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Multi-Information Integrated Trip Specific Optimal Power Management for Plug-In Hybrid Electric Vehicles

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Abstract— **Plug-in hybrid electric vehicles (PHEV) are widely received as a promising means of green mobility by utilizing more battery power. Recently, we have proposed a scheme of two-scale spatial-domain dynamic programming (DP) as a nearly global optimization approach to trip based optimal power management for PHEV through the combination with traffic data and trip modeling. Previously, the segment-wise power demand and SOC change was calculated through numerical integration based on the average speed and acceleration of the segment, and lookup tables were obtained. When more parameters are involved into power management, such as road grade and load change, such process becomes very tedious. In this paper, the spatial-domain DP is improved by calculating the power demand and SOC change in an analytical manner. The power demand is first calculated based on length, initial speed, acceleration, road grade, payload and wind of a road segment. The SOC change is then calculated for different PSR. An adjustable segment scheme used of analytical function is developed in order to improve the computation efficiency of the optimal power management without losing much of fuel economy. Simulation study shows that incorporating additional trip information such as road grade and predictable payload change into the optimization can significantly improve the fuel economy. The computational efficiency is also evaluated. The proposed method can greatly facilitate the development of optimal power management strategy for PHEV with multiple information inputs.**

I. Introduction

Hybrid electric vehicle (HEV) has become an important means to sustainable mobility, by including two or more energy sources and associated energy converters [1-3]. 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 [4]. Compared to the conventional HEV, the PHEV can sustain a much longer all-electric range (AER) as more fossil fuel can be replaced by much cheaper grid electricity. PHEV has promise great improvement in reduction of fuel consumption [5]. However, the seemingly exciting numbers of high fuel economy are compromised by the tremendous battery cost. It is widely accepted that moderate size of battery pack is more realistic [6]. Optimal power management, i.e. optimizing the use of on-board battery energy, can thus make significant impact on fuel economy for limited battery size. For PHEV power management, it is desirable to use up the on-board battery power when the vehicle reaches the trip destination as battery can be recharged. The charge depletion mode is thus appropriate in comparison with the typical charge sustaining mode for conventional HEV. Trip specific optimization will benefit the charge depleting operation of PHEV power management.

HEV power management has been extensively studied from control and optimization perspectives in the past decade, such as the rule-based control [3] [7], driving mode classification [11] [12] and optimal control [13] [14]. To obtain the trip specific global optimization solution, the dynamic programming (DP) techniques have been investigated among others [15-19], based on the standard driving cycles provided by the government agencies collected by test vehicles. For actual vehicle operation, such solutions are limited due to the a priori nature of trip information. Also, the computational load is too high for on-board implementation. Other alternative approaches have also been studied. The equivalent consumption minimization strategy (ECMS) was developed in [20] based on the on-line adaptive estimation of an equivalence factor. In [21], an intelligent energy management scheme was presented by combining the driving cycle with accessories load, slope and wind drag.

In the past couple of years, the research group of the authors has developed a nearly global optimal strategy PHEV power management, based on the incorporation of the trip information from Intelligent Transportation Systems (ITS) [22-24]. A two-scale DP algorithm has been developed for adapting to the actual traffic variation and improving the computation efficiency while maintaining the nearly global optimality for the power management. Later on, the trip modeling was improved by applying the advanced traffic flow theory. A gas-kinetic model and a Gipps car following model were applied to the highway segment and local road segment respectively. Also, the traffic signal sequence is used to synchronize the local road trip modeling. Although the two-scale DP scheme demonstrated significant reduction of computation time for segment-wise (or micro-scale) DP, the computation time for the macro-scale DP remains high as conventional as it still follows the time-domain framework. With such limitation, the macro-scale DP has to be performed on some external computational infrastructure, and the two-scale DP would be disabled for impromptu change of driving decision. To solve this problem, a spatial domain optimization was proposed as a computationally efficient improvement [25]. The electric vehicle (EV) mode is assumed for the significant deceleration and acceleration segments around traffic stops. The trip is segmented in approximately a certain length, with the power split ration (PSR) assumed constant for each segment. The power demand and the change of the battery state of charge (SOC) for different

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power split ratio (PSR) are pre-calculated for each trip segment in numerical integration manner based on road segment length, average speed and acceleration/ deceleration. Lookup-table (LUT) based interpolation was applied. The DP problem can thus be set up in the spatial domain so as to obtain the optimal solution to power management. Dramatic improvement on computational efficiency was demonstrated, which indicates a promising perspective for the fully on-board implementation of the two-scale DP.

A major drawback of the work in [25] is tedious process of numerical calculation of segment-wise power demand and SOC change. It becomes dramatically difficult when more parameters other than the speed profile are involved in power management, e.g. road grade and payload change (for service vehicles). All these information can have significant impact on the fuel economy [21], and thus should be incorporated. When more trip parameters are included, the numerical integration based calculation for power demand and SOC change becomes very tedious for development. It is thus necessary to develop a generic method that fits the spatial domain DP based power management with multiple trip information.

In this paper, we propose to obtain a closed-form analytical solution to the segment-wise power demand and SOC change. The segment-wise energy demand is first calculated based segment length, initial speed, acceleration/deceleration, road grade, payload and wind speed. Next, the SOC change, under the power demand and different choice of PSR, is calculated through a linearized battery model. The accuracy and the computational efficiency of the proposed method are evaluated by comparing with the numerical integration method. The proposed method is validated with a simulation example that illustrates the impact of road grade and payload change on the fuel economy.

The remainder of this paper is organized as follows. The PHEV optimal power management is overviewed in Section II, along with the dynamic optimization and hybrid vehicle configuration. Section III presents the trip modeling with multiple trip information. The simulation study is presented in Section IV. The paper is concluded in Section V.

II. Overview of PHEV Optimal Power Management

PHEV optimal power management relies on a dynamic model for the vehicle along with the power-train 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. Problem Formulation

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

$$x(k+1) = f\left[\ x(k), u(k)\ \right] \tag{1}$$

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 or motor, and gear shift command to the transmission. We focused our research on the fuel consumption as the main cost. Then, the optimization problem is to find the control input $u(k)$ in order to minimize the following cost function:

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

where N is the duration of the driving cycle, L is the instantaneous cost including fuel consumption and engine-out NO_x and particulate matter (PM) emissions. In the current study, only the fuel consumption is considered.

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

$$\omega_{e\_\min} \le \omega_e(k) \le \omega_{e\_\max} \tag{3a}$$

$$T_{m\_\min}[\omega_m(k), SOC(k)] \le T_m(k) \le T_{m\_\max}[\omega_m(k), SOC(k)] \tag{3b}$$

$$T_{e\_\min}[\omega_e(k)] \le T_e(k) \le T_{e\_\max}[\omega_e(k)] \tag{3c}$$

$$SOC_{\min} \le SOC(k) \le SOC_{\max} \tag{3d}$$

$$v_v(k) = v_{v\_req}(k) \tag{3e}$$

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

where ω_e is the engine speed, T_e is the engine torque, T_m is the motor torque, SOC is the battery state of charge, v_v is the vehicle velocity, v_{v_req} is the requested velocity of the vehicle, and subscript min and max refer to the minimum and maximum value of the relevant variables, respectively.

To make the DP algorithm feasible, a simplified but sufficiently complex vehicle model has been adopted [20].

B. DP Based Charge-Depletion Power Management

DP is a general dynamic optimization approach which can provide globally optimal solution to the constrained nonlinear programming problems [26]. The optimal policy can solved from the sub-problems of optimization backward from the terminal condition. The (N–1)-th step minimizes

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

while previous steps ($0 < k < N$–1) minimize

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

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.

As the numerical solution to DP, the quantization and interpolation from [27] has been adopted as in our previous study [22-24]. For PHEV, it is desirable to use the battery charge as much as possible, within the healthy range of SOC, when the vehicle reaches the destination. For most cases, the vehicle can be assumed fully charged to the highest healthy level, typically initial SOC of 0.8, while the healthy low level of terminal SOC is 0.3. The constraints to the DP procedure are the system dynamics throughout the trip to be made. The vehicle velocity profile should follow the driving cycles generated from trip model described in the next section, and the corresponding torque demands can then be obtained as reference for deriving the optimal power splitting policies throughout the trip.

III. TRIP MODELING USING MULTIPLE TRIP INFORMATION

The purpose of the trip modeling is to find the driving cycle (e.g., travel speed, time, acceleration and deceleration) for each trip. A trip is defined as a driving path from an origin to a destination. For each trip, we can use path-finding algorithms inside the geographic information system (GIS) technology to search for the driving path and associated road information for each segment such as segment length, slope, speed limit and intersection/traffic light distribution. For arterial and express roads, historical and real-time traffic information can be obtained from roadside sensors. Traffic speed and flow information can be modeled based on such data [28] [29]. After the origin and destination of a trip are defined in the digital map, the trip model (i.e., driving cycle) can be generated based on the above-mentioned information.

Figure 1 shows the map of the example trip, which is between two locations within the greater Milwaukee area in Wisconsin. The origin is 124 West Freistadt Road at Thiensville, while the end location is 3200 North Cramer Street in Milwaukee. The total travel time was estimated as 2183 seconds, and the total distance is 27.2 km. The road elevation altitude is recorded by GPS. Then, the road grade can be calculated by the road altitude and road distance. Figure 2 shows the driving cycle with road grade information. The grade was within a range of ±2°.

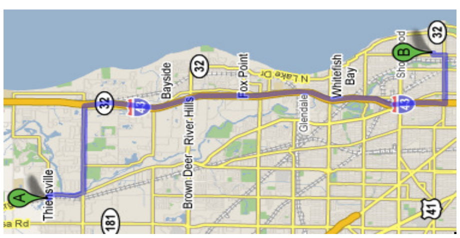

Fig.1. Route map of the example trip from www.mapquest.com

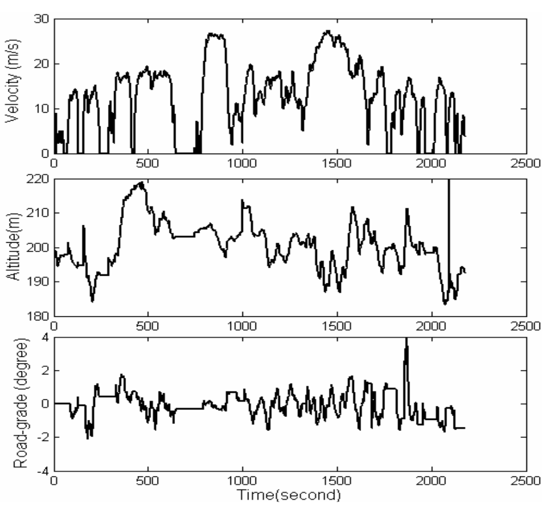

Fig.2. Actual velocity profile and road grade profile

A computationally efficient strategy is proposed in our previous work to reduce the computation time of conventional DP, which is based on a simple trip model and a LUT method. The simple trip model consists of three driving patterns: the constant acceleration rate (1.5 m/s^2), constant braking deceleration rate (-2 m/s^2) and the constant speed defined with speed limit. Therefore, there could be a large error between actual data and simple trip model. Besides, LUT methods become tedious when multiple trip information is involved, e.g. the road grade and payload change. In order to overcome such odds, an analytical solution of segment-wise energy consumption is developed in this paper. As the first step, the trip model is modified to fit the scenario of multiple trip information.

In general, the road grade may change frequently at the actual road environment, especially in the mountain terrain. It has become a major impact on the fuel economy by using DP to obtain optimal power management.

Road grade information can be integrated into the trip model by transforming the road grade from the time domain to the spatial domain. Note that spatial domain representation of road grade fits well with the GPS built-in information. Figure 3 illustrates the transformation from time domain to spatial domain. On the top left side, it is a road grade profile over the time domain. Then, the integral will be conducted along the profile of velocity and presented on the bottom left side. Finally, the road grade profile over the spatial domain is obtained by applying the interpolate method and presented on the top right side.

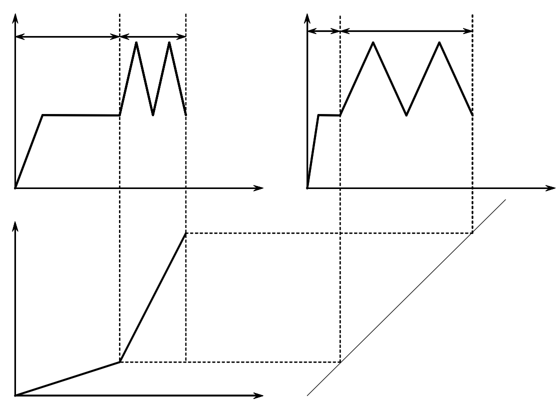

Fig.3. Transformation of road grade from time domain to spatial domain

To overcome the huge database and the trip model error, a developed algorithm is proposed by using an analytical function. An acc/deceleration based trip model is proposed by transforming the velocity from the time domain to spatial domain. Figure 4 illustrates the idea of transformation, similar to that in Fig. 3. It can be seen that the pattern of sharply acceleration has been broadened significantly over spatial domain. Similarly, a plenty of information within this range can be detected and used to improve the accuracy of trip model.

Based on the trip model with an assumption of constant acc/deceleration, the energy of resistance can be described as an analytical function over the spatial domain:

$$E_{rst}(s)=\int_{s_n}^{s_{n+1}}\left[\left(\frac{\rho}{2}A_f C_d g v^2(s)+M\left(1+\cos\Theta\right)\mu_r g \right.\right. \\ \left.\left. +M\sin\Theta\cdot g\right)+\frac{M}{g}\left(1+\frac{\delta_{eqm}}{g}\right)a(s)\right]ds \qquad (6)$$

where, M is the mass of the car body, δ_{eqm} is the mass factor, v is velocity, ρ is the air density, A_f is the effective area of vehicle, C_d is the aerodynamic drag factor, μ_r is the coefficient of rolling resistance, Θ is the road grade, g = 9.8m/s^2.

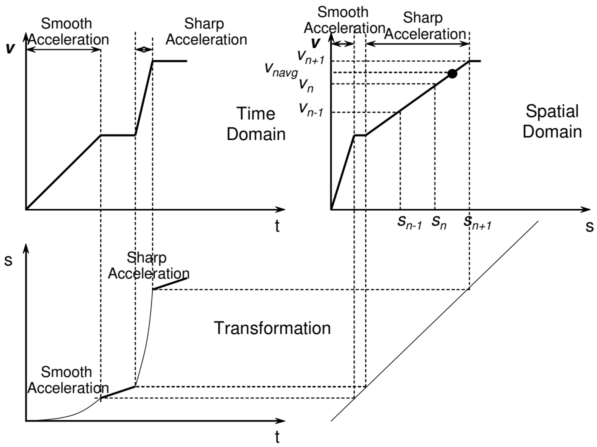

Fig. 4. Transformation of acc/deceleration based trip from time domain to spatial domain

The following transformation from the time domain to spatial domain should be satisfied:

$$a(s_i) = a(t_i)\frac{t_{n+1} - t_n}{s_{n+1} - s_n} \quad (7)$$

$$v(s_i) = v(t_i) \quad (8)$$

$$v \cdot dt = ds \quad (9)$$

Then, the energy is obtained:

$$\begin{aligned} E_{rst}(s) = & \frac{\rho}{2} A_f C_d g \frac{v_{n+1}^3 + v_{n+1}v_n^2 + v_{n+1}^2 v_n + v_n^3}{4a(s)} \\ & + \Big[\left(M(1+\cos\Theta)\mu_r g + M \sin\Theta \cdot g \right) \\ & + \frac{M}{g}\left(1 + \frac{\delta_{eqm}}{g}\right) a(s) \Big] (s_{n+1} - s_n) \end{aligned} \quad (10)$$

Since the resistance energy is calculated over the spatial domain, the trip model can be divided into some segmentation with a pre-defined length:

$$\Delta L = s_{n+1} - s_n \quad (11)$$

In each segment, an average velocity v_{avg} between upstream and downstream data is used to match the continuous profile (shown as Fig. 4):

$$v_{navg} = \frac{v_{n+1} + v_n}{2} \quad (12)$$

Finally, the influence of velocity, acc/deceleration and road grade is lumped together, and the power for each segment can be obtained:

$$P_{rst}(s) = f(\dot{v}, v_{navg}, \Theta) = \frac{E_{rst}(s)}{\Delta t} \quad (13)$$

$$\Delta t = \frac{\Delta L}{v_{navg}} \quad (14)$$

A. Trip Modeling and Changeable Segment Scheme

In this section, an example route was studied according to above modeling approach of *A* and *B*. Based on the traffic information, the route in Fig.2 is divided into three different road portions: 1) interstate expressway (I-43 South) with speed limit of 105 km/h, 2) local highway with speed limit of 64 km/h, 3) urban street with speed limit of 48 km/h.

Historical traffic data of 10 weekdays in early January 2007 from WisTransPortal were used to model the portion of interstate expressway. A traffic data based freeway trip model was obtained, shown as the dashed line in Fig. 5. Since this plot is time based, the two profiles are off by the time delay due to different travel time on the freeway portion.

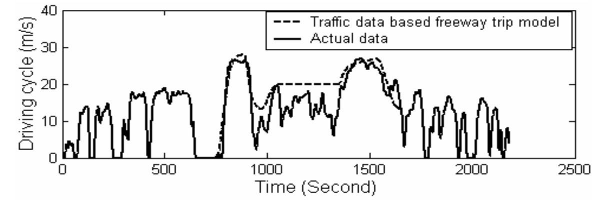

Fig.5. Comparison of traffic data based freeway trip model and actual data

The tendency of different road types can be identified from the traffic data based freeway trip model. Then, a detailed trip model is generated by dividing the route into 12 parts, as the solid lines in Fig. 6. Section 1 (0~250 second) and 12 (1600~2183 second) are the urban streets, Section 2 (250~760 second) is the local highway, Sections 3 through 11 (760~1600 second) are the I-43S freeway. Comparing with conventional simple trip model, more acc/deceleration information with respect to the part of interstate expressway has been considered in detailed trip model. It consists of 3 parts of sharply acceleration, 2 parts of sharply deceleration and 1 part of smooth acceleration. Finally, both of the detailed trip model and the road grade are transformed from the time domain into spatial domain, shown as Fig. 6.

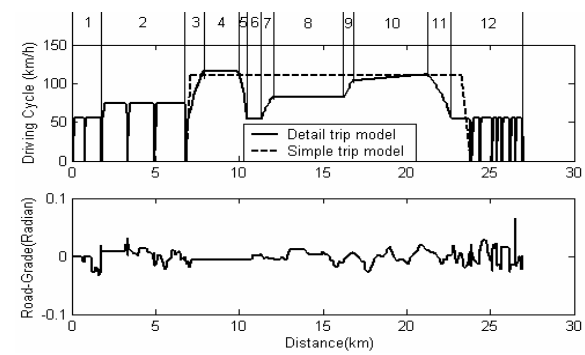

Fig. 6. Trip modeling and segmentation for the example trip

The multi-information fusion based power management scheme has thus been obtained in the spatial domain, which can be applied to DP algorithm by dividing the detailed trip model into different constant-speed segment length. A changeable segment scheme is developed by regulating the length of segment with respect to various traffic patterns. Comparing with the uniform segment length what we have applied in previous study, it can be an effective way to save time and reduce the error of fuel economy at a whole trip. The basic principle of changeable segment scheme can be summarized as two issues:

1) The sharply traffic pattern is assigned with finest segmentation to obtain more detailed information,

2) The smooth traffic pattern is assigned with roughest

segmentation to save computing time on the other hand.

Since the detailed trip model has been divided into several segments with constant acc/deceleration, the segment length can be defined as following piece-wise function:

$$\Delta_i\left(v_{\text{int}}, \dot{v}\right) = \frac{\int_0^{t_{part_i}} \left(v_{\text{int}} + \dot{v} \cdot t\right) dt}{\alpha_1 \cdot |\dot{v}| + \alpha_2 \cdot \left(2 \cdot v_{\text{int}} + \dot{v} \cdot t_{part_i}\right)} \tag{15}$$

$$\Delta l_i = \begin{cases} 100m, \quad if \quad 0 \le \Delta_i\left(v_{\text{int}}, \dot{v}\right) < 150m \\ (j+1) \cdot 100m, \\ if\ (100 \cdot j + 50) \le \Delta_i\left(v_{\text{int}}, \dot{v}\right) < \left[100 \cdot (j+1) + 50\right] \end{cases} \tag{16}$$

where $\Delta_i(*)$ is the actual segment length for Part_i, $|*|$ is the absolute value of "*", Δl_i is desired segment length for Part _i, $j = 1, 2, \cdots$, $i = 1, 2, \cdots, 12$, a is the acc/deceleration, v_{int} is the initial velocity at the beginning of acc/deceleration, t_{part_i} is the time interval for Part_i, $\alpha_1 = 4\left(s^2/m\right), \alpha_2 = 0.17\left(s/m\right)$ are two coefficients which can be obtained by experience.

IV. SIMULATION RESULTS

The simulation used the same SUV model from the ADVISOR program as in our previous. Two issues of power management strategies are implemented: 1) the road grade impact on the fuel economy, 2) the evaluation of computational efficiency for different segment length based on the detailed trip model. All issues were studied with the initial and terminal battery *SOC* of 0.8 and 0.3, respectively. The operating case by applying the conventional DP to the velocity and road grade profile over time domain has been simulated as a benchmark.

A. Simulation of Road Grade Impact on Fuel Economy

In order to evaluate the impact of different road grade on the fuel economy, four basic cases are considered in this issue: 1) road grade = 0°, 2) actual road grade, 3) positive road grade only (by flattening the descent segments of the actual road grade), 4) negative road grade only (by flattening the ascent segments of the actual road grade (i.e. making the trip downhill overall)). Furthermore, two other interesting cases were discussed since the power splitting ratio (P.S.R, i.e. control algorithm) of Case1 has been obtained. Case5: the P.S.R obtained from Case1 is directly applied to Case2, Case6: the P.S.R obtained from Case 1 is directly applied to Case3, Case7: the P.S.R obtained from Case 1 is directly applied to Case4. The simulation results of *SOC*, P.S.R and power profile over the spatial domain for the first four cases are compared in the Fig.7.

The positive parts of power profile indicate that the resistant power needs to be conquered by the engine and motor. The negative parts of power profile indicate the regeneration power caused by the road grade with negative degree, which can be stored in the battery. The collected fuel economy and fuel economy ratio are shown in Table I.

The results show that the road grade takes a great impact on the fuel economy both at ascend, descend and also the random conditions. Particularly, the fuel economy ratio of Case5, 6 and 7 confirms that the fuel economy could be worsen if the P.S.R, which is obtained from DP without considering the road grade, is applied directly into the actual road condition with grade. The simulation results convince us that the road grade should be considered further in order to obtain an efficient control system.

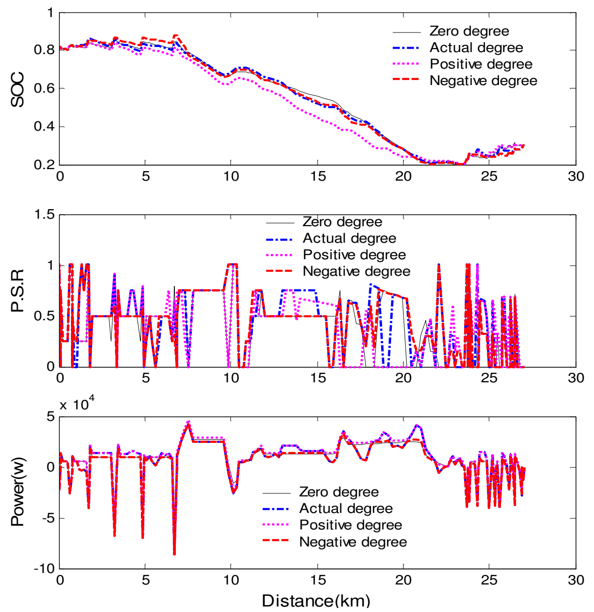

Fig.7. Simulation results of different road grade

TABLE I
COMPARISON OF DIFFERENT ROAD GRADE IMPACT ON THE FUEL ECONOMY

	Fuel economy (L/100km)	FE ratio
Case 1	3.4495	
Case 2	3.4336	
Case 3	3.9113	
Case 4	2.1239	
Case 5	3.8875	13.22% degradation
Case 6	4.4626	14.1% degradation
Case 7	2.5591	20.49% degradation

B. Simulation of Segment Length Impact on Computational Efficiency

The advantage of detailed trip model is that the route can be divided into different sub-segmentation over the spatial domain, and hence reduces the computation task significantly by applying changeable segment length to different operating conditions respectively. In this issue, six cases were considered based on a uniform condition of road grade=actual degree. Case1: conventional DP was applied directly to the detailed trip model, Case2~5: the route of detailed trip model was divided into a number of equivalent segment length=100m, 200m, 400m, 600m, Case6: the route of detailed trip model was divided into a number of different lengths by using the changeable segment scheme. Based on the equation (15) and (16), the segment length from Part_1 to Part_12 are 400m, 800m, 200m, 300m, 100m, 200m, 100m, 600m, 100m, 500m, 300m, 900m. The collected fuel economy, computing time and their ratio are shown in the Table II.

Figure 8 shows that the computation time was greatly reduced by increasing the length of trip segmentation. The conventional DP took about 31 hours (111,640 seconds) to handle whole trip for getting the macro-scale *SOC* profile, while the analytical function approach based on the detailed trip model saved more than three hundred of computation task. On the other hand, the deviation of fuel economy and *SOC* is limited within a bearable range. Compared with equivalent segment scheme, the variable segment scheme represents much reduction of computation time, whereas the deviation of fuel economy and *SOC* less than before.

TABLE II
IMPACT OF SEGMENT LENGTH ON FUEL ECONOMY AND COMPUTATION TIME

	FE (L/100km)	Computing Time	FE_{rel} (%)	CT (%)
Conventional DP	3.4336	111640	0	100
About 100 m	3.4871	31028	1.56	27.7
About 200 m	3.5220	6170	2.57	5.53
About 400 m	3.6807	1540	7.2	1.38
About 600 m	3.8012	580	10.7	0.52
Changeable segment length	3.5205	610	2.53	0.55

FE_{rel}: Relative difference in FE compared with conventional DP.
CT: Computing time as percentage of conventional DP.

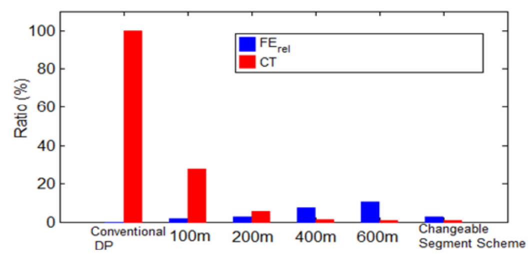

Fig.8. Comparison of different segment lengths impact on fuel economy and computation time over bar chart

V. CONCLUSION

In this paper, a multiple trip information fused framework is proposed for the trip based optimal power management for PHEV. The idea of spatial domain DP is retained, while the segment-wise computation of energy consumption is determined in an analytical rather than numerical manner. Simulation results have supported the validness of the proposed method. Such improvement will greatly help the development of spatial domain DP for the trip based PHEV power management, especially when more trip information is involved in the optimization process, such as road grade and payload variation.

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