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–Demonstration–

A COMPARATIVE ANALYSIS OF ROUTE-BASED ENERGY MANAGEMENT SYSTEMS FOR PHEVs

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ABSTRACT

Plug-in hybrid electric vehicle (PHEV) development seems to be essential step on the path to widespread deployment of electric vehicles (EVs) as the zero-emission solution for the future of transportation. Because of their larger battery pack in comparison to conventional hybrid electic vehicles (HEVs), they offer longer electric range which leads to a superior fuel economy performance. Advanced energy management systems (EMSs) use vehicle trip information to enhance a PHEV's performance. In this study, the performance of two optimal control approaches, model predictive control (MPC) and adaptive equivalent consumption minimization strategy (A-ECMS), for designing an EMS for different levels of trip information are compared. The resulting EMSs are fine-tuned for the Toyota Prius plug-in hybrid powertrain and their performances are evaluated by using a high-fidelity simulation model in the Autonomie software. The results of simulation show that both MPC and A-ECMS can approximately improve fuel economy up to 10% compared to the baseline Autonomie controller for EPA urban and highway drive cycles. Although both EMSs can be implemented in real time, A-ECMS is 15% faster than MPC. Moreover, it is shown that the engine operating points are more sensitive to the battery depletion pattern than to different driving schedules.

Key Words: *Plug-in hybrid electric vehicle*, *Energy management system*, *Model Predictive Control*, *Adaptive equivalent consumption minimization strategy*

I. INTRODUCTION

Stringent environmental standards and rising fuel costs have made the development of the hybrid electric vehicle (HEV) and plug-in hybrid electric vehicle (PHEV) inevitable as viable alternatives to internal combustion engine (ICE) powered vehicles. A hybrid electric powertrain consists of two propulsion systems: an ICE and an electric drive system. To optimize the energy flow between two power sources, an energy management system (EMS) is used. This EMS makes use of the onboard electric drive system for minimizing the hybrid vehicle environmental footprint, while maintaining its drivability performance [1].

EMSs for HEV/ PHEVs can be categorized in two major classes: reactive and route-based. The reactive EMS schemes generate approximate optimal solutions for the problem, since they only use the current driving conditions. For instance, rule-based controllers, charge depleting charge sustenance (CDCS) strategy, and equivalent consumption minimization strategy (ECMS) are reactive control schemes. On the other hand, route-based EMSs use the driving schedule information to

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enhance the performance of the controller.

Several optimal control methods for route-based energy management schemes were studied in the literature [2], including: dynamic programming (DP), Pontryagin's minimum principle (PMP),model predictive control (MPC), and Adaptive ECMS (A-ECMS). DP suggests a global optimal solution to the vehicle's energy management problem [3, 4], but it is not real-time implementable. Lin et al. [5] have found near-optimal rules for a parallel HEV EMS by using DP, and improved the fuel economy and emissions performance of the vehicle. A two-scale DP method is used for optimal EMS design in [6, 7, 8], where the power demand is calculated according to the prior knowledge from the trip, and the best battery depletion profile is derived using a simple model of the battery.

Razavian et al. [9, 10] have developed a real-time EMS for a series HEV based on the PMP technique. The proposed controller requires the cruise time as well as the restored amount of energy during regenerative braking in order to adjust the related parameters independent of speed trajectory. In this way, they could use the instantaneous Hamiltonian minimization procedure instead of the integral cost minimization for the optimal control problem to improve the fuel economy significantly.

MPC is a suitable approach for designing controls with application to automotive systems, since it can handle constrained optimal control problems [11]. This approach can effectively integrate the performance of optimal control with the robustness of feedback control. Wang [12] proposed real-time control schemes for different hybrid architectures using the MPC approach. Borhan et al. [13] applied MPC to a power-split HEV, by ignoring the faster dynamics of the powertrain for obtaining the control-oriented model inside MPC, which led to a better fuel economy as compared to the rule-based PSAT simulation software. Taghavipour et al. [14] applied MPC to a power-split PHEV and used dynamic programming as a benchmark for evaluating the EMS performance. In another work [15], the authors developed a MPC EMS and applied it to a high-fidelity model of a power-split PHEV in the MapleSim software in order to minimize fuel consumption and emissions.

ECMS has been extensively utilized for designing EMSs. The objective of this approach is to minimize total energy consumption, including fuel (consumed by the engine) and electric energy (stored in the battery). Tulpule et al. [16] employed the ECMS approach to design an EMS for series and parallel PHEVs by considering two operation modes of EV and Blended. Musardo et al. [17] introduced an A-ECMS method based on the driving condition to find the equivalency factor in ECMS technique for parallel HEVs. Wollaeger and Rizzoni [18] demonstrated a near-optimal EMS by depleting the battery SOC based on a prior knowledge of the travelling distance without speed trajectory. Stockar et al. [19] proposed a supervisory EMS for series-parallel PHEVs by minimizing the overall vehicle CO_2 emissions that are indirectly produced during electric power generation, followed by a PMP approach for finding optimum power distribution between the engine and the electric motor. Moreover, a novel approach was proposed to find an optimum battery depletion profile in real time based on the available preview trip information for a power-split PHEV [20, 21]. A route-based real-time EMS based on A-ECMS is designed to optimally control the energy management in a PHEV [22]. It is noteworthy that PHEV fuel economy can be significantly improved by employing the trip information preview in the EMS [23].

However, to the best of our knowledge there is no comparative study of route-based EMSs for PHEVs regarding real-time implementation capabilities. In this study, the performance of two popular route-based EMSs, MPC and A-ECMS, are compared for different levels of trip information and evaluated by using a high-fidelity simulation model in the Autonomie software (which is widely used in the automotive industry for EMS design purposes). The EMSs are evaluated in terms of resultant fuel economy as well as computational effort. The EMSs are fine-tuned for the Toyota Prius plug-in hybrid powertrain.

The paper is organized as follows: the high-fidelity model of Toyota Prius plug-in hybrid powertrain in the Autonomie software is introduced in chapter II. Different levels of trip information and resulting energy management strategies are described in section III. In section IV, real-time EMSs are designed based on the MPC and A-ECMS approaches. Section V provides a comparison between the performance of different strategies in terms of fuel economy, simulation time, and the pattern of engine operating points.

II. TOYOTA PRIUS PLUG-IN HYBRID POWERTRAIN MODEL

A high-fidelity powertrain model in the Autonomie software is used for evaluating the performance of EMSs. This forward-looking model is built on MATLAB and Simulink according to the experimental data that is obtained through real-world testing of HEV/PHEVs; it can simulate the performance, fuel

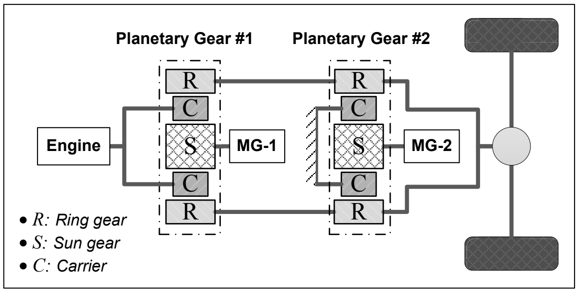

Fig. 1. Schematic of power-split PHEV powertrain [20].

economy and emissions of the vehicle in a more realistic way [24]. Therefore, one can validate the EMS by using high-fidelity models available in Autonomie with high confidence.

This software is widely accepted by OEMs as a simulation tool for powertrain controls performance evaluation. In this study, we use the Autonomie software for modeling the Toyota Prius plug-in hybrid powertrain. The powertrain of this vehicle is similar to the 3rd generation Toyota Prius except for the battery pack. The larger Lithium-ion battery pack used here provides longer full electric driving range while reducing the environmental footprint considerably. Fig. 1 shows a schematic of this powertrain. There are 2 electric motors (MG1 and MG2) which are connected to the engine and the final drive with 2 planetary gear sets. More information about this model of the power-split PHEV powertrain can be found in [20, 25].

III. LEVEL OF TRIP INFORMATION

By taking advantage of advancements in vehicle intelligence and communications technologies to acquire preview knowledge of the trip, a significant improvement of the EMS performance can be made. Look-ahead trip data to predict future driving conditions can be provided by Global Positioning Systems (GPS), Intelligent Transportation System (ITS), Geographic Information Systems (GIS), radars, and other on-board sensors.

In terms of the level of access to the preview trip information, the EMSs can be categorized into three groups: I) no information, II) travelling distance, and III) speed trajectory. In fact, these levels of trip information suggest different battery depletion profiles, which lead to the EMS performance improvement.

As mentioned before, Reactive EMSs don't require any preview of the trip information. In CDCS, the vehicle is initially operated in charge depleting mode (CD) by depleting battery electric energy. When the SOC drops to a certain level, the operation mode is switched into the charge sustenance mode (CS) to maintain SOC close to that predefined level. The operation mode can be manually switched between CS and CD in the manual CDCS strategy. In this way, one can select CS mode to run the engine during driving in the highways in order to save stored electric energy in the battery for the situations that engine doesn't operate efficiently, especially in urban area driving. The Autonomie default control strategy is rule-based and similar to the CDCS strategy. The only difference is the engine operation in CD mode while the driver's demanded power is high.

The designed EMSs in this study (based on MPC and A-ECMS approaches) employ a blended strategy and optimally utilize two energy sources, engine and battery, simultaneously to maintain the high performance of the powertrain. These EMSs can be implemented with two different levels of information. If the travelling distance is known in advance, a linear battery depletion profile is used as a reference SOC. Another possible way is to acquire traffic conditions via some sensors in order to find an optimum battery depletion profile. The optimum profile helps further improvement in EMS performance. Fig. 2 shows the proposed architecture for the optimal route-based energy management of PHEVs [20], which consists of three main subsystems: a SOC trajectory builder, route-based EMS, and low level controllers.

The SOC trajectory builder is designed to predict the optimum SOC profile based on the preview knowledge of the trip. This optimum SOC is employed in the route-based EMS to find the optimum power distribution between the engine and battery, in real time. Finally, the low-level controllers make the engine (P_e) and the electric motors (P_m) provide the demanded power (P_d) based on the optimum power distribution. To optimize SOC trajectory, first the future speed trajectory is predicted based on the traffic speed profile, maximum permissible speed, and

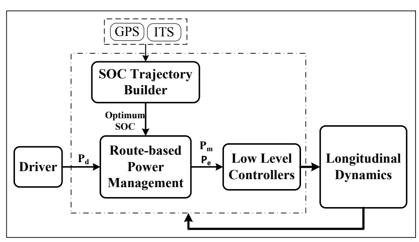

Fig. 2. Schematic of the real-time route-based EMS [20].

road signs. The route is divided into some segments, considering that obstacles such as bridge ramps, traffic lights, or stop signs are located at the margin of the segments. A math-based trip model was developed to calculate the fuel consumption and SOC profile based on the power distribution for the proposed speed trajectory. Finally, the optimum SOC profile is obtained by minimizing total fuel consumption considering constraints on the powertrain components. The power distribution is formulated by the power ratio parameter (PR), which is the ratio of the battery power (P_b) to the demanded power (P_d). For the real-time implementation, the segments are clustered into groups based on the demanded power. It is assumed that the PR in the segment of each group is constant. This clustering reduces the number of optimization parameters and makes the algorithm independent of the trip distance [20].

IV. ENERGY MANAGEMENT SYSTEMS

4.1. Model Predictive Control

In the MPC approach, the future behavior of the plant output is optimized by computing a trajectory of inputs. The optimization procedure is done within a time window by using the measured information from the plant. The length of this time window is called the prediction horizon which determines how far we need to predict the future. Additionally, a sufficiently accurate and simple model of the system is required to perform prediction and find the appropriate array of control inputs through an optimization procedure. This model must capture the essential dynamics of the plant and give an accurate and consistent prediction of the future. The length of the input array is called the control horizon. In the receding horizon control approach, the first sample of control inputs array is applied to the plant, and the rest of the trajectory is ignored [12]. An integrator is embedded into the design in order to make the predictive control system track constant references and reject constant disturbances without steady-state errors. This approach does not need steady-state information about the control inputs or state variables to be implemented.

As a control-oriented model inside MPC, the vehicle longitudinal dynamics and an internal resistance model for the battery are considered. The equations of the system are written as (1), (2) and (3):

$$\begin{aligned}
&(\frac{I_v(s_1+r_1)^2}{r_1 I_e K}+\frac{I_v S^2}{r_1 I_g K}+r_1)(\frac{r_2}{s_2})\dot{\omega}_r \\
&=(\frac{(s_1+r_1)^2}{r_1 I_e}+\frac{{s_1}^2}{r_1 I_g})(\frac{s_2}{r_2})T_m+(\frac{(s_1+r_1)}{I_e})T_e \\
&+(\frac{s_1}{I_g})T_g-(\frac{(s_1+r_1)^2}{r_1 I_e K}+\frac{{s_1}^2}{r_1 I_g K})T_d \qquad (1)
\end{aligned}$$

$$\begin{aligned}
&(\frac{I_e {r_1}^2 K}{(r_1+s_1)I_v}+\frac{I_e {s_1}^2}{(r_1+s_1)I_g}+r_1+s_1)\dot{\omega}_e=-(\frac{r_1}{I_v})T_d+ \\
&(\frac{{r_1}^2 K}{(s_1+r_1)I_v}+\frac{{s_1}^2}{(r_1+s_1)I_g})T_e+(\frac{r_1 K}{I_v})(\frac{s_2}{r_2})T_m-(\frac{s_1}{I_g})T_g \qquad (2)
\end{aligned}$$

$$\dot{SOC}=-\frac{V_{oc}-\sqrt{V_{oc}^2-4(T_m\omega_r\eta_m^{-k}-T_g\omega_g\eta_g^k)R_{batt}}}{2R_{batt}Q_{batt}} \qquad (3)$$

The parameters are adjusted according to the Toyota Prius plug-in hybrid powertrain, where V_{oc} is the open-circuit voltage of the battery, R_{batt} is the battery resistance, Q_{batt} is the battery capacity, η_m is motor efficiency, η_g is generator efficiency, (r_1, s_1) and (r_2, s_2) are the number of ring and sun gear teeth for two planetary gear sets, and I_v, I_e, and I_g are the equivalent inertia of the vehicle, the engine and the generator, respectively. In this system, there are 3 state variables: ring speed (ω_r) which is proportional to the vehicle velocity, engine speed (ω_e), and battery state of charge (SOC). Also, there are 3 inputs: engine torque (T_e), motor torque (T_m) and generator torque (T_g) in order to provide the driver's demanded torque (T_d). When the battery is discharged $k=1$, where as $k=-1$ for battery charging [14, 25].

In each prediction window, a cost function is minimized to maximize fuel economy and track a predefined reference SOC trajectory while maintaining drivability. The cost function is:

$$\begin{aligned}
J(k)=\sum_{i=1}^{N_p}(w_1(SOC_{ref}(k+i)-SOC(k+i))^2 \\
+w_2(\dot{m}(k+i))^2). \qquad (4)
\end{aligned}$$

where w_1 and w_2 are the weighting parameters for SOC tracking and fuel minimization, respectively. The performance of a control system can significantly be degraded when the control signals from the original design meet with the constraints. To solve this issue, all the constraints must be changed in the form of variation in input signal. The constraints on this problem are defined as follows:

$$\begin{aligned} T_{e,min} &< T_e < T_{e,max} \\ T_{m,min} &< T_m < T_{m,max} \\ T_{g,min} &< T_g < T_{g,max} \\ \omega_{e,min} &< \omega_e < \omega_{e,max} \\ \omega_{r,min} &< \omega_r < \omega_{r,max} \\ \omega_{g,min} &< \omega_g < \omega_{g,max} \\ SOC_{min} &< SOC < SOC_{max} \end{aligned} \quad (5)$$

For finding a simpler form of the controller, the equations of the system are linearized for each time step around the operating point. According to the engine fuel consumption map, a linear fit to the fuel rate versus squared engine speed and engine power is quite satisfactory. Therefore, the fuel consumption rate of the engine is estimated as:

$$\dot{m}_f = \alpha\omega_e^2 + \beta T_e \omega_e \quad (6)$$

where α and β are constants [26].

4.2. Adaptive ECMS

The ECMS approach was proposed to optimally determine energy distribution between one external energy source (fuel), and the electric energy of the battery in HEVs. The energy stored in the battery is indirectly generated by the fuel in the tank. As a result, the energy consumption is determined by the equivalent fuel consumption of both fuel and electric energy.

However, the larger battery pack in a PHEV mainly stores the grid electric energy. Therefore, the main portion of the battery energy is not generated from the fuel. As a result, the total cost of the grid electric energy and fuel is considered as a criterion to evaluate the vehicle performance, which is formulated in Eq. 7 [22]:

$$Cost = k_f \dot{m}_f - \ k_e \eta_{ch} Q_{max} \dot{SOC} \quad (7)$$

where $\dot{m}_f$ is the fuel consumption rate, Q_{max} is the maximum battery capacity, η_{ch} is the charger efficiency, and k_f, k_e are the unit price for the gas and electric energy, respectively.

The objective of the ECMS EMS is to minimize the total energy cost (Eq. 8,9) which is subjected to the constraints (Eq. 10) on the battery SOC, the engine, and battery power:

$$J = \int_{t_0}^{t_f} \left(k_f \dot{m}_f + S\ k_e \eta_{ch} \eta_b P_b\right)\ dt \quad (8)$$

$$\dot{SOC} = -\frac{\eta_b}{Q_{max}} P_b \quad (9)$$

$$\begin{aligned} SOC(t_0) &= SOC_0 \\ SOC(t_f) &= SOC_f \\ SOC_{min} &\leq SOC \leq SOC_{max} \\ P_{b,min} &\leq P_b \leq P_{b,max} \\ P_{e,min} &\leq P_e \leq P_{e,max} \end{aligned} \quad (10)$$

where S is an equivalency factor, η_b is the battery efficiency, and P_b, P_e are the battery and engine power, respectively.

The equivalency factor is a design parameter to make a balance between the supply and demand of electric energy during a trip by regulating the electrical cost. To find the optimum value of the equivalency factor, the future driving condition should be available. However, one can consider the adaptive ECMS (A-ECMS) to make the EMS independent of the trip information. To this end, the reference SOC which is generated by the SOC trajectory builder helps finding the equivalency factor. This reference SOC may be found by the least trip information, which is linear profile versus travelling distance, or by the whole trip information which leads to the optimum battery depletion profile.

V. RESULTS AND DISCUSSIONS

In this section, the performance of the two designed EMSs are evaluated in terms of real-time implementation and fuel economy for different battery depletion trajectories using the high-fidelity model which was introduced in section II. Two different driving schedules for urban driving and combined highway and urban driving are used for the simulation. The first one is a combination of three UDDS drive cycles (3U drive cycle) and the latter is a HWFET drive cycles and two UDDS and (UHU drive cycle). Then, the engine operating points pattern for different cases are discussed in order to explain the contribution of trip information in improving the fuel economy.

5.1. Drivability and fuel economy

According to Fig. 3 to Fig. 9, the solid (battery SOC) and bold (fuel consumption) curves represent the energy stored in the battery and the fuel tank for propelling the vehicle. The summation of these two curves with appropriate coefficients represents the demanded power from the driver along the drive cycle, shown as the dashed line. Now, the challenge is how to change the rate of using energy from both sources so that we get the best fuel saving along the trip. The simulation results for EMSs without any preview trip information according to the UHU drive cycle are shown in Fig. 3, 4, and 5.

In CDCS strategy, the energy stored in the battery propels the vehicle approximately for the first half of the trip ($t = 1715\ s$), then the engine takes over and the operating mode switches to CS (Fig. 3). The rule-based controller of Autonomie has a similar approach, but it starts the engine even when SOC is more than the predefined value. As shown in Fig. 4 for acceleration at $t = 220\ s$ and $t = 1720\ s$, the engine assists the electric drive to propel the vehicle. This leads to a longer charge depletion period and 2.1% improvement in fuel economy (MPG) over CDCS.

The engine operates more efficiently at high speeds in comparison to low speeds. As a result, engine operation while the vehicle is driven on the highway

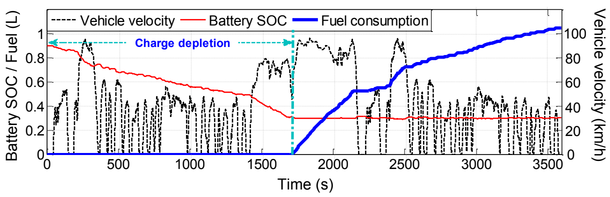

Fig. 3. Charge depleting/charge sustenance (CDCS) strategy performance over the UHU driving schedule-with no trip information

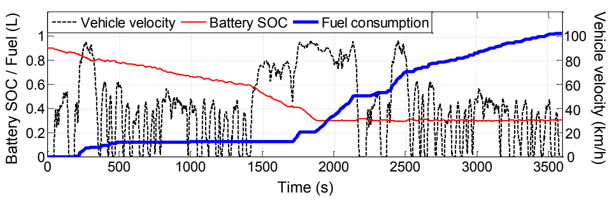

Fig. 4. Autonomie default rule-based strategy performance over the UHU driving schedule-with no trip information

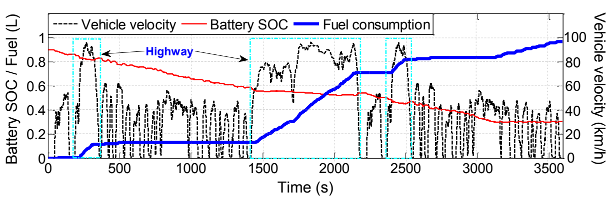

Fig. 5. Manual charge-sustenance/charge depleting strategy performance over the UHU driving schedule-with no trip information

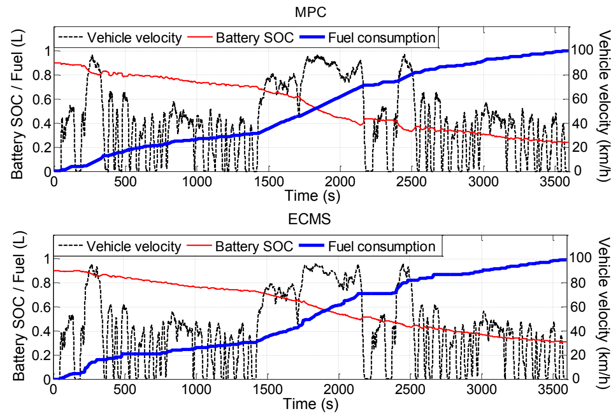

Fig. 6. Linear blended mode strategy performance over the UHU driving schedule-level of trip information: Distance

can improve fuel economy. On the other hand, it is preferable to use electric energy for driving in urban areas. In manual CDCS, the driver can manually switch between EV mode (CD) and HEV mode (CS) depending on the traffic condition. This can improve fuel economy even further. It is found that the manual CDCS strategy utilizes more engine power in the highway rather than rule-based strategy, and extends the CD operating mode until $t = 3100\ s$ (Fig. 5). This strategy enhances the fuel economy by 5.6% compared to the default rule-based controller in Autonomie software.

The trip information and the battery depletion profile improves the EMS performance by enhancing the PHEV fuel economy. The battery depletion profile can be obtained based on different levels of trip information. If the travelling distance is available beforehand, the linear depletion profile is used as the reference SOC. In the case of a modern vehicle with on-board sensors, the future driving condition can be predicted. Then, the optimum depletion profile is generated by the SOC trajectory builder in real time and applied to the EMS. The simulation results of MPC and A-ECMS for linear reference SOC and optimum reference SOC are shown in Fig. 6 and 7, respectively. It is shown that both EMSs satisfy the constraint on SOC at the end of the trip.

Since the MPC controller solves a quadratic programming (QP) problem at each time step, it is generally slower than the ECMS strategy. Therefore, the MPC implementation procedure is modified to make the controller faster at the price of compromising its performance, so that when we run the model and the controller using a fixed time step scheme ($\Delta t = 10\ ms$), we get comparable simulation times for both

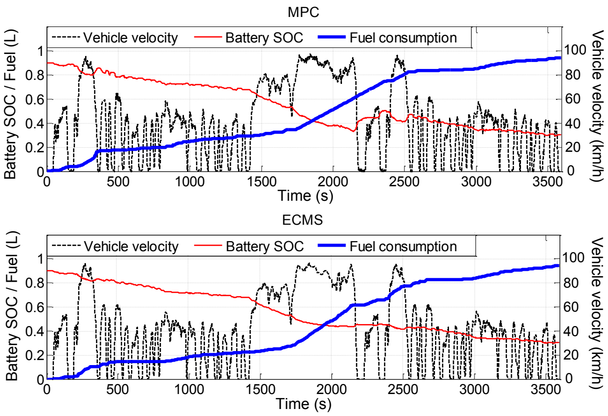

Fig. 7. Blended mode strategy with optimized reference SOC performance over the UHU driving schedule-level of trip information: Speed trajectory

controllers. To do this, we increase the MPC sampling time to solve fewer QP problems over the driving schedule.

By comparing Fig. 6 and 7, the effect of the increasing control period for MPC can clearly be seen in degrading its battery depletion trajectory tracking performance. Nonetheless, MPC performance for reducing fuel consumption is still comparable with ECMS controller.

For linear blended mode and optimized reference SOC case (Fig. 6 and 7), the reference SOC tracking performance of A-ECMS is better than MPC approach. MPC decides on more battery power to propel the vehicle while accelerating (at $t = 210\ s$ and $t = 2400\ s$), which results in smoother engine operation to avoid engine inefficient operation in such transients. On the other hand, A-ECMS utilizes more engine power for acceleration in order to follow SOC reference trajectory.

On the highway, A-ECMS utilizes more engine power for the acceleration part, but MPC uses battery power in acceleration mode and then restores the battery energy by operating the engine to track the reference SOC.

For instance, in the time period of 180s to 360s, the fuel consumption and ΔSOC are 0.122 L, 0.032% for MPC, and 0.087 L, 0.049% for A-ECMS, respectively. As a result, MPC increases SOC (decrease ΔSOC of the segment) by utilizing more engine power at the end of the segment.

Fig. 8, 9 show the simulation results for evaluating the EMSs performance in an urban driving experience (3U drive cycle). Both EMSs perform similarly in terms of reducing the fuel consumption.

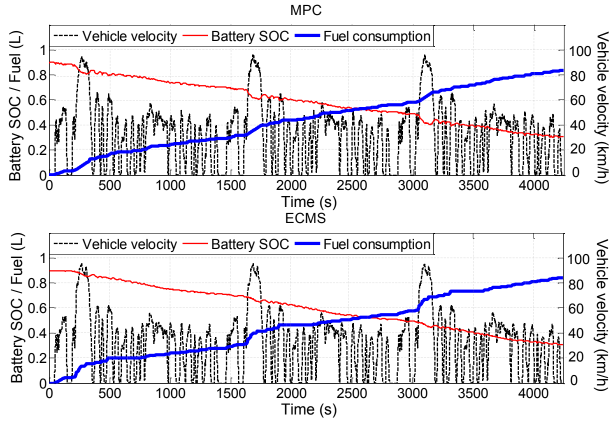

Fig. 8. Linear blended mode strategy performance over the 3U driving schedule-level of trip information: Distance

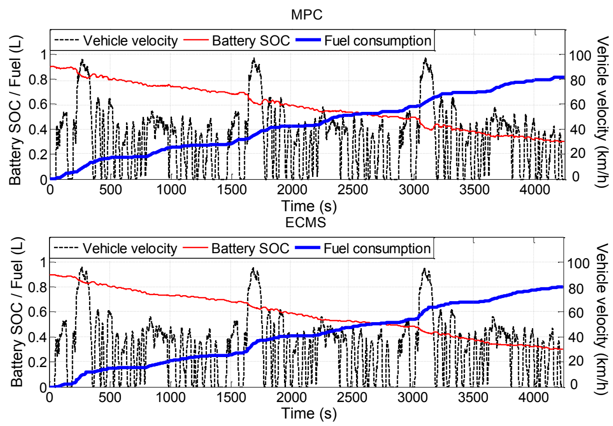

Fig. 9. Blended mode strategy with optimized reference SOC performance over the 3U driving schedule-level of trip information: Speed trajectory

Table 1 summarizes the fuel consumption by using different EMSs with different levels of trip information in UHU and 3U drive cycles. The manual CDCS strategy shows the best performance, when the future trip information is not available. The manual CDCS or linear blended mode strategies result in close fuel consumption for two driving schedules, which shows the potential of manual CDCS for reducing fuel consumption with no information about the trip in advance.

In urban drive cycle (3U), the linear blended mode leads to a better performance for both EMSs, because the electric energy is available until the end of the trip. For the combined urban and highway driving schedule (UHU), manual CDCS operates the engine more efficiently and therefore leads to a better fuel economy.

Table 1. Fuel economy for different levels of trip information

Strategy	Level of trip information	MPG UHU cycle	MPG 3U cycle
CDCS	No	93.1	94.9
Rule-based	No	95.1	97.7
Manual CDCS	No	100.5	99.6
A-ECMS, linear SOC	Distance	98.3	104.7
MPC, linear SOC	Distance	97.4	105.4
A-ECMS, optimized SOC	Speed	103.4	107.7
MPC, optimized SOC	Speed	102.9	108.5

For the optimized reference SOC where the whole future speed trajectory is available, both MPC and A-ECMS result in the best fuel economy. Using these EMSs, the fuel economy is improved by 8.5% and 10.2% for UHU and 3U drive cycles in comparison to the results of the default rule-based controller of the Autonomie software.

According to Table 1, the MPC controller performs better in the 3U drive cycle, where we have a more predictable driving pattern.

Although the MPC performance is negatively affected by increasing the sampling time, it still suggests a comparable fuel economy with A-ECMS, which shows the flexibility of this approach for designing an EMS. It is noteworthy that MPC outperforms A-ECMS without considering the mentioned compromise due to real-time implementation concerns.

The computational effort for both EMSs should be considered for comparing their real-time implementation capabilities. To compare the computational effort, all simulations were run on a PC with Intel Core 2 Duo CPU (E8500, 3.17GHz) and 4GB RAM. The average computation time of MPC and A-ECMS strategies are 240, 208s for UHU drive cycle, and 290, 252 s for 3U drive cycle, respectively.

5.2. Engine operating points

To have a closer look at the designed EMSs performances, we investigate the engine operating points for different strategies along the 3U and UHU schedules. Fig. 10 shows the engine operating points for CDCS and manual CDCS strategies. Fig. 11 and Fig. 12 show the engine operating points for blended mode strategies by employing the MPC and A-ECMS approaches to design EMS.

The engine operating points are more sensitive to different battery depletion strategies than to changing the drive cycle. For instance, Fig. 10-a and Fig. 10-b are remarkably similar. The same argument can be mentioned for Fig. 11 and Fig. 12 in linear blended mode case. However, a significant pattern change can be observed by comparing Fig. 10-b and Fig. 10-d. For the blended mode strategy with optimized reference SOC, we expect to see a different pattern of the engine operating points along different drive cycles, since the battery depletion profile is specifically derived for a drive cycle, which is a different approach compared to the other battery depletion strategies.

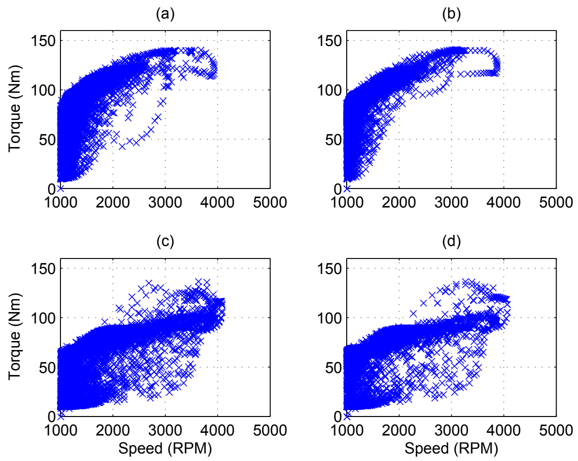

Fig. 10. Engine operating points for (a) CDCS strategy along 3U (b) CDCS strategy along UHU (c) manual CDCS along 3U (d) manual CDCS along UHU

Fig. 10-d pattern is very close to Fig. 11-d and Fig. 12-d. Moreover, Table 1 shows the advantage of using manual CDCS for reducing fuel consumption with less information about the driving pattern compared to the case where we are using an optimized SOC depletion trajectory. This shows the potential of manual CDCS in improving the EMS performance specially in the combined UHU schedule by involving the driver in the energy management procedure.

As shown in Fig. 11 and Fig. 12, the MPC and A-ECMS approaches result in a similar pattern of the engine operating points. Since fuel consumption reduction is one of the objectives of optimal control in both methods, the engine operating points are pushed to approach the engine optimal operating line. As a result, a considerable fuel saving is observed by using the mentioned EMSs.

VI. CONCLUSIONS

In this paper, the performance of two real-time implementable PHEV EMSs (MPC and A-ECMS) were

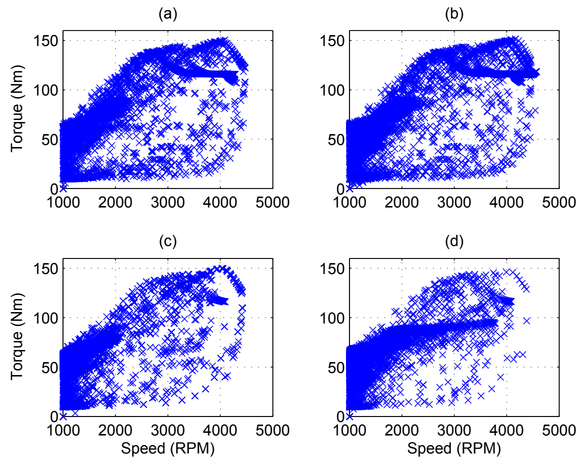

Fig. 11. MPC engine operating points for (a) Linear blended strategy along 3U (b) Linear blended strategy along UHU (c) Blended strategy with optimized SOC along 3U (d) Blended strategy with optimized SOC along UHU

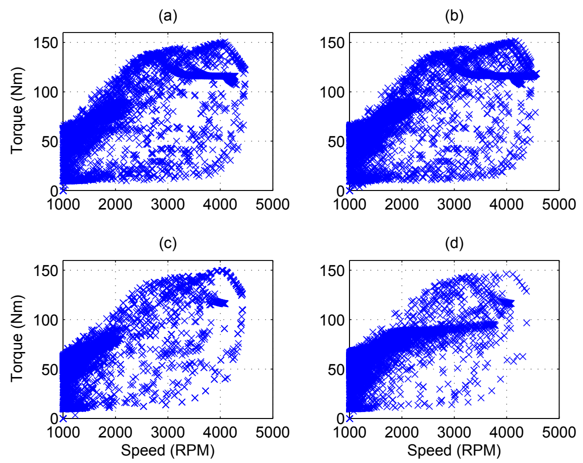

Fig. 12. A-ECMS engine operating points for (a) Linear blended strategy along 3U (b) Linear blended strategy along UHU (c) Blended strategy with optimized SOC along 3U (d) Blended strategy with optimized SOC along UHU

compared in terms of fuel economy and computational effort. We evaluated the performance of two systems by using Toyota Prius Plug-in Hybrid high-fidelity model in Autonomie software for different levels of trip information. It was concluded that the fuel economy from the MPC and A-ECMS approaches are close with similar level of trip information. Without any information about the future driving condition, manual CDCS strategy has the best performance. By having more trip information, the performance of control systems is improved. It was shown that MPC and A-ECMS strategies can improve the fuel economy up to 10% compared to the Autonomie software baseline controller. Although A-ECMS is 15% faster than MPC in terms of simulation time, both approaches can be implemented in real-time. Finally, it was shown that the engine operating points are more sensitive to the battery depletion pattern than to different driving schedules. We are currently implementing the proposed controllers on commercial real-time hardware to evaluate their performance in hardware-in-the-loop testing procedure. Afterwards, the performance of the proposed controllers on the Prius plug-in powertrain will be evaluated on rolling dynos and on our test track.

REFERENCES

1. Cook J., J. Sun, J. Buckland, I. Kolmanovsky, H. Peng,and J. Grizzle "Automotive Powertrain Control A Survey". *Asian Journal of Control*, Vol. 8, No. 3 (2006).
2. Serrao L., S. Onori, and G. Rizzoni. "A Comparative Analysis of Energy Management Strategies for Hybrid Electric Vehicles". *Journal of Dynamic Systems, Measurement, and Control*, Vol. 133, No. 3 (2011).
3. Hellstrom E., M. Ivarsson, J. Aslund, and L. Nielsen. "Look-ahead control for heavy trucks to minimize trip time and fuel consumption". *Control Engineering Practice*, Vol. 17, No. 2, pp. 245-254 (2009).
4. Katsargyri G.E., I. Kolmanovsky, J. Michelini, M. Kuang, A. Phillips, M. Rinehart, and M. Dahleh. "Optimally controlling Hybrid Electric Vehicles using path forecasting". In *American Control Conference*, pp. 4613-4617 (2009).
5. Lin C.C., H. Peng, and J.W. Grizzle. "Power management strategy for a parallel hybrid electric truck". *IEEE Transactions on Control Systems Technology*, Vol. 11, No. 6, pp. 839-849 (2003).
6. Gong Q. and Y. Li. "Power Management of Plug-In Hybrid Electric Vehicles Using Neural Network Based Trip Modeling". In *American Control Conference*, pp. 4601-4606 (2009).
7. Abdul-Hak M. and N. Al-Holou. "ITS based Predictive Intelligent Battery Management System for plug-in Hybrid and Electric vehicles". In *Vehicle Power and Propulsion Conference, 2009. VPPC'09. IEEE*, pp. 138-144 (2009).
8. Bin Y., Y. Li, and Q. Gong. "Multi-Information Integrated Trip Specific Optimal

Power Management for Plug-In Hybrid Electric Vehicles". In *American Control Conference*, pages 4607-4612 (2009).
9. Razavian R., A. Taghavipour, N. L. Azad, and J. McPhee. "Design and evaluation of a real-time fuel-optimal control system for series hybrid electric vehicles". *International Journal of Electric and Hybrid Vehicles*, Vol. 4, No. 3, pp. 260-288 (2012).
10. Razavian R., N. L. Azad, and J. McPhee. "On real-time optimal control of a series hybrid electric vehicle with an ultra-capacitor". In *American Control Conference*, pp. 547-552 (2012).
11. Re L., P. Ortner, and D. Alberer. "Chances and Challenges in Automotive Predictive Control". *Springer*, pp. 1-22 (2010).
12. Z. Wang. *Model Predictive Control for Hybrid Electric Vehicle*. PhD thesis, The Chinese University of Hong Kong (2008).
13. Borhan H., A. Vahidi, A. Phillips, and I. Kolmanovsky. "Predictive Energy Management of a Power-Split Hybrid Electric Vehicle". In *American Control Conference*, pp. 3970-3976 (2009).
14. Taghavipour A., N. L. Azad, and J. McPhee. "An Optimal Power Management Strategy for Power Split Plug-in Hybrid Electric Vehicles". *International Journal of Vehicle Design*, Vol. 60, No. 3, pp. 286-304 (2012).
15. Taghavipour A., N. L. Azad, and J. McPhee. "Design and Evaluation of a Predictive Powertrain Control System for a PHEV to Improve Fuel Economy and Emissions". *IMechE, Part D: Journal of Automobile Engineering (accepted for publication)*.
16. Tulpule P., V. Marano, and G. Rizzoni. "Effects of different PHEV control strategies on vehicle performance". In *American Control Conference*, pp. 3950-3955. (2009).
17. Musardo C., G. Rizzoni, and B. Staccia. "A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management". *European Journal of Control*, pp. 509-524, 2005.
18. Wollaeger J. and G. Rizzoni. *ITS in Energy Management Systems of PHEV's*. Master of science, Ohio State University (2012).
19. Stockar S., V. Marano, M. Canova, G. Rizzoni, and L. Guzzella. "Energy-Optimal Control of Plug-in Hybrid Electric Vehicles for Real-World Driving Cycles". *IEEE Transactions on Vehicular Technology*, Vol. 60, No. 7, pp. 2949-2962 (2011).
20. Vajedi M., M. Chehrehsaz, and N. L. Azad. "Intelligent power management of plug-in hybrid electric vehicles , part I : real-time optimum SOC trajectory builder". *International Journal of Electric and Hybrid Vehicles (accepted for publication)*.
21. Vajedi M., A. Taghavipour, and N. L. Azad. "Traction-Motor Power Ratio and Speed Trajectory Optimization for Power Split PHEVs Using Route Information". In *ASME 2012 International Mechanical Engineering Congress & Exposition*, Houston, Texas, USA (2012)
22. Vajedi M., M. Chehrehsaz, and N. L. Azad. "Intelligent power management of plug-in hybrid electric vehicles , part II : real-time route based power management". *International Journal of Electric and Hybrid Vehicles (accepted for publication)*.
23. Taghavipour A., M. Vajedi, N. L. Azad, and J. McPhee. "Predictive Power Management Strategy for a PHEV Based on Different Levels of Trip Information". In *Engine and Powertrain Control, Simulation and Modeling*, Vol. 3, pp. 326-333 (2012).
24. Bogosyan S., M. Gokasan, and D. Goering. "A Novel Model Validation and Estimation Approach for Hybrid Serial Electric Vehicles". *Vehicular Technology, IEEE Transactions on*, Vol. 56, No. 4, pp. 1485-1497 (2007).
25. Taghavipour A., R. Masoudi, N. L. Azad, and J. McPhee. "High-fidelity Modeling of a Power-split Plug-in Hybrid Electric Powertrain for Control Performance Evaluation". In *ASME 15th International Conference on Advanced Vehicle Technologies (AVT)* (2013).
26. Kohut N., K. Hedrick, and F. Borrelli. "Integrating Traffic Data and Model Predictive Control to Improve Fuel Economy". In *12th IFAC Symposium on Control in Transportation Systems* (2009).