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Fuel Saving Potential of Optimal Route-Based Control for Plug-in Hybrid Electric Vehicle

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In this paper, we evaluate the fuel savings of a plug-in hybrid electric vehicle (PHEV) that uses an optimal controller, itself based on the Pontryagin Minimum Principle (PMP). A process was developed to synthesize speed profiles through a combination of Markov chains and information from a digital map 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. 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. Multiple real-world itineraries were defined in urban areas with various environments, and for each of them multiple speed profiles were synthesized so as to provide a statistically representative dataset, and finally fuel savings were evaluated with the optimal control.

***Keywords**:* hybrid vehicle, energy management, optimization.

1 INTRODUCTION

Hybrid electric vehicles (HEV) and their plug-in version (PHEV) combine two sources of power, providing freedom in control, and thus presenting opportunities for optimization. The intuitive control logic for HEVs is to use the engine at high power demands (accelerations, high speed driving). For PHEVs, conventional strategies aim at using the grid electricity stored in the battery first, and then switch to a charge-sustaining (CS) HEV control. Optimal control theory can however provide the means to achieve the lowest fuel consumption in a more systematic way.

Numerous studies on optimal control applied to electrified vehicles showed that significant fuel savings can be achieved with knowledge of future speed. Dynamic programming (DP) using the Bellman principle is one such method, and in the context of a PHEV, it shows that a blended charge-depleting strategy is optimal for longer trips (Karbowski et al., 2006). Stochastic dynamic programming (Moura et al., 2011) is similar, but uses a probabilistic distribution of drive cycles, rather than a single cycle. Another technique is mixed-integer linear programming (Wu et al., 2014).

In this study, we use the Pontryagin's Minimization Principle (PMP) (Kim et al., 2011; Shen et al., 2015), which under certain assumptions can be simplified to an Equivalent Consumption Minimization Strategy (ECMS) method (Musardo et al., 2005; Paganelli et al., 2002; Serrao et al., 2009), 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 (EQF).

One key challenge for implementing optimal controllers is the full knowledge of the future speed, given the non-deterministic nature of driving. However it is conceivable that some information about the future is available thanks to global navigation satellite systems (GNSS) and digital maps. The destination and route can be known, either through driver's direct input or through statistical learning (Froehlich and Krumm, 2008). However, the information typically available, such as average speeds on road segments is too coarse for properly estimating energy consumption and therefore minimizing it.

In this paper, we present a method that combine Markov chains (Ivanco et al., 2009; Lee and Filipi, 2010) and digital map information, which allows to generate a set of speed profiles for the trip ahead. These speed profiles can provide a horizon for a PMP controller, implemented for a forward-looking model, Autonomie (Argonne National Laboratory), of a Toyota Prius PHEV, and can also be used to evaluate the effectiveness of the PMP controller.

2 SPEED PROFILE GENERATION

2.1 *Vehicle trip profile*

We define a vehicle trip profile (VTP) as a set of attributes describing a trip made on the road. These attributes may include the route, grade, road class, speed, etc. In the present study, we consider two kinds of VTP:

- Macroscopic VTP (M-VTP): contains macroscopic attributes for each subsection of the trip, including road category, speed limit, traffic signs, etc.
- Microscopic VTP (µ-VTP): time-series for the entire trip with a frequency of 1 Hz or less, including vehicle speed and grade.

M-VTPs can be obtained from a digital map. In our case, we use HERE's digital maps, by defining an origin and a destination in a geographical interface. While the M-VTPs thus created contain very useful attributes, their spatial resolution (hundreds to a few thousands of meters) is not compatible with a high-fidelity vehicle energy model, such as Autonomie. One notable exception is the grade, which can be used as-is because of its higher resolution. M-VTPs can be

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obtained in a modern car equipped with a digital map, and with the knowledge of current position and trip destination.

2.2 Markov Chain Generation under Constraints

In a M-VTP generated from HERE's data, the trip is divided in segments of a few hundred meters up to a few kilometers, and for each segment, the average speed and the speed limit can be known, as well as whether the segment ends with a stop. One possible way of "augmenting" the data with naturalistic speed changes occurring in the real-world is to use Markov chains. We use $X = (v, a)$ as the state of the process, similarly to previous research (Ivanco et al., 2009; Lee and Filipi, 2010). The transition from one state to another is governed by a transition probability that is not time-dependent, and the collection of these probabilities forms the transition probability matrix (TPM) M:

$$\forall k \in [1, T],\ \ P\big(X(k+1) = X_i \big| X(k) = X_j\big) = M_{i,j} \qquad (1)$$

where $X_i = (v_n, a_m)$ and $X_j = (v_p, a_q)$, and k is the discretized time.

Given that speed and acceleration are related, using both together as a state makes the process equivalent to a 2$^{\text{nd}}$ order Markov chain, i.e. where the transition probability at any given time depends on the states at the previous two time steps.

We build the TPM by processing all the data points of a real-world trip database. In our case, we used data from the 2007 Chicago Metropolitan Agency for Planning (CMAP) travel survey. Approximately 6,000,000 data points were filtered, processed, and quality-checked.

One fundamental aspect of the "classic" Markov chain is that the outcome is stochastic, and the only control over the result is the time at which we stop the Markov chain generation. We designed a "constrained" Markov chain algorithm (Fig. 1) that generates a naturalistic speed profile for a segment defined by its distance, speed limit, target average speed and initial speed. The algorithm consists, for a given segment, in generating stochastic speed profiles until a result with characteristics "close" enough to the deterministic prediction emerges. The Markov chain generation is stopped when the current distance is higher than, or close to the target distance. Once the candidate stochastic speed profile is generated, we check whether it satisfies a stopping criterion, so that the average speed and distance match the ones of the target, and so that the speed limit constraint is satisfied. If the stopping criterion is not met, the algorithm starts a new Markov generation, and the process continues until a speed profile that meets the stopping criterion is found.

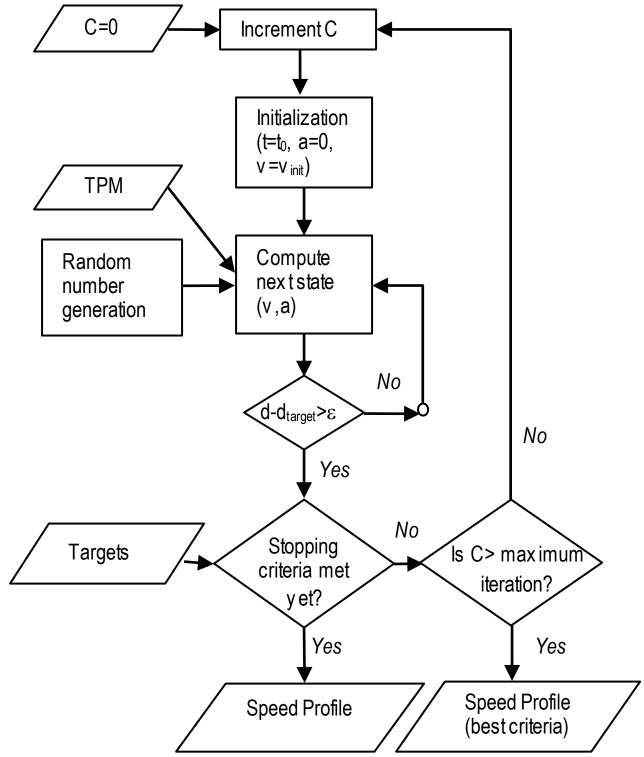

Fig. 1. Flowchart sumarizing the "constrained" Markov chain algorithm

Fig. 2 shows an example of output from the algorithm for one example segment. Three vehicle speed traces were generated for the same short target segment: the resulting average speeds are close to the target speed of 31 km/h, and do not exceed the 50 km/h speed limit. Because of the stochastic nature of the method, no two synthesized speed traces are the same.

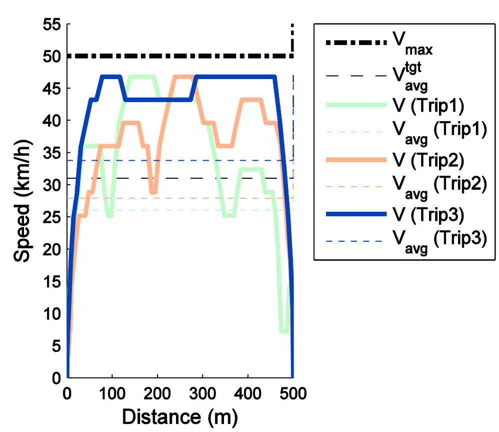

Fig. 2. Three vehicle speed profiles synthesized by a Markov Chain under the same constraints

This process can be repeated for each segment of a M-VTP, with the final speed of one segment being the initial speed of the following one, so as to ensure continuity of the speed signal. An example is shown in Fig. 3. A μ-VTP, usable in a high-fidelity vehicle model, is thus created from a M-VTP coming from the digital map. By generating multiple μ-VTPs for the same M-VTP, it is possible to have a set of μ-VTPs statistically representative of the same future M-VTP.