Using Trip Information for PHEV Fuel Consumption Minimization

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Optimal Energy Management of xEVs Needs Trip Prediction

Vehicle energy use can be reduced through application of control theory or fine tuning:
- Dynamic Programming (DP): finds the global optimum for the command law
- Instantaneous optimization:
  - ECMS: Equivalent Minimization Consumption Strategy
  - PMP: Pontryagin Minimization Principle
- All techniques require knowledge of the trip!

Increased connectivity and increased availability of data opens the door to trip prediction
Trip Prediction
Modeling Vehicle Speed with Markov Chains

- What is a Markov chain?
  - Collection of random variables \( \{ X_1, X_2, \ldots, X_p \} \)
  - **Memoryless**: the future only depends on the present, not the past
    \[
    P(X_{k+1} = j \mid X_1 = i_1, X_2 = i_2, \ldots, X_k = i_k) = P(X_{k+1} = j \mid X_k = i_k) = P_{i,j}
    \]
  - Homogenous, i.e. the probability \( P_{i,j} \) does not depend on time

- Vehicle speed can be represented by a Markov chain:
  - Random variable can be vehicle speed:
    *Speed at time \( t+1 \) only depends on speed at time \( t \)*
  - Random variable can be vehicle speed and acceleration:
    *Speed at time \( t+1 \) depends on speed and acceleration at time \( t \)*

- The Markov chain is defined by a **Transition Probability Matrix** (TPM):

\[
P = \begin{bmatrix}
P_{1,1} & \cdots & P_{1,n} \\
\vdots & \ddots & \vdots \\
P_{n,1} & \cdots & P_{n,n}
\end{bmatrix}
\]
TPM Is Created from Real-World Trips

- From the CMAP Database:
  - CMAP = Chicago Metropolitan Agency for Planning
  - Data acquired as part of a comprehensive travel and activity survey for northeastern Illinois in 2007-2008

- 9000+ trips / 400+ drivers / 6,000,000 data points
- Data filtered to remove outliers and unrealistic trips
Constraining the Markov Chain to the Characteristics of a Given Segment

- Target segment defined by representative variables:
  - Average speed $V_{tgt}$
  - Distance $d_{tgt}$
  - Speed limit $V_{lim}$

- Generated segment:
  - Actual speed $V(t)$
  - Average speed $V_{avg}$
  - Distance $d_{seg}$
  - Number of stops $N_{stop}$

- The Performance Value $PV$ quantifies how close to the target the generated segment is:

$$PV = w_1 \frac{|V_{avg} - V_{tgt}|}{V_{tgt}} + w_2 \frac{N_{stop}}{d_{seg}} + w_3 \sum_{t=t_1\ldots t_2} \max((V(t) - V_{lim}),0)^2$$

$$+ w_4 \frac{|d_{seg} - d_{tgt}|}{d_{tgt}}$$
Example of Segment

Speed Limit
50 km/h

Target Speed
32 km/h

Graph showing speed as a function of distance with various lines representing different speeds and trips.
Combining Markov Chains and Geographical Information

Itinerary in GIS (ADAS-RP)

Raw Data Formatting + Segmentation

Vehicle Speed

Distance

Synthesized Trip

Iterative Stochastic Generation for each Segment

for segment = 1 to n

end
Example of Entire Trip

![Graph showing speed vs. time with various lines and labels: 
- V
- Vmax
- Vtgt_avg
- Vact_avg
- t_stop]
Itinerary Used for Study on Control

Munich area
~ 36 km
Speed limited to 100 km/h

Same target, but 10 different synthesized trips

Grade is same for all synthesized trips
Optimal Control
Definition of the Problem

- Simulation environment: Autonomie, forward-looking
- ~ Prius 2012 PHEV:
  - Battery: 4 kWh, 200 V, Li-ion
  - Rated all-electric range: 26 km
  - Top EV speed = 100 km/h

Baseline Control Strategy

Charge-Sustaining:
- Rule-based
- Optimum system efficiency look-tables

Can the knowledge of the trip help reduce the fuel consumption?
Optimal Control Uses Pontryagin’s Minimization Principle

- The high-level command variable is the battery power $P_b$
- At each time step, the optimal command is the one that minimises the Hamiltonian:

\[
P_b^* = \arg\min_{P_b} \left( P_f(P_b) + r(t) \vartheta(P_b) P_b \right)
\]

- In our study we make the assumption that $r(t) = r_0$
- PMP only in Charge-depleting mode, then baseline Charge-Sustaining mode control
The Challenge of PMP: the Equivalence Factor Depends on the Trip!

- \( r_0 \) too high:
  - Electricity is too “expensive”
  - There is battery energy left at the end of the trip
  - Worst fuel consumption than baseline

- \( r_0 \) optimal

- \( r_0 \) too low:
  - Electricity is too “cheap”
  - Battery is discharged too early
  - Missed opportunity to displace more fuel
Case 1: Equivalence Factor Is Optimal for each Trip

- Equivalence factor optimal for each trip = best case scenario
- Different eq. factor for each trip
- Fuel savings: 3.5 to 5.7 %, 4.6% on average
After this point, control switches to CS mode.
In Real-World, the Exact Speed Profile Is not Known!

- Prediction will never match actual speed because of the stochastic nature of driving => Eq. factor will not necessarily be optimal
- How good is the optimization if this case?

* Both trips are synthesized; “Predicted” and “Actual” labels for illustration purpose
Using an Equivalence Factor not Optimized for Actual Speed Profile still Brings Benefits

1 point = 1 trip, 1 eq. factor
1 shape/color = 1 trip

Average benefit for a given eq. factor over all 10 trips
Average benefit for a given eq. factor over top 8 trips
Conclusion

- Improving vehicle energy efficiency through connectivity requires both control optimization and trip prediction. Each has to be implementable!

- Trip prediction is achieved using a combination of Markov chains and GIS:
  - A GIS (e.g.: ADAS-RP) provides trip-specific information
  - Predicted Trip = aggregation of stochastic “micro-trips” that fits constraints from GIS

- Optimal control using trip prediction:
  - Achieved through PMP controller
  - Key factor for PMP efficacy, equivalence factor, depends on trip

- Benefits of the technology can be evaluated in simulation; in our sample itinerary (not statistically representative):
  - best case scenario (eq. factor is adapted to trip): 4-6 % fuel savings
  - “real-world” scenario (one eq. factor per itinerary): 3-4% fuel savings

Future Work

- Trip prediction: refine process and integrate in Autonomie

- Optimal control:
  - Develop fast optimal equivalence factor prediction algorithm for PMP
  - Implement an adaptive equivalence factor

- Run large-scale study to quantify in a statistically representative way the benefits of trip-based control
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See also [www.autonomie.net](http://www.autonomie.net)
Backup Slides
From Itinerary Definition to Simulation of Optimal Control

Define Itinerary in GIS (ADAS-RP)

Generate Speed Profile Using Markov Chains

Compute Controller Optimal Tuning

Optimal Controller

Simulate in a Forward-Looking Model (Autonomie)

- Our approach:
  - Work on both optimal control and prediction
  - Propose implementable solutions
Operating the Powertrain Optimally (with a few Givens) Requires Optimal Operation Maps

- One mode power-split offers freedom, and no-easy “optimum”:
  - Engine speed can be controlled independently from vehicle speed
  - Depending on vehicle and engine speed, there is energy recirculation (inefficient)
- An offline algorithm computes the optimal operating point for given output speed, torque demand and battery power
Argonne Published Work

- **Adaptive control:**

- **Dynamic Programming:**

- **PMP / ECMS:**

- **Trip prediction:**