = \$0.11$ per kW h, $\eta_C = 88\%$ and $c_{\text{GAS}} = \$3.00$ per gallon.

The average operation GHG emission per mile v_{OP} is calculated by [21]

$$v_{\text{OP}} = \frac{1}{d}\left(\frac{d_{\text{CD}}}{\eta_{\text{CD}}}\frac{v_{\text{ELEC}}}{\eta_C} + \frac{d_{\text{CS}}}{\eta_{\text{CS}}}v_{\text{GAS}}\right) \tag{5}$$

where v_{ELEC} is the emissions associated with electricity; v_{GAS} is the emissions associated with gasoline assuming $v_{\text{ELEC}} = 0.730$ kg $CO_2 - \text{eq}$ per kW h, $v_{\text{GAS}} = 11.34$ kg $CO_2 - \text{eq}$ per gallon.

Constraints, $d_{\text{AER}} = 20$ or 40 miles; ACC time = 10.5 s for 0–60 mph.

Design variables, vector $\mathbf{x} = \{x_1, x_2, x_3\}$, $x_1 =$ battery type, $\in [1,20]$; $x_2 =$ motor type, $\in [1,14]$; $x_3 =$ engine type, $\in [1,16]$.

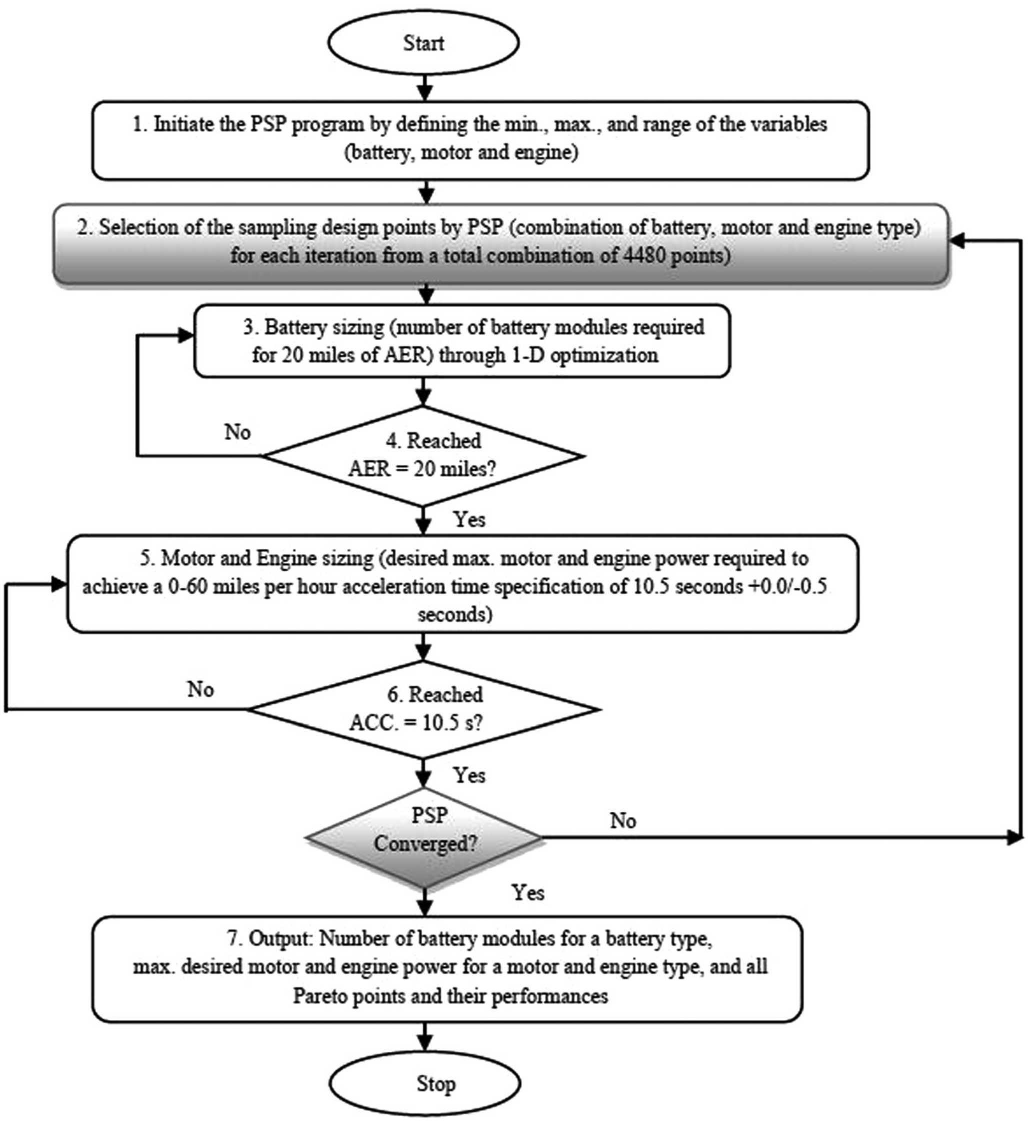

Fig. 4 Flow chart of the program structure for the automated optimization process

Table 2 Pareto design points and their key performance values

Sample point	Number of modules in a battery	Motor power (kW)	Engine power (kW)	Battery capacity (kW h)	Hybridization factor	Electric efficiency in CD mode (miles/kW h)	Fuel efficiency in CS mode (miles/gallon)
PHEV20 UDDS drive cycle							
31	101	57.20	65.63	7.67	0.47	5.96	129.31
72	101	86.00	54.00	7.67	0.61	6.02	122.73
114	25	122.0	8.63	8.40	0.93	5.39	193.20
128	51	80.00	60.00	2.20	0.57	7.05	67.21
PHEV20 Winnipeg weekday drive cycle							
30	7	100.00	33.00	9.07	0.75	4.97	108.54
56	51	80.00	60.00	2.39	0.53	6.24	60.49
71	15	105.00	25.50	9.72	0.80	4.74	109.96
PHEV40 UDDS drive cycle							
29	69	110.50	66.38	13.91	0.62	6.09	156.48
63	202	95.00	60.75	13.08	0.61	5.89	160.19

It is to be noted that the fuel economy parameters defined in Eqs. (4) and (5) are obtained from calling the PSAT simulation for each given $\boldsymbol{x}$.

Figure 4 shows the program structure for the automatic process of hybridization and PSP multiobjective optimization of PHEV. Constants used in the above formulations are taken from Ref. [21]; these values can be changed according to specific situations when applying the proposed methodology.

4 Results and Discussion

4.1 Sampling Design Points for PHEV20 and PHEV40. The results of simulation and optimization for PHEV20 show a total of 139 sampling design points for each drive cycle, UDDS and WWDC (based on PSP convergence criterion of $G_{\text{avg}} = 1.015$). Four Pareto design points representing the most efficient hybridization combination of battery, motor, and engine for UDDS drive cycle, and three Pareto design points for WWDC are obtained from each of these 139 sampling design points for the PHEV20 vehicle. There are 72 design points for PHEV40 obtained from 48 iterations using UDDS drive cycle. Out of these 72 sampling design points, only two combinations are Pareto design points that represent the most efficient hybridization for PHEV40 on UDDS drive cycle.

4.2 Simulation Results Using UDDS and WWDC. Each sampling design point represents a combination of battery, motor, and engine under the given constraints of desired 20 or 40 miles AER and acceleration requirement. Tables 2 list the final Pareto points and their key performance indicators for the two drive cycles. Details on their readings of the three objective function values, as well as their specific types, are omitted for brevity.

As one can see from Table 2, among the optimum solutions on UDDS drive cycle, the hybridization factor varies from 0.47 to 0.93 for PHEV20, from 0.61 to 0.62 for PHEV40; while for PHEV20 on WWDC, the number varies from 0.53 to 0.80. Similar behavior can be observed from the data for WWDC. In general higher hybridization factors tend to lead to higher fuel efficiency but lower electrical efficiency. However when three objectives are simultaneously considered, the hybridization factor alone is not sufficient to characterize the performance of PHEV. One can see from Table 2 that the optima can exist with a wide spectrum of hybridization factor values.

To show the convergence of the multiobjective optimization process, the 139 sample points of PHEV20 are shown in Fig. 5. The 3D plot shows in gray the best design points obtained through iterations. At the end of the final iteration, four Pareto design points for UDDS drive cycle are marked as black dots, representing the final optimal hybridization combinations of battery, motor, and engine. As shown in these figures, the search starts from the left upper corner and gradually converges to the right lower section, where the Pareto points can be found.

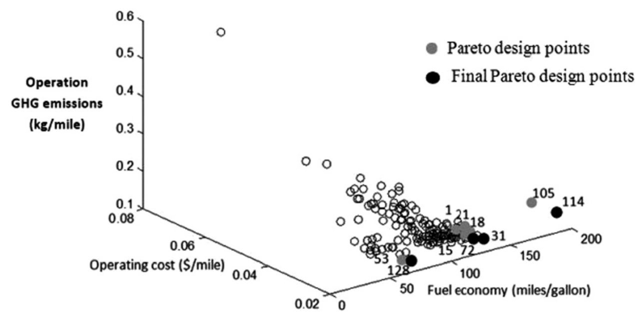

Fig. 5 Fuel efficiency, operation cost, and GHG emissions for PHEV20 using UDDS

5 Discussions

The proposed work automates the optimal design by integrating PSP with PSAT using multiple objectives. The proposed work is found to be efficient and effectively finding good combination for PHEV 20 and PHEV 40 with respect to a given drive cycle. This in fact may be the first multiobjective optimization that has been applied for PHEV hybridization design. There are a couple of caveats, however, that need to be noted. First, the optimal design is obtained on the basis of a set of given conditions: (1) Prius vehicle platform with a fixed generator and transmission, (2) AER is specified at either 20 or 40 miles and the acceleration requirement is fixed at 10.5 0.0/−0.5 s from 0 to 60 mph, (3) the weights of the three objectives are equal, which in practice may not be the case, (4) the parameters and constants used in the hybridization model defined in Eqs. (3)–(5) may be adjusted according to the changing market condition, and (5) the battery cost model is based only on operational cost; a complete life-cycle cost model should be used to reflect the total cost of a battery. Therefore the obtained optimal designs only make sense under all of these conditions. Second, the optimization of sizing and hybridization are based on black-box functions. As such there is no guarantee of the absolute global optimum. Third, although PSP is the more efficient choice for the purpose thus far, the integrated design approach does not dictate the exclusive use of PSP.

6 Conclusions

PSP algorithm for multiobjective optimization is used in conjunction with the PSAT simulation tool for optimizing the type and size of ICE, electric motor, and storage battery for PHEVs. The objective functions in this study are fuel economy, operating cost, and GHG emissions simultaneously. The modeling and optimum hybridization is presented for Toyota Prius PHEV20 and PHEV40 vehicles under two drive cycles, i.e., UDDS and WWDC.

In summary, the proposed simulation and optimization model automated with PSAT simulator is a promising method in finding the optimal hybridization combination for PHEVs drivetrain components with respect to a given drive cycle. Multiobjective optimization applied for PHEV drivetrain components hybridization design is a novel approach to achieve sustainable mobility. In the PHEV design context, it was found that:

1. The proposed approach can efficiently search for the optimal hybridization for PHEV's considering multiple objectives. The optimization problem is in essence an expensive simulation-based optimization problem with discrete variables. For the test problem with 4480 combinations, the exhaustive search approach will have taken 560 days; while our approach only takes 17 days (139 points with 3 h each) for PHEV 20 on the UDDS drive cycle.
2. Simulation results demonstrate that battery, motor, and engine work collectively in defining a hybridization scheme for optimum performance of PHEVs. The commonly used hybridization factor alone is insufficient to capture all of the objectives; it is however strongly correlated with the electrical or fuel efficiency of the vehicle.
3. The optimal hybridization scheme varies with drive cycles. In this study we compared the optimal results with two drive cycles and obtained different optimal schemes and performances.
4. The optimal hybridization scheme varies with AERs. This study also found that the optima for PHEV20 and PHEV40 vary on the same drive cycle.

The PSP approach can be potentially applied to similar problems in the area of powertrain optimization for HEV/PHEVs.

Acknowledgment

Financial support from AUTO21, a network of centers of excellence of Canada, for this project is gratefully acknowledged: Project number DF302-DBS.

References

[1] Shan, S., and Wang, G. G., 2005, "An Efficient Pareto Set Identification Approach for Multiobjective Optimization on Black-Box Functions," ASME J. Mech. Design, **127**(5), pp. 866–874.
[2] Khokhar, Z. O., Vahabzadeh, H., Ziai, A., Wang, G. G., and Menon, C., 2010, "On the Performance of the PSP Method for Mixed-Variable Multi-Objective Design Optimization," ASME J. Mech. Design, **132**, p. 071009.
[3] Åhman, M., 2006, "Government Policy and the Development of Electric Vehicles in Japan," Energy Policy, **34**(4), pp. 433–443.
[4] Liu, J., 2007, "Modeling, Configuration and Control Optimization of Power-Split Hybrid Vehicles," Ph.D. Dissertation, Mechanical Engineering, The University of Michigan.
[5] Graham, R., Bradely, T., and Duvall, M., 2003, "Development of Plug-In Hybrid Electric Light-Duty and Medium Duty Commercial Vehicles," The 20th International Electric Vehicle Symposium and Exposition (EVS-20), 15–19 Nov., Long Beach, CA.
[6] Wu, J., Emadi, A., Duoba, M., and Bohn, T. P., 2007, "Plug-In Hybrid Electric Vehicles: Testing, Simulations, and Analysis," Proceeding of Vehicle Power and Propulsion Conference, VPPC 2007, IEEE, pp. 469–476.
[7] Larminie, J., Lowry, J., and NetLibrary, I., 2003, *Electric Vehicle Technology Explained*, Wiley Online Library.
[8] Reynolds, C., and Kandlikar, M., 2007, "How Hybrid-Electric Vehicles Are Different From Conventional Vehicles: The Effect of Weight and Power on Fuel Consumption," Environ. Res. Lett., **2**, p. 014003.
[9] Liot, C., Fadel, M., Grandpierre, M., and Sans, M., 2005, "Global Energy Management for Vehicle in GERICO Project," EVS21 Monaco, session Energy Efficiency and Energy Security.
[10] Pesaran, A., Markel, T., Tataria, H., and Howell, D., 2009, "Battery Requirements for Plug-In Hybrid Electric Vehicles—Analysis and Rationale," National Renewable Energy Laboratory (NREL), Golden, CO.
[11] Quinn, C., Zimmerle, D., and Bradley, T. H., 2010, "The Effect of Communication Architecture on the Availability, Reliability, and Economics of Plug-In Hybrid Electric Vehicle-to-Grid Ancillary Services," J. Power Sources, **195**(5), pp. 1500–1509.
[12] Bradley, T. H., and Frank, A. A., 2009, "Design, Demonstrations and Sustainability Impact Assessments for Plug-In Hybrid Electric Vehicles," Renew. Sustain. Energy Rev., **13**(1), pp. 115–128.
[13] Lukic, S. M., and Emadi, A., 2004, "Effects of Drivetrain Hybridization on Fuel Economy and Dynamic Performance of Parallel Hybrid Electric Vehicles," IEEE Trans. Veh. Technol., **53**(2), pp. 385–389.
[14] Shidore, N., Bohn, T., Duoba, M., Lohse-Busch, H., and Sharer, P., 2007, "PHEV 'All Electric Range' and Fuel Economy in Charge Sustaining Mode for Low SOC Operation of the JCS VL41M Li-Ion Battery Using Battery HIL," Proceeding of the Electric Vehicle Symposium 23, Anaheim, CA, December 2–5.
[15] Karbowski, D., Haliburton, C., and Rousseau, A., 2007, "Impact of Component Size on Plug-In Hybrid Vehicles Energy Consumption Using Global Optimization," Proceeding of 23rd International Electric Vehicle Symposium, Anaheim, CA, Dec.
[16] "PSAT (Powertrain System Analysis Toolkit), Software for the Modeling and Simulation of Vehicle Drivetrain Configurations," Argonne National Laboratory, http://www.transportation.anl.gov/. Last access date: Feb. 2012.
[17] Fontaras, G., Pistikopoulos, P., and Samaras, Z., 2008, "Experimental Evaluation of Hybrid Vehicle Fuel Economy and Pollutant Emissions Over Real-World Simulation Driving Cycles," Atm. Environ., **42**(18), pp. 4023–4035.
[18] Markey, J., 1993, "Federal Test Procedure Review Project: Technical Report," EPA 420-R-93-007, Certification Division, Office of Mobile Sources, Environmental Protection Agency.
[19] Tara, E., Shahidinejad, S., Filizadeh, S., and Bibeau, E., 2010, "Battery Storage Sizing in a Retrofitted Plug-In Hybrid Electric Vehicle," IEEE Trans. Veh. Technol., **59**(6), pp. 2786–2794.
[20] Shahidinejad, S., Bibeau, E., and Filizadeh, S., 2010, "Winnipeg Driving Cycle: WPG02," http://mspace.lib.umanitoba.ca/handle/1993/3997. Last access date: Feb. 2012.
[21] Shiau, C. S. N., Samaras, C., Hauffe, R., and Michalek, J. J., 2009, "Impact of Battery Weight and Charging Patterns on the Economic and Environmental Benefits of Plug-In Hybrid Vehicles," Energy Policy, **37**(7), pp. 2653–2663.