Route-Based Energy Management for PHEVs: A Simulation Framework for Large-Scale Evaluation

Dominik Karbowski, Namwook Kim, Aymeric Rousseau
Argonne National Laboratory, USA
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.
Our Vision for Route-Based Control

Scope of Argonne’s Research

- Original research on **speed prediction**, an often overlooked problem
- Research on **implementable solutions** for route-based control
- Evaluation of **real-world benefits** of route-based control
Speed Prediction
Future Speed: Stochastic or Deterministic? Both!

Impossible to know the exact future speed profile: driving is not deterministic!

**But not completely random either...**

**DETERMINISTIC**
- the driver follows an itinerary selected at the beginning of the trip
- OR the driver selects an itinerary in the navigation unit, and follows directions

**STOCHASTIC**
- Free flow: natural variations (accelerations vary, not always same speed)
- Interactions with other cars & environment
Maps / GIS Can Provide Information About a Given Itinerary

- Traffic pattern speed: average traffic speed for a given time/day
- Road slope: modeled with splines, not simply from GPS altitude data
- Speed limitations
- Position of traffic lights, stop signs, intersections, and other signs
- Category of road
- Number of lanes
- Etc.

But not enough to predict fuel consumption!
Chicago Real-World Data Provides Stochastic Aspect

- 2007 travel survey for the Chicago Metropolitan Agency for Planning (CMAP)
- GPS loggers
- 267 households surveyed
- 10k vehicle trips
- 6M data points

59% of points deemed valid (=1000h)
From Database to Actual Speed Profiles: Constrained Markov Chains

Valid Real-World Micro-Trips

Transition Probability Matrix

Markov Chains

Constrained Markov Chain

Initialzation (t=0, a=0, v=0)

Random number generation

Compute next state

Speed Profile

Metadata matches target?

Yes

No

Yes

No

v=v_{end}?

d>d_{target}?

Computing next state

Yes

No
Examples of Synthesized Speed Profiles

Multiple stochastic speed profiles for the same target micro-trip

One synthetic speed profile for one entire itinerary

Speed Limit
50 km/h

Target Speed
32 km/h

<table>
<thead>
<tr>
<th>Time (s)</th>
<th>Speed (km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>100</td>
<td>20</td>
</tr>
<tr>
<td>200</td>
<td>30</td>
</tr>
<tr>
<td>300</td>
<td>40</td>
</tr>
<tr>
<td>400</td>
<td>50</td>
</tr>
<tr>
<td>500</td>
<td>60</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>V</th>
<th>V_max</th>
<th>V_avg</th>
<th>V_avg (Trip1)</th>
<th>V_avg (Trip2)</th>
<th>V_avg (Trip3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>100</td>
<td>20</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>200</td>
<td>30</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>300</td>
<td>40</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>400</td>
<td>50</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>500</td>
<td>60</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
</tbody>
</table>

Graph showing speed profiles over distance and time, with markers for maximum speed, average speed, and trip-specific average speeds.
Optimal Energy Management
Pontryagin’s Minimization Principle

- **System**: one-mode power-split PHEV (similar to Toyota Prius PHEV)
- **Not influenced by control**: Vehicle speed, torque demand decided by driver
- **State of the system**: battery state-of-charge (SOC)
- At any given time, for any given vehicle speed / wheel torque / battery power, one optimal operating point minimizing fuel consumption exists
  \[ \Rightarrow \text{Battery power } P_b = \text{command variable} \]
- Constraints: final SOC is 30%
- PMP:

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

- In our study we make the assumption that EQF \( r(t) = r_0 \)
- Optimal EQF: one that results in SOC=30% for the first time at the end of the trip
PMP Implementation in the Vehicle Controller

- Optimal Operating Points
- Minimization of cost function
- Filtering of the optimal power demand
- Computation of corresponding torque/speed targets

Battery power “Candidates”

Fuel and battery power computation

PMP w/ ICE

Optimal Speed/Torque Targets (HEV)

Cost HEV

ICE ON/OFF Logic

Cost EV

EV Mode

Speed/Torque Targets (EV)

ICE ON/OFF
Simulation Framework
Driver & Powertrain

A forward-looking model of the Prius PHEV in Autonomie

Driver presses on pedals

Vehicle energy management computes torque demands

Powertrain = all components

Components: dynamics + look-up tables from test data
Route Selection

User can select route in HERE’s ADAS-RP

Route export plug-in
Speed Prediction

Input = Route from ADAS-RP

Output = n speed profiles + grade
Route-Dependent Optimization

Start

Run EV+CS

\[ \exists t_{SOC=30\%} ? \]

No

No PMP

Yes

\[ t_{SOC=30\%} < t_{end - \delta t} \]

No

Yes

Increase EQF

Run PMP

Decrease EQF

\[ \exists t_{SOC=30\%} ? \]

No

No

SOC_{end} > SOC_{tgt} + \delta SOC?

No

Yes

SOC_{end} > SOC_{tgt} + \delta SOC?

No

Yes

t_{SOC=30\%} < t_{end - \delta t}?

No

Yes

EQF Found

Optimal SOC drop

Battery not used enough

SOC drops too fast

SOC_{tgt} vs. t_{end}

SOC_{tgt} vs. t_{end}

SOC_{tgt} vs. t_{end}

SOC_{tgt} vs. t_{end}
Actual Driving

In the real-world, actual speed prediction will be different from prediction...

P Speed profiles for EQF optimization (before driving)

≠

Q Speed profiles for actual driving
Large-Scale Evaluation

- 30 itineraries
- 8 Generations
- 3 SOC\textsubscript{init}
- 9 EQFs

1 EQF Optimization

+ 8 suboptimal values around optimal EQF
Example of Result (1 Itinerary, 1 generation)

Fuel savings need to be SOC adjusted: final SOC in optimal case is always 30%, but it varies for reference case (stays in the [28,32] range)
Preliminary Results Show Strong Benefits (Best Case Scenario)
Conclusion

- Optimal energy management for xHEVs theoretically requires full knowledge of duty cycle, which is **not possible in the real-world**
- A **realistic** and **stochastic prediction** can be achieved, through a combination of **Markov chains** and data from **digital maps**
- PMP is a convenient way of achieving **optimal control** in a real-world controller
- Efficacy depends on one tuning parameter, the **equivalence factor (EQF)**
- EQF depends on the **future route**
- A **framework** was designed to evaluate route-based control along with its uncertainties:
  - Detailed **powertrain model** in Autonomie
  - **Vehicle speed prediction** for a given itinerary
  - Optimal **route-based tuning**
  - **Large-scale** simulation to evaluate benefits in a broad range of situations
- **Future work:**
  - Further statistical analysis: can the optimal EQF be **inferred** from simple parameters, or full simulation is needed?
  - Make the controller **adaptive**, i.e. update EQF periodically (vs. simply at start of the trip)
Acknowledgement

U.S. Department of Energy
Energy Efficiency and Renewable Energy
Funded by the Vehicle Technology Office
Program Manager: David Anderson

HERE (a Nokia company) provided free license for ADAS-RP

Contact

Dominik Karbowski (Principal Investigator): dkarbowski@anl.gov / 1-630-252-5362
Aymeric Rousseau (Systems Modeling and Control Manager): arousséau@anl.gov

www.autonomie.net

www.transportation.anl.gov