Power-cycle-library-based Control Strategy for Plug-in Hybrid Electric Vehicles

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***Abstract*- It has been demonstrated that considering the knowledge of drive cycle as a priori in the PHEV control strategy can improve its performance. The concept of power cycle instead of drive cycle is introduced to consider the effect of noise factors in the prediction of future drivetrain power demand. To minimize the effect of noise factors, a practical solution for developing a power-cycle library is introduced. A control strategy is developed using the predicted power cycle which inherently improves the optimal operation of engine and consequently improves the vehicle performance. Since the control strategy is formed exclusively for each PHEV rather than a preset strategy which is designed by OEM, the effect of different environmental and geographic conditions, driver behavior, aging of battery and other components are considered for each PHEV. Simulation results show that the control strategy based on the driver library of power cycle would improve both vehicle performance and battery health.**

I. INTRODUCTION

A plug-in hybrid electric vehicle (PHEV) is a hybrid vehicle whose batteries can be recharged by plugging into an electric power source. A PHEV combines features of conventional hybrid electric vehicles and battery electric vehicles. It is possible to convert all hybrid drivetrains consisting of series, parallel, series-parallel, and two-mode power split hybrids to a PHEV. Drivetrain compatibility for PHEVs has been studied in [1, 2]. In spite of the fact that the series-parallel architecture has the most efficient charge sustained (CS) mode, when a high capacity battery similar to that of GM Volt PHEV is available, the series drivetrain is appealing [2, 3]. The first option for the power management of a PHEV is to run the vehicle on pure electric energy similar to an electric vehicle in EV mode, until all energy stored in the battery is depleted. The distance covered in this mode is named all electric range (AER) in a PHEV. Afterward, the vehicle acts as a conventional HEV in CS mode to sustain the battery state of charge (SOC) around minimum applicable range. The second option is the charge depletion (CD) or blended strategy, using both battery and engine simultaneously during driving. Generally, the engine and drivetrain efficiencies are higher, therefore CD is more efficient in comparison with AER/CS [4, 5]. The control rules for CD should be fine tuned to prevent any surplus battery SOC at the end of journey, where grid energy is available, as the economical benefit of PHEVs is based on the difference between electricity and petrol costs.

Local and global optimization approaches can be considered as main strategies for optimized control applications. The local approach focuses on optimizing specific characteristics of vehicle operation in certain time or position. On the other hand, the global approach optimizes PHEV's operation in the entire or a section of journey. The full classification of control-strategies has been outlined in [6]. Since the knowledge of future driving cycle has been proven to be essential for global optimization approaches, drive cycle simulations have been considered in published works. Gao et al. [4] suggested a manual shifting mode between the EV/CS and CD modes to affect the knowledge of future drive cycle. Sharer et al. [5] have selected different engine-ignition power thresholds for different journey distances. Gong et al. [7] suggested drivecycle modeling based on recent advancement in intelligent transportation system (ITS) and global positioning system (GPS) and geographical information system (GIS). A more sophisticated trip modeling, including road grade using predefined accelerating and based on speed limits, has been reported in [8].

Dynamic programming (DP) has been used for global optimal solution; however, it is not applicable for real-time problems because it has high computational costs [9, 10]. A two-scale DP has been developed for adapting to traffic variations and improving the computational efficiency while maintaining the nearly global optimality for the power management [7, 11]. Gong et al. [12] improved DP and developed a simplified vehicle model and a spatial domain optimization.

This paper presents a semi optimized global control approach suitable for practical implementation. By considering a more accurate vehicle model, it is possible to take into account the noise factors that the vehicle encounters during its operation. Similar to recently reported works, the knowledge of drive cycle as a priory is used as the key factor for optimal decision making. However, this paper introduces the concept of power cycle in place of drive cycle. The main reason is that several noise factors dramatically alter power demand even in identical drive cycles. These factors include: driving style and traffic diversity, grade load, wind, and ambient temperature. Besides, battery aging affects the performance of different PHEVs with various duty cycles. The proposed control strategy allocates the battery energy to lower power demand sections of each specific power cycle. This coincides with conventional control approaches which

978-1-4244-8218-4/10/$26.00 ©2010 IEEE

use the engine in higher power demand close to its most efficient operation points as much as possible. This research focuses on an idea which is practical and feasible for implementation rather than redeveloping a globally optimized method which is mostly non practical because of both computational loads and neglecting different noises altering real power demand. Due to the complexity of the optimization approaches, researchers have mainly tried to simplify the vehicle model and ignore many noise factors associated with real vehicle operation.

II. Power Cycle and Noise Factors

Apart from velocity that is defined in drive cycle, many other parameters affect power demand of vehicle including driver behaviour, road grade, different components temperature, air conditioning power demand, wind, and even change in the wheel air pressure. The required traction power, P_t, is given in (1). Fig. 1 reviews the loads and parameters that affect longitudinal dynamic of vehicle and its load demand.

$$\boldsymbol{P_t = F_t V = \left(M\frac{dV}{dt} + F_r + F_d + F_g\right)V} \qquad (1)$$

where F_t is tractive effort, M is mass of vehicle, dV/dt is linear acceleration of the vehicle along longitudinal direction, F_r, F_d, F_g are rolling, drag, and grading resistances, respectively. Equation (1) can predict the power demand of vehicle if the velocity drive cycle is known. However, there are different parameters which affect the power demand of vehicle that are named “noise factors” in this paper. Since the knowledge of power cycle is essential for achieving an accurate globally optimized power management, the following noises should be taken into account.

A. *Driving style and traffic diversity*

Velocity can dramatically change the power demand of vehicle but as energy consumption is related to both power and duration of journey, judgment about the most efficient velocity needs to consider all effective factors. Lower velocities reduce drag and rolling resistances; on the other hand, the fuel economy may deteriorate by accessories load and lower engine efficiency in lower loads during CS or CD. The term $MV(dV/dt)$ in (1) is the power required for acceleration and braking. There is always waste during regenerative braking, thus aggressive driving would reduce efficiency. Driving style and traffic diversity can affect the performance of vehicle and its energy consumption even in identical journeys.

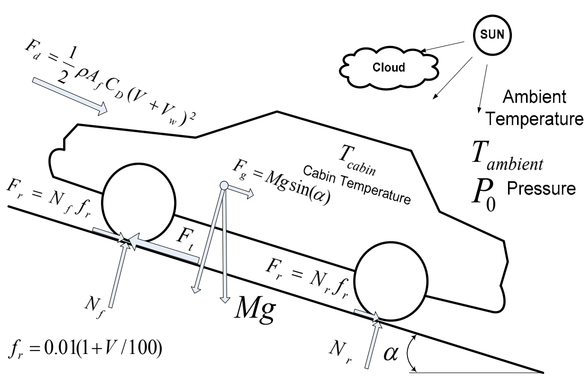

Fig. 1. Vehicle loads and environmental parameters which affect the longitudinal dynamic of a vehicle.

B. *Road grade*

The road grade has significant effect on power demand. Drive cycle modelling that neglects this factor would be far from reality. Since the road grade cannot be defined in time domain, it is essential to consider route elevation in spatial domain by using a GPS. Since most of the daily journeys are reciprocal, this means that if we have uphill road, we will have downhill in return or vice versa. The road grade load shows its significance in alpine area where correctly allocating electric power for downhill or uphill part of the journey would help both efficiency and battery health. Vehicle weight changes caused by the number of passengers and the cargo load can be considered as a noise factor for the prediction of both grade and rolling loads.

C. *Wind*

Component of wind speed in the direction of vehicle movement may alter power demand of vehicle especially during high speed driving in highways. Hence, the drag force varies as the square of velocity. For instance, the drag force in 100 km/hr is around 30% higher with 20 km/hr crosswind.

D. *Effect of ambient temperature*

Ambient temperature affects the following parameters which alter the power demand or the performance of vehicle:

1. *Temperature and aerodynamic force:*

Drag force is proportional to air density which changes around 25% between temperatures -25 ℃ and 35 ℃.

2. *Engine operation temperature*

It is well known that the engine cold operation increases fuel consumption and pollution of the vehicle [13, 14]. For instance, the hydrocarbon and carbon monoxide emissions could be increased by 650% and 800% at -20 ℃, compared to standard certification values at 25 ℃, respectively. The low ambient temperature raises lubricating oil viscosity and thus results in higher mechanical losses for the engine’s cold start. In addition, combustion would be affected due to lower ignitability of fuel mixture. The low ambient temperature can also delay Three-Way Catalyst (TWC) activation, which is one of the most important reasons accounted for high emissions at cold start. To achieve appropriately functioning TWC, its temperature needs to get around 400 ℃. The issue of cold start and warm-up period is even more significant for HEVs and PHEVs because the engine on/off shifting occurs regularly. This noise factor does not directly affect the power demand of the vehicle but influences the total efficiency and pollution of PHEVs.

3. *Battery temperature*

Battery thermal management is the current state of the art in battery designing. The battery temperature affects both aging process and performance of the battery. Very low temperature degrades battery performance so engine start up is necessary to propel the vehicle. On the other hand, high temperature severely accelerates the battery aging and in critical temperature may cause fire and permanent damages.

E. Air-conditioning

Unlike conventional vehicles in which the compressor of air conditioning (AC) is mechanically connected to the engine, a separate electric motor propels the compressor in PHEVs. The most significant auxiliary load in a vehicle is the air conditioning. A 3000 W accessory load will decrease AER on a repeated EPA Urban Dynamometer Driving Schedule (UDDS) by 38% [15]. The required power for cabin heater and safety related demister of front window is also another concern during AER in which there is no hot water available from engine coolant. Using electric energy for heating would be a great waste. With such a large AC and heater power demands, any global optimization power management strategy without considering the effect of AC and heater would not be accurate. Besides, the AC power demand is related to ambient temperature, humidity, soaking time in sun shine, time of journey, colour of vehicle, latitude position of vehicle, clouds, amount of fresh air required for ventilation, metabolic heat load and clothing of passengers, and even the driver's perception of comfort temperature.

F. Battery ageing

The battery ageing is not considered as a direct power cycle noise factor; however, battery's state of health determines the amount of onboard available electric energy that PHEV could allocate for a specific power cycle. Temperature has a significant effect on battery aging. For instance, a battery stored in 35°C would have around 6% lower capacity in comparison with the same battery stored at 20°C after 5 years [16]. Since a PHEV would be used under various geographical locations, climates, and duty cycles, state of health of each battery would be different during the effective life of a PHEV. Therefore, considering the battery aging for developing a globally optimal control strategy is essential. That is, the amount of energy available in the battery is a variable input in the global energy management strategies throughout the life of battery. An electric vehicle (EV) mode followed by CS control strategy would not be affected by this noise factor.

III. Power Cycle Prediction and Library Development Based on Noise Factors

Around 60% of the average daily travel of passenger cars is less than 64 km in the USA and around 53% is less than 20 km in Japan. This makes PHEVs appealing for daily home to work commuters. The simple fact that most of the drivers use their car on a regular basis on the same routes brings the idea that each PHEV could build and store its own power cycle in both time and spatial domains by means of GPS. To develop a power cycle library, each vehicle logs its own power demands for routine commutes such as home-work, home-shopping centre, etc based on the vehicle real power demand. The global optimization approach instead of using anticipated drive cycle employs the power cycle library to define the control strategy. Each PHEV will have its own normal in-built AER/CS control strategy; however, for known power cycles, which would be built later for each driver, a more sophisticated control strategy would improve the performance of the vehicle. Saving power cycle information does not need any expensive hardware especially for PHEVs in which drive-by-wire control is completely dominant. The power demand, time and duration, and position information can be stored in cheap data loggers. The stated procedure would be simpler to implement for series PHEVs such as GM Volt in which the power which propels the wheels only passes through the electric motor. For other PHEV drivetrains in which power passes through both mechanical and electrical paths, the engine power contribution in power cycle can be computed based on engine-operation-points look-up-tables.

The stored power cycle has the potential to reasonably predict many of the introduced noise factors such as driver general behaviour, traffic condition at the routine time of journey, and effect of both change of speed and elevation on power. In particular, for journeys such as home-work which mostly occurs in specific times and during rush hours, the drive cycle prediction based on maximum speed limits suggested by literature would be far from reality. Since the power cycle library saves real speeds and power demand of daily commute, there will be still a chance to predict traffic changes during different working days of week or even specific time of year such as school holiday periods. The power cycle library inherently considers aggressiveness factor for different drivers by gathering acceleration statistics of a specific journey. The effect of battery aging noise could be considered by capturing the amount of available battery energy delivered each time to the powertrain. Consequently, the capacity fade is measured and taken to account before each journey.

Although the power cycle library based on real past commute history gives valuable information about power demand, the real future power demand would be affected by some other stochastic noise parameters like wind, ambient temperature, and AC loads. The effect of these parameters should be simulated based on currently available power cycle in the library and daily weather forecasts. Direction of wind and the specific route could be compared and the effect of daily wind velocity on power demand is computable. The effect of temperature on aerodynamic load is similarly predictable. The effect of temperature on the battery and engine performances is significant when compared in extreme cold or hot temperatures in winter and summer; however, it is negligible when compared to the average of a week before the journey. That is, the library based control management intrinsically eliminates this noise factor. Prediction of the AC power demand is the more challenging part of the power cycle prediction because there are many parameters which alter the AC power demand particularly when driver or passenger perception comes to account. It is possible to derive power demand equation experimentally based on only four variables of ambient and required temperatures, humidity, and sun radiation heat flux. It is now possible to calibrate the AC power demand equation for each journey as the direction of sun and soaking time are still case dependant.

To simulate the development of power cycle library, a PHEV similar to GM Volt is sized in ADVISOR, NREL's ADvanced VehIcle SimulatOR. Fig. 2 illustrates the required inputs for developing a power cycle library. A sample power cycle is derived from a commute which is longer than AER and similar to home-work journey. This journey starts with UDDS then HWFET and ends with another UDDS. The return journey is the mirror of the drive cycle which is not available from the drive cycle library of ADVISOR so a Matlab code is developed for this part. To simulate the considerable effect of the road grade on the power demand, a constant slope of 1% uphill and downhill is selected for go and return journeys respectively. In reality, power is logged by means of GPS in spatial domain. A power cycle demand for the AC is defined and logged in the power cycle library. Fig. 3 shows speed, elevation, levelled electric motor power demand, and AC power demand of the simulated home-work commute.

In the next section, the development of a control strategy based on the power cycle library is explained. Whilst the library of power cycle considers almost all noise factors, the prediction of real power cycle is impractical because of the nature of noises and effects of human behaviour. The trend of power cycle is investigated for developing a control strategy and minor and local fluctuations in power demand would not affect the proposed control approach.

IV. CONTROL STRATEGY AND SIMULATION RESULTS

To simulate how the knowledge of power cycle could bring more efficiency, the simulated PHEV operation in the AER/CS control approach is compared with that of a library based CD control strategy. First, a modified rule based ADVISOR power follower control approach is utilized for the EV and CS modes simulation. This control strategy is named power follower as the engine, unlike thermostatic control approach, follows the power demand by the electric bus if

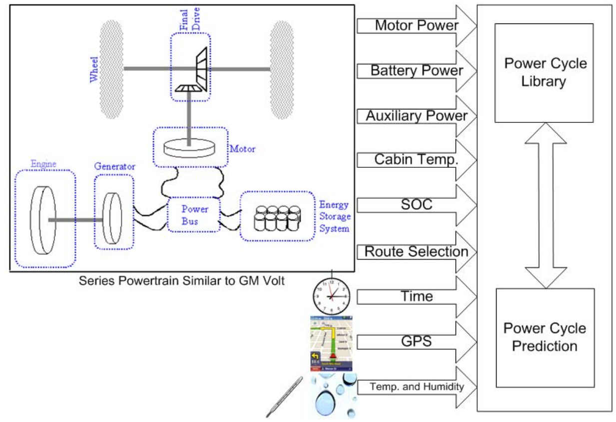

Fig. 2. Power cycle library development.

conditions defined by the following rules are met.

- Engine may be turned off if ESS packs SOC is too high (over 31%).
- Engine may be turned on again if the power required by the bus gets high enough.
- Engine may be turned on again if SOC goes too low (lower than 29%).
- When engine is on, its power output tends to follow the power required by the bus, accounting for losses in the generator so that the generator power output matches the bus power requirement.
- The engine output power may be adjusted by SOC, tending to bring SOC back to the centre of its operating range (30%).
- The engine output power may be kept above some minimum value.
- The engine output power may be kept below some maximum value (which is enforced unless SOC gets too low).
- The engine output power may be allowed to change no faster than a prescribed rate

The high and low SOCs are set to 31% and 29%, respectively. The EV mode rule enforces battery depletion up

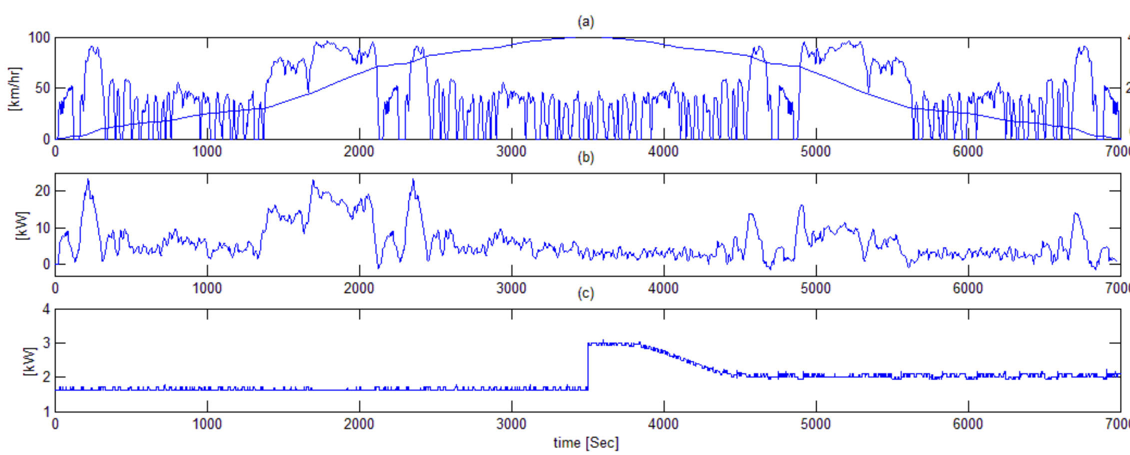

Fig. 3. (a) Defined mirrored drive cycle and elevation. (b) Levelled power demand of electric motor. (c) Accessories consisting AC power demand.

to defined SOC range. The auxiliary load model in ADVISOR has been modified to simulate the air conditioning load as an electric load.

The objective of the suggested CD control strategy is to allocate battery power (EV mode) for more efficient times/positions for a known power cycle. All control strategies in HEVs are based on the fact that the engine is not efficient in low power operation. A known power cycle is explored for more stabilized, longer, and higher power demand during the journey. Thus, an average power cycle similar to Fig. 4 based on the first EV-CS simulation is developed where each point is the average value of the power demand during 60 seconds. Looking at the average power cycle, it is more appealing to run the engine in higher power demand where efficiency of the engine is higher. A code has been developed to find the horizontal power line shown in Fig. 4. The position of the power line is defined such that the amount of energy delivered by the engine in the shaded portion of the power cycle would be equal to the energy that the engine provides in the CS mode of AER-CS simulation. Here, the code calculates the power line around 10 kW. In other words, if the engine is turned on and controlled by the rules of power follower strategy in the CS mode when/where the average power demand of the cycle is higher than 10 kW, the CS mode is not necessary at the end of journey. Besides, the battery would be depleted completely to CS SOC range. Allocation of the battery energy to appropriate portion of the journey forces the engine to operate in higher loads and efficiency. In the developed code, for finding the appropriate power line, it is assumed that it is not appealing to switch the engine on and off for less than 60 seconds.

The performance of the vehicle in the developed power cycle without change in the noise factors is compared in both AER/CS and CD strategies. Fig. 5 compares the SOC history for both AER/CS and the proposed CD. The controller propels the engine with the power flower approach when the vehicle gets to a specific part of the cycle. Practically, the engine on command would be based on position in the journey instead of time.

In Table I, the performance of the CD strategy is compared against that of the AER-CS strategy. The table shows that the fuel consumption is reduced by around 8.7% in this specific defined power cycle. The engine operation points are shown in Fig. 6. It is clear that the engine operates more efficiently

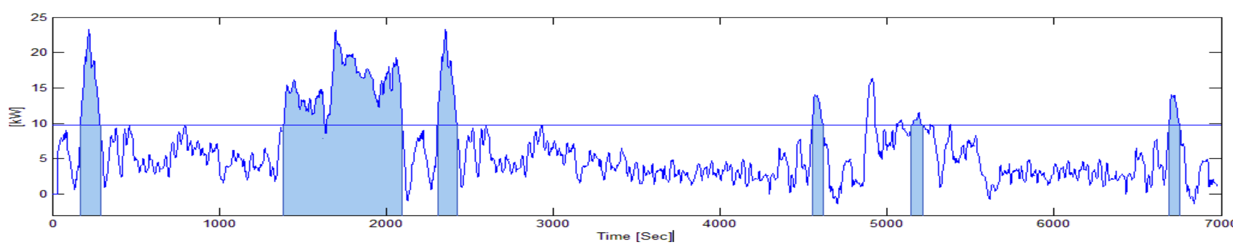

Fig. 4. Average power cycle and power line.

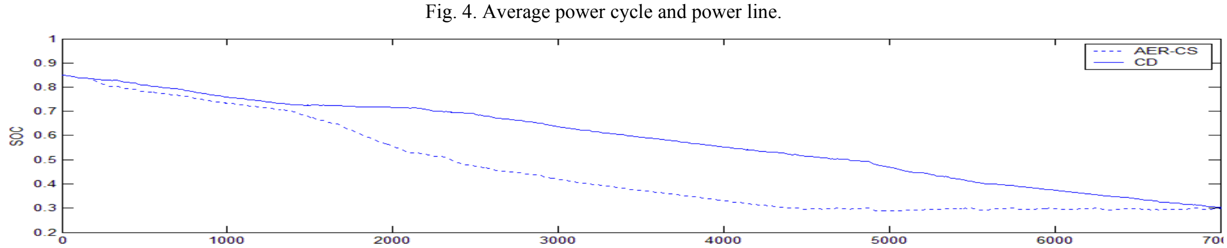

Fig. 5. SOC history for CD and CS followed by AER.

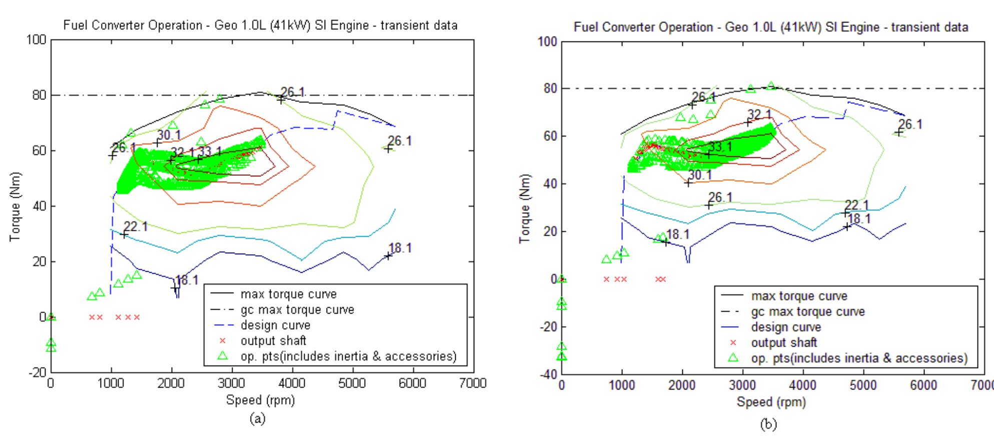

Fig. 6. Engine operation points in the efficiency map. (a) AER/CS strategy. (b) Library based CD strategy.

with the CD control strategy. One of the major benefits of the CD approach is the 10% and 140% reduction in the amount of energy that flows from and to the battery, respectively. This means that the energy provided by the engine directly is transferred through the power bus to the motor bypassing the battery. The elimination of the battery charging/discharging losses is not the only benefit of the developed strategy, lesser use of the battery would slow down the aging of the battery which is the most precious part of PHEVs. Moreover, when the engine propels the vehicle in the most vigorous part of the power cycle, the C-rate of battery and accordingly the temperature of battery would be reduced. It has been proven that the temperature is one of the major parameters which reduce the battery's state of health.

V. CONCLUSION

An applicable approach for the development of a globally optimized power management strategy considering realistic limitations and noise factors has been presented. The concept of power cycle instead of drive cycle is introduced to consider the effect of noise factors. As most of drivers use their cars on repeatable routes during daily commutes, each PHEV could store its own power cycle in both time and spatial domains forming a power cycle library. The control strategy based on the predicted power cycle is defined to efficiently manage the utilization of available battery energy. The engine would operate in higher load demand portion of the power cycle resulting in higher efficiency. The simulation results show 8.7% improvement in the fuel economy of the simulated PHEV for the defined sloped commute consisting of four UDDS and two HWFET. The reduction of temperature and power recycling in the battery and also the elimination of CS in the shallow battery SOC are beneficial for the battery health.

TABLE I
PERFORMANCE COMPARISION OF AER/CS AND CD.

	AER-CS	CD	%
Fuel consumption [l/100km]	2.5	2.3	-8.7
Engine Energy in [kJ]	63735	58538	-8.9%
Engine Energy out [kJ]	19120	18883	-1.3%
Engine Efficiency [%]	30%	32%	+6.7%
Battery Energy in [kJ]	7376	3092	-140%
Battery Energy out [kJ]	45932	41792	-10%
Final SOC	30.4%	30.4%	0%

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