

Trip Based Optimal Power Management of Plug-in Hybrid Electric Vehicle with Advanced Traffic Modeling

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ABSTRACT

The plug-in hybrid electric vehicles (PHEV), utilizing more battery power, has become a next-generation HEV with great promise of higher fuel economy. A nearly global optimization based charge-depletion control strategy is developed for PHEV power management by using the Intelligent Transportation Systems (ITS). Trip model is obtained via GPS, GIS, real-time and historical traffic flow data and advanced traffic flow modeling. The Gipps car-following model [42] is used for the local road trip modeling along with the synchronization of the traffic signal sequences. The gas-kinetic model [53] was used for the freeway trip modeling. These trip modeling schemes are validated with simulation.

INTRODUCTION

Energy shortage and environmental concern have jeopardized the sustainability in the contemporary world. The hybrid electric vehicle (HEV) has provided a promising alternative means for sustainable mobility [1-4]. The benefits of HEV include the improvement of fuel economy and the reduction of emissions. The propulsion power of HEV comes from two or more kinds of energy sources, e.g., the gasoline internal combustion engine (ICE) and battery, diesel engine and battery, battery and fuel cell (FC), battery and ultra-capacitor, and battery and flywheel [4-6].

The plug-in hybrid electric vehicle (PHEV) is a new generation of HEV with higher battery capacity and the ability to be recharged from an external electrical outlet. Unlike the conventional HEV (i.e., the so-called HEV-0) which can sustain little purely electric range, the PHEV can sustain a longer all-electric range (AER). More fuel can be replaced by the four times cheaper grid electricity in the US [7]. The great potential of PHEV in fuel economy enhancement indicates a tremendous saving of fuel consumption for the nation and a possibly shorter payback time for the customer with regard to the modified powertrain and battery pack. Such encouraging promise has attracted significant attention to PHEV

technology from both government and private sectors, e.g. the President's Advanced Energy Initiatives announced in early 2006 [8] and the Department of Energy (DOE)'s FreedomCar program [9].

Similar to conventional HEV, power management is an important operational factor for PHEV to enhance fuel economy and reduce emissions. HEV power management is generally concerned about how to split the power demand between the two power sources in order to achieve the best fuel economy, minimize the emission and maintain the health of the battery. Limited by the current battery technology, the PHEV with 10 ~ 20 miles AER is considered, according to the DOE authority [9], to be more commercially feasible within the near future, although much higher AER can be obtained from showroom vehicles by using more battery packs. For PHEV-10 or PHEV-20, the electric vehicle (EV) mode cannot sustain the whole trip for most commuters. Therefore, it is necessary to optimize the power management strategies for PHEV. While most conventional HEV's are operated to maintain the battery state-of-charge (SOC) at a constant level (known as "charge-sustaining" mode), PHEV presents a somewhat different scenario: it is desirable to use as much battery power as possible when the vehicle reaches the destination, i.e., the SOC is expected to drop to the lowest possible level. Such an operation is known as the "charge-depleting" mode. A key issue is how to achieve the optimal charge-depleting mode or what kind of depleting profile is the best. A simple strategy is to run the PHEV in the charge-depleting mode (i.e., the EV mode) first until a low threshold of SOC, e.g., 0.3, is reached. Then the vehicle is operated in the charge-sustaining mode, maintaining the SOC constant until the end of the trip. But this naive approach, shown in Fig. 1, is far from optimal in terms of fuel efficiency.

In the past decade, HEV power management has been studied from both control and optimization perspectives. The rule-based control strategies, such as fuzzy logic control techniques, were investigated in power management, by dividing the actual driving conditions into different scenarios [5] [11]. Rule-based controllers

are easier to implement, while the resultant operation may be quite far from optimal due to the omission of the detailed dynamic models. Driving mode classification was also studied by using a pattern recognition approach [12] based on the current and previous driving condition. A blend of pattern learning and fuzzy classification was presented in recent work by Langari and Won [13] [14]. Dynamic feedback control approaches solve for the control strategies based on the current and previous operation, which are easier for the real-time implementation purpose. An optimal control design approach was studied [15] [16]. A sliding mode control has also been studied to achieve better robustness regarding parameter and model variation and external disturbances [17]. For the power management problem in particular, a major drawback of rule-based, driving-mode based, and the dynamic feedback control based approaches is the absence of global optimality, i.e. the power distribution is not optimized for the whole trip. In order to obtain the globally optimal solutions, dynamic programming (DP) techniques have been investigated [18-22] for the power management of various types of HEV. The application of a DP algorithm have relied on certain driving cycles, e.g., the standard driving cycles provided by the U. S. Department of Transportation (DOT). The DP based work has all been considered not applicable for real-time implementation because the trip model (driving cycle) is future information for vehicle operation. Therefore, it was claimed that global optimization result can only used as reference for power management design. More research has been done to seek other alternative methods to optimize the power control. In addition to DP, quadratic programming and model predictive control frameworks were also explored [22]. An adaptive algorithm based on the equivalent consumption minimization strategy (ECMS) was developed based on the on-line adaptive estimation of an equivalence factor based on the current driving conditions [23]. Good parameter tuning was required in order to achieve similar performance as the DP methods. Dependency on the current driving conditions makes this method more suitable for charge-sustaining strategy, but quite difficult to be extended to the plug-in HEV for which charge-depleting operation is desired.

The global optimization type of approaches such as using the DP method is more appropriate for PHEV power management. For conventional HEV, the battery power is very limited. The charge and recharge of the battery occurs within short time periods. Thus the overall fuel economy is more affected by the transient behavior. In comparison, PHEV has much larger on-board battery power; i.e., it takes much longer time to use up this power. The fuel economy of PHEV is more dependent on the optimal balance for different segments of the trip. A global optimization method, e.g., DP, is more desirable. Recent work on global optimization based PHEV power management obtained by Argonne National Laboratory [10] which is in Fig. 1, shows the significant improvement in fuel economy when the global

optimization is applied compared to the depleting-sustaining strategy.

In order to achieve the global optimality for a trip, the trip model for an individual trip is required in advance. Another difficulty is the computational load for global optimization algorithms in the micro-processor inside the vehicle. A two-scale dynamic programming algorithm is developed for improving the computation efficiency while maintain the optimality of the power management [24]. The computation time is greatly shortened by using the approach, which shows a great potential for the real time implementation.

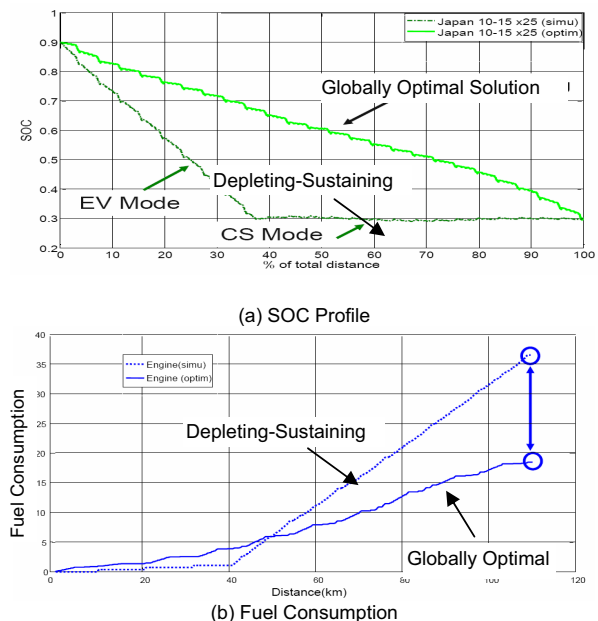


Fig. 1. PHEV power management using global optimization method [10] Recently, trip prediction and modeling has been greatly facilitated by the rapid development of the Intelligent Transportation Systems (ITS), Geographical Information Systems (GIS) and Global Positioning Systems (GPS) [25-27]. Modern GIS platforms can retrieve the road condition, segment length, spatial profile of road grade, speed limit, and traffic stops to the traveller with a high accuracy. For each trip with defined origin and destination, the shortest distance or shortest travel-time path can be generated with some optimal searching algorithm. On-board GPS can report the vehicle location in real-time. Vehicle-to-vehicle and vehicle-infrastructure interaction have been made realistic with readily available wireless technology. Traffic flow monitoring systems have been developed for many arterial and express roads. Real time and historical traffic information can be obtained from roadside sensors. Combining all these information will greatly reduce the uncertainty of trip prediction. If the trip becomes predictable to a large extent, global optimization techniques such as DP will then be realizable. The paper presents a two-scale DP based nearly global optimal power management scheme for plug-in hybrid vehicles by trip modeling with traffic data. In this study, the usage of advanced traffic modeling techniques is

explored to enhance the trip modeling. Traffic models may be classified according to the level of detail with which they represent the traffic systems. This categorization can be operated by considering the distinguished traffic entities and the description level of these entities in the respective flow models [28]. Based on the understanding of different types of traffic models, we have made difference choices for different situations of trip modeling. The gas-kinetic model, a representative mesoscopic model, was applied to the highway segments with on/off ramp traffic. The Gipps car following model, a microscopic model, is applied to local road trip modeling with assumption of the availability of vehicle position/speed on a road segment via GPS transmitting devices. Also, the traffic signal sequence is used to synchronize the local road trip modeling.

The remainder of this paper is organized as follows: In Section II, the configuration of the hybrid electric SUV for simulation study is described, followed by the description of dynamic programming problem of HEV power management. In Section III, Two-scale dynamic programming based charge-deplete control is introduced. The trip modeling approach described in Section IV is based on advance traffic modeling approaches. The simulation results are presented in Section V. The conclusions are presented in Section VI.

PHEV POWER MANAGEMENT WITH TWO-SCALE DYNAMIC PROGRAMMING

VEHICLE CONFIGURATION - The SUV model for this study was derived from the ADVISOR program [29-30]. Its parameter and characteristic data were obtained by averaging the data of 1998 models of Ford Explorer, Jeep Grand Cherokee, and Chevy Blazer with the conventional powertrains. For the resultant SUV has the ICE power of 102 kW. Then the hybrid design was performed by downsizing the engine and adding an electric motor. The ICE was downsized to 75 kW, and a 50 kW AC electric motor was selected from the database in ADVISOR. The total power capability can meet the requirement for most DOT standard driving cycles. The energy storage unit is a 15 A-h lead-acid battery. The ICE and motor are connected through a typical parallel configuration, i.e. the ICE and electric

TABLE I: Basic hybrid SUV components parameters

Vehicle mass (kg)	2000	Final drive speed ratio R_{fd}	1
Vehicle CD	0.44	ICE (SI) power (kw)	75
Vehicle FA (m ²)	2.66	Electric motor (kw)	50
Wheel radius (m)	0.343	Battery capacity (Ah)	15
Coupler speed ratio R_c	1	Battery voltage (V)	240
Transmission	5 speed automatic: I:13.45; II: 7.57 III: 5; IV: 3.77 V: 2.84		

motor are coupled together with a torque coupler, and both coupled to the transmission directly. The key parameters of the hybridized SUV model are given in TABLE I, where CD is the coefficient of drag and FA is

the facing area. Notice that the transmission is a 5-speed automatic.

DYNAMIC OPTIMIZATION OF HEV POWER MANAGEMENT - The dynamic optimization approach of HEV power management relies on a dynamic model for the vehicle along with the powertrain to compute the best control strategy. For a given driving cycle, the optimal operation strategy which minimizes fuel consumption, or combined fuel consumption and emissions can be obtained. A numerical dynamic programming approach [20] is adopted to solve this finite horizon dynamic optimization problem.

Problem Formulation - In the discrete-time format, the hybrid electric vehicle model can be expressed as

$$x(k+1) = f[x(k), u(k)] \quad (1)$$

where $x(k)$ is the state vector of the system, such as vehicle speed, transmission gear number, and battery SOC; $u(k)$ is the vector of control variables such as desired output torque from the engine, desired output torque from the motor, and gear shift command to the transmission. The optimization problem is to find the control input $u(k)$ in order to minimize the following cost function:

$$J = \sum_{k=0}^{N-1} L[x(k), u(k)] = \sum_{k=0}^{N-1} [fuel(k) + \mu \cdot NOx(k) + \nu \cdot PM(k)] \quad (2)$$

where N is the duration of the driving cycle, L is the instantaneous cost including fuel use and engine-out NOx and particulate matter (PM) emissions. In the current stage of study, we only consider the fuel consumption minimization, i.e. $\mu = \nu = 0$.

During the optimization process, it is necessary to satisfy the following inequality and equality constraints to satisfy the speed and torque demands and meanwhile to ensure safe/smooth operation of the engine/battery/motor.

$$\omega_{e_min} \leq \omega_e(k) \leq \omega_{e_max} \quad (3a)$$

$$T_{e_min}(\omega_e(k)) \leq T_e(k) \leq T_{e_max}(\omega_e(k)) \quad (3b)$$

$$T_{m_min}[\omega_m(k), SOC(k)] \leq T_m(k) \leq T_{m_max}[\omega_m(k), SOC(k)] \quad (3c)$$

$$SOC_{min} \leq SOC(k) \leq SOC_{max} \quad (3d)$$

$$v_v(k) = v_{v_req}(k) \quad (3e)$$

$$T_m(k) + T_e(k) = T_{req}(k) \quad (3f)$$

where ω_e is the engine speed, T_e is the engine torque, T_m is the motor torque, v_v is the vehicle velocity, v_{v_req} is the requested velocity of the vehicle, SOC is the state of charge for the battery, and subscript min and max refer to the minimum and maximum value of the relevant variables, respectively. The vehicle is always required to meet the speed and load (torque) demands at each sampling instant throughout the driving cycle, which leads to the two equality constraints in (3e) and (3f).

Simplified HEV Models - The detailed model in ADVISOR [29] is not suitable for dynamic optimization due to its high number of states (curse of dimensionality). Thus, a simplified but sufficiently complex vehicle model has been adopted [20] in our previous study [30]. In this study, we have kept the adoption of this model [20] [30].

DYNAMIC PROGRAMMING - Dynamic programming is a general dynamic optimization approach which can provide globally optimal solution to the constrained nonlinear programming problems [31]. Based on Bellman's Principle of Optimality, the optimal policy can be obtained by solving the sub-problems of optimization backward from the terminal condition. The subproblem for the $(N-1)$ -th step is to minimize

$$J_{N-1}^*[x(N-1)] = \min_{u(N-1)} \{L[x(N-1), u(N-1)] + G[x(N)]\} \quad (4)$$

For step k ($0 < k < N-1$), the sub-problem is to minimize:

$$J_k^*[x(k)] = \min_{u(k)} \{L[x(k), u(k)] + J_{k+1}^*[x(k+1)]\} \quad (5)$$

where $J_k^*[x(k)]$ is the optimal cost-to-go function at state $x(k)$ starting from time stage k . The above recursive equation is solved backward to find the control policy. The minimizations are performed subject to the inequality constraints and the equality constraints imposed by the driving cycle.

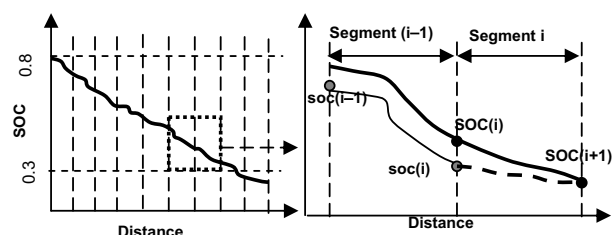
An effective way to solve the above cost function numerically is to do the quantization and interpolation [32] [33]. For continuous state space and control space, the state and control values are first discretized into finite grids. At each step of the optimization search, the function $J_k[x(k)]$ is evaluated only at the grid points of the state variables. If the next state $x(k+1)$ does not fall exactly on a quantized value, then the value of $J_k[x(k+1)]$ as well as $G[x(N)]$ are determined through linear interpolation. At each step, the backward DP with interpolation method was used [31] [34]. For most cases, the vehicle can be assumed fully charged to the highest healthy level, typically SOC of 0.8, while the healthy low level of SOC is 0.3. Therefore, for the DP problem to be solved, the initial and terminal values of SOC are 0.8 and 0.3, respectively.

TWO-SCALE DYNAMIC PROGRAMMING BASED CHARGE-DEPLETION POWER MANAGEMENT - After the driving cycles are obtained by trip models for individual trip, we start to use the dynamic programming technique to find trip-based global optimization in power management. The major issue remained is that the computation of seeking global optimization is too complex to be completed in on-board processor and that the actual driving cycle may be different from that produced by the trip model because of the stochastic nature of the traffic flow. To address this issue, we propose a two-scale global optimization procedure, as described as follows.

1. The DP based global optimization is first performed for the macro-scale trip model for the whole trip based on historical traffic data. With a given origin, destination and departure time, the trip model can generate a driving cycle for the entire trip based on

the historical traffic data at each monitoring point. A global optimization (e.g. dynamic programming) problem is then solved with the known starting and end SOC values. The globally optimal SOC profile will then be obtained, as the example shown in Fig. 2(a).

2. Real-time global optimization with a micro-scale DP based on route segmentation. The whole route is first divided into a number of nearly equal-distance segments. When the vehicle gets close to the beginning of a segment, real-time traffic flow data at all the monitoring sites within the segment will be acquired from the transportation operation center, e.g., through a wireless data transmission device. The real-time traffic data is available for many urban areas such as the great Milwaukee area [27]. The short-range trip model for this segment will be predicted based on the acquired real-time traffic data. As shown in Fig. 2(b), assume that the vehicle is about to complete the $(i-1)$ -th road segment, and the trip model for the i -th road segment is needed. The bold solid line indicates the globally optimal SOC profile obtained in Step 1, denoted as upper case notation "SOC(i)", while the actual SOC history in the $(i-1)$ -th segment is shown as the thin solid line, denoted as the lower case notation "soc(i).". For the DP based power management algorithm for the i -th segment, the actual value of battery state-of-charge soc(i) will be used as the initial value, and the SOC($i+1$), the battery state-of-charge value at the end of the road segment in the macro-scale optimal profile, will be used as the terminal value. The dynamic programming algorithm is then applied to the short-range trip model for Segment i . The optimal power management strategy will result in the predicted SOC profile as the bold dashed line in Fig. 2(b). As the vehicle runs along the route, such a process will be repeated for each segment in sequence, i.e. from the starting location to the destination.



(a) Macro-scale Optimal SOC (b) Zoomed View of Two-Scale DP
Fig. 2. Illustration of two-scale global optimization method for PHEV power management

Note that the computation for Step 1 can be carried on off-line in advance by some high capacity computational servers, and the obtained SOC profile can be transmitted to the vehicle through wireless communication devices. Step 2 can be carried out by the vehicle on-board processors, and the on-board wireless devices can obtain the real-time traffic data information needed for trip modeling. This paper will not deal with the issue of wireless communication directly and take it