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Real-Time Optimal Energy Management for Hybrid and Plug-In Hybrid Electric Vehicles

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Abstract: In this work, a systematic approach for real-time optimal energy management of hybrid electric vehicle (HEV) and plug-in hybrid electric vehicle (PHEV) has been introduced and validated through two HEV/PHEV case studies. Firstly, a new analytical model of the optimal control problem for Toyota Prius HEV with both offline and real-time solutions was presented and validated through Hardware-in-Loop (HIL) real-time simulation. Secondly, the new online or real-time optimal control algorithm was extended to a multi-regime PHEV by modifying the optimal control objective function and introducing a real-time implementable control algorithm with an adaptive coefficient tuning strategy. A number of practical issues in vehicle control, including drivability, controller integration, etc. are also investigated. The newly proposed real-time optimal control algorithm identifies the optimal operational mode and the corresponding torque split among each components at each time step. The control objective was to minimize the well-to-wheel energy use (PEU and GHG), where both the fuel and electric energy consumption was taken into account. The optimal torque split was computed based on Pontryagin's Minimum Principle. To reduce computational burden, the original 2 degree of freedom (DOF) powertrain control problem has been converted into a 1-DOF search algorithm in the optimization search. For practical implementation, an adaptive technique was utilized to update the equivalence factor based on battery SOC and current driving distance. The newly proposed fast PMP algorithm was investigated through Model-in-the-loop (MIL) simulation tests using the simplified vehicle model, showing improved PEU consumption by 3-5%, comparing to the baseline rule-based controller for which the battery SOC is just depleted at the end of the trip. The new algorithm was also validated on various driving cycles using both Model-in-Loop (MIL) and HIL environment. This research better utilizes the energy efficiency and emissions reduction potentials of hybrid electric powertrain systems, and forms the foundation for the developments of next generation HEVs and PHEVs.

Key words: hybrid electric vehicles, HEV, PHEV, real-time optimal energy management, HIL simulation, pontryagin's minimum principle

1. Introduction

Increasing concerns about environmental issues have made hybrid electric vehicles (HEVs) with considerably improved energy efficiency and reduced emissions a promising alternative to conventional Internal Combustion Engine (ICE) vehicles. The energy efficiency improvement of HEVs is partially due to their capability of recovering braking energy, and partially due to their ability to allow the ICE to operate at the high efficiency operation conditions with the additional degree of freedom from two energy sources on board of the vehicle, electrical energy storage system (ESS) and fuel tank. The presence of this additional degree of freedom, however, also demands an appropriate energy management strategy to exploit the optimal operation effectively.

Recently, plug-in hybrid electric vehicles (PHEVs), HEVs with oversized batteries that can be recharged using grid power at station, present an even more promising solution to greener vehicles due to their ability to further reduce the petroleum consumption and greenhouse gas (GHG) emissions by using grid

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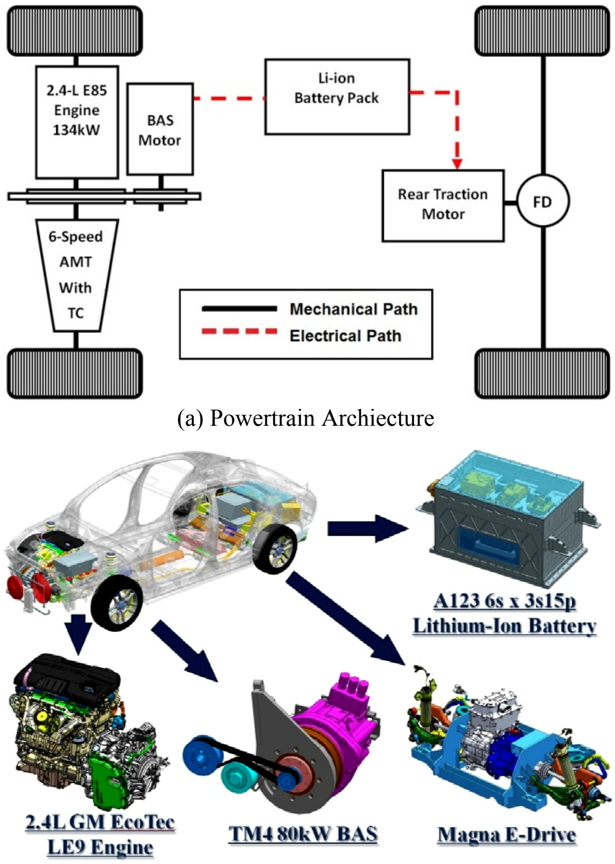
power generated from renewable energy sources and excess electric generation capacity at off-peak hours. The added part-time pure electric vehicle (PEV) mode supports better emissions control in highly populated urban areas and contributes to further improvement of powertrain efficiency. PHEVs also eliminate the problem of “range anxiety” associated to PEVs, because the ICE functions as a backup when the batteries are depleted, giving PHEVs driving range comparable to other vehicles with gasoline tanks.

2. Modeling, Optimal Control and Its Real-Time Validation for PHEV

2.1 PHEV Research Vehicle and Modeling of Its Multi-Regime PHEV Powertrain System

The prototype plug-in hybrid electric vehicle (PHEV) developed through the EcoCAR 2 program at the University of Victoria. The new PHEV was produced by re-engineering a 2013 Chevrolet Malibu donated by General Motors as the integration platform for advanced vehicle design to reduce emissions and environmental impact while retaining performance and consumer appeal.

The series-parallel multi-regime powertrain architecture of the PHEV is shown in Fig. 1. This architecture provides many substantial improvements over the production 2013 Malibu. The powertrain includes a powerful motor coupled to the engine through a belt system functioning as a belt-alternator-starter (BAS) at the front wheel, as well as a rear traction motor (RTM) and large battery. The battery and RTM make this architecture a full hybrid, giving it a significant electric-only range. This configuration was identified as having several advantageous operating modes. With the transmission set in neutral, the vehicle could essentially function as a series EREV, with the ICE charging the batteries through the BAS system. When additional power is required, or when it is more efficient to do so, the ICE and transmission could be used to propel the vehicle. For high-performance driving situations, the BAS



(a) Powertrain Archiecture

(b) Key Powertrain Components

Fig. 1 Series-parallel, Multi-regime Powertrain of the PHEV.

could provide a power-assist function to smooth out the torque curve of the ICE, and the RTM could add its power such that all available power sources propel the vehicle.

2.2 Forward-oriented Simulation Model

A forward-oriented vehicle model is shown in Fig. 2.

2.3 Rule-Based Controller Design for the Proposed PHEV Powertrain

A deterministic rule-based controller is developed first for the proposed PHEV powertrain, which will also serve as the baseline controller for the optimization-based controller that will be developed later to compare with. Depending on different driving situations, the Charge Depleting-Charge Sustaining (CDCS) rule-based controller produces simulation results as shown in Fig. 3 and Table 1.

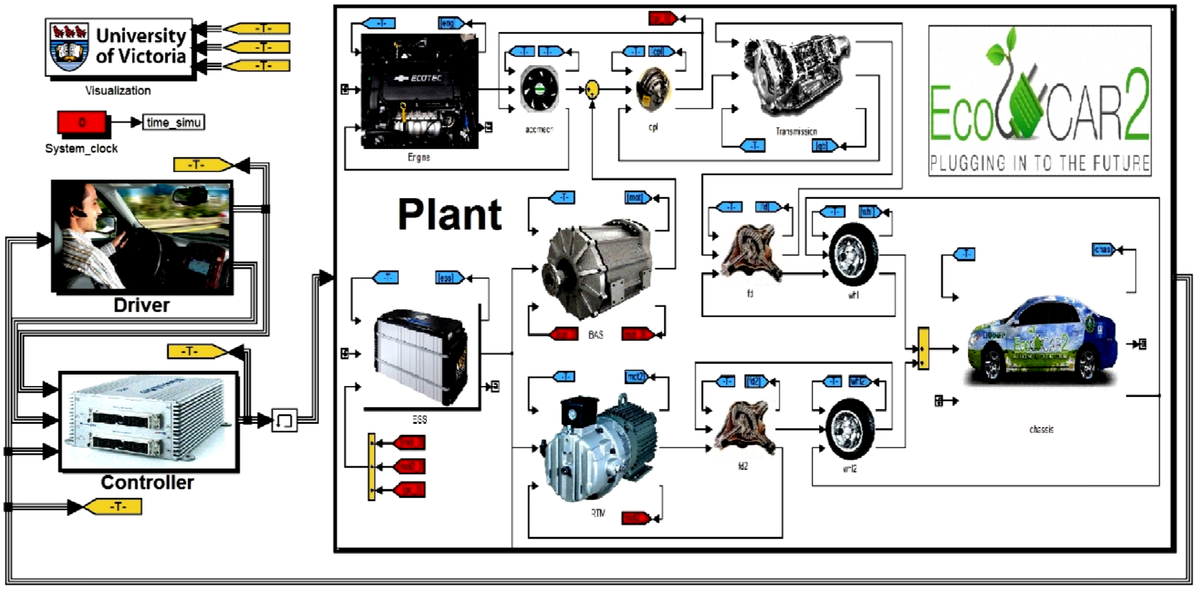


Fig. 2 Forward-oriented vehicle model in MATLAB/Simulink.

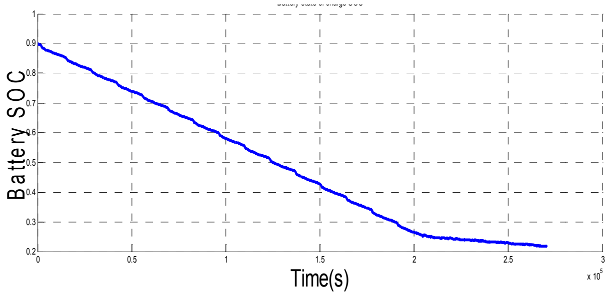


Fig. 3 Battery SOC result over 20*UDDS.

Table 1 Simulation results on 20*UDDS cycle.

(based on E85 fuel)	Results
Total Distance (miles)	148.32
Fuel Economy (MPG)	174.897
WTW GHG (g CO_2 eq/km)*	126.881
Initial SOC	0.9
Final SOC	0.2386
AER range (miles)	65.1147

3. Extension of the Proposed Real-Time Optimal Control Algorithm to PHEV

In this work, new formulation for the optimal control of the PHEV has been introduced, considering the amount of energy consumed and the well-to-wheel (WTW) greenhouse gas (GHG) emissions.

$$PEU_{WTW} = E_{fuel} \cdot \eta_{PEU,fuel} + E_{elec} \cdot \eta_{PEU,elec} \tag{1}$$

where E_{fuel} and E_{elec} are the per-kilometer amounts of fuel and alternating current (AC) electric energy (kWh/km) used. The WTW PEU factor η_{PEU} is used to relate fuel (or electric) energy use to the well-to-wheel petroleum energy use considering both upstream and downstream (at the vehicle).

$$GHG_{WTW} = E_{fuel} \cdot \eta_{GHG,fuel} + E_{elec} \cdot \eta_{GHG,elec} \tag{2}$$

where the WTW GHG factor η_{PHG} is used to relate vehicle energy use to the WTW amount of GHGs generated.

The new cost function for PHEV optimal control is thus redefined as follows:

$$\min\left\{ J = \int_{t_0}^{t_f} [\dot{m}_{fuel}(t) \cdot \eta_{FSE} \cdot \eta_{PEU,fuel} + P_{bat}(t) \cdot \eta_{PEU,elec}]dt \right\} \tag{3}$$

Subject to various operational constraints

where $\dot{m}_{fuel}$ is the fuel consumption rate (kg/s) and P_{bat} is the battery DC electric power (kW) used at each time step. η_{FSE} is the fuel-specific energy by mass (kWh/kg), the value of which can be found in Table 6. T_{BAS} refers to the torque of the motor coupled with the BAS system and T_{RTM} refers to the torque of the rear traction motor.

The powertrain model described in 3.4 can be summarized as in the following two equations:

$$(T_{eng} + T_{BAS} \cdot R_{belt}\eta_{belt}^{k}) \cdot R_{tx}\eta_{tx}R_{fd}\eta_{fd} + T_{RTM} \cdot R_{rd}\eta_{rd}^{k} = T_{req}$$
$$P_{bat} = \eta_c^{m}(\eta_{BAS}T_{BAS}\omega_{BAS} + \eta_{RTM}T_{RTM}\omega_{RTM}) \quad (4)$$

The series-parallel powertrain has a degree of freedom of two. We chose battery power P_{bat} and rear traction motor torque T_{rtm} as the two independent control variables. To apply Pontryagin's Minimum Principle to the optimal control problem, we first have the Hamiltonian as follows:

$$H(P_{bat}(t), T_{rtm}(t), t) = \dot{m}_{fuel}(P_{bat}(t), T_{rtm}(t), t) \cdot \eta_{FSE} \cdot \eta_{PEU,fuel} + P_{bat}(t) \cdot \eta_{PEU,elec} - p(t) \cdot \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_{in}P_{bat}(t)}}{2C_{bat}R_{in}} \quad (5)$$

where $p(t)$ is the costate.

The optimal control variables are determined such that the Hamiltonian is minimized at each time step:

$$\mathbf{u}^*(t) = [P_{bat}^*(t), T_{rtm}^*(t)]^T = \min_{\mathbf{u}(t)} H(\mathbf{u}(t), t) \quad (6)$$

For Prius, a 1D search has been conducted at each time step to get the optimal cost function (minimum Hamiltonian in this case). For this PHEV, a 2D search has to be carried out at each time step. The ultimate optimal point was the one that gave lowest cost (Hamiltonian) value.

The results of different optimal control strategies are given in Table 2 for comparison. The control algorithms have been implemented and tested on the dSPACE Hardware-in-Loop simulator as shown in Fig. 5. The Fast PMP optimal control method is practical and superior in fuel economy and GHG emission reduction.

The work was an extended study based on the EcoCAR2 development, where a 2013 GM Chevrolet Malibu was retrofitted into a PHEV to improve energy efficiency, reduce emissions while retaining and increasing performance. Following the model-based-design (MBD) process, two sets of plant model were developed: a simplified control-oriented plant model to allow initial conceptual validation of the optimal control algorithm and a more sophisticated

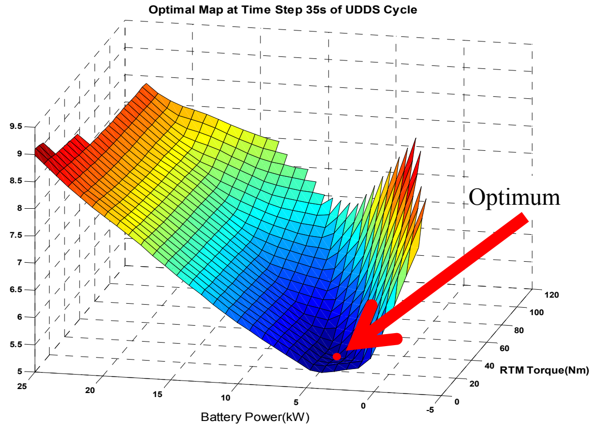


Fig. 4 Cost function at 35s step of UDDS cycle.

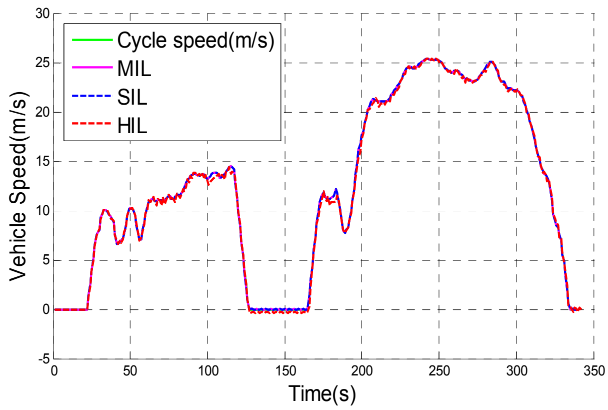


Fig. 5 Desktop simulation and HIL result.

4. Summary

Table 2 Fuel energy consumptions for different control strategies on the same UDDSx10 cycle.

	Fuel Economy MPG	WTW PEU (Wh PE/km)	Energy Consumption Improvement*	Computation Time** (Sample Time = 0.01s)
Mild-hybrid: Production Malibu	26.64	774	/	/
PHEV: Rule-based	47.98	101.96	(baseline)	10 min
PHEV: Slow PMP with fixed p	51.02	97.01	4.8%	6h
PHEV: Fast PMP with fixed p	50.69	97.319	4.5%	20 min
PHEV: Fast PMP with adaptive p	49.38	98.56	3.3%	20 min

* Compared to the baseline model. ** With same plant model and driver model, on a 32 GB, 4 core, 2.5 GHz computer.

implementation-oriented plant model based on dSPACE Automotive Simulation Models (ASM) tool, where I/O interface was the same as in the real vehicle.

Based on the above vehicle model, a real-time optimal control algorithm was developed, which identifies the optimal operational mode and the corresponding torque split among each components at each time step. The control objective in this study was to minimize the well-to-wheel petroleum energy use (PEU), where both the fuel and electric energy consumption was taken into account. The optimal torque split was computed based on Pontryagin's Minimum Principle. Since the powertrain system has a degree of freedom of two in terms of free control variables, a 2D search algorithm were initially developed to find the optimal point. To reduce the computational burden, the 2D search algorithm was further converted into a 1D-search algorithm based on optimization techniques. For practical implementation, an adaptive technique was utilized to update the equivalence factor based on battery SOC and current driving distance.

The proposed fast PMP algorithm was first investigated through Model-in-the-loop (MIL) simulation tests by using the simplified vehicle model. Simulation results have shown that the PMP algorithms have improved the PEU consumption by 3-5% when comparing to the baseline rule-based controller and the lowest PEU consumption was obtained when battery SOC is just depleted at the end of the trip. Among all algorithms, the fast PMP with adaptive costate p was the best one that has balanced both energy consumption, computation efficiency, and the ability for practical implementation, since only driving distance was needed for this algorithm.

After the control algorithm was validated in the MIL environment, it was then migrated to the more complex model and integrated with other system modules (such as subsystem diagnostic modules) in the rapid prototype controller (MicroAutobox II). The real-time performance of the developed controller was investigated through the rapid-prototyping controller HIL platform, where plant model was uploaded into dSPACE midsize real-time simulator and the controller model was uploaded into MicroAutobox II. HIL simulation has proved that the proposed control algorithm is able to run in real time and can track the driving cycle very well.