Approaches to Energy Management of Hybrid Electric Vehicles: Experimental Comparison

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Abstract: This paper reports the results of experimental comparison in a Land Rover Freelander2 HEV prototype vehicle, of two different energy management controllers. The first controller is a rule-based controller that was calibrated using optimal time trajectories obtained by application of a deterministic dynamic programming algorithm over the NEDC drive cycle. The second controller is Jaguar Land Rover's (JLR) HEV controller which uses off-line computed maps based on application of the Game Theory (G.T.). The controllers were tested on a rolling road with the prototype vehicle over different drive cycles: NEDC, FTP75 and HYZEM Part2. The results demonstrate that over NEDC the G.T. controller, with a minimal calibration effort, provides as good performance as the rule-based controller (which was calibrated to replicate the dynamic programming solution over NEDC). It also demonstrate that the G.T. controller outperforms the rule-based controller over more real world focused driving cycles.

Keywords: Hybrid Electric Vehicles, Energy Management, Fuel Economy, Emissions, Optimal Control, Game Theory

1. INTRODUCTION

Hybrid Electric Vehicles (HEVs) have been steadily growing in market popularity due to their advantages in improving vehicle fuel efficiency. Unlike conventional vehicles, in typical HEVs there are multiple degrees of freedom for delivering wheel torque, by splitting wheel torque request into a mechanical engine torque request and an electric motor/battery power request. The term HEV energy management generally refers to control allocation for delivering wheel torque to maximize average fuel economy and sustain on average battery state of charge (SoC).

Several systematic approaches to HEV energy management have been proposed in the literature, with specific algorithms based on applications of rule sets, fuzzy logic, neural networks, deterministic dynamic programming, stochastic dynamic programming, and game theory. Sciarretta et al (2007) surveys many of the approaches that have been applied to these problems in the past.

In a sequel of papers, Dextreit et al (2007, 2008) have proposed an energy management strategy for a parallel HEV based on an application of the Game Theory (G.T.) approach. In this approach, the vehicle operating conditions (wheel speed and wheel torque) and the powertrain are viewed as two players in a finite horizon zero sum game. A cost functional of this game weights fuel consumption, the deviation of SoC of the battery from the set-point and the deviation of vehicle operating conditions from the nominal operating conditions. The control policy for deciding on power to be drawn for the battery as a function of wheel torque, wheel speed and SoC of the battery can then be determined as a feedback Stackelberg equilibrium of the game (Von Stackelberg, 1952; Basar and Olsder, 1999). Unlike the conventional dynamic programming, the G.T. based solution is time and drive cycle independent (Kolmanovsky and Siverguina, 2001). It also compares favourably with stochastic dynamic programming in terms of computations, as the value function depends on less variables.

In Dextreit et al (2007, 2008), vehicle model simulations were used to establish that the G.T. based solution can outperform the stochastic dynamic programming based solution and two conventional energy management strategies in terms of fuel economy.

Recently, the G.T. solution was extended to handle NOx emissions (important for diesel engines) in addition to fuel consumption. This solution was then evaluated experimentally in an HEV with a diesel engine along with a rule-based strategy calibrated to approximately replicate the deterministic dynamic programming based solution over NEDC. The controller is known as: rule based dynamic programming calibrated (RBDPC) controller. The results of this evaluation are reported in this paper. They demonstrate that the G.T. controller, with minimal calibration effort, matches the performance of the RBDPC controller solution over NEDC. At the same time, the G.T. controller outperforms the rule-based controller over more real world focused driving cycles.

This paper is organized as follows. Section 2 describes the Freelander2 HEV vehicle prototype used for implementation of different energy management controllers. Then Section 3 discusses the dynamic programming based solution and comment on aspects important to its implementation in the vehicle. Section 4 describes the G.T. based solution and comments on aspects important to its implementation in the vehicle. The fuel economy and NOx emission reduction results which highlight the benefits of the G.T. based controller are reported in Section 5. Finally, concluding remarks are made in Section 6.

2. FREELANDER2 HEV PROTOTYPE

The Freelander2 HEV prototype (see Figure 1) is based on a Land Rover Freelander2 TD4 vehicle with automatic transmission. The main change to the powertrain has been the replacement of the automatic transmission by a prototype 6 speeds gearbox Dual Clutch Transmission in which a Crankshaft Integrated Starter Generator (CISG) is placed between the dual mass flywheel of the DW12-b diesel engine and the clutches.

On the rear of the vehicle, an electric motor has been integrated within the differential and is permanently geared with the rear axle. This motor is termed the ERAD (Electric Rear Axle Drive).

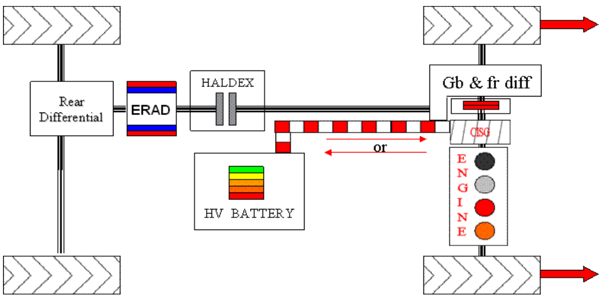

Fig. 1. Freelander2 HEV powertrain architecture.

Table 1 and Table 2 summarize feasible hybrid powertrain operating modes that have been considered in the optimization. These modes correspond to different combinations of CISG and ERAD operating states: Regen, Inactive and Drive.

Table 1. Operating mode when engine is on. Feasible modes correspond to YES.

		ERAD		
		Regen	Inactive	Drive
CISG	Regen	NO	YES	NO
	Inactive	NO	YES	NO
	Drive	NO	YES	YES

Table 2. Operating mode when engine is off. Feasible modes correspond to YES.

		ERAD		
		Regen	Inactive	Drive
CISG	Regen	NO	NO	NO
	Inactive	YES	NO	YES
	Drive	NO	NO	NO

The emissions targets to be achieved with this vehicle over the NEDC are based on EURO 4 diesel class 3 vehicle standards and are summarized in Table 3.

Table 3. EURO 4 diesel class 3 vehicle standards

NOx:	0.39 g/km
HC+NOx:	0.46 g/km
CO:	0.74 g/km

In this paper, simultaneous optimization of the gear shifts and battery power output is not pursued. Since the gearbox used on Freelander2 HEV is different than the gearboxes used on conventional donor vehicles (Freelander2), the gear-shifting map has been optimized to shift in a range favourable to reduce NOx emissions whilst keeping in mind that in parallel mode, engine and CISG will be able to optimize engine operating point to a more efficient load region. Figure 2 represents the upshift map chosen for the Freelander2 HEV vehicle. This map defines the gear as a function of pedal position and vehicle speed, assuming the vehicle has been upshifting; a similar map is available for downshifting.

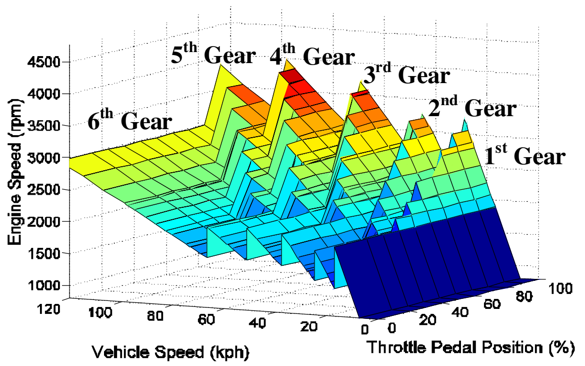

Fig. 2. Gear shifting map chosen for Freelander2 HEV.

Using this gear shifting map, the prototype vehicle has been run on a rolling road over the NEDC cycle. The resulting time histories of wheel speed, wheel torque and gear are shown in Figure 3. From this test the following data were extracted:

A baseline to compare emission and fuel consumption between the different controllers,

The wheel speed and torque demand over NEDC that will feed the offline optimisations.

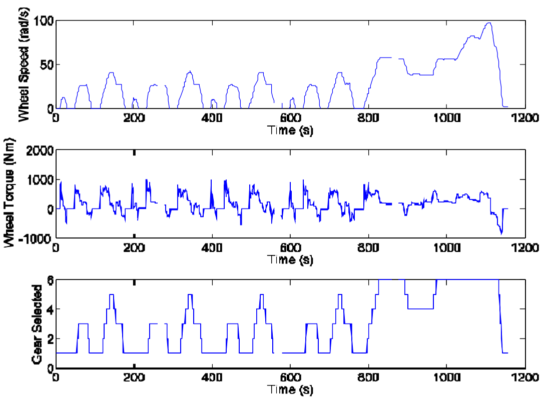

Fig. 3. Time histories of wheel speed (top), wheel torque (middle) and gear (bottom) of the Freelander2 HEV over NEDC.

3. DYNAMIC PROGRAMMING SOLUTION USING OFFLINE SIMULATION MODEL

First optimal deterministic dynamic programming trajectories were generated offline using a simulation model. Then a rule-based strategy was tuned using these trajectories and evaluated in vehicle experiments.

A control-oriented simulation model of Freelander2 HEV was created using the following components:

Steady state engine outputs: NOx and Brake Specific Fuel Consumption,

CISG motor/generator and inverter efficiency,

ERAD motor/generator and inverter efficiency,

Gearbox box efficiency,

High Voltage Battery efficiency.

A discrete set of modes has been defined consistently with feasible powertrain operating modes:

EV Mode, where the ERAD only is used to provide the driver torque demand at the wheel,

Engine only Mode,

A set of Charging Modes, where CISG torque is set to a negative torque and the engine provides the driver demanded torque plus the CISG torque.

A set of Boosting Modes, where CISG torque is set to a defined positive torque and the engine fills in for the rest of the driver demanded torque.

The dynamic programming was applied to the optimization of the cost functional based on the incremental cost function of the form

$$L(x,u,w)=\alpha\times Fuel+\beta\times NOx+\mu\times[SoC_{SetPoint}-f(x,u,w)]^2 \qquad (1)$$

where $u\in U$ is the control (powertrain operating mode in this case), $x\in X$ is the state (high voltage battery SoC in this case) and $w\in W$ is the vector of operating variables which is also referred to as the load site (wheel speed, wheel torque and gear selected in this case). In (1), $Fuel$ denotes engine fuel consumption, NOx denotes engine NOx emission mass flow rate, $SoC_{SetPoint}$ denotes the desired SoC set-point at the end of the cycle, $f(x,u,w)$ denotes the SoC resulting from a defined control action at a given load site and starting from a given SoC.

The dynamic programming reduces to the backward in time iterative construction of the cost-to-go function. This approach of going from the end of the cycle to the beginning of the cycle enables the cost of each control vector, at a defined point of the cycle and defined state of the system, to reflect what could happen next if the optimal control action is taken. If t denotes the time instant during the cycle and V denotes the cost-to-go function, the iterations take the following form:

$$\begin{cases} V(x,t)=\min\limits_{u(t)\in U}\{L(x,u,w)+V(f(x,u,w(t)),t+1)\}, t\in[T-1;1] \\ V(x,T)=\mu\times[SoC_{SetPoint}-x]^2, \text{ is the terminal cost.} \end{cases} \qquad (2)$$

At each time step throughout the cycle, the total cost K will be:

$$K(x,u,t)=L(x,u,w(t))+V(f(x,u,w(t)),t+1) \qquad (3)$$

Once the cost-to-go function has been constructed, the optimal control can be determined as follows:

$$u_{opt}(x,t)\in \arg\min_{u(t)\in U}\{K(x,u,t)\} \qquad (4)$$

The optimal trajectories generated by the deterministic dynamic programming algorithm and simulated using the Freelander 2 HEV model are illustrated in Figure A1.

A simulated NOx EURO4 compliant solution gave a saving of 25% of CO2 compared to the same vehicle running in conventional mode.

4. APPLICATION OF GAME THEORY TO FULL HYBRID CONTROL

The non-cooperative approach of G.T. was applied considering a multi-stage game played by the following two players:

The driver, represented by a discrete set of load sites (wheel torque, wheel speed and gear selected), covering the powertrain operating range,

The powertrain, represented by a discrete set of operating modes.

The first player is interested in minimizing a cost functional while the second player is interested in maximizing a cost functional. The cost functional is formed as a sum of incremental cost values over a finite horizon. The cost functional of the game is based on the following incremental cost function L related to the control action, u, the state vector, x, and the operating variable, w,

$$L(x,u,w) = \alpha \times Fuel(u,w) + \beta \times NOx(u,w) + \mu \times [SoC_{SetPoint} - (x - \Delta SoC(u,w))]^2 + \gamma \times G(w) \quad (5)$$

Here G denotes a positive Gaussian function with the centre at the centre of mass of a defined drive cycle. This function is introduced to focus the optimization on specific load sites.

The control policy is based on constructed off-line feedback Stackelberg equilibrium of the game. The process to construct this solution is based on the following iterations, applied to the cost-to-go function, V :

$$\begin{cases} V(x,T) = \max\limits_{w \in W} \min\limits_{u \in U} \{L(x,u,w)\} \\ V(x,t) = \max\limits_{w \in W} \{v(x,w,t)\}, t \in [T-1, T-2, \cdots, 0]. \\ v(x,w,t) = \min\limits_{u \in U} \{L(x,u,w) + V(f(x,u,w), t+1)\}, t \in [T-1, T-2, \cdots, 0] \end{cases} \quad (6)$$

Here $f(x,u,w)$ denotes the SoC resulting from a defined control action at a given load site and starting from a given SoC. The control policy is defined as

$$u(x,w) \in \arg\min_{u \in U} \{L(x,u,w) + V(f(x,u,w), 0\} \quad (7)$$

The solution is constructed offline using a grid for state, control, and load site values and interpolated on-line to generate the control action.

It is noted that for a sufficiently large number of stages, T, the algorithm will converge towards a quasi-optimal, time and drive-cycle independent solution, which is also independent of T.

5. VEHICLE EVALUATION RESULTS

Vehicle evaluation results of different controllers over NEDC and over alternative drive cycles (see Barlow et. al (2009) for the definition of various driving cycles, including NEDC, FTP-75 and Hyzem used in this work) are now reported.

5.1 NEDC results of the Freelander2 HEV with RBDPC controller

Using the optimal trajectories discussed in Section 3, a rule-based controller was created to provide the vehicle with a behaviour that replicated the offline solution including stop/start and charge/discharge of the engine over NEDC. Figure A2 illustrates the prototype operating points over NEDC, and also overlays the prototype results to the simulation results.

It can be seen that the battery model used for optimisation was not a perfect representation of the battery installed on the prototype, which is in part due to battery dynamics being (essentially) an integrator and affected by drift. This discrepancy resulted in trying to balance the SoC on the extra urban part of the cycle with increased charging demand. Also the amplitude of the torque assist has been spread at the end of the cycle but its duration has been prolonged in order to get a more constant engine torque demand. The offline maps were obtained from steady state measurements and this did not help the optimisation to react optimally to transient behaviours.

This solution resulted in a 21.5% CO2 saving over NEDC, was EURO4 compliant and the SoC was balanced over the cycle. The baseline vehicle for this comparison was the same vehicle, running in engine only mode with a feedback loop on the CISG torque acting as a alternator in order to sustain the energy drained by the 12V system over the cycle and a lighter road load to replicate the mass of the conventional Freelander2 diesel vehicle.

5.2 NEDC results of the Freelander2 HEV with Game Theory controller

The G.T. solution was represented by a set of offline computed maps. These were then implemented in the JLR full hybrid controller in the Freelander2 HEV.

The JLR controller based on offline computed G.T. maps delivered 22.5% reduction in CO2 compared to the baseline vehicle. It is emphasized that the JLR G.T. controller was calibrated for drivability on the test track whilst the rule based controller was not and did not provide the same level of drivability when driving the vehicle. The vehicle trajectories over the NEDC with the G.T. based controller are shown in Figure A3.

It can be observed than the G.T. controller performs a tighter control of the battery SoC within a more narrow window than the RBDPC controller. This is the result of not precisely knowing what could happen next in G.T. controller case.

Table 4 compares RBDPC and G.T. based results. The G.T. controller demonstrates better fuel economy and substantially better NOx emissions as compared to the RBDPC controller results.

Table 4. NEDC results for Game Theory compared to dynamic programming solution.

Drive Cycle	Output	Base line	RBDPC	GT
NEDC	CO_2	X	-21.5%	-22.5%
	NOx	Y	0%	-11.1%
	ΔSoC	N/A	-1%	-2%

5.3 *Comparison between Game Theory and Dynamic Programming controllers over different drive cycles*

The G.T. based controller is drive cycle independent. Hence it is expected that the G.T. based controller can perform well over drive cycles other than NEDC and can perform better than a rule-based controller calibrated using dynamic programming results.

The two controllers have been benchmarked against each other over NEDC, HYZEM phase 2 (urban phase of HYZEM) and FTP75 drive cycles. Results are summarized in Table 5.

Table 5. Game Theory controller performance against dynamic programming controller over FTP75 and HYZEM phase 2.

Drive Cycle	Output	RBDPC	GT
NEDC	CO_2	X	-4.5%
	NOx	Y	-11.1%
	ΔSoC	-1.0%	-2.0%
FTP75	CO_2	X	-0.2%
	NOx	Y	-7.3%
	ΔSoC	-3.2%	-3.0%
HYZEM Phase2	CO_2	X	-4.5%
	NOx	Y	-4.0%
	ΔSoC	-12.3%	-11.2%

It can be observed that over 3 different drive cycles, the G.T. controller with minimum calibration effort provides better fuel economy and NOx emissions than a rule based controller calibrated for a specific drive cycle using optimal trajectories obtained with the help of optimal control theory.

6. CONCLUSION

Experimental evaluation of JLR HEV controller based on the application of the G.T. was recently completed. This controller is a drive cycle and time-independent controller which selects powertrain operating mode based on the wheel torque request, wheel speed, gear selected and SoC of high voltage battery. Over several cycles, including NEDC, the G.T. based controller showed improved CO_2 and NOx results compared to a RBDPC controller solution over NEDC. In addition, the subjective assessment of vehicle drivability was better in the case of G.T. controller than RBDPC controller solution over NEDC.

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ANNEX A. SIMULATION AND ROLLING ROAD RESULTS OVER NEDC

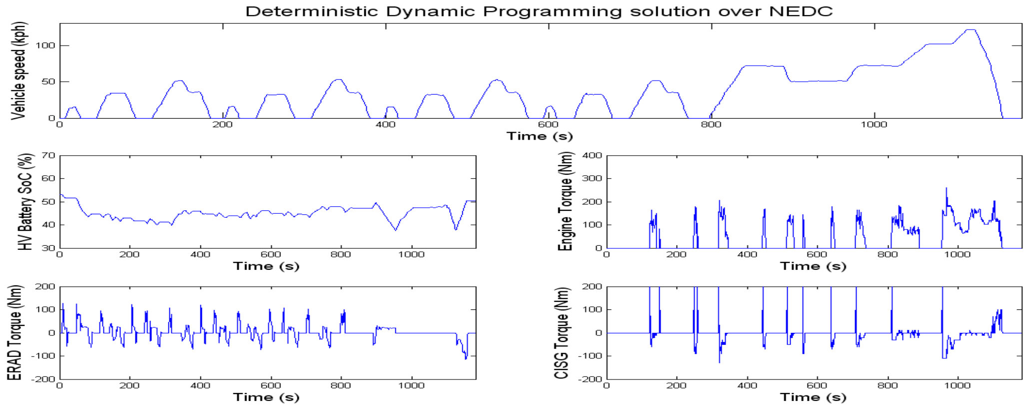

Fig. A1. Simulated deterministic dynamic programming (DDP) solution for the Freelander 2 HEV over NEDC.

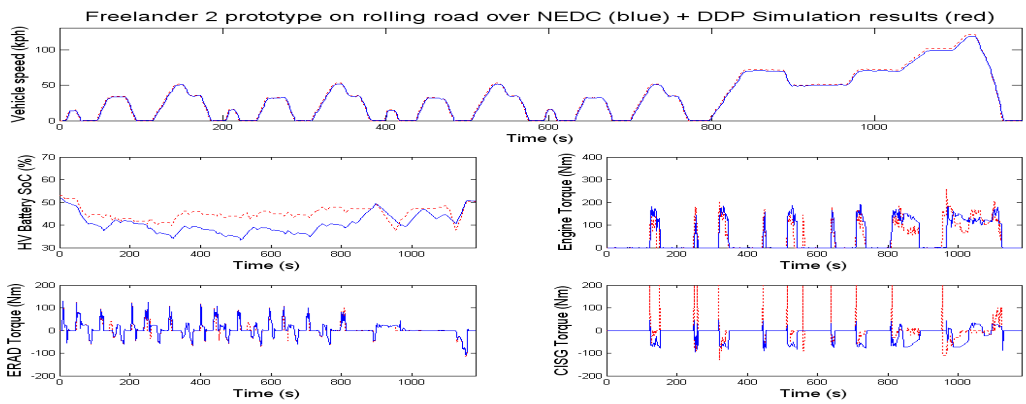

Fig. A2. RBDPC controller tested on rolling road over NEDC (solid) compared with DDP simulation results (dashed).

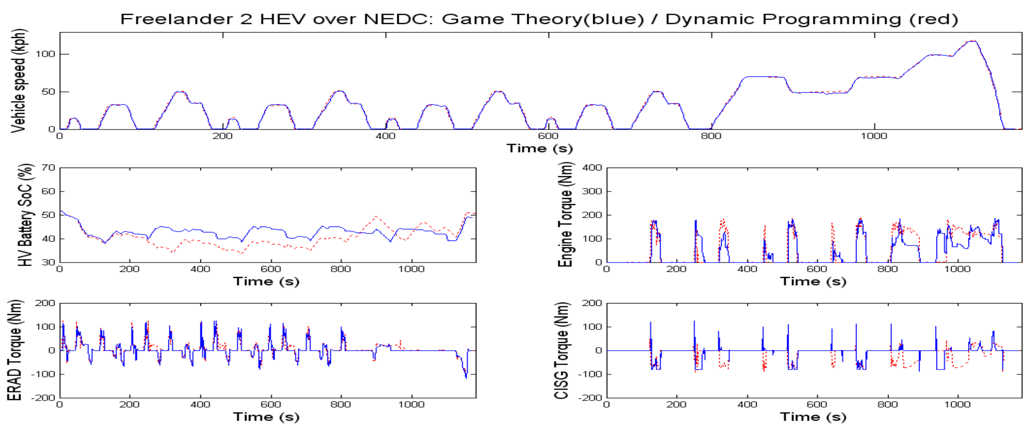

Fig. A3. Time histories of Freelander2 HEV variables with Game Theory based controller (solid) on rolling road over NEDC compared to dynamic programming results (dashed).