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Trip Based Near Globally Optimal Power Management of Plug-in Hybrid Electric Vehicles Using Gas-Kinetic Traffic Flow Model

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Abstract: The plug-in hybrid electric vehicle (PHEV), utilizing more battery power, has become the next-generation HEV with great promise of higher fuel economy. Global optimization charge-depletion power management would be desirable. However, this has so far been hampered due the a priori nature of the trip information and the almost prohibitive computational cost of global optimization techniques such as dynamic programming (DP). This situation can be changed by the current advancement of Intelligent Transportation Systems (ITS) based on the use of on-board GPS, GIS, real-time and historical traffic flow data and advanced traffic flow modeling techniques. In this paper, gas-kinetic base trip modeling approach was used for the highway portion trip and for the local road portion the traffic light sequences throughout the trip will be synchronized with the vehicle operation. Several trip models approaches were studied for a specific case. For DP based charge-depletion control of PHEV, the SOC is forced to drop to a specific terminal value at the final time of the trip. Simulation study has been performed on a hybrid SUV model from ADVISOR, for the different trip modeling approaches. The simulation results demonstrated significant improvement in fuel economy using DP based charge-depletion control compared to rule based control. The gas-kinetic based trip model for the highway portion can describe the dynamics of the traffic flow on highway with on/off ramps which may be missed by the model which used only the main road detectors data. The modeling approach shows a step to the more accurate trip model prediction which can be used for the power management of PHEV.

1. INTRODUCTION

The hybrid electric vehicle (HEV) has provided a promising alternative means for sustainable mobility (Powell *et al.*, 1998; Chan 2002; Ahman 2003; Ehsani *et al.*, 2004). 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 (Baumann *et al.*, 2000, Ehsani *et al.*,2004, Emadi *et al.*, 2005). 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 (Romm *et al.*, 2006). Unlike the conventional HEV, the PHEV can sustain a longer all-electric range (AER). More fuel can be replaced by the four times cheaper grid electricity in USA (Romm *et al.*, 2006).

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 (Baumann *et al.*, 2000; Schouten *et al.*, 2002). 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 (Jeon *et al.*, 2002) 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 (Langari and Won 2005; Won and Langari, 2005). 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 (Delprat *et al.*, 2004; Sciarretta *et al.*, 2004). A sliding mode control has also been studied to achieve better robustness regarding parameter and model variation and external disturbances (Gokasan *et al.*, 2006). 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 (Zoelch *et al.*, 1998; Brahma *et al.*, 2000; Lin *et al.*, 2003; Perez *et al.*, 2006; Koot, *et al.*, 2005) 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 be 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 (Koot *et al*., 2005). 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 (Musardo *et al*., 2005). 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. However, in spite of the attractive benefit that could be brought by the global optimization method, application of such methods to the actual vehicle operation is very difficult. 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-scaled dynamic programming algorithm is developed for improving the computation efficiency while maintain the optimality of the power management (Gong, Q., *et al*., 2007b).The computation time is greatly shortened by using the approach, which shows a great potential for the real time implementation.

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) (de Dios Ortúzar *et al*., 2001; McQueen *et al*., 2003; Peng *et al*., 2003). 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. 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 DP based global optimal power management scheme for plug-in hybrid vehicles by trip modelling with traffic data. The charge-depleting strategy is followed.

2. Hybrid SUV configuration and Dynamic Optimization Problem

2.1 System Configuration

The SUV model for this study was derived from the ADVISOR program (National Renewable Energy Laboratory, 2002; Gong *et al*., 2007a). The resultant SUV has the ICE power of 102 kW. 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.

2.2. Dynamic Programming Based Charge-Depletion 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 (Lin *et al*., 2003) is adopted to solve this finite horizon dynamic optimization problem.

In the discrete-time format, the hybrid electric vehicle model can be expressed as $x(k+1) = f[x(k), u(k)]$, 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:

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

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. $\mu = v = 0$. 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 (Gong *et al*., 2007a).

A simplified but sufficiently complex vehicle model has been adopted (Lin *et al*., 2003) in our previous study (Gong *et al*., 2007a) for the DP based optimization. Discretization and interpolation methods were used for the backward calculation of DP. For a plug-in HEV, 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. 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 modeling described in the next section.

3. Driving Cycle Model Using Gas-Kinetic Traffic Flow Model

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. Trip modeling includes two scenarios: local road and freeway. A simplified trip modeling approach with using of the traffic lights signals which can be obtained from the traffic management center was discussed (Gong *et al*., 2007c). On most freeways around metropolitan areas, traffic flow sensors have been widely deployed and thus both historical and real-time traffic data are available for trip modeling. There are large databases of the archived ITS data. For example, the Wisconsin Department of Transportation has archived the traffic flow data in its WisTransPortal that is maintained by the Wisconsin Traffic Operations and Safety (TOPS) Laboratory (http://transportal.cee.wisc.edu). The procedures for traffic data based model were discussed (Gong *et al*., 2007a,b). In this paper, gas-kinetic base traffic model will be used for the modeling of traffic flow on the highway portion with on/off ramps.

3.1. Problem Description for the Traffic Modeling

For the trip modeling in the highway portion, it is not enough to model the trip using only the speed values obtained from the detectors, and interpolating, since traffic flow in the highway is a dynamic problem. Different modeling approaches have been applied to understand various characteristic properties of traffic flow that are common on freeway. Some early pioneers were Lighthill and Whitham and Richards, who developed independently a continuum (macroscopic) model for traffic flow operations on freeways. This model is known as LWR model and is still applied and extended frequently. In the 1960s, Prigogine and Herman developed gas-kinetic modeling, which was based on the analogy between traffic flow and gas dynamics and has become the basis for further development of high-order continuum traffic models by many researchers such as Phillips, Helbing, and Hoogendoorn. In general, these efforts concentrated mainly on describing uninterrupted traffic flow. Relatively little progress has been made in investigating interrupted traffic flow such as with on- and off-ramps (Helbing *et al*., 1998). Helbing derived a gas-kinetic based traffic model considering on- or off-ramps. Ngoduy proposed a continuum traffic model for freeway with on- and off-ramp (Ngoduy *et al*., 2006). In his model, multilane situation is considered, and lane changing is studied in this model. Also the effect of the length of the ramp is studied in his paper. Papageorgiou *et al*. (2003) gave a comprehensive review on the control strategy for the road traffic, which focus on the control aspect of the traffic problem.

The case of our research is the trip model on the freeway considering the effect of the on- or off-ramp. At current step, we consider only the one lane situation, which means lane changing is not considered right now.

3.2. Gas-Kinetic-Based Traffic Model

On a macroscopic scale, many aspects of traffic flow are similar to those of aggregated physical systems. In particular, if one abstracts from the motion of the single vehicles, traffic can be modeled as a continuum compressible fluid (Lighthill et *al*., 1955; Helbing *et al*., 1998). Kerner and Rehborn (1997) presented experimental data indicating a first-order transition to “synchronized” traffic (ST). Traffic data indicate that ST is the most common form of congested traffic. ST typically occurs at on-ramps when vehicles are added to already busy “freeways” (Helbing *et al*., 1998). Helbing proposed a gas-kinetic-based traffic model which can explain the characteristic properties of ST. The model is based on a kinetic equation for the phase-space density $\tilde{\rho}(x,v,t)$, which corresponds to the spatial vehicle density $\rho(x, t)$ times the distribution $P(v; x, t)$ of vehicle velocities v at position x and time t (Lighthill *et al*., 1955). The model equation for the lane-averaged vehicle density $\rho(x,t) = \int dv\tilde{\rho}(x,v,t)$ and the average velocity $V(x,t) = \rho^{-1}\int dvv\tilde{\rho}(x,v,t)$ are (Ngoduy *et al*., 2006)

$$\partial\rho / \partial t + \partial(\rho V) / \partial x = Q_{rmp} /(nL) \tag{2}$$

$$\begin{aligned}(\partial / \partial t + V \cdot \partial / \partial x)V &= -\partial(\rho\theta)/[\rho(\partial x)] + (V_0 - V)/\tau \\ &- V_0 A(\rho)(\rho_a TV)^2 B(\delta_V)/[\tau A(\rho_{\max})(1-\rho_a/\rho_{\max})^2]\end{aligned} \tag{3}$$

Along on-ramps (or off-ramps), the source term $Q_{rmp}/(nL)$ is given by the actually observed inflow $Q_{rmp} > 0$ from (or outflow $Q_{rmp} < 0$ to) the ramp, divided by the merging length L and by the number n of lanes. The velocity equation (3) contains the velocity variance $\theta(x,t) = \rho^{-1}\int dv[v - V(x,t)]^2 \tilde{\rho}(x,v,t)$. Helbing used constitutive relation $\theta = A(\rho)V^2$ with $A(\rho) = A_0 + \Delta A \tanh[(\rho - \rho_c)/\Delta\rho]$, where A_0 = 0.008, ΔA = 0.015, $\rho_c = 0.28\rho_{\max}$, and $\Delta\rho = 0.1\rho_{\max}$. These coefficients can be obtained from single-vehicle data (Helbing *et al*., 1998). The relaxation time $\tau \in$ [10 s, 50 s]. A gas-kinetic derivation leads to the Boltzmann factor (Kerner *et al*., 1997) $B(\delta_V) = 2\left[\delta_V e^{-\delta_V^2/2}/(\sqrt{2\pi}) + (1+\delta_V^2)\int_{-\infty}^{\delta_V} dy e^{-y^2/2}/(\sqrt{2\pi})\right]$ where $\delta_V = (V - V_a)/\sqrt{\theta + \theta_a}$ is dimensionless velocity difference between the actual location x and the interaction point $x_a = x + \gamma(1/\rho_{\max} + TV)$. The average safe time headway T is of the order of one second. For the “anticipation factor” γ, it is assumed between one and two (Helbing *et al*., 1998).

3.3. Finite Difference Method Used for the Model

The simulations are carried out with an explicit finite-difference integration scheme. The conservative form of the traffic equation reads (2) and the flowing equation

$$\partial Q / \partial t + \partial (Q^2 / \rho + P) / \partial x = (\rho V_e - Q) / \tau + Q_{rmp} V_a / (nL) \tag{4}$$

where dynamic equilibrium velocity V_e is:

$$V_e = V_0 \left[1 - [(\theta + \theta_a) / 2A(\rho_{\max})][\rho_a T / (1 - \rho_a / \rho_{\max})]^2 B(\delta_V)\right] \tag{5}$$

Writing the equations in the form of $\partial u/\partial t + \partial f(u)/\partial x = s(u)$, we have $u = [\rho, Q]$, $f = [Q, (Q^2/\rho + P)]$, $s = [Q_{rmp}/(nL), (\rho V_e - Q)/\tau + Q_{rmp} V_a/(nL)]$.

For the explicit numerical solution methods, x and t are discretized with uniform values of $\Delta x \Delta t$. Hence we calculate u at the discrete points ($j\Delta x$, $n\Delta t$) with j, $n \in \{0, 1, 2, \ldots\}$. For brevity, we use the notation $u_j^n = u(j\Delta x, n\Delta t)$. The Lax-Friedrichs method is as

$$u_j^{n+1} = \frac{u_{j-1}^n + u_{j+1}^n}{2} - \frac{\Delta t}{2\Delta x}(f_{j+1}^n - f_{j-1}^n) + \Delta t s_j^n \tag{6}$$

3.4. Simulation Results for the Case

For our study case (Gong *et al.*, 2007a), there are 11 ramps along the trip which can present correct and complete data. The distance of the ramps to the roads that intersect with the highway is approximately 200 m.

The parameters used in the gas-kinetic based trip model are: L = 0.4km, ρ_{max} = 160 vehicles/km, Q_{max} = 2300 vehicles/h, τ = 32 s, V_0 = 105 km/h, γ = 1.2, Q_{rmp} = 840 vehicles/h, T = 1.8 s. The length of the simulation for each segment near the ramp is chosen as 0.4 km, with 0.2 km before the ramp and 0.2 km after the ramp. The initial conditions for the simulation are $\rho(x, 0)$ = 30 vehicles/km, $Q(x, 0)$ = 1700 vehicles/h. The initial condition was studied that may not affect the simulation results much in (Helbing *et al.*, 1998; Helbing *et al.*, 1999). The left boundary condition for the simulation is chosen as the state of the main road condition before the ramp, and the right boundary condition for the simulation is chosen as the state of the main road condition after the ramp. For the first on ramp, the main-road speeds before and after the ramp were 113 km/h and 112 km/h, respectively. The simulation results of the gas-kinetic-based model for the first on ramp case are shown in Fig. 1. There was an evident speed slowing down near the ramp which was cased by the inlet flow of the on ramp.

Combing the model of the highway portion with the model of local road portion (Gong *et al.*, 2007c), four different models were obtained. Trip model I is the traffic data based highway portion model combining with simple local road model, trip model II is the traffic data based highway portion model combining with traffic signal based local road model, trip model III is the gas-kinetic based highway portion model combining with simple local road model, and trip model IV is the gas-kinetic based highway portion model combining with traffic signal based local road model. The comparison of the four trip models in time based plot is shown in figure 2.

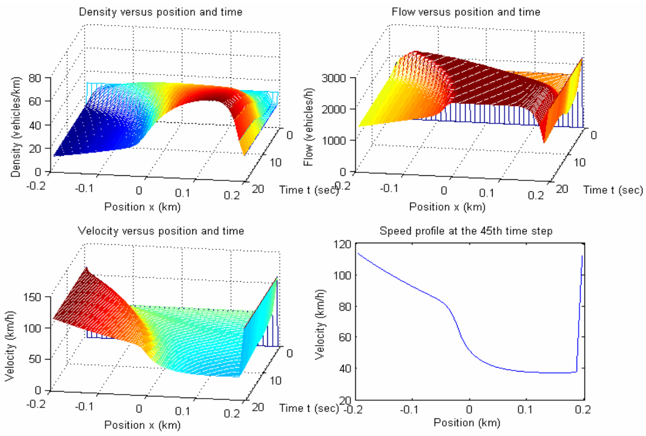

Fig. 1. Simulation results of the first on-ramp case

By using the gas-kinetic traffic flow model for the segments with on/off ramps, the trip model can describe the dynamic characteristics of the highway segments with on/off ramps. Usually synchronized traffic which is a common traffic congestion phenomenon happened near on ramps, where the on ramp vehicles try to merge into the already busy traffic, happens during the peak hours. Trip model using only traffic data on main road will miss such kind phenomenon near the ramps. The computation time for each short segment within one minute prediction is less then several seconds on a common Intel Pentium-IV PC, which makes the online calculation possible., since in our two scale DP the route is divided into segments (Gong *et al.*, 2007b).

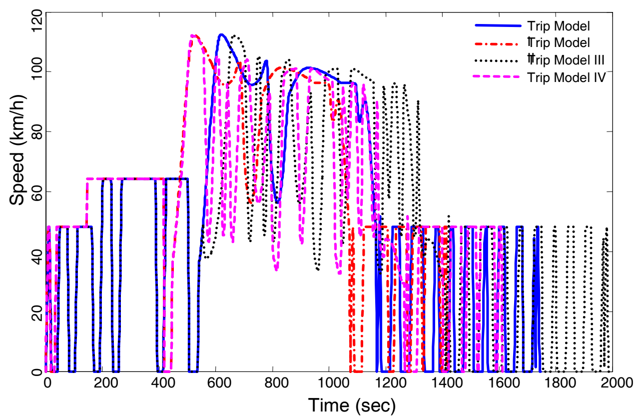

Fig. 2. Comparison of the four trip models

4. Simulation Results

4.1. Benefits of DP-Based Control

With the hybrid SUV model in (Gong *et al.*, 2007a), three power management strategies have been implemented: 1) the DP based charge-depletion control, 2) the rule-based control; and 3) the charge-depleting-then sustaining (simplified as "depletion-sustenance") control. The operation of the conventional SUV before hybridization has also been simulated as benchmark. The rule-based control strategy is obtained from the references (Baumann *et al.*, 2000; Lin *et al.*, 2003). The algorithms for depletion-sustenance are presented in Gong *et al.* (2007a). These four scenarios were simulated for the four trip models for the example route generated in the previous section. For all cases, the initial and terminal battery SOC's were selected to be 0.8 and 0.3, respectively. The power management of the conventional SUV, the rule-based control, the depletion- sustenance control and DP based charge-depletion control for the hybrid SUV were simulated for the four trip models.

For the four trip model, the results show that the SOC for the DP based charge-depletion control can deplete to 0.3 at the final time of the driving cycle, while for the rule-based control the terminal SOC were dropped only to 0.4916, 0.5205, 0.4633, 0.5047 respectively. For the depletion-sustenance control, the terminal SOC were 0.2947, 0.2861, 0.2999, and 0.2971, respectively. The fuel economy results are summarized in Table 1. For the four trip models, the fuel economy of DP based charge-depletion control is the best. Taking the average fuel economy as an example, the fuel economy of DP based charge-depletion control is 3.992 L/100 km, which has 54.9%and 55.9% improvement compared with rule-based control and the depletion-sustenance control respectively, and 61.1% improvement compared with conventional SUV. The standard deviation results also show the consistence of the DP based charge-depletion control results. The fuel economy of the gas-kinetic based model has a little worse fuel economy than only main road data based model, since the synchronized traffic was described in the gas-kinetic model which causes speed down and up in the highway portion. The results of model considering traffic lights signals for the local road portion have a little better improvement than the ones do not. The more accurate traffic model can be used for the prediction of the traffic for the power management of the PHEV system.

Table 1.Simulation results of fuel economy

Trip Models / Fuel Economy (L/100 km)	Trip Mode 1 I	Trip Mode 1 II	Trip Mode 1 III	Trip Mode 1 IV	Average	Standard Deviation
DP Charge-depletion	3.832	3.751	4.283	4.1	3.992	0.245
Depletion-Sustenance	8.7	7.8	10.3	9.4	9.05	1.06
Rule-based	8.7	8	9.6	9.1	8.85	0.676
Conventional	10.5	8.9	11.5	10.1	10.25	1.076

4.2. Two-Scale DP Simulation Results

Using the SOC profile of average historical traffic data based trip model as the macro SOC profile, and implement the two scale DP algorithm to the trip model III described above (gas kinetic based model for the highway portion, and simple model for local road). The detailed description of two-scale DP is in (Gong et *al.*, 2007b). The fuel economy result of the adapted approach is 4.677 L/100 km, which is 9.2% worth then the global optimal results of trip model III in Table 1. But the great benefit of this approach is the computation efficiency which is detailed discussed in our previous paper (Gong et *al.*, 2007b). The SOC profiles of the simulation results are shown in figure 3.

5. Conclusion

DP based optimal power management was carried out for a plug-in hybrid SUV, based on the usage of trip modelling to obtain the driving cycle. Trip modeling was approached differently for local road and freeway situations. Gas-kinetic based traffic modeling approach was used for freeway trip model, which can better describe the traffic dynamics for the freeway with on/off ramps. Four trip models have been simulated for four different scenarios: conventional SUV, hybrid SUV with rule-based control and the depletion-sustenance control, and hybrid SUV with the DP based charge-depletion control. The results have shown the significant improvement of fuel economy of the last method. Two-scale DP can get nearly optimal results while greatly reduce the computation time. The more accurate traffic model can be used for the prediction of the traffic for the power management of the PHEV system.

Since there are cars interactions exist on the road including the local road, so traffic signal may not enough for the traffic model for the local road. Car following model which describe the interaction of cars on the road may be studied in the next step for the trip modeling for the local road portion.

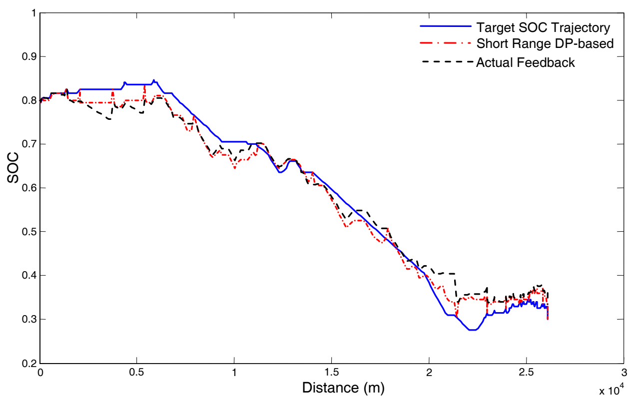

Fig. 3. SOC profiles of the two-scale DP simulation

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REFERENCES

Ahman, M. (2003). "Assessing the Future Competitiveness of Alternative Powertrains," *International Journal of Vehicle Design,* **33**(4), p 309-331

Baumann, B. M., Washington, G., Glenn, B. C. and Rizzoni, G. (2000). "Mechatronic Design and Control of Hybrid

Electric Vehicles," *IEEE/ASME Transactions on Mechatronics,* **5**(1), p 58-72

Brahma, A., Guezennec, Y. and Rizzoni, G. (2000). "Optimal Energy Management in Series Hybrid Electric Vehicles," *Proc. of the American Control Conference,* v 1, p 60-64.

Chan, C.C. (2002). "The State of the Art of Electric and Hybrid Vehicles," *Proc. of the IEEE,* **90**(2), p 247-275

de Dios Ortúzar, J. and Willumsen, L. G. (2001). Modelling Transport, 3rd edition. John Wiley & Sons.

Delprat, S., Lauber, J., Guerra, T. M. and Rimaux, J. (2004). "Control of a Parallel Hybrid Powertrain: Optimal Control," *IEEE Transactions on Vehicular Technology,* **53**(3), p 872-881

Ehsani, M., Gao Y., Gay, S. E., Emadi, A. (2004). Modern Electric, Hybrid Electric, and Fuel Cell Vehicles. *CRC Press.*

Emadi, A., Rajashekara, K., Williamson, S. S. and Lukic, S. M., (2005). "Topological Overview of Hybrid Electric and Fuel Cell Vehicular Power System Architectures and Configurations," *IEEE Transactions on Vehicular Technology,* **54** (3), p 763-770.

Gokasan, M., Bogosyan, S. and Goering, D. J. (2006). "Sliding Mode Based Powertrain Control for Efficiency Improvement in Series Hybrid-Electric Vehicles," *IEEE Transactions on Power Electronics,* **21** (3), p 779-790.

Gong, Q., Li, Y. and Peng, Z.-R. (2007a). "Optimal Power Management of Plug-in Hybrid Electric Vehicle with Intelligent Transportation Systems," *Proceedings of 2007 Int. Conf. for Advanced Intelligent Mechatronics.*

Gong, Q., Li, Y. and Peng, Z.-R. (2007b). "Trip Based Power Management of Plug-in Hybrid Electric Vehicle with Two-Scale Dynamic Programming," *Proc. of 2007 IEEE Vehicle Power and Propulsion Conference (VPPC)*

Gong, Q., Li, Y. and Peng, Z.-R. (2007c) "Optimal Power Management of Plug-in Hybrid Electric Vehicle with Trip Modeling," *IMECE2007-41638.*

Helbing, D.. (1996) "Derivation and empirical validation of a refined traffic flow model" *Physica A,* **233**(1-2), 253-282

Helbing, Dirk; Treiber, Martin. (1998) "Gas-kinetic-based traffic model explaining observed hysteretic phase transition," *Physical Review Letters,* v 81, n 14, p 3042

Helbing, Dirk; Treiber, Martin. (1999). "Numerical Simulation of Macroscopic Traffic Equations," *Computing in Science and Engineering,* **1** (5), p 89 - 99

Jeon, S.-I., Jo, S.-T., Park, Y.-I. and Lee, J.-M. (2002). "Multi-Mode Driving Control of a Parallel Hybrid Electric Vehicle Using Driving Pattern Recognition," *Journal of Dynamic Systems, Measurement and Control, Transactions of the ASME,* **124** (1), p 141-149.

Kerner, B.S.; Rehborn, H. (1997). "Experimental properties of phase transitions in traffic flow," *Physical Review Letters,* **79** (20), p 4030

Koot, M., Kessels, J. T. B. A., de Jager, B., Heemels, W. P. M. H., van den Bosch, P. P. J. and Steinbuch, M. (2005) "Energy Management Strategies for Vehicular Electric Power Systems," *IEEE Transactions on Vehicular Technology,* **54** (3), p 771-782

Langari, R. and Won, J.-S. (2005). "Intelligent Energy Management Agent for a Parallel Hybrid Vehicle - Part I: System Architecture and Design of the Driving Situation Identification Process," *IEEE Transactions on Vehicular Technology,* **54** (3), p 925-934.

Lin, C.-C., Peng, H., Grizzle, J. W. and Kang, J.-M. (2003). "Power Management Strategy for A Parallel Hybrid Electric Truck," *IEEE Transactions on Control Systems Technology,* Vol. 11, No. 6, p 839-849.

Lighthill, M.J., and G.B. Whitham (1955). On kinematic waves II: a theory of traffic flow on long, crowded roads. *Proceedings of the Royal Society of London,* series A, 229, 317-345.

McQueen B. and McQueen, J. (2003). *Intelligent Transportation Systems Architectures*. Artech House Publishers.

Musardo, C., Rizzoni, G., Guezennec, Y. and Staccia, B. (2005). "A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management," *European Journal of Control,* p 509-524.

M. Papageorgiou, C. Diakaki, V. Dinopoulou, A. Kotsialo, Y. Wang, "Review of Road Traffic Control Strategies," *Proc. of the IEEE*, **91** (12), p. 2043--2067, 2003.

National Renewable Energy Laboratory. ADVISOR 2.0 Help Documentation. 2002.

Ngoduy, D.; Hoogendoorn, Serge P.; Van Zuylen, H.J. (2006). "Continuum traffic model for freeway with on-And off-ramp to explain different traffic-congested states," *Transportation Research Record,* n 1965, Traffic Flow Theory, p 91-102

Peng, Z.-R. and Tsou M.-H. (2003). Internet GIS: Distributed Geographic Information Services for the Internet and Wireless Network. Wiley.

Perez, L. V., Bossio, G. R., Moitre, D. and Garcia, G. (2006). "Optimization of Power Management in an Hybrid Electric Vehicle Using Dynamic Programming," *Mathematics and Computers in Simulation,* Vol. 73, No. 1-4, Special. Issue, p 244-254.

Powell, B. K., Bailey, K. E. and Cikanek, S. R. (1998). "Dynamic Modeling and Control of Hybrid Electric Vehicle Powertrain Systems," *IEEE Control Systems Magazine,* 18 (5), p 17-33

Romm, J. J. and Frank, A. A. (2006). "Hybrid Vehicles Gain Traction," *Scientific American,* **294** (4), p 72-79.

Schouten, N. J., Salman, M. A. and Kheir, N. A. (2002). "Fuzzy Logic Control for Parallel Hybrid Vehicles", *IEEE Transactions on Control Systems Technology,* **10** (3), p 460-468

Sciarretta, A., Back, M. and Guzzella, L. (2004). "Optimal Control of Parallel Hybrid Electric Vehicles," *IEEE Transactions on Control Systems Technology,* **12** (3), p 352-363

Wisconsin Traffic Operations and Safety Laboratory. *http://transportal.cee.wisc.edu*.

Won, J.-S. and Langari, R. (2005). "Intelligent Energy Management Agent for a Parallel Hybrid Vehicle - Part II: Torque Distribution, Charge Sustenance Strategies, and Performance Results," *IEEE Transactions on Vehicular Technology,* **54** (3), p 935-953.

Zoelch, U. and Schroeder, D. (1998). "Dynamic Optimization Method for Design and Rating of the Components of a Hybrid Vehicle," *International Journal of Vehicle Design,* **19** (1), p 1-13.