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Trip-oriented Energy Management Control Strategy for Plug-in Hybrid Electric Vehicles

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Abstract— **This paper presents a trip-oriented Plug-in Hybrid Electric Vehicle (PHEV) energy management control (EMC) strategy that aims to improve the real world PHEV energy usage efficiency, economy and flexibility. The designed control architecture and methodologies enable the energy management control to utilize different levels of available trip foreknowledge, from as limited as distance between charges to as much as driving patterns, routing and real time traffic information, to optimize the onboard energy (fuel and electricity) usage. The proposed EMC first programs a battery SOC profile along a specific trip that governs an optimized energy consumption process with respect to a customer's energy usage budget and foreseeable trip information. Next, a feedback controller manages the fuel consumption to electricity depletion ratio to achieve the preplanned energy consumption process by following the SOC profile and controlling the PHEV powertrain to its most efficient admissible operating states.**

I. INTRODUCTION

A Plug-in Electric Hybrid Vehicles (PHEV) is an extension of existing hybrid electric vehicles (HEV) with added energy flexibility. A PHEV utilizes a larger capacity battery pack that can be recharged from the electric utility grid. With the additional source of energy supply, the control system can bias the PHEV towards electrical propulsion. It is regarded as one of the most promising technologies for sustainable mobility and emission reduction.

The achievement of PHEV's energy economy comes not only from the PHEV design and extended energy storage, but also from the PHEV energy management control strategy. The PHEV energy management control problem is generally similar to that of the HEVs, with the main objective of minimizing energy cost and emissions without compromising the vehicle drivability and system constraints. A default EMC operates the PHEV in electric drive (EV) mode or in blended operation mode to maximize the battery depletion before the next plug-in recharge event without differentiation on usage patterns. Thanks to the intelligent transportation and information systems, knowledge about a trip and a customer's usage pattern becomes available to the vehicle controls. The achievement of the PHEV energy management control objective is no longer just to optimize the system efficiency with minimized instantaneous operating power loss, but to find a customer and trip oriented solution that optimizes the energy consumption in a globally manner with respect to a customized energy replenish lifestyle. As claimed in [1], [2], [14] and [13], a PHEV energy management strategy that incorporates the trip distance information can achieve better fuel economy by allowing an extended scale of system optimization.

In literature, the PHEV energy optimization is mainly developed along two parallel pathes [4]. The first applies dynamic programming (DP) to determine the optimal powertrain operating states and the energy consumption distribution between the fuel and the electricity based on a full trip knowledge [7]. The DP based PHEV energy management control is mainly used to explore the energy economy potential offline due to its non-causal nature and heavy computation loads. The insights obtained from a DP control process can serve as a guideline for rule based control design and calibrations [22]. In paper [19], a comparison is made between the performances of an electric-centric charge-depleting hybrid vehicle control strategy with a near-optimal DP-optimized control strategy. The second path works on online implementable PHEV energy management control rules. A well known method is the Equivalent Consumption Minimization Strategy (ECMS). This strategy was originated by Paganelli et al. [11] [6] [8] and other researchers [10] based on the concept of instantaneous equivalent fuel consumption. Theoretically based on Pontryagin's Minimum Principle, this method provides a metric such that the fuel energy and the battery electric energy consumption can be evaluated simultaneously towards a global optimization objective. An adaptive ECMS control strategy was proposed in [9], [23] and [24] that incorporated real time driving cycle information into the adjustment of the ECMS control setpoint. A stochastic optimal control based PHEV energy management appeared in reference [5]. While a DP based solution can realize an optimal energy management process using full trip knowledge for one specific trip, the result can not be applied online to real world driving cycles. On the other hand, the afore-mentioned implementable energy management methods assume no trip foreknowledge or just a short range preview information but their optimality in control is only valid with respect to an averaged customer usage or driving patterns.

Applying optimal control theory, this paper presents a Trip-oriented Energy Management Control (TEMC) strategy that further optimizes the trip specific PHEV energy economy given scalable trip foreknowledge. The proposed TEMC strategy fills in the gap between the DP and the rule based methods by providing a systematic control architecture that is able to optimize PHEV energy management using limited available trip information. The trip oriented energy management problem is solved at two levels of optimization. At the

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higher level, i.e. the trip domain optimization, a global energy usage/consumption optimization is carried out such that the battery electric energy and the fuel usage is pre-planned based on scalable trip foreknowledge and energy storage states. An optimal trip domain battery SOC depletion/usage profile is generated, which serves as a feedforward guideline for the PHEV online energy management control towards global energy economy improvement over a given driving schedule. Next, the trip-specific optimal fuel consumption to electricity depletion ratio index is adaptively searched online through a feedback control mechanism such that the overall controlled energy consumption process achieves approximately the preplanned optimal process. At the vehicle system level, the most efficient PHEV system power split state and power sourcing state are optimally resolved for the Ford PowerSplit PHEV with respect to vehicle states, system constraints and the trip domain energy consumption ratio index. Such a proposed control architecture is depicted later in Figure 4.

Due to space limit, this paper focuses on the the vehicle domain optimization and the trip domain feedback control with respect to a reference SOC profile. The concept about the trip domain feedforward SOC reference generation is only briefly introduced. More comprehensive results about the driving pattern based energy preplanning using DP algorithm are presented in a separated paper [21]. This paper is organized as follows: The PHEV system model for energy management control is provided in section II; The trip domain PHEV energy management optimization that maximizes power delivery efficiency and minimizes trip fuel consumption is presented in section III; Based on that, the trip oriented PHEV energy management control strategy is proposed and described in section IV. Simulation results using the Ford PowerSplit PHEV Model-in-loop (MIL) platform are discussed in section V to validate the effectiveness of the proposed TEMC strategy for PHEV fuel economy improvement using customized driving cycles. Finally, the contributions and conclusions of the work are summarized in section VI.

II. PHEV System Configuration and Energy Management Control Model

In this study, a Ford PowerSplit Plug-in Escape is used as the platform for studies and simulations. Figure 1 portrays the main components and configuration of the electrified powertrain architecture considered in this paper. A comprehensive description of the PowerSplit HEV structure and model can be found in [4] [20]. In this study, the following PowerSplit HEV powertrain model is used:

$$J_{eng}\frac{d\omega_{eng}}{dt} = \tau_{eng} + T_{e2g}\tau_{sun} \qquad (1)$$

$$J_{mot}\frac{d\omega_{mot}}{dt} = \tau_{mot} - \frac{T_1T_2}{\varrho}\tau_{sun} - \frac{T_2}{T_g}\tau_{dft} \qquad (2)$$

$$J_{gen}\frac{d\omega_{gen}}{dt} = \tau_{gen} - \tau_{sun} \qquad (3)$$

where J_i are inertias, τ_i are torques and T terms are speed and torque transfer ratio between driveline components.

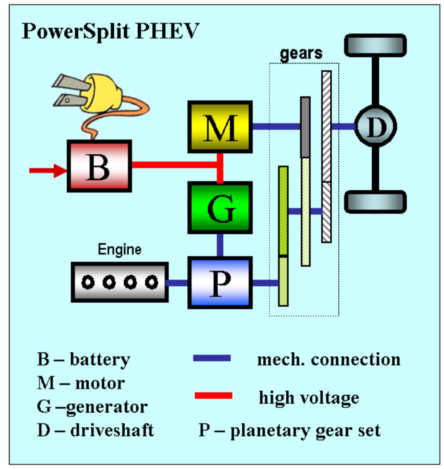

Fig. 1. PowerSplit PHEV configuration

Subscript $i = eng, mot, gen$ indicate the engine, motor and generator respectively.

Kinematic relationships:

$$\omega_{dft} = \frac{T_2}{T_g}\omega_{mot} \qquad (4)$$

$$\omega_{gen} = \frac{(1+\varrho)}{\varrho}\omega_{eng} - \frac{T_1T_2}{\varrho}\omega_{mot} \qquad (5)$$

Power relationships:

$$P_{whl} = P_{fuel} + P_{batt} - P_{loss} \qquad (6)$$

$$= \tau_{dft}\omega_{dft}$$

$$P_{loss} = P_{epath\_loss} + P_{ice\_loss} \qquad (7)$$

$$P_{epath_{l}oss} = P_{batt} - \omega_{gen}\tau_{gen} - \omega_{mot}\tau_{mot} \qquad (8)$$

$$= P_{mot\_loss} + P_{gen\_loss} + P_{elec\_loss} \qquad (9)$$

$$P_{mot\_loss} = f_lm(\omega_{mot}, \tau_{mot}) \qquad (10)$$

$$P_{gen\_loss} = f_lg(\omega_{gen}, \tau_{gen}) \qquad (11)$$

$$P_{ice\_loss} = P_{fuel}(\dot{m}_f(\omega_{eng}, \tau_{eng})) - P_{eng} \qquad (12)$$

ω represents rotational speed and ϱ is the planetary gear ratio. The mechanical power transfer loss is ignored in this study since the ICE engine loss P_{ice_loss} and the electrical power transfer loss P_{epath_loss} dominate the total power loss in PHEV operations. In the above equations, P_{whl} is the drive power request at wheels. P_{fuel} is the total power supplied from the fuel at current fuel flow rate. P_{batt} is the battery power that takes positive sign for discharge and negative sign for charge. P_{loss} is the PHEV system power transfer loss. The overall PHEV system's operating point is externally determined by the driveshaft torque τ_{dft} that is propelling the vehicle at the current driveshaft rotational speed ω_{dft}.

Define the high voltage battery capacity, Q_{batt}. The battery electric dynamic model is:

$$\dot{SOC} = f_\beta(P_{batt}) = -\frac{P_{batt}}{Q_{batt}V_{oc}^h\eta} \qquad (13)$$

where V_{oc}^h is the nominal battery open circuit voltage at the highest SOC level. η is defined as the equivalent battery discharge power efficiency representing the useful battery power ratio to the total battery power consumption at degraded battery open circuit voltage level. η is battery SOC dependent [20].

The system subjects to the following operation constraints:

$$\mathcal{C}(X)=\left\{\begin{array}{c}\omega_{i\_min}\leq\omega_i\leq\omega_{i\_max}\\ \tau_{i\_min}\leq\tau_i\leq\tau_{i\_max}\\ SOC_{min}\leq SOC\leq SOC_{max}\\ P_{elec\_chg\_lim}\leq P_{batt}\leq P_{elec\_dch\_lim}\end{array}\right\}$$

where $i=eng,mot,gen$. $P_{elec\_chg\_lim}$ and $P_{elec\_dch\_lim}$ are electrical power discharge and charge limits at certain battery SOC levels. The engine pull up and pull down strategy is primarily determined with respect to a vehicle speed, drive power demand, and battery SOC thresholds.

III. Trip Domain PHEV Energy Management Optimization

In the trip domain, the analysis focuses on the battery SOC dynamic $x(s)=SOC$ and the steady state control input $u(s)=P_{batt}$. The system equation is rewritten as:

$$\frac{dx}{ds}=\frac{f_\beta(u)}{V_{veh}}=f_\beta^s(u) \tag{14}$$

where s is the trip domain distance variable and the superscript s indicates a trip domain function.

The trip domain fuel economy optimization problem can be formulated as: find the optimal power sourcing state $u^*(s)$ and determine steady state power split state $\omega_{eng}(s)$ with respect to given $\omega_{dft}(s)$ and $\tau_{dft}(s)$, $s\in[s_0,s_f]$, such that

$$\min_{u,\omega_{eng}\in\mathcal{C}} J \;=\; S(x(s_f))+\int_{s_0}^{s_f} v(\omega_{eng},u)ds \tag{15}$$

where

$$\begin{aligned}S(x(s_f)) &= \begin{cases} c_f(x(s_f)-x_{cs})^2, & if\ x(s_f)-x_{cs}\leq 0\\ 0, & else\end{cases}\\ v(\omega_{eng},u) &= \frac{dm_f}{ds}=\left.\frac{\dot{m}_f}{V_{veh}}\right|_{\omega_{eng},u}\end{aligned}$$

$S(x(s_f))$ is the terminal cost on SOC at the end of the trip and x_{cs} is the predetermined nominal battery SOC level for default charge sustaining operation. $\dot{m}_f$ is the instantaneous fuel flow when the vehicle is moving, $V_{veh}>0$. The interval $[s_f-s_0]$, where $s_f=s(t_f)$ and $s_0=s(t_0)$, is the total trip distance. This paper focuses on the PHEV energy management in the range of usable battery DOD, it is assumed that battery charge sustaining operation is assured after battery is depleted for convenience of analysis.

Propostion 0.1: An optimal solution to this quasi-steady state optimization problem is the optimal trip domain battery power trace $u^*(s)$ and corresponding system operating setpoint $\omega^*_{eng}(s)$ that minimizes a constantly indexed tradeoff function of the trip domain fuel consumption rate and the battery electricity depletion rate.

Proof: Based on the optimization objective function (15) and the system constraints $\mathcal{C}(X)$, the Hamiltonian of the optimization problem is:

$$H(s,\lambda)=v(\omega_{eng},u)-\lambda(s)f_\beta^s(u) \tag{16}$$

where λ is the optimization costate variable.

Applying Pontryagin's Minimum Principle to this constraint optimization problem, the costate dynamic along the optimal SOC trajectory satisfies:

$$\begin{aligned}\dot{\lambda}^*(s) &= -\left.\frac{\partial H}{\partial x}\right|_{x^*}=\lambda^*(s)\frac{\partial}{\partial x}f_\beta^s(u^*)\\ &= -\lambda^*(s)\frac{u^*}{V_{veh}Q_{batt}V_{oc}^h\eta^2}\frac{\partial\eta}{\partial x}\end{aligned} \tag{17}$$

$$[u^*(s),\omega^*_{eng}(s)] \;=\; \arg\min_{u,\omega_{eng}\in\mathcal{C}} H(s)|_{\lambda^*} \tag{18}$$

The optimal control problem specified by equation (17) and (18) can be solved using DP method. However, it is difficult to find analytic optimization solution across the battery SOC range due to the inter-dependence of the optimal control u^* and the costate λ^*. Instead, the problem can be solved in a local small SOC interval by applying zero order η-approximation with respect to the battery SOC state, i.e. $\partial^n\eta/\partial x^n=0$ for $n=1,2,3,\ldots$, such that:

$$\dot{\lambda}^*(s)=0,\quad \lambda^*=const. \tag{19}$$

The above equation indicates that the optimal costate λ^* with respect to steady state $\omega_{dft}(s)$ and $\tau_{dft}(s)$, $s\in[s_0,s_f]$, is constant if ignoring the effect of battery SOC on the equivalent battery discharge power efficiency in a local SOC region. This is a reasonable simplification since $\partial\eta/\partial x$ is actually very small in the usable depletion range of battery SOC.

At steady state, the trip-domain fuel consumption rate is determined if only P_{batt} and ω_{eng} is resolved. As a result, the original optimization problem can be simplified to:

$$\begin{aligned}[u^*(s),\omega^*_{eng}(s)] &= \arg\min_{u,\omega_{eng}\in\mathcal{C}} H(s)|_{\lambda^*} \\ &= \arg\min_{u,\omega_{eng}\in\mathcal{C}}\frac{1}{V_{veh}}\left(\dot{m}_f+\frac{\lambda^*}{\eta(x)}\frac{u}{Q_{batt}V_{oc}^h}\right)\\ &= \arg\min_{u,\omega_{eng}\in\mathcal{C}}\left(\dot{m}_f^s-\lambda^*\dot{SOC}^s\right)\end{aligned} \tag{20}$$

where $\dot{m}_f^s$ and $\dot{SOC}^s$ represents the trip domain fuel consumption rate and battery SOC depletion rate, respectively. ■

A. Boundary Layer PHEV Power Split Optimization

In the boundary layer time scale, P_{batt} and SOC are slow dynamics. They are treated as in their steady state such that the second term of the Hamiltonian is constant with respect to a constant costate λ. Since the boundary dynamic is stable in $\mathcal{C}$, the optimal control problem is simplified to be an optimal system operating setpoint search problem over the range of drive power request, vehicle speed and power sourcing state determined by P_{batt}. That is, an optimal PHEV power split state, which is determined by ω_{eng}, has to be found to minimize the instantaneous fuel consumption:

$$\omega^*_{eng}|_{u,\tau_{dft},\omega_{dft}}=\arg\min_{\omega_{eng}\in\mathcal{C}} H(s)=\arg\min_{\omega_{eng}\in\mathcal{C}}\dot{m}_f^s|_u \tag{21}$$

This is equivalent to finding the most efficient power split state between the electrical path and the mechanical path such that the powertrain output power for vehicle propulsion is maximized:

$$\max_{\omega_{eng}\in\mathcal{C}} J_1 = \eta_{sys}(\omega_{eng})|_{\omega_{dft},\tau_{dft},P_{batt}} = \frac{P_{whl}}{P_{fuel}+P_{batt}} \quad (22)$$

The PHEV steady state operation optimization is carried out offline based on the system configuration and components' parameters. Optimal ω_{eng} is resolved with respect to each combination of vehicle speed, drive power request and at a candidate battery power value. A library of ω^*_{eng} maps are obtained across a set of admissible battery power values. Among them, an exemplary ω^*_{eng} maps at sourcing states $P_{batt} = 0\ kW$ is shown in Figure 2.

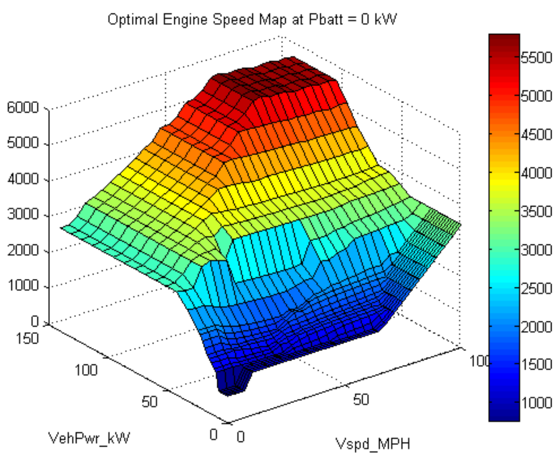

Fig. 2. Optimal engine speed map at 0 kW battery discharge power state

The PHEV power split optimization prepares the PHEV energy management control for solving a higher level drive power demand distribution problem with guaranteed most efficient powertrain operations.

B. Quasi-Steady State PHEV Power Sourcing Optimization

After the battery power associated PHEV system operating state ω_{eng} has been optimally determined, the steady state system optimization has to be carried out in order to determine the best driver power allocation command such that the Hamiltonian is minimized in the quasi-steady state time scale:

$$\begin{aligned} u^*(s) &= \arg\min_{u|_{\omega^*_{eng}}\in\mathcal{C}} H(s)|_\lambda \qquad (23)\\ &= \arg\min_{u|_{\omega^*_{eng}}\in\mathcal{C}} \left(\dot{m}^s_f(u) + \frac{\lambda}{\eta(x)}\frac{u}{Q_{batt}V_{veh}V^h_{oc}}\right)\Bigg|_{\omega_{dft},\tau_{dft}} \end{aligned}$$

Equation (23) indicates that the PHEV power sourcing optimization has to be carried out with respect to a given value of the fuel consumption rate to electricity depletion rate index ratio λ.

Given a drive power demand and vehicle speed, the optimal battery power can be calculated by comparing all the possible options and selecting the optimal one that achieves the Hamiltonian minimization with respect to a certain costate value. Such an optimal search process has to be repeated for each candidate value over an admissible λ set offline. Furthermore, according to equation (23), the equivalent battery efficiency η adjusts the weight of the energy consumption ratio index λ at different battery SOC levels. From the proof of Proposition 0.1, η is approximated by a constant in small battery SOC regions and it takes different values in different SOC states. As a result, the above optimization programming has to be repetitively executed in all partitioned intervals of battery SOC with different nominal values of η to incorporate the effect of battery equivalent discharge efficiency. This results in a library of optimal P_{batt} vs. $(P_{whl},\ V_{veh})$ maps with respect to λ and SOC. The contribution of the proposed method is that it solves the optimal control problem without ignoring the η-SOC nonlinearity even though it does not appear in the analytic solution. Such a η-SOC dependency is reintroduced back by carrying out optimization programming in each partitioned battery SOC interval. By embedding the battery efficiency into the power sourcing optimization results, a constant optimal λ^* can thus be used for specific trips. The optimal battery power maps over a set of nominal λ values, $(2\sim 4)$, are depicted in Figure 3. According to the optimization results, it is observed that the larger the value of λ, which means the higher the ratio of fuel consumption rate to the battery depletion rate, the less the drive power is to be satisfied by the battery electric energy.

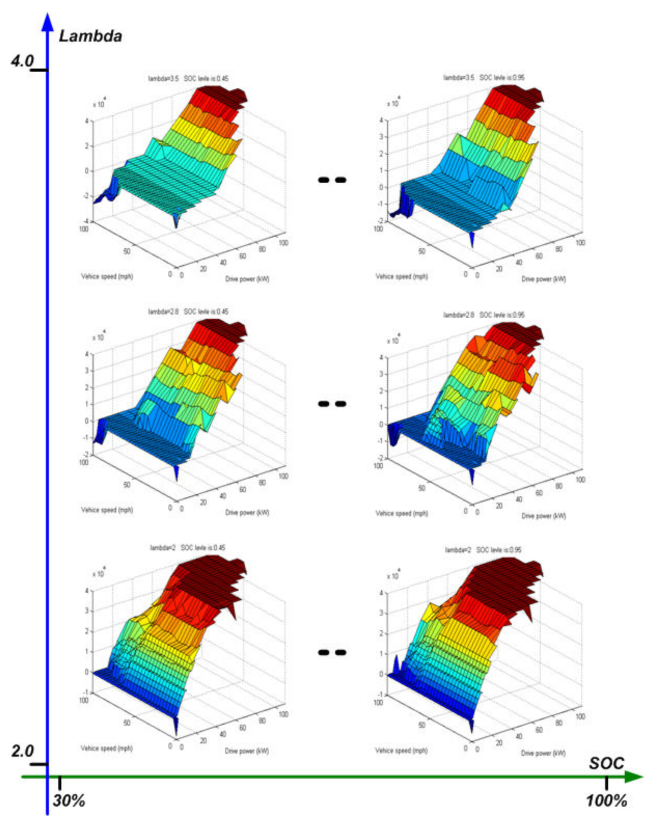

Fig. 3. Optimal battery discharge power evaluated at different costate and SOC values

IV. Trip-oriented Energy Management Control

The power-split and power-sourcing optimization results prepare the PHEV energy management control for achieving the fuel consumption minimization objective by selecting the best battery power and engine power partition at the most efficient system operating state with respect to instantaneous drive power demand in the vehicle operating speed range. However, all the maps are obtained with respect to a specific value of λ^* from the candidate λ set. The results can only be useful if the value of λ^* is known for a target trip. Given limited trip information a priori, especially when only trip distance is known, predetermination of the trip specific optimal value λ^* is impossible. The only realistic method to solve this problem is to search for a quasi-optimal value of λ^* based on the already experienced trip knowledge after a target trip has started and by assuming such knowledge will persist to the rest of the trip. To this end, a λ^* searching strategy needs to be constructed.

With only knowledge of the driving distance between charges S_{ccd}, the best assumption that can be made for a future trip is that it contains a single driving pattern. That is, the driving process contains relatively consistent drive power demand at almost constant vehicle speed. For such a simplified driving cycle, it had been proved [20] that the optimal battery SOC trace will exhibit a nearly linear trajectory, called the battery efficient CD (charge depletion) profile, in the spatial domain. This SOC profile starts depleting at the initial SOC until reaching the charge sustaining SOC near the end of the trip and it is plotted as the green curve in Figure 5. Alternative, without considering the battery discharge efficiency variation across the range of SOC, a linear trajectory, called trip averaging CD profile, is commonly used for simplicity.

Using such a SOC depletion process as the target optimal process, a feedback control strategy can be designed to adjust the setpoint of λ used in EMC such that the real battery SOC trajectory following the reference SOC profile in an asymptotically stable manner. The control strategy proposed in this paper is called Trip-oriented Energy Management control (TEMC). The trip specific optimal energy management solution is thus found reversely by using λ as a control variable. By doing this, it is expected that the controlled energy consumption process can approximate the optimal fuel economy process by adaptively searching for the unknown trip-dependent λ^*. The TEMC strategy implements a feedforward plus feedback control structure as shown in Figure 4. The feedback controller continuously adjust the energy optimization setpoint λ according to the current power load vs. the energy usage budget. As a result, the battery SOC is maintained within a vicinity of the reference SOC profile such that the global fuel consumption minimization target is achieved by adapting to the past and the predicted energy usage demands. In general, the TEMC strategy provide a systematic method of realizing a trip domain quasi-optimal control process without having the knowledge of λ^* a priori. The energy consumption ratio λ is controlled in the spatial domain as:

$$\Delta\lambda = \lambda(k) - \lambda(k-1) = Ct_{fb}(soc_{ref}(s) - SOC(s)) \quad (24)$$

where $\lambda(k)$ is the value of lambda in spatial domain control station $k\Delta s \leq s < (k+1)\Delta s$. Δs is the station length. Similar control updating law but implemented in time domain also appeared in [23] and [24]. Ct_{fb} represents a set of feedback control functions that can be designed with different reference tracking algorithms, among which, a PID controller is commonly used.

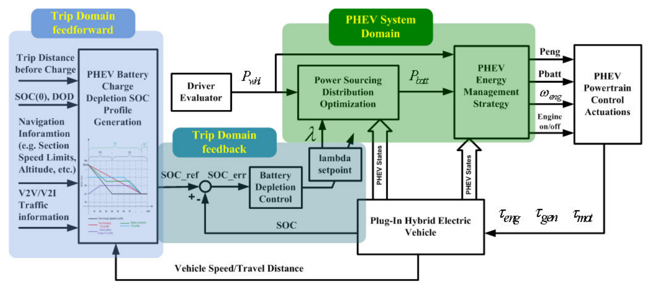

Fig. 4. Conceptual trip-oriented energy management control structure

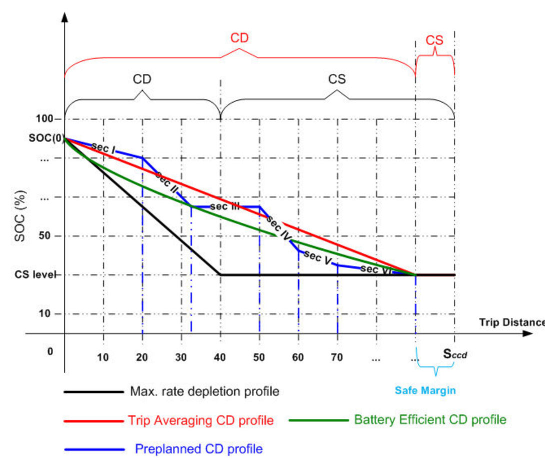

Fig. 5. Candidate reference battery SOC depletion profiles

When additional trip information is known a priori, a better optimized reference SOC profile can be generated through driving pattern based trip domain dynamic programming. The optimality of such trip oriented energy consumption plan depends on the amount of trip foreknowledge used. The better availability of the trip information, the closer the preplanned SOC profile is to the true optimal SOC depletion process. The proposed TEMC strategy is able to synthesize scalable trip foreknowledge by applying driving pattern classification and association methods. A driving pattern characterizes certain properties of driving behaviors, especially on drive power demand. Technically, the driving pattern defined for this research is the Probability Mass Function (PMF) of the the Spatial Domain Normalized Drive Power (S-NDP). The concept of S-NDP is developed as follows: for a trip partitioned into p interconnected sections of different driving behaviors, the total energy demand can be evaluated by the following equation:

$$\begin{aligned} E_{prop} &= \int_0^T P_{whl} dt = \Sigma_{i=1}^p \int_0^{T_i} P_{whl}^i dt \\ &= \int_0^{S_{ccd}} P_{sn} ds = \Sigma_{i=1}^p \int_0^{S_i} P_{sn}^i ds \\ &= P_{set}^{sn} \Sigma_{i=1}^p \wp_i(P_{set}^{sn}) S_i \end{aligned} \quad (25)$$

where P_{whl} is the time domain drive power demand. T is the total trip time duration. Variables with index i indicates the corresponding signals in the i-th section along the trip. Equation (25) translates the time domain energy consumption to the spatial domain where S is the section distance and P_{sn} denotes the spatial domain normalized drive power:

$$P_{sn} = P_{whl}/V_{veh} \quad (26)$$

$\wp(P_{set}^{sn})$ denotes a PMF with respect to a predefined discrete S-NDP set P_{set}^{sn}. Generically, it represents the equivalent wheel force distribution during a period of driving process. The S-NDP distribution is an effective mathematic model to find the consistency among various driving behaviors. For example, the S-NDP distribution for some standard emission test cycles, California Unified (CA), IM240, JP-JC08, NYCC, CSC, FTP72, FTP75, JP-JE05, FTP-SC03 and UDDS, are plotted in Figure 6. Based on their S-NDP property and average speed, it is easy to identify their commonality in drive demand and to classify them into different driving patterns even though their time domain profiles are very different and do not provide any identity to associate them together.

The advantage of the proposed driving pattern based method is its capability to capture countless different driving behaviors (e.g. speed/power profiles) into a limited number of driving patterns. As a result, the time-consuming PHEV energy consumption optimization can be first achieved offline by carrying out full scale system dynamics based DP optimization with respect to representative full trip information for each identified driving pattern. A library of driving patterns and their corresponding energy consumption characteristic tables will thus be established. The trip information and optimization results can be reused to real world and real time driving processes that are associated to a common driving pattern. In online application, a predicted trip is first partitioned into a sequence of spatial domain driving sections where a driving pattern is identified for each of them. Next, a trip specific global energy consumption preplanning needs only be done by a much simplified DP algorithm to allocate different amount of available electric energy to the limited number of sections. The most heavy computation load associated to PHEV system dynamics is separatively processed in offline optimization. The online optimal energy allocation programming needs only be carried out over a grid of spatial domain sections instead of time steps. The size of the optimization space is largely reduced. Furthermore, the energy cost at each step is directly obtained from the offline programmed characteristic consumption tables based on identified driving patterns along the trip. The proposed two step optimization technique significantly minimizes the online computational resource and information accessibility requirements and costs. Thus, it enables the online implementation of the proposed PHEV energy consumption optimization strategy with respect to scalable trip foreknowledge. An exemplary pattern based optimal SOC profile preplanned is plotted as the blue piecewise liner trajectory in Figure 5. Interested reader can refer to [21] for more comprehensive description about this pattern based global energy preplanning technology.

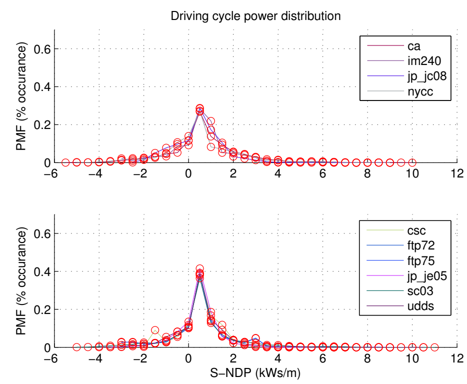

Fig. 6. S-NDP distribution for stop-and-go and low speed city patterns

V. Simulation Analysis and Verification

The proposed TEMC strategy had been validated through both simulation study on the Ford PowerSplit PHEV MIL platform and vehicle tests. However, only simulation results will be presented in this paper. The first group of simulation cases assume only the knowledge of the charge cycle distance. The optimal battery power is determined from the optimal power sourcing maps with respect to the controlled λ setpoint such that a nearly consistent battery electricity depletion rate is maintained with respect to the total trip distance. A default PHEV energy management strategy without incorporating any trip information is also used in the simulation studies for comparison purposes. The default strategy applied a fixed constant λ value that is calibrated to achieve a 35 mile PER in FTP cycle at near maximal rate of depletion. It is important to point out that the TEMC strategy retains the same engine on/off criteria as the default control strategy in the reported results in order to focus on the energy consumption optimization effectiveness.

TABLE I
FUEL ECONOMY IMPROVEMENT ON CUSTOMIZED DRIVING CYCLES

#	S_{ccd} (km)	SOC (%)	Cycle Sequence [1 2 3]	Base FC(kg)	TEMC FC(kg)	FEI
1	120	75	[322122123]	5.73	5.40	5.65%
2	128	87	[311221213]	5.20	4.94	4.78%
3	160	97	[31122112113]	6.55	6.23	4.6%
4	160	95	[322122112233]	7.41	6.97	5.9%
5	96	60	[3221223]	4.44	4.24	5.59%

The first group of simulation used driving cycles constructed from arbitrarily combining three standard test cycles: 1. HWYFET; 2. US06; 3. FTP72. The simulation results provided insights about the TEMC real-world application potential in fuel economy (FE) improvement. Table I summarized 5 example simulation cases. More than 2% to 7% fuel economy improvement (FEI) had been observed in the artificial cycle simulations. The controlled process from the first simulation case with a 120 km trip distance and 75% initial battery SOC were presented in Figure 7. For this simulation case, it can be identified through offline programming that $\lambda^* = 2.83$. The TEMC controlled λ setpoint converged to the λ^* adaptively and asymptotically. Throughout the adaptive searching process, the fuel economy obtained from the TEMC controlled process was only 0.87% worse than that from the λ^* trace, which has total fuel consumed (FC) $5.40\ kg$. But it achieved 5.65% fuel economy improvement by using only trip distance information.

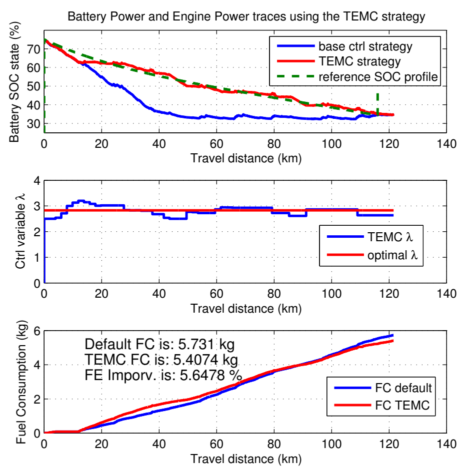

Fig. 7. Artificial combined cycle simulation results

Given additional trip information, a real life commuting cycle, shown in Figure 8, was used to verify the pattern based global SOC preplanning. Regarding it as a predictive speed profile, this trip was partitioned into five sequential sections by a pattern based trip partitioning algorithm. The first, third and fifth sections were linked to a low speed city pattern and the second and fourth sections were related to a high speed freeway pattern. The preplanned optimal SOC profile and its associated feedforward λ setpoint preplanned from the energy allocation DP algorithm were plotted in Figure 9. It is necessary to point out that the preplanned λ setpoint was not nearly constant because λ was also used to control the powertrain operating mode (EV vs. HEV) besides indicating power sourcing ratio. An EV operating mode was preferred when the reference λ took smaller value.

Applying the optimally planned SOC profile to the TEMC control strategy, the simulation results from the customer commuting cycle were shown in figures 10 to 12. For the same test cycle, the base control strategy had a total fuel consumption of $7.92\ kg$. The TEMC using the battery efficient SOC profile assuming known charge cycle distance consumed $7.4\ kg$, which realized a 6.73% fuel economy improvement. The TEMC using the preplanned SOC profile assuming driving pattern information consumed $7.29\ kg$, which realized a 7.93% fuel economy improvement. It can be observed from Figure 11 and Figure 12 that the engine operating efficiency from the TEMC controlled trace had been largely elevated with more operating points distributed to the high efficiency region.

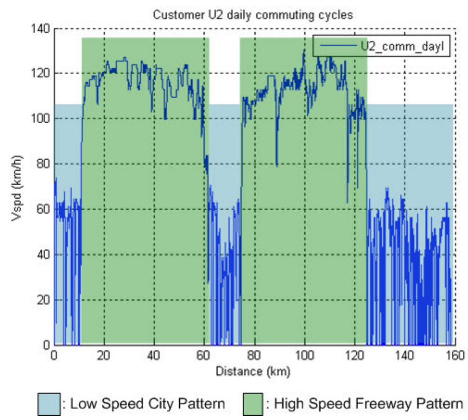

Fig. 8. Customer commuting cycle and driving pattern classification

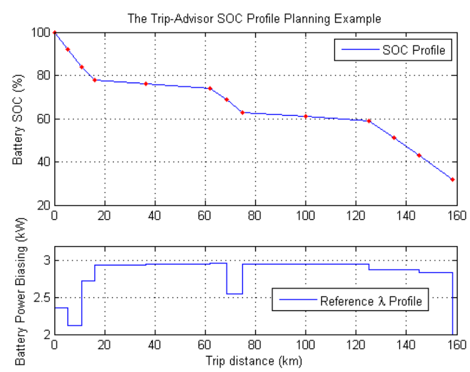

Fig. 9. Battery SOC profile preplanned from trip domain energy allocation DP

VI. CONCLUSIONS

This paper presents a PHEV energy management control strategy that aims to improve real world fuel economy and energy usage flexibility. The success of the proposed energy management strategy assumes scalable trip foreknowledge from only charge cycle distance to more trip and drive behavior information in order to shape driving patterns. By optimally distribute the battery electric energy to the whole trip, the system operation efficiency is further elevated by taking advantage of sufficient e-drive assistance throughout the driving process. The proposed TEMC strategy was validated through simulation based verification tests with demonstrated fuel economy improvement results.

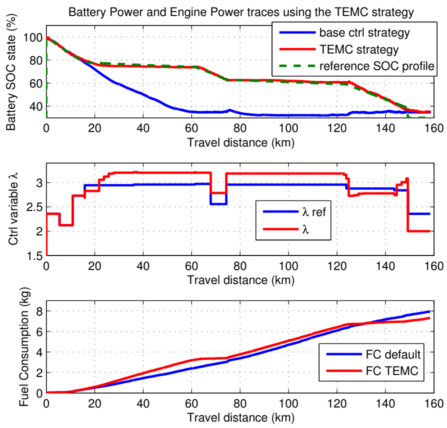

Fig. 10. Customer cycle simulation results using SOC preplanning

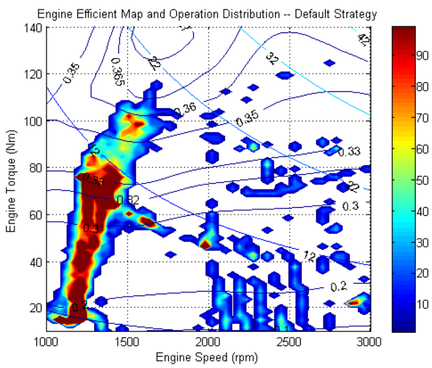

Fig. 11. Engine operation distribution from the default control strategy

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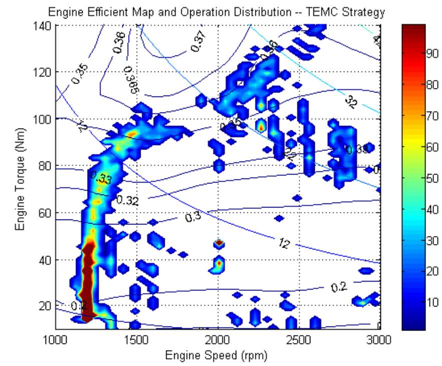

Fig. 12. Engine operation distribution from the TEMC strategy with preplanned SOC profile

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