Route-Based Online Energy Management of a PHEV and Sensitivity to Trip Prediction

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Abstract—In this paper, we present a method of optimizing the energy management of a plug-in hybrid electric vehicle (PHEV) using GIS-assisted stochastic trip prediction. A process was developed to synthesize speed profiles through a combination of Markov chains and information from a geographical information system (GIS) about the future route. In a potential real-world scenario, the future trip (speed, grade, stops, etc.) can be estimated, but not deterministically known. The stochastic trip prediction process models such uncertainty. The route-based energy management presented in this paper uses the Pontryagin Minimum Principle (PMP). A PMP strategy was implemented in a Simulink controller for a model of Prius-like PHEV and compared to a baseline strategy using Autonomie, an automotive modeling environment. An itinerary was defined, and several speed profiles were synthesized. It was then possible to evaluate the sensitivity of PMP tuning to the speed profile, providing insights about the applicability of PMP control in real-world situations.

Keywords—energy management; optimization; PHEV; route prediction; Pontryagin Minimum Principle

I. INTRODUCTION

Numerous studies on optimal control applied to electrified vehicles showed that significant fuel savings can be achieved with knowledge of future speed. More often than not the premise in those studies is that the future speed profile is fully known. One such method is dynamic programming [1], which provides a global optimum. It is highly computer-intensive and is hardly implementable because of the very nature of the algorithm, which runs backwards. Stochastic dynamic programming [2] is similar, but uses a probabilistic distribution of drive cycles, rather than a single cycle. Another technique is mixed-integer linear programming [3].

In this study, we use the Pontryagin’s Minimization Principle (PMP) [4][5], which under certain assumptions can be simplified to an Equivalent Consumption Minimization Strategy (ECMS) method [6][7][8], and which is generally more compatible with real-world implementation. PMP too relies on the future trip prediction through a constant called co-state or equivalence factor.

Full knowledge of the future speed is simply not possible given the non-deterministic nature of driving. It therefore questions the possibility of any optimization technique relying on it. Partial knowledge is however conceivable, thanks to detailed maps of the road network, increased on-board computing capabilities, connectivity to cloud-based computing resources, live traffic information and ever-increasing availability of global navigation satellite systems, such as GPS. This type of knowledge is unfortunately too coarse to be directly used as input to optimization. It can nonetheless be exploited to produce predictions that would be usable. We presented in [9] a method of generating a speed profile using Markov chains “under constraints”; that is, an algorithm generates a speed profile until its characteristics matches certain targets (average speed, distance, etc.). As a result it is possible to generate an unlimited number of stochastic speed profiles that corresponds to a predefined itinerary. We used over 1,000 hours of recorded vehicle speed from the 2007 CMAP Travel Survey [10] to build the Markov model.

These stochastic speed profiles are an interesting opportunity for energy management. First, they are stochastic in nature and model the unpredictable nature of driving, however they are not completely random because they are constrained by the actual itinerary. Secondly, a set of stochastic trip predictions can be used to find the optimal equivalence factor that would work well for a variety of driving situations within that itinerary. Thirdly, another set of trip predictions can be used to evaluate whether the optimal energy management is really optimal in practice.

In this paper we present a route-based energy management using PMP, and we evaluate its sensitivity to trip prediction, using stochastic speed predictions for the same itineraries.

II. BASELINE VEHICLE MODEL

A. Vehicle Definition

We consider a PHEV with a medium all-electric range (AER). It is likely to be driven past its AER, and therefore likely to require engine use. Among the existing or planned vehicles, the Toyota Prius PHEV corresponds to such a profile. The vehicle powertrain model incorporates the publicly available specifications of the actual 2012 Prius PHEV. It has a 200-V, 21-Ah Li-ion battery with 168 cells. The top speed in all-electric mode is 100 km/h. The AER of the vehicle is 26 km using the JC08 test cycle, according to Toyota (23 km for our model). Some key specifications were not available and had to be supplanted by our own assumptions, which explains the differences in the AER.
We modeled the vehicle in Autonomie [10]. It is important to note that this is a forward-looking model and replicates the causality of the real world. In particular, the vehicle controller in the model uses the same type of inputs as those available from sensors in modern cars.

B. Baseline "EV+CS" Control Strategy

The baseline control strategy is to run the vehicle in "electric vehicle" (EV) mode as long as possible, i.e. until the SOC reaches the discharge level, at which point the vehicle starts operating in charge-sustaining (CS) mode, like a conventional HEV. The EV mode may also be interrupted if the vehicle speed is too high (above 100 km/h) or the power demand exceeds what the components can provide.

In CS mode, the high-level energy management strategy follows commonly used rules. The engine is turned on (respectively shut down) when the driver power demand is higher (respectively lower) than an SOC-dependent threshold. When the engine is on, the battery power demand is computed from an SOC-dependent look-up table: the battery is charged below the target SOC and discharged above the target SOC.

The computation of the optimal speed and torque targets are made thanks to a 3-input look-up table that is computed offline once – it is unique to the vehicle and does not depend on the duty cycle. The inputs to that look-up table are gearbox output torque demand, gearbox output speed and battery power. A schematic of view of the strategy is shown in Fig. 1.

![Schematic view of the baseline high-level energy](image)

**Fig. 1. Schematic view of the baseline high-level energy**

Since the controller is meant to be used within forward-looking Autonomie, the high-level control strategy is completed by a combined constraint computation block upstream, which is relatively complex for the Prius, and a target tracking block downstream that computes the necessary torque demands so that the target speeds and torques are met.

III. ENERGY MANAGEMENT STRATEGY WITH PMP

A. Theoretical Considerations

The goal of this project is to optimize a PHEV so that it uses less fuel energy than the baseline version. The vehicle must meet the driver demands, so we assume that vehicle speed and gearbox output torque are given. The battery state of charge $S_p$ is the state of the vehicle. Since fixing the battery power $P_b$ is enough to compute an optimal operating point, we consider $P_b$ as the command variable. Thanks to the optimal speed/torque look-up tables, we can link the fuel power to the battery power such that $P_f = g(P_b, S_p, t)$. The battery SOC is linked to the battery power by the following dynamic equation:

$$\dot{S}_b = -\frac{P_b}{Q V_n} \frac{2 V_n V_{oc}}{1 + \sqrt{1 - \frac{4 P_b R}{V_{oc}^2}}}$$  \hspace{1cm} (1)

where Q is the battery capacity, $V_n$ is the battery nominal voltage, $V_{oc}$ is the open-circuit voltage, and R is its internal resistance.

In equation (2), we introduce $\lambda_0$, a negative constant, and $\theta$, a scalar function of $P_b$ and $S_b$ (via $V_{oc}$ and $R$) close to 1 in the operating range of the system.

$$\lambda_0 = -\frac{1}{Q V_n}; \theta = \frac{2 V_n}{1 + \sqrt{1 - \frac{4 P_b R}{V_{oc}^2}}}$$  \hspace{1cm} (2)

As a result, equation (1) is equivalent to equation (3):

$$S_b = \lambda_0 \theta (P_b, S_p) P_b$$  \hspace{1cm} (3)

Therefore, the optimization problem consists of finding successive optimal battery power demands that will minimize the fuel energy while reaching the target SOC $S_{tgt}$ at the end of the trip:

$$P_b^* = \argmin_{P_b} \int_0^T P_f(P_b, S_b, t) dt$$  \hspace{1cm} (4)

The Hamiltonian $H$ of the system is:

$$H = P_f + p(t) \dot{S}_b$$  \hspace{1cm} (5)

where $p$ is the co-state. The PMP states that a necessary condition of optimality is that the optimum command $P_b^*$ minimizes the Hamiltonian (equation (6)) with the co-state verifying equation (7), as well as boundary conditions, especially regarding SOC.

$$P_b^* = \argmin_{P_b} H(P_b, S_b, p, t)$$  \hspace{1cm} (6)

$$\dot{p} = -p(t) \frac{\partial S_b}{\partial S_b}$$  \hspace{1cm} (7)

In this study, the characteristics of the battery ($V_{oc}$ and $R$) do not vary much as a function of the SOC. As a result, we will assume the co-state to be constant: $p(t) = p_0$. We also introduce in (8) the equivalence factor.

$$r_0 = \lambda_0 p_0$$  \hspace{1cm} (8)
This allows to rewrite (5) into (9), which then gives a physical interpretation of the Hamiltonian: it is the equivalent power used by the system at any given time.

\[ H = P_t + r_0 \theta(P_b, S_b)P_b \] (9)

The practical implementation of the PMP requires to find the battery power that minimizes the Hamiltonian at each time step. However, there is another problem to solve, which is to find \( r_0 \) such that the final SOC is the target SOC (30%).

B. Implementation in a Forward-Looking Controller

The PMP optimal controller is derived from the baseline controller. Only the high-level energy management is different. The other three blocks are the same. The PMP is implemented only for the charge-depleting mode (i.e., until the battery reaches the low SOC threshold used in the baseline control). Once that happens, the control switches to the same CS control as in the baseline control.

The first step is to compute the Hamiltonian for both the EV and engine-on modes. For the EV mode, the computation is straightforward as there is only one way of controlling the vehicle in that mode. For the engine-on mode, the computation of the Hamiltonian first relies on computing it for a vector of battery power demands and resulting fuel powers. The lowest Hamiltonian and the corresponding power demand are then selected.

The ON/OFF decision is based on the relative difference of the respective Hamiltonians in the EV and engine-on mode: in the ON/OFF logic block, we select the mode with the lowest Hamiltonian. Some filters are implemented to prevent an excessive number of state changes and ensure an acceptable drivability.

A schematic of the PMP energy management is shown in Fig. 2.

![Schematic of the high-level energy management in the PMP controller](image)

IV. BENEFITS OF ROUTE-BASED ENERGY MANAGEMENT

A. Design of Experiments

We presented in [9] a process to generate a second-by-second speed profile for a predefined itinerary, based on Markov chains and a geographical information system (GIS), ADAS-RP, developed by HERE, a Nokia company. The process allows the user to first select an itinerary in ADAS-RP, and export all the available attributes of all the segments of the trip; attributes include speed limit, traffic pattern, traffic signs position, grade, etc. These data are then an input to an algorithm that we developed which can synthesize an unlimited number of speed profiles. These speed profiles combine a deterministic nature (stops position, and average speed on each segment are given by ADAS-RP) and a stochastic aspect, because on each segment, the speed profile is the result of a Markov chain.

In this study, we selected a 36-km itinerary in the Munich area, combining urban and highway driving, as well as some uphill grades. Ten speed profiles were synthesized by using the stochastic vehicle speed profile generation process. One such speed profile is shown in Fig. 3. The reference vehicle and the one with the PMP controller were run on each of those trips. For the vehicle with the PMP controller, equivalence factors of 2.795 to 2.83 were used, with a 0.005 step. We also assumed that the goal was to minimize fuel use (no fuel/electricity trade-off was sought), and that the battery was fully charged at the beginning of the trip.

![One synthetic speed profile for the “Munich” itinerary](image)

B. Operation with Optimal Choice of Equivalence Factor

In this section, we assume that the equivalence factor is optimally chosen. As shown in Fig. 4, this means that the equivalence factors may be different from one trip to another.
The fuel consumption for each trip with optimal equivalence factors is shown in Fig. 5. There is close to 10% difference between the most fuel intensive trip (#7) and the least intensive trip (#6) because of the stochastic nature of the process used to generate them. We observe that the PMP controller leads to fuel savings in all cases and reduces the consumption by as much as 5.8% (Trip #1) and by 4.6% on average.

Fig. 6 shows how the energy is used throughout one trip (trip 10, equivalence factor of 2.81).

Throughout the trip, the engine and the battery are used in conjunction with the PMP controller, whereas the engine stays off during the first 18 km in the reference case (at which point it switches to CS mode). With the PMP controller, the CS mode is reached at 34.2 km (highlighted in Fig. 6 by a green dot), about 2 km from the end of the trip.

The engine is used less with the PMP controller, both in terms of energy (Parameter 1) or time (Parameter 4), and slightly more efficiently at that (Parameter 2). Parameter 5 is intended to give a sense of the level of recirculation, which occurs when part of the engine output is converted into electricity by motor 2 (or generator) and converted back to
mechanical power by motor 1. Recirculation is a source of inefficiency, but it is at times necessary to preserve engine efficiency and system efficiency as a whole. It appears here that recirculation is lower with the PMP controller, which means more engine energy goes directly to the wheels. Better efficiency is gained thanks to more frequent engine state changes: the number of engine starts (Parameter 3) almost tripled.

C. Sensitivity of PMP Controller to Equivalence Factor

In the previous section, full knowledge of the future speed was assumed: we used the same speed profile for estimating the optimal equivalence factor and to measure the fuel consumption benefits. In a potential real-world setting, the speed profile used to find the optimal co-state will be different from the actual speed driven. The results previously shown are therefore best-case scenarios. A more realistic scenario would be to obtain an equivalence factor based on a set of trip predictions and apply it to a different set, thus modeling the prediction/actuality discrepancy. For that purpose, we are going to analyze all the simulations, not just the ones with the optimal equivalence factor. The analysis of whether the PMP controller will still bring benefits with sub-optimal equivalence factors will provide valuable guidance.

Fig. 8 shows the outcome of simulations over three different trips using the entire sweep of equivalence factor values, along with the reference case (in red).

If the equivalence factor is too high, battery energy is too expensive, and as a result the final SOC is too high: there is battery energy left at the end of the trip that could have been used to displace fuel consumption. In that case, the performance of the PMP controller vehicle is actually worse.

On the other hand, if the equivalence factor is too low, the battery will be discharged prematurely, and the fuel consumption will approach the reference case. As a result, the benefits will diminish. However, it is unlikely that it will do worse than the reference strategy.

Fig. 9 provides another way to look at these results and shows fuel savings for all trips and equivalence factors. We adjusted the fuel mass value to account for differences in final SOC between the PMP and reference case for those PMP runs in which the CS mode was reached. We also included the average savings for any given equivalence factor, which peaks at 3.3%, for an equivalence factor of 2.805. Another curve shows the average over the best eight savings, which provides a slightly better result of 4.3%, for an equivalence factor of 2.81.

Note that there is a high sensitivity to the equivalence factor for certain trips. For example, an equivalence factor of 2.81 can bring 5.7% savings on one trip while increasing the consumption by over 2% on another one. This suggests that the “one-size-fits-all” equivalence factor approach may not be the best for yielding the highest results; an adaptive algorithm could resolve this issue.

Fig. 9. Fuel savings as a function of Equivalence factor for all 10 trips (one shape is one trip)

V. CONCLUSION

We demonstrated an implementation of PMP in a vehicle-level controller for a forward-looking powertrain model. Besides using inputs and outputs similar to those available in the real world, the controller also takes into account the main dynamic aspects of control and addresses some drivability issues (e.g., unrealistic and excessive engine state changes). Furthermore, we deployed best efforts to ensure the baseline controller using the “EV+CS” strategy is itself efficient, to limit the effect of a “bad” reference control on the results.
We used stochastic trip prediction, a technique that combines Markov chains with deterministic route attributes (such as stop position, average speed, speed limit, grade, etc.) to generate driving schedules for the study. The assumption is that the driver inputs its destination and selects a route to follow, which are very reasonable expectations. Thanks to this process, we can model the stochastic variations of speed for a given itinerary, and therefore better estimate the real-world potential of route-based energy management.

In our limited scenario (1 route, 10 synthetic speed profiles), we find that our PMP controller performs well even when a sub-optimal co-state or equivalence factor is used. However, in some cases there is a penalty; this suggest it is necessary to implement an adaptive algorithm to adjust the equivalence factor periodically during the trip. This is one aspect of our future work. Another one is to significantly expand the study to include many more trips, in order to give more statistical value to our results.

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