Optimal Control Strategy for PHEVs using Prediction of Future Driving Schedule

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Abstract
Optimization based control methods for Plug-in Hybrid Electric Vehicles require the knowledge of an entire driving cycle and an elevation profile to obtain the optimal performance over fixed driving route. In this paper, the method using traffic information to predict the future driving cycle and the optimal control strategy based on Pontryagin’s Minimum Principle (PMP) are investigated in order to minimize the fuel consumption on a given trip distance as well as develop a real-time implementable control strategy. To predict future driving patterns, Dynamic Programming theory is proposed for the calculation of the vehicle speed with respect to the driving distance with the knowledge of traffic condition received from the external traffic information like ITS. This is achieved by minimizing the proposed cost function on each segment. The result of the generated speed profile can well estimate the driving pattern of the real driver. Also, 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 out the estimated initial co-state similar to the optimal co-state. Simulation results show that this approach guarantees the best efficiency under reasonable condition and the minimization of the fuel consumption on the trip distance between 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 tightening emission regulations and the need of more fuel-efficient vehicles. The PHEVs are functionally similar to the conventional hybrid electric vehicles (HEVs) in the way that the PHEVs can take advantage of regenerative braking and a reduction in engine size to operate more efficiently. But the PHEVs are different from the conventional HEVs in that they allow recharging from the electrical grid. In these vehicles, higher capacity batteries are used that can store charge from the electrical outlet along with the on-board engine charging and regenerative brake charging. By utilizing the high-capacity battery the PHEVs can travel such as a pure electric vehicle for specific distance according to operating mode of the powertrain [1-2].

The performance or efficiency of PHEVs also relies on energy management strategy that is the supervisory control algorithm which determines power split ratio between the combustion engine and the electric diving motor in order to meet the
required power at driving wheels [3]. Of several control strategies, optimization based control methods like Equivalent Consumption Minimization Strategy (ECMS) or Pontryagin’s Minimum Principle (PMP) based control require the knowledge of an entire driving cycle and an elevation profile to result in optimal performance [4-5]. Some researches have shown in [1, 6-7] that the fuel consumption of PHEVs is minimized when the battery and the engine are used consistently during entire trip such that the battery SOC decreases continuously and reaches the minimum value at the end of the trip. But the blended mode control ensuring the minimum fuel consumption requires more accurate information about the trip, such as driving duration, driving profile, etc.

In this paper, under the assumption that the vehicle can use the information extracted from Intelligent Transportation System (ITS) over driving road, the method using the traffic knowledge for prediction of the future driving cycle, and the optimal control strategy based on PMP are investigated in order to minimize fuel consumption on the trip distance which is determined from the driver’s navigation system. This paper is organized as follows. Section II summarizes the concept of the control scheme using the traffic information and the navigation system (including a GPS receiver) in a vehicle. In Section III, the method for the driving schedule estimation is proposed. With the help of the GPS and ITS, it is possible to directly predict the future driving cycle through Dynamic Programming (DP) theory. Section IV presents the PMP based control and the correlations between the predicted driving cycle and the control parameter, co-state $p$, used in PMP control theory. The simulation results are presented in Section V. The real driving profile from the on-board GPS device and the predicted speed profile are compared, along with the result of the fuel economy improvement through the PMP based controller. Finally, Section VI presents conclusions about utility of 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 the various information through the transmitter of the ITS and GPS into the information or data being suitable for the supervisory control algorithm. Figure 2 shows the schematics of the information flow among required modules and a hybrid control unit. The 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 components like the battery SOC value and signals.
that convey the information concerning status of a powertrain. Because the present available ITS and GPS device provide only limited information on the circumstance of traffic, 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, etc. The ITS model using information based on measured data on certain real road provides the knowledge required for the speed prediction algorithm module. Then the module employing the dynamic programming algorithm calculates the predictable speed of a vehicle on the specific segment of the road with 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 overall trip distance is able to be extracted by the navigation system and 3D-Map [8]. From the estimated speed profile, the module for 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 (HCU) instantaneously computes the ratio of the power split between the engine and the electric driving motor by using the predicted co-state value.

3 The Algorithm for Prediction of Driving Speed

The process to generate the speed profile from the traffic information is shown in Figure 3. To obtain the speed profile for future driving, Dynamic programming (DP) theory using distance based technique has been adopted, which is reflecting some constraints that are determined by traffic information on each trip segment. Generally, because DP is a representative technique to obtain optimal policy, DP theory in many researches 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

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

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

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

In general, DP requires gridding of the state and time variables, and thus the optimal trajectory is calculated only for discretized values of time and battery SOC [3]. DP algorithm explained above, on the other hand, can also be applied to find out the future speed profile satisfying some physical constraints. If the performance measure (or cost function) in 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

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

where \(s\) is position, and \(x(s)\) and \(u(s)\) denote 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 segment of the whole travel distance, the speed profile that minimizes the performance index (3) subject to equations of powertrain and speed limit on the road can be numerically obtained by solving a dynamic programming problem. Here the cost function \(L(\cdot)\) at each calculation step intuitonally

Figure 3: Algorithm process to obtain the predicted speed profile on a segment
consists of driving energy, $E_{dvr}$, time consumed in driving, $T$, and the terms regarding the level of acceleration, $a$ and deceleration, $d$, as described by

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

where $k$ is the stage on the grid of considered distance; $w_a$, $w_{a^4}$, and $w_d$ are the weighting factors for time consumed, acceleration, and deceleration, respectively. The weighting factors are decided from map data founded by considering the speed limit, average speed, cruising speed and length of each segment for traveling distance. Figure 4 and Figure 5 show the predefined value of each weighting factors.

The prediction of speed profile on the certain road can be carried out by selecting just the three factors regarding driving states such as the driving time, acceleration and deceleration on the given distance of the segment. Figure 6 shows the result of the short range prediction as an example. The predicted speed profile is similar to real speed profile which is extracted from the GPS receiver in a vehicle. We can also observe that the level of acceleration and deceleration of the predicted speed in the Figure considerably reflects the driving tendency of a real driver.

The performance of the proposed method for the relatively longer distance including the traffic signals was studied via measurement of required data on real road.

Figure 7 depicts the real driving speed and the information of traffic signals on the specific street near Argonne National Laboratory, which is saved in the ITS model. The total driving distance is 7.5km and there are 13 traffic signals on the road. Through the information, it is possible to estimate the duration and the number of vehicle’s stop. The real and estimated velocity profiles are shown as a function of trip time in Fig. 8. The acceleration of the real vehicle until around 40 seconds initially is lower than that of predicted speed due to the uphill elevation of real road. Except for the initial driving state in Fig. 8, the speed prediction algorithm can estimate the anticipated vehicle speed very well during the whole trip.
Therefore, if it is realizable to obtain the precise information from the ITS, GIS or GPS, predicting the vehicle speed on the fixed trip distance can be possible in advance, and the result is considerably similar to actual driving pattern. The fact that the future speed profile can be obtained accurately is very important because the parameter i.e., co-state, 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 Pontryagin’s Minimum Principle (PMP) is a promising solution because it provides a simple solution for controlling HEVs or PHEVs and guarantees the best performance under reasonable condition [5]. With known the information for the future driving schedule and elevation profile, it is possible to find the optimal value for the co-state, \( p \) depending on the future power demand, and then run the PHEV in blended mode that the battery is nearly depleted at the end of trip.

4.1 Analytical method for the minimum fuel consumption

The optimal control based on PMP is simple enough to 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

\[
H = \dot{m}_e(P_{mot}) + p(t) \cdot S\dot{O}C(SOC, P_{bat})
\]  

(5)

where \( \dot{m}_e \) 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 the minimum fuel consumption is the goal of optimal control, the problem of PHEVs can be defined as (6) and (7), in which the engine speed \( S_e \) and the engine torque \( T_e \), can be used to determine the fuel consumption

\[
\min J = \int_{t_f}^{t_i} L(S_e, T_e, t) \, dt
\]  

(6)

subject to

\[
\begin{align*}
SOC(t_i) &= SOC_{\text{actual}} \\
SOC(t_f) &= SOC_{\text{desired}} \\
SOC_{\text{min}} \leq SOC \leq SOC_{\text{max}} \\
S_{\text{min}} \leq S_e \leq S_{\text{max}} \\
T_{\text{min}} \leq T_e \leq T_{\text{max}}
\end{align*}
\]

(7)

where \( L(S_e, T_e, t) \) is the rate of fuel consumption of the engine. \( SOC \) is determined by a battery model described in (8).

\[
S\dot{O}C = -\frac{1}{Q_{bat}} \frac{V_{bat}}{2R_{bat}} \frac{\sqrt{V_{bat}^2 - 4R_{bat}P_{bat}}}{2R_{bat}} = f(SOC, S_e, T_e)
\]  

(8)

Further \( T_e \) and \( S_e \) 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 components, such as the maximum motor speed, maximum torque, or maximum battery power. This optimal control problem can be solved from 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]

\[
\begin{align*}
S\dot{O}C &= \frac{\partial H}{\partial p} \\
p &= -\frac{\partial H}{\partial SOC} \\
H(SOC, u^*, p^*, t) &\leq H(SOC, u, p, t)
\end{align*}
\]  

(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 whole trip. The optimal co-state value that is subject to above condition on given driving schedule can be found by running simulation repeatedly on the various initial value of \( p(t_0) \) or shooting method [1,14]. But for the optimal control algorithm to have the potential for a real time implementation, it needs to estimate the value of 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, \( E_{bat} \). 

\[
p(t) = f(SOC_{drv,eff}, E_{bat})
\]

\[
= a(E_{bat}) \cdot SOC_{drv,eff} + b(E_{bat})
\]

\[
\begin{cases}
\sum_{i=1}^{n} C_{ai} \cdot E_{bat}^{n-i} & (n = 4) \\
\sum_{i=1}^{n} C_{bi} \cdot E_{bat}^{n-i} & (n = 4)
\end{cases}
\]

where, \( a \) and \( b \) are the coefficient determined by the useable battery energy; \( C_{ai} \) and \( C_{bi} \) are the constant value as shown in Table 1.

<table>
<thead>
<tr>
<th>( C_{ai} )</th>
<th>( C_{a2} )</th>
<th>( C_{a3} )</th>
<th>( C_{a4} )</th>
<th>( C_{a5} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>45.944</td>
<td>-907.16</td>
<td>8778.6</td>
<td>-131289</td>
<td>225126</td>
</tr>
<tr>
<td>( C_{bi} )</td>
<td>( C_{b2} )</td>
<td>( C_{b3} )</td>
<td>( C_{b4} )</td>
<td>( C_{b5} )</td>
</tr>
<tr>
<td>-0.0191</td>
<td>0.2721</td>
<td>-1.9148</td>
<td>-138.94</td>
<td>0.7025</td>
</tr>
</tbody>
</table>

And 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 in equation (12)

\[
S\dot{O}C_{drv,eff} = \frac{\Delta SOC_{drv,eff}}{\Delta T_{drv,eff}}
\]

where, \( \Delta SOC_{drv,eff} \) denotes the decreased value of SOC when considering only the battery’s discharging state during whole trip, and \( \Delta T_{drv,eff} \) is effective driving time except for the time during the stop and deceleration condition of a vehicle. For instance, this relation is shown in Fig. 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 condition.

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

\[
\Delta SOC_{drv,eff} = SOC_i - SOC_f - \Delta SOC_{reg,eff}
\]

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 Fig. 10(a)

![Effective SOC profile divided into the propulsion and the regeneration state](image)

![Real speed profile and estimated speed profile](image)

![Required positive and negative power for the driving speed](image)
Then the future power demand with respect to driving time is determined as described by

$$P_t(t) = F_t(t) \cdot v(t)$$ (14)

where $P_t(t)$ is required tractive power, $F_t(t)$ is tractive force and $v(t)$ is 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. And then we can guess the increasing amount of the battery SOC, $\Delta$SOCreg eff from regenerative breaking power ($P_t(t)<0$) over whole trip time by using equation (8) and (15) under assumption that the voltage and resistance of the battery is average value.

$$\Delta$SOCreg eff $= \int_0^T \dot{SOC}(P_{red}(t))dt$$ (15)

$$P_{red}(t) = \eta_{reg} \cdot P_t(t) \quad (\forall P_t(t) < 0)$$ (16)

where, $P_{red}(t)$ is the electrical power charged to the battery, $\eta_{reg}$ 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 distance, which is calculated through the backward-looking simulation on repeated UDDS cycles.

![Figure 11: The results of the effective SOC drop using the backward-looking simulation based on optimal control theory](image)

Table 2 summarizes the validation results of the predicted co-state to the optimal value calculated from the driving cycles repeated until 5 times and the various battery capacities. In a PHEV using 3.4kWh battery pack, the vehicle can be operated in EV mode only (charge-depleting mode) on a single driving of UDDS cycle. Thus the prediction of the initial co-state on just one cycle could be meaningless because do not use the engine is more efficient on the whole trip. When the traveling distance is known to be less than or equal to the vehicle’s electric range, the powertrain can be run in its all-electric mode [1]. This is also the same as the PHEV using 5.2kWh battery capacity if the driving cycle is repeated until 2 times. 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>
<thead>
<tr>
<th>Battery Capacity</th>
<th>Co-state</th>
<th>UDDS ×1</th>
<th>UDDS ×2</th>
<th>UDDS ×3</th>
<th>UDDS ×4</th>
<th>UDDS ×5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.4 kWh</td>
<td>Optimal</td>
<td>-299.09</td>
<td>-316.26</td>
<td>-323.32</td>
<td>-326.84</td>
<td>-328.96</td>
</tr>
<tr>
<td></td>
<td>Predicted</td>
<td>-296.52</td>
<td>-317.41</td>
<td>-323.57</td>
<td>-326.63</td>
<td>-328.55</td>
</tr>
<tr>
<td></td>
<td>Error</td>
<td>0.48%</td>
<td>0.36%</td>
<td>0.08%</td>
<td>-0.06%</td>
<td>-0.12%</td>
</tr>
<tr>
<td>3.4 kWh</td>
<td>Optimal</td>
<td>-695.86</td>
<td>-737.71</td>
<td>-758.63</td>
<td>-771.19</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Predicted</td>
<td>-696.45</td>
<td>-738.34</td>
<td>-760.34</td>
<td>-770.82</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Error</td>
<td>0.08%</td>
<td>0.09%</td>
<td>0.23%</td>
<td>-0.05%</td>
<td></td>
</tr>
<tr>
<td>5.2 kWh</td>
<td>Optimal</td>
<td>-1188.5</td>
<td>-1221.8</td>
<td>-1241.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Predicted</td>
<td>-1191.4</td>
<td>-1224.1</td>
<td>-1244.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Error</td>
<td>0.24%</td>
<td>0.19%</td>
<td>0.19%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

## 5 Simulation result

The performance of the PMP based control using the speed profile predicted via Section 3 is studied through 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 then switched to a charge-sustaining mode and 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 Fig. 12. All of the data for the component models and vehicle model as shown in Table 3 are based on a 2004 Toyota Prius in Autonomie developed by Argonne National Laboratory [7, 16]. And the battery capacity was decreased to 3.4kWh to just verify the optimality for the estimated driving condition.

![Figure 12: The power-split hybrid system used in this study](image)
Table 3: Vehicle parameters used in simulation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle mass</td>
<td>1490 kg</td>
</tr>
<tr>
<td>Engine</td>
<td>1500cc</td>
</tr>
<tr>
<td>Motor 1</td>
<td>25kW (Peak Power 50kW)</td>
</tr>
<tr>
<td>Motor 2</td>
<td>15kW (Peak power: 30kW)</td>
</tr>
<tr>
<td>Battery</td>
<td>3.4kWh</td>
</tr>
<tr>
<td>Planetary gear ratio</td>
<td>2.6 (78/30)</td>
</tr>
<tr>
<td>Final gear ratio</td>
<td>4.113</td>
</tr>
<tr>
<td>Rolling resistance</td>
<td>0.007+0.00012×Vehicle speed</td>
</tr>
<tr>
<td>Frontal area</td>
<td>2.25m$^2$</td>
</tr>
<tr>
<td>Drag coefficient</td>
<td>0.29</td>
</tr>
<tr>
<td>Wheel radius</td>
<td>0.305m</td>
</tr>
<tr>
<td>Air density</td>
<td>1.23kg·m$^{-3}$</td>
</tr>
</tbody>
</table>

5.2 Simulation result

To evaluate the performance of the proposed control method, we used the real speed data saved in the GPS device after driving a vehicle over a distance of almost 15 km. And the speed prediction was carried out through the traffic information on the road. Then the final speed profile for the simulation was repeated 2 times for long distance as shown in Fig. 10(a). In this study, the simulation used the initial SOC, $SOC_i$ as 80% and allowed the system to consume the electrical energy until the final SOC, $SOC_f$ fell to 30%.

For the fuel consumption analysis, it needs the following procedure. First of all, the future speed profile is predicted through the traffic information on the segments of the real road, and then we calculate the initial co-state from the predicted speed profile. Finally, the PMP based controller using the co-state is applied to 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: Result of the co-state prediction

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta SOC_{\text{av,ref}}$</td>
<td>-0.70673</td>
</tr>
<tr>
<td>$\Delta T_{\text{av,ref}}$</td>
<td>1416 sec</td>
</tr>
<tr>
<td>$SOC_{\text{av,ref}}$</td>
<td>-0.00049991</td>
</tr>
<tr>
<td>Estimated co-state $p_0$</td>
<td>-689.5761</td>
</tr>
<tr>
<td>Optimal co-state $p_0^*$</td>
<td>-687.4118</td>
</tr>
<tr>
<td>Error</td>
<td>0.315%</td>
</tr>
</tbody>
</table>

In 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 whole trip is lower than that of the CD+CS mode control as shown in Fig. 14. The final SOC of the PMP based control does not exactly reach the minimum value at the end of the trip. It is because the simulation is executed over the real speed profile after we deriving the initial co-state from the estimated speed profile. Nonetheless, as a result, the PMP based control results in a 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 results. And the output power of the engine for each control method is shown in Fig. 15.

Table 5: Comparison of the fuel consumption

<table>
<thead>
<tr>
<th>Control Method for PHEVs</th>
<th>Fuel Economy (Km/L)</th>
<th>Final SOC</th>
<th>FE Increasing rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>CD+CS control</td>
<td>58.9518</td>
<td>0.2901</td>
<td>Ref.</td>
</tr>
<tr>
<td>Prediction based PMP control</td>
<td>69.1480</td>
<td>0.2896</td>
<td>+17.3%</td>
</tr>
</tbody>
</table>

Figure 13: Fuel consumption result 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 investigated the optimal control strategy, PMP based control, for PHEVs using prediction of future driving schedule. To predict the future driving patterns if it is available to get the traffic information on the road, the Dynamic Programming method based on driving distance was proposed over the given trip. This is achieved by minimizing the proposed cost function on each segment. The result of the generated speed profile can well estimate the driving pattern of the real driver. Deriving the co-state used in the optimal control from the predicted speed profile is very important procedure to minimize the fuel consumption over the whole travel. The co-state generation algorithm was 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 find out the estimated initial co-state similar to the optimal co-state. Using the parameters, PMP based control algorithm instantaneously calculates the optimal power split ratio of power sources. Simulation results show that this approach guarantees the minimization of the fuel consumption on the trip distance between origin and destination under reasonable assumptions.

Acknowledgments

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