EVS26
Los Angeles, California, May 6–9, 2012

Optimal Control Strategy for PHEVs Using Prediction of Future Driving Schedule

Daeheung Lee[1], Suk Won Cha[1], Aymeric Rousseau[2], Namwook Kim[2]
[1]*Seoul National University, Seoul, South Korea, ideal02@snu.ac.kr*
[2]*Argonne National Laboratory, Argonne, Illinois, USA*

Abstract

Optimization-based control methods for plug-in hybrid electric vehicles require knowledge about an entire driving cycle and an elevation profile to obtain optimal performance over a fixed driving route. This paper details our investigation into the method of using traffic information to predict the future driving cycle, as well as an examination of the optimal control strategy based on Pontryagin's Minimum Principle, in order to minimize fuel consumption on a given trip distance and to develop a real-time implementable control strategy. To predict future driving patterns, the Dynamic Programming theory is proposed for the calculation of vehicle speed with respect to driving distance, under the assumption that data about traffic conditions are obtained from external traffic information, such as Intelligent Transportation Systems. Prediction of future driving speed is achieved by minimizing the proposed cost function on each segment. The results of the generated speed profile can properly estimate the driving pattern of the driver. Also, a co-state generation algorithm is applied to determine the parameters with respect to the required power deduced from the predicted driving cycle. The proposed co-state generation model can find the estimated initial co-state that is similar to the optimal co-state. Simulation results indicate that this approach guarantees the best efficiency under reasonable conditions and the minimization of fuel consumption on the trip distance between the origin and destination.

Keywords: PHEV (plug-in hybrid electric vehicle), EREV (extended range electric vehicle), power management, control system, city traffic

1 Introduction

Plug-in hybrid electric vehicles (PHEVs) have become an effective solution to meet the need for more fuel-efficient vehicles and to address tightening emission regulations. The PHEVs are functionally similar to conventional hybrid electric vehicles (HEVs), since they can take advantage of regenerative braking and a reduction in engine size to operate more efficiently. However, PHEVs differ from conventional HEVs in that they allow recharging from the electrical grid. In these vehicles, higher energy batteries can be recharged from the electrical outlet in addition to the engine and regenerative braking. By using a high-energy battery, PHEVs can travel in pure electric mode for a specific distance according to the operating mode of the powertrain [1, 2].

The performance or efficiency of PHEVs also relies on its vehicle energy management strategy, which determines the power-split ratio between the combustion engine and the electric diving motor to meet the required power at the driving wheels [3]. Optimization-based control methods, such as the Equivalent Consumption Minimization Strategy (ECMS) or Pontryagin's Minimum Principle (PMP)-based control, require knowledge of an entire driving cycle and an elevation profile to result in optimal performance [4, 5]. Some researchers have shown [1, 6, 7] that the fuel consumption of PHEVs is minimized when the battery and engine are used consistently during an entire trip, such that the battery state of charge (SOC) decreases continuously and reaches the minimum value at the end of the trip. Figure 1 shows the SOC trajectory results with different control strategies. However, the blended mode control that ensures the minimum fuel consumption requires more accurate information about the trip, such as driving duration, driving profile, and so forth.

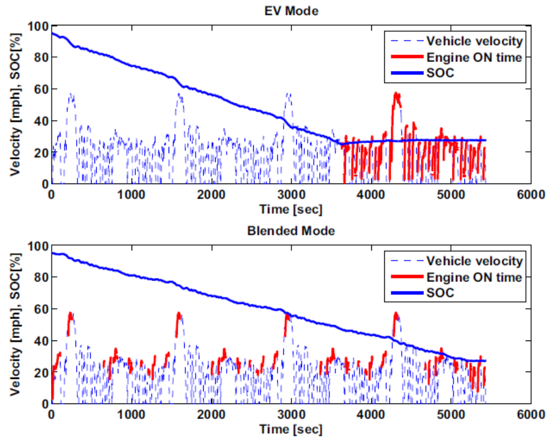


Figure 2: SOC profile and engine ON time for EV mode and blended mode control [6]

Our research was conducted under the assumption that the vehicle can use the information extracted from Intelligent Transportation Systems (ITS) over the driving road. This paper describes our investigation into the method of using traffic knowledge for prediction of the future driving cycle, as well as the optimal control strategy based on PMP, to minimize fuel consumption.

This paper is organized as follows. Section 2 summarizes the concept of the control scheme using the traffic information and the navigation system (including a Global Positioning System [GPS] receiver) in a vehicle. Section 3 describes the proposed method for the driving schedule estimation. With the help of the GPS and ITS, it is possible to directly predict the future driving cycle through Dynamic Programming (DP) theory. Section 4 focuses on the PMP-based control and the correlations between the predicted driving cycle and the control parameter, co-state p, used in PMP control theory. Section 5 details the simulation results. The real driving profile from the on-board GPS device and the predicted speed profile are compared, along with the results of the fuel economy improvement through the PMP-based controller. Finally, Section 6 presents conclusions about the utility of the proposed control method.

2 The Control Concept of PHEVs Using Traffic Information

To apply external information such as the traffic knowledge and the road profile to the optimal control for PHEVs, it is necessary to convert various information through the transmitter of the ITS and GPS into information or data suitable for the supervisory control algorithm. Figure 2 shows the schematics of the information flow among the required modules and a hybrid control unit. The

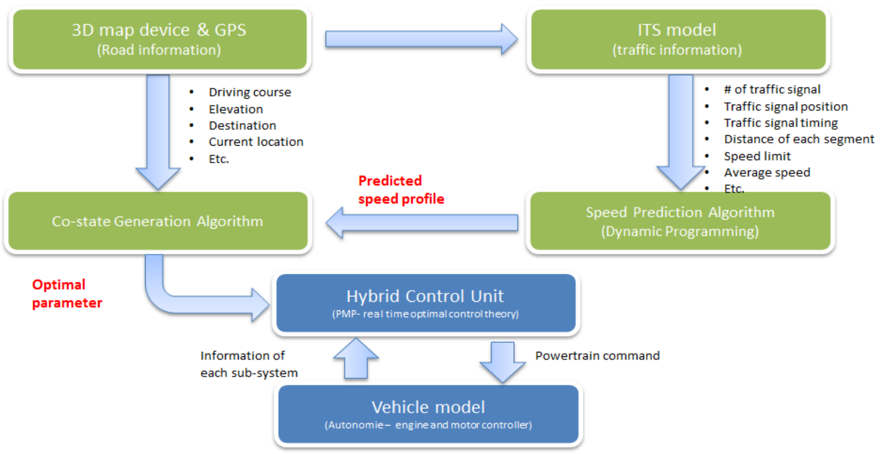


Figure 1: Schematic of the control procedure for the PHEV using external information

hybrid control unit, in general, includes the algorithm to determine the operating state of a combustion engine and an electric driving motor. To calculate the proper output power of the components, the control algorithm uses the external information and operating state of the components, such as the battery's SOC value and signals that convey information concerning the status of a powertrain.

The currently available ITS and GPS devices provide only limited information on traffic circumstances. Therefore, as the initial part of this study, we have developed the ITS model in order to generate the required traffic information over each road segment, such as the location and timing of traffic signals, the speed limit, the average speed and trip distance, and so forth. The ITS model uses information based on measured data on certain real roads to provide the knowledge required for the speed prediction algorithm module. Then the module that employs the DP algorithm calculates the predictable speed of a vehicle on the specific segment of the road, while considering the traffic and road information. For the elevation profile, we use the real data observed from the GPS device in this study, under the assumption that the elevation profile of the overall trip distance can be extracted by the navigation system and 3D-Map [8]. From the estimated speed profile, the module for the co-state generation algorithm can determine the optimal co-state to minimize the fuel consumption, while the final SOC of the battery reaches the lower limit at the end of the trip. Finally, the optimal control theory applied to the hybrid control unit instantaneously computes the ratio of the power split between the engine and the electric driving motor by using the predicted co-state value.

3 Driving Speed Prediction Algorithm

The process to generate the speed profile from the traffic information is shown in Figure 3. To obtain the speed profile for future driving, DP theory using a distance-based technique has been adopted, which reflects some constraints that are determined by traffic information on each trip segment.

Generally, because DP is a representative technique to obtain optimal policy, in many studies DP theory has been used to analyze the optimal performance of a hybrid vehicle system on a given driving cycle [9–11]. This method can be used to minimize the performance index:

$$J = \phi(x(T)) + \int_0^T L(t, x(t), u(t))dt \qquad (1)$$

where, $\Phi(x(T))$ is a penalty function to represent constraints on the final SOC, $x(T)$; $L(\cdot)$ is the cost function for fuel consumption; $x(t)$ is the state variable that should be controlled; and $u(t)$ is the control variable in the system. The optimal solution also should be subject to the constraints for physical limitations of components and the constraints for SOC operation, as implied by:

$$\dot{x} = f(x(t), u(t), t) \qquad (2)$$

In general, DP requires gridding of the state and time variables, and thus the optimal trajectory is calculated for only discretized values of time and battery SOC [3]. The DP algorithm explained above, on the other hand, also can be applied to determine the future speed profile that satisfies some physical constraints. If the performance measure (or cost function) in the DP algorithm could be chosen properly, it is possible to generate the speed profile similar to the driving pattern of a real driver. The performance measure for generating the distance-based speed profile is defined as:

$$J = \int_{s_0}^{s_f} L(x(s), u(s))ds \qquad (3)$$

where, s is position, and $x(s)$ and $u(s)$ denote the state and control variable regarding position s, respectively. For the defined distance from the initial position, s_0, to the final position, s_f, as a

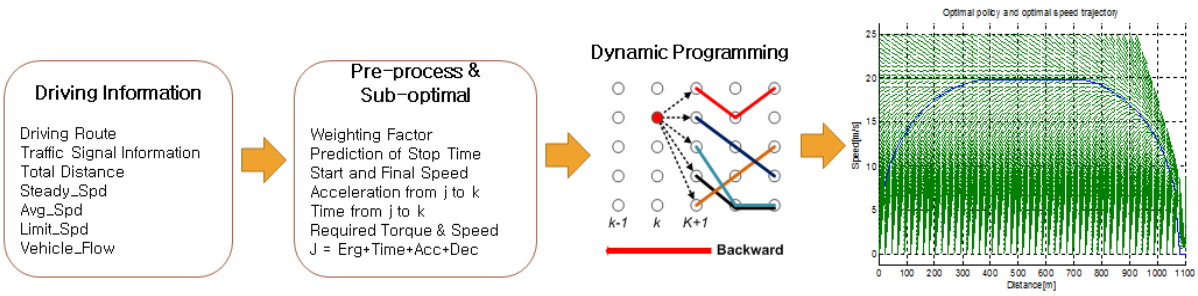


Figure 3: Algorithm process to obtain the predicted speed profile on a segment

segment of the whole travel distance, the speed profile that minimizes the performance index (3) subject to the equations of powertrain and speed limit on the road can be obtained numerically by solving a DP problem. Here, the cost function $L(\cdot)$ at each calculation step intuitionally consists of the driving energy, E_{drv}, the time consumed in driving, T, and the terms regarding the level of acceleration, a, and deceleration, d, as described by:

$$L(k) = E_{drv}(k) + w_t \cdot T(k) + w_a \cdot a^4(k) + w_d \cdot d^4(k) \quad (4)$$

where, k is the stage on the grid of considered distance, and w_t, w_a, and w_d are the weighting factors for time consumed, acceleration, and deceleration, respectively. The weighting factors are determined from map data found by considering the speed limit, average speed, cruising speed, and length of each segment for traveling distance. Figures 4 and 5 show the predefined value of each weighting factor.

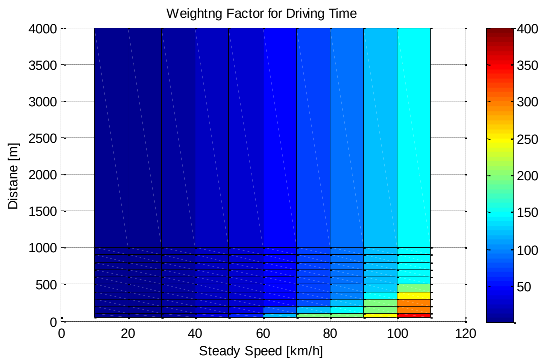


Figure 4: Weighting factor value for the consumed time in driving

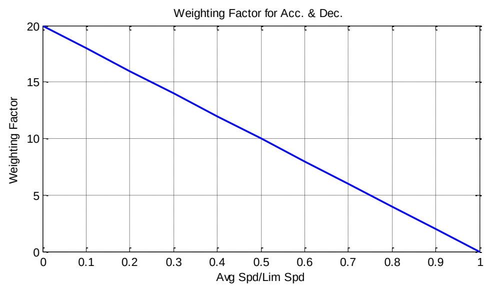


Figure 5: Weighting factor value for the level of acceleration and deceleration

Prediction of the speed profile on a certain road can be accomplished by selecting only the three factors regarding driving states — driving time, acceleration, and deceleration on the given distance of the segment. Figure 6 presents the result of the short-range prediction as an example.

The predicted speed profile is similar to the real speed profile, which is extracted from the GPS receiver in a vehicle. We also can observe that the level of acceleration and deceleration of the predicted speed in the figure properly reflects the driving tendency of a real driver.

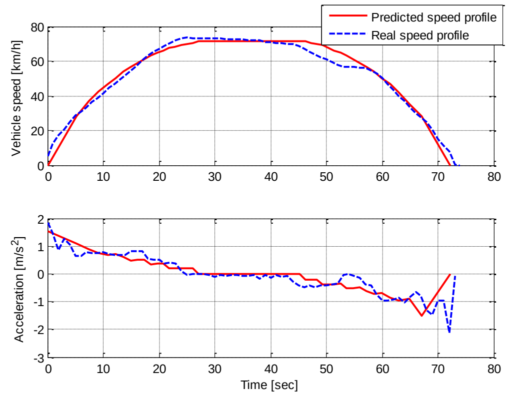


Figure 6: Comparison between predicted speed and real speed for the short-range prediction

The performance of the proposed method for the relatively longer distance, including traffic signals, was studied via measurement of the required data on the real road. Figure 7 depicts the real driving speed and the information for traffic signals on a specific street near Argonne National Laboratory. This information is saved in the ITS model. The total driving distance is 7.5 km, and 13 traffic signals are located on the road. Through this information, it is possible to estimate the duration and number of the vehicle's stops. The real and estimated velocity profiles are shown as a function of trip time in Figure 8. The acceleration of the real vehicle, until around 40 seconds, initially is lower than that of the predicted speed due to the uphill elevation of the real road. Except for the initial driving state shown in Figure 8, the speed prediction algorithm can estimate the anticipated vehicle speed very well during the entire trip.

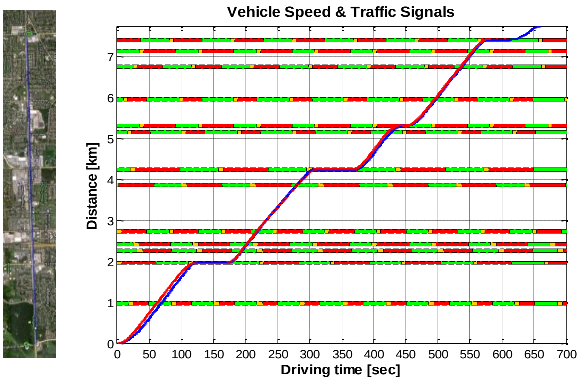


Figure 7: Traffic signal information and comparison of real and estimated speeds

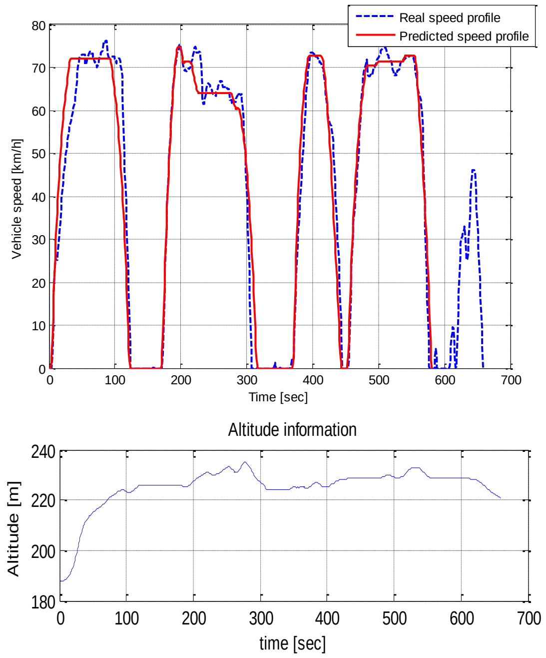


Figure 8: Prediction of the speed profile over a 7.5-km distance and elevation profile

Therefore, if it is realizable to obtain the precise information from the ITS, GIS, or GPS, then predicting the vehicle speed on the fixed trip distance can be possible in advance, and the result is similar to the actual driving pattern. The fact that the future speed profile can be obtained accurately is very important, since the parameter (i.e., co-state *p*) used in the optimal control theory should be derived by using the result of the predicted speed.

4 Optimal Power Management Based on PMP Theory

An optimal control strategy based on PMP is a promising solution. It provides a simple solution for controlling HEVs or PHEVs and guarantees the best performance under reasonable conditions [5]. With information about the future driving schedule and elevation profile, it is possible to determine the optimal value for the co-state, *p*, depending on the future power demand. Then, the PHEV can run in blended mode, so the battery is nearly depleted at the end of the trip.

4.1 Analytical Method for the Minimum Fuel Consumption

The optimal control based on PMP can be implemented in real-time applications because it is based on instantaneous optimization. Assuming that the cost function to be optimized involves only fuel consumption, the control concept minimizes the Hamiltonian [3, 5, 7], which is defined as:

$$H = \dot{m}_{fc}(P_{bat}) + p(t)\cdot S\dot{O}C(SOC, P_{bat}) \qquad (5)$$

where, $\dot{m}_{fc}$ is the rate of fuel consumption; *p(t)* is an adjustment variable, which is called "co-state" in PMP; and $S\dot{O}C$ is a time derivative of battery SOC. As stated above, assuming that minimum fuel consumption is the goal of the optimal control, the problem of PHEVs can be defined as (6) and (7), in which the engine speed, W_e, and the engine torque, T_e, can be used to determine the fuel consumption:

$$\min J = \int_{t_0}^{t_f} L(W_e, T_e, t)dt \qquad (6)$$

subject to:

$$\begin{cases} SOC(t_0) = SOC_{initial} \\ SOC(t_f) = SOC_{desired} \\ SOC_{\min} \le SOC \le SOC_{\max} \\ W_{\min} \le W_e \le W_{\max} \\ T_{\min} \le T_e \le T_{\max} \end{cases} \qquad (7)$$

where, $L(W_e, T_e, t)$ is the rate of fuel consumption of the engine. The *SOC* is determined by a battery model described as:

$$S\dot{O}C = -\frac{1}{Q_{bat}}\cdot\frac{V_{bat} - \sqrt{V_{bat}^2 - 4R_{bat}P_{bat}}}{2R_{bat}} = f(SOC, W_e, T_e) \qquad (8)$$

Further T_e and W_e are restricted by operating constraints, such as the maximum possible engine speed or the maximum possible engine torque, given by considering the impact of constraints on the components (i.e., maximum motor speed, maximum torque, or maximum battery power). This optimal control problem can be solved with optimal control techniques. When the final time and the final state are fixed, the principle requires that the optimal solution satisfies the following conditions [7, 12, 13]:

$$\begin{cases} S\dot{O}C = \dfrac{\partial H}{\partial p} \\ \dot{p} = -\dfrac{\partial H}{\partial SOC} \\ H(SOC^*, u^*, p^*, t) \le H(SOC^*, u, p^*, t) \end{cases} \qquad (9)$$

Equation (9) is the necessary condition of the optimal problem by PMP theory. It is necessary to find the optimal control, *u*, which satisfies (9).

4.2 Estimating the Initial Co-state from the Predicted Speed Profile

The optimal value of the co-state $p(t)$ should ensure that the final SOC (SOC_{final}) is equal to the desired SOC ($SOC_{desired}$) at the end of the entire trip. The optimal co-state value that is subject to the above condition on a given driving schedule can be found by running the simulation repeatedly on the various initial values of $p(t_0)$ or the shooting method [1, 14]. However, for the optimal control algorithm to have the potential for a real-time implementation, it needs to estimate the value of the co-state close to the optimal value. If the future driving cycle is known a priori through the method proposed in Section 3, it is possible to predict the initial co-state value $p(t_0)$ of the differential equation $\dot{p}$ in (9), which can execute the optimal control to minimize the fuel consumption on the estimated trip schedule. In this study, $p(t_0)$ can be formulated as (10) and (11) because the initial co-state has a significant influence on the effective SOC drop rate, $S\dot{O}C_{drv,eff}$, and the usable battery energy, E_{bat} [MJ], at the initial driving state:

$$p_0 = f(S\dot{O}C_{drv,eff}, E_{bat}) = a(E_{bat}) \cdot S\dot{O}C_{drv,eff} + b(E_{bat}) \tag{10}$$

$$\begin{cases} a(E_{bat}) = \sum_{i=1}^{n+1} C_{ai} \cdot E_{bat}^{n+1-i} \quad (n=4) \\ b(E_{bat}) = \sum_{i=1}^{n+1} C_{bi} \cdot E_{bat}^{n+1-i} \quad (n=4) \end{cases} \tag{11}$$

where, a and b are the coefficients determined by the useable battery energy, and C_{ai} and C_{bi} are the constant values, as shown in Table 1.

Table 1: Numerical values of the coefficients in equation (11)

C_{a1}	C_{a2}	C_{a3}	C_{a4}	C_{a5}
45.944	-907.16	8,778.6	-131,289	225,126
C_{b1}	C_{b2}	C_{b3}	C_{b4}	C_{b5}
-0.0191	0.2721	-1.9148	-138.94	0.7025

The effective SOC drop rate, $S\dot{O}C_{drv,eff}$, in equation (10), which should be calculated from the speed profile, can be written as:

$$S\dot{O}C_{drv,eff} = \frac{\Delta SOC_{drv,eff}}{\Delta T_{drv,eff}} \tag{12}$$

where, $\Delta SOC_{drv,eff}$ denotes the decreased value of SOC when considering only the battery's discharging state during the entire trip, and $\Delta T_{drv,eff}$ is the effective driving time, except for the time during the stop and deceleration condition of a vehicle. For instance, this relation is shown in Figure 9. The effective SOC profile represents the cumulative value of positive or negative deviation of the SOC with respect to time, which is divided into the propulsive driving and the regenerative driving conditions.

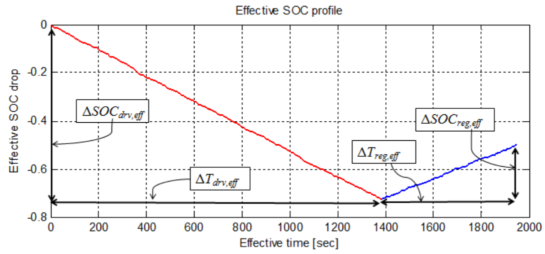
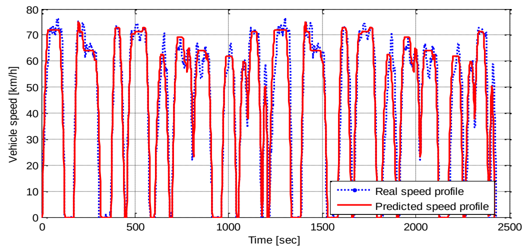


Figure 9: Effective SOC profile divided into the propulsion and the regeneration state

Because we cannot directly observe $\Delta SOC_{drv,eff}$ if we do not execute the simulation on a computer, alternatively one can use a cumulative deviation of SOC by regeneration, $\Delta SOC_{reg,eff}$, to predict $\Delta SOC_{drv,eff}$ as follows:

$$\Delta SOC_{drv,eff} = SOC_i - SOC_f - \Delta SOC_{reg,eff} \tag{13}$$

where, $\Delta SOC_{reg,eff}$ is the increased value of SOC when considering only the battery's charging through the regenerative breaking. This value can be directly determined if the upcoming driving pattern is predicted as shown in Figure 10(a).



(a) Real speed profile and estimated speed profile

(b) Required positive and negative power for the driving speed

Figure 10: Speed profile and required power

Next, the future power demand with respect to driving time is determined as described by:

$$P_t(t) = F_t(t) \cdot v(t) \tag{14}$$

where, $P_t(t)$ is the required tractive power, $F_t(t)$ is the tractive force, and $v(t)$ is the vehicle speed. The tractive force F_t is determined by the longitudinal vehicle dynamics model [15]. Figure 10(b) shows the positive required power for propulsion and the negative required power for deceleration. Then we can surmise the increasing amount of battery SOC, $\Delta SOC_{reg,eff}$, from regenerative breaking power, ($P_t(t)$<0), over the entire trip time by using equations (8), (15) and (16), under the assumption that the voltage and resistance of the battery are of average value:

$$\Delta SOC_{reg,eff} = \int_0^T \dot{SOC}(P_{bat}(t))dt \tag{15}$$

$$P_{bat}(t) = \eta_{reg} \cdot P_t(t) \qquad (\forall P_t(t) < 0) \tag{16}$$

where, $P_{bat}(t)$ is the electrical power charged to the battery, and η_{reg} is the ratio of electrical braking with respect to the total braking power at a wheel.

Figure 11 shows the results of the optimal SOC effective drop to the various driving distances, which is calculated through the backward-looking simulation on repeated Urban Dynamometer Driving Schedule (UDDS) cycles.

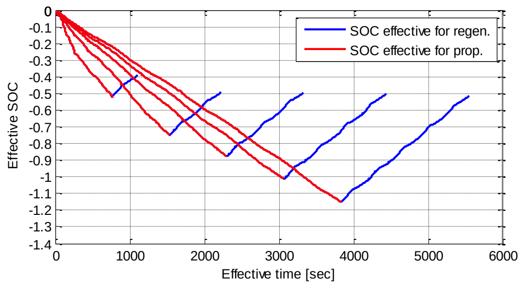


Figure 11: Results of the effective SOC drop using the backward-looking simulation based on the optimal control theory

Table 2 details the validation results of the predicted co-state and the optimal value calculated from driving cycles repeated five times, as well as the various battery capacities. In a PHEV using a 3.4-kWh battery pack, the vehicle can be operated in electric vehicle (EV) mode (charge-depleting [CD] mode) only on a single driving of a UDDS cycle. Thus, the prediction of the initial co-state on just one cycle could be meaningless, since not using the engine is more efficient during the entire trip. When the traveling distance is known to be less than or equal to the vehicle's electric range, the powertrain can run in its all-electric mode [1]. This is also the same as the PHEV using 5.2-kWh battery capacity, if the driving cycle is repeated twice. Except for the trip distance on which the PHEV can be operated in EV mode only, the co-state estimated from (10) is very close to the optimal co-state value.

Table 2: Results of the co-state validation on the UDDS cycle

Total Battery Energy	Co-state	UDDS ×1	UDDS ×2	UDDS ×3	UDDS ×4	UDDS ×5
1.4 kWh	Optimal	-295.09	-316.26	-323.32	-326.84	-328.96
	Predicted	-296.52	-317.41	-323.57	-326.63	-328.55
	Error	0.48%	0.36%	0.08%	-0.06%	-0.12%
3.4 kWh	Optimal	EV mode	-695.86	-737.71	-758.63	-771.19
	Predicted		-696.45	-738.34	-760.34	-770.82
	Error		0.08%	0.09%	0.23%	-0.05%
5.2 kWh	Optimal	EV mode	EV mode	-1188.5	-1221.8	-1241.8
	Predicted			-1191.4	-1224.1	-1244.1
	Error			0.24%	0.19%	0.19%

5 Simulation Results

The performance of the PMP-based control, with the speed profile prediction described in Section 3, is studied by comparing the control method using a typical power management scheme for PHEVs. This scheme is to run the PHEV in its all-electric mode until the battery is nearly depleted and switched to a charge-sustaining (CS) mode, and then to run the PHEV similar to an HEV [1].

5.1 Vehicle Model

The vehicle model used in this study is a power-split hybrid system that has a single planetary gear set as a power-split device, like that shown in Figure 12. All data for the component models and vehicle model (shown in Table 3) are based on a 2004 Toyota Prius in Autonomie, a software tool developed by Argonne National Laboratory [7, 16]. The total battery energy was decreased to 3.4 kWh to verify the optimality for the estimated driving condition.

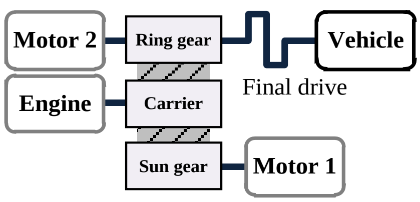


Figure 12: Power-split hybrid system used in this study

Table 3: Vehicle parameters used in the simulation

Vehicle mass	1,490 kg
Engine	1,500 cc
Motor 1	25 kW (peak power: 50 kW)
Motor 2	15 kW (peak power: 30 kW)
Battery	3.4 kWh
Planetary gear ratio	2.6 (78/30)
Final gear ratio	4.113
Rolling resistance	0.007+0.00012×vehicle speed
Frontal area	2.25 m^2
Drag coefficient	0.29
Wheel radius	0.305 m
Air density	1.23 $kg{\cdot}m^{-3}$

5.2 Evaluation and Results

To evaluate the performance of the proposed control method, we use the real speed data saved in the GPS device after driving a vehicle over a distance of almost 15 km. The speed prediction is carried out through the traffic information on the road. Then the final speed profile for the simulation is repeated two times for long distance, as shown in Figure 10(a). In this study, the simulation uses the initial SOC, SOC_i, as 80% and allows the system to consume the electrical energy until the final SOC, SOC_f, falls to 30%.

The fuel consumption analysis requires the following procedure. First of all, the future speed profile is predicted through the traffic information on the segments of the real road. Next, we calculate the initial co-state from the predicted speed profile. Finally, the PMP-based controller using the co-state is applied to the vehicle model driving on the real speed profile.

The value of the estimated co-state and other regarding values for the predicted speed profile are shown in Table 4. The estimated P_0 is very close to the optimal value P_0^* obtained from the backward-looking simulation. Figure 13 shows the fuel consumption results on the real speed profile with respect to the control methods, the CD+CS mode control and the PMP-based control.

Table 4: Results of the co-state prediction

$\Delta SOC_{drv,eff}$	-0.70673
$\Delta T_{drv,eff}$	1,416 seconds
$\dot{SOC}_{drv,eff}$	-0.0004991
Estimated co-state p_0	-689.5761
Optimal co-state p_0^*	-687.4118
Error	0.315%

In the PMP mode control, the fuel usage continuously increases with driving time as blended mode control, while the decreasing rate of the battery SOC value on almost the entire trip is lower than that of the CD+CS mode control, as shown in Figure 14. The final SOC of the PMP-based control does not exactly reach the minimum value at the end of the trip. This occurs because the simulation is executed over the real speed profile after we derive the initial co-state from the estimated speed profile. Nonetheless, as a consequence, the PMP-based control results in smaller fuel consumption at the end of the given trip, and the fuel economy is increased by around 17% compared with the CD+CS mode control method. Table 5 summarizes these findings. The output power of the engine for each control method is shown in Figure 15.

Table 5: Comparison of the fuel consumption

Control Method for PHEVs	Fuel Economy (Km/L)	Final SOC	FE Increasing rate
CD+CS control	58.9518	0.2901	Ref.
Prediction-based PMP control	69.1480	0.2896	+17.3%

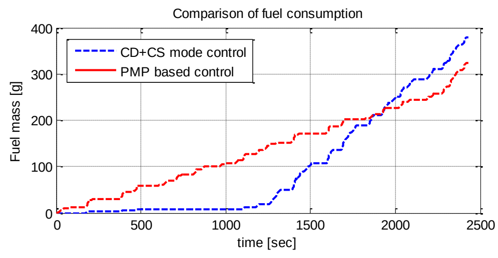


Figure 13: Fuel consumption results for the control method

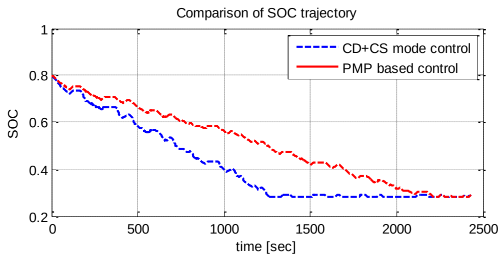


Figure 14: SOC trajectory for the control method

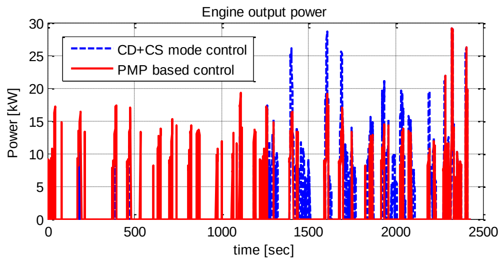


Figure 15: Engine output power for the control method

6 Conclusion

This study has investigated the optimal control strategy, PMP-based control, for PHEVs by using prediction of the future driving schedule. To predict the future driving patterns, if the traffic information is available, the DP method based on driving distance can be used over the given trip. This is achieved by minimizing the proposed cost function on each segment. The result of the generated speed profile can properly estimate the driving pattern of the driver. Deriving the co-state used in the optimal control from the predicted speed profile is a very important procedure to minimize the fuel consumption over the entirety of the travel. The co-state generation algorithm is applied in order to determine the parameters with respect to the required power deduced from the predicted driving cycle. The proposed co-state generation model can estimate an initial co-state similar to the optimal co-state. Using the parameters, the PMP-based control algorithm instantaneously calculates the optimal power-split ratio of power sources. Simulation results indicate that this approach guarantees the minimization of fuel consumption on the trip distance between the origin and destination under reasonable assumptions.

Acknowledgments

This work was supported by DOE's Vehicle Technology Office under the direction of Lee Slezak and the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (No. 2012-0000921).
The submitted manuscript has been created by UChicago Argonne, LLC, Operator of Argonne National Laboratory ("Argonne"). Argonne, a U.S. Department of Energy Office of Science laboratory, is operated under Contract No. DE-AC02-06CH11357. The U.S. Government retains for itself, and others acting on its behalf, a paid-up nonexclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government.

References

[1] C. Zhang, et al., *Route Preview in Energy Management of Plug-in Hybrid Vehicles*, IEEE Trans. Cont. Sys. Tech., ISSN 1063-6536, 20 (2012), 546-563.

[2] H. Banvait, et al., *A Rule Based Energy Management Strategy for Plug- in Hybrid Electric Vehicle (PHEV)*, American Control Conference, ISSN 0743-1619, 2009, 3938-3943.

[3] A. Sciarretta, et al., *Control of Hybrid Eelectric Vehicles*, IEEE Control Systems, ISSN 1066-033X, 27 (2007), 60-70.

[4] Q. Gong, et al., *Trip Based Optimal Power Management of Plug-in Hybrid Electric Vehicles*, IEEE Trans. on Veh. Tech., ISSN 0018-9545, 57 (2008), 3393-3401.

[5] N. Kim, et al., *Optimal Control for Hybrid Electric Vehicles Based on Pontryagin's Minimum Principle*, IEEE Trans. Cont. Sys. Tech., ISSN 1063-6536, 19 (2011), 1279-1287.

[6] V. Marano, et al., Comparative Study of Different Control Strategies for Plug-in Hybrid Electric Vehicles, SAE conference, 2009-24-0071, 2009.

[7] N. Kim, et al., *A Jump Condition of PMP-Based Control for PHEVs*, Journal of Power Sources, ISSN 0378-7753, 196 (2011), 10380-10386.

[8] K. Moran, et al., *Digital Maps, Connectivity and Electric Vehicles — Enhancing the EV/PHEV Ownership Experience*, SAE Int. Journal, Passeng. Cars-Electron. Electr. Syst, 3 (2010), 76-83.

[9] C. Musardo, et al., *A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management, in Proc. 44th IEEE Conf. Decision Control*, 2005 European Control Conf., 2005, 1816-1823.

[10] Y. Zhu, et al., *A Four-Step Method to Design an Eenergy Management Strategy for Hybrid Vehicles*, in Proc. 2004 American Control Conf., 2004, 156-161.

[11] C.-C. Lin, et al., *Power Management Strategy for a Parallel Hybrid Electric Truck, IEEE Trans. Cont. Sys. Tech.*, ISSN 1063-6536, 11(2003), 839-849.

[12] P. Pisu, et al., *A Comparative Study of Supervisory Control Strategies for Hybrid Electric Vehicles*, IEEE Trans. Cont. Sys. Tech., ISSN 1063-6536, 15 (2007), 506-518.

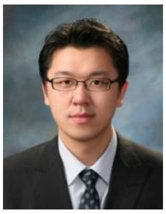
[13] J. Jeong, et al., *Fuel Economy Analysis of a Parallel Hybrid Bus Using the Optimal Control Theory*, VPPC2011, 2011.

[14] N. Kim, et al., Optimal Control of a Plug-in Hybrid Electric Vehicle (PHEV) Based on Driving Patterns, EVS24, 2009.

[15] T. Keulen, et al., *An Adaptive Sub-Optimal Energy Management Strategy for Hybrid Drive-Trains*, 2008 IFAC, 2008, 102-107.

[16] A. Rousseau, et al., *Integrating Data, Performing Quality Assurance, and Validating the Vehicle Model for the 2004 Prius Using PSAT*, SAE Technical Paper, 2006-01-0667, 2006.

Authors



Daeheung Lee
Ph. D. Candidate, Seoul National University, South Korea
Email: ideal02@snu.ac.kr
Daeheung Lee received his bachelor's degree in Department of Mechanical Engineering from Hanyang University, South Korea, in 2006. He is currently working towards Ph.D. degree in School of Mechanical and Aerospace Engineering at the Seoul National University.

Suk Won Cha
Associate Professor, Seoul National University, South Korea
Email: swcha@snu.ac.kr
Suk Won Cha received his M.S. and the Ph.D. degree in Department of Mechanical Engineering from Stanford University, in 1999 and 2004, respectively. His research interests are fuel cell systems, design of hybrid vehicle systems and application of nanotechnology to energy conversion devices.

Aymeric Rousseau
Program Manager, Argonne National Laboratory, USA
Email: arousseau@anl.gov
Aymeric Rousseau received his Master of Science in Industrial Systems from EIGSI in La Rochelle, France, in 1997. He is currently leading Argonne's vehicle modeling and simulation group.

Namwook Kim
Postdoctoral Appointee, Argonne National Laboratory, USA
Email: nakim@anl.gov
Namwook Kim received his bachelor's degree and doctor's degree from Seoul National University, South Korea. He is currently working on modeling dynamic systems and developing supervisory control strategies for Autonomie.