Using Trip Information for PHEV Fuel Consumption Minimization

27th International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium (EVS27)
Barcelona, Nov. 17-20, 2013

Dominik Karbowski, Vivien Smis-Michel, Valentin Vermeulen

Work funded by the U.S. DOE Vehicle Technology Office
(Program Managers: David Anderson, Lee Slezak)

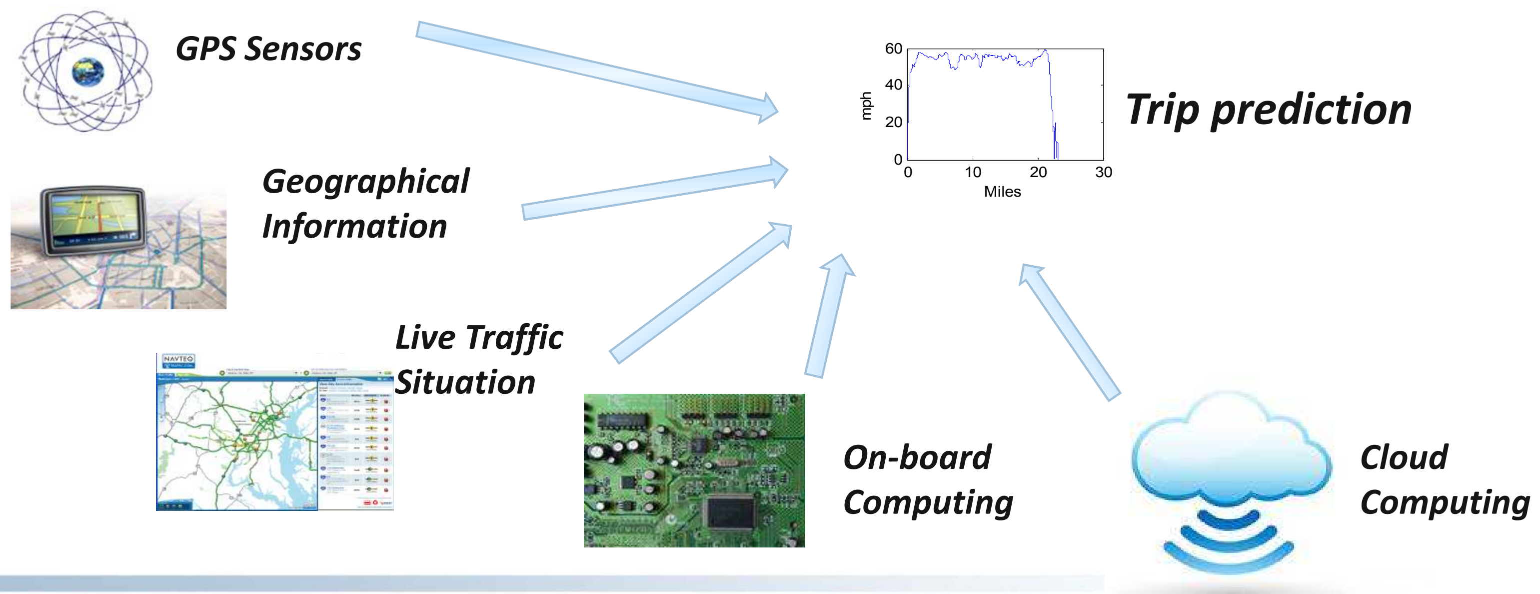
U.S. Department of Energy
Energy Efficiency and Renewable Energy
Bringing you a prosperous future where energy is clean, abundant, reliable, and affordable

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



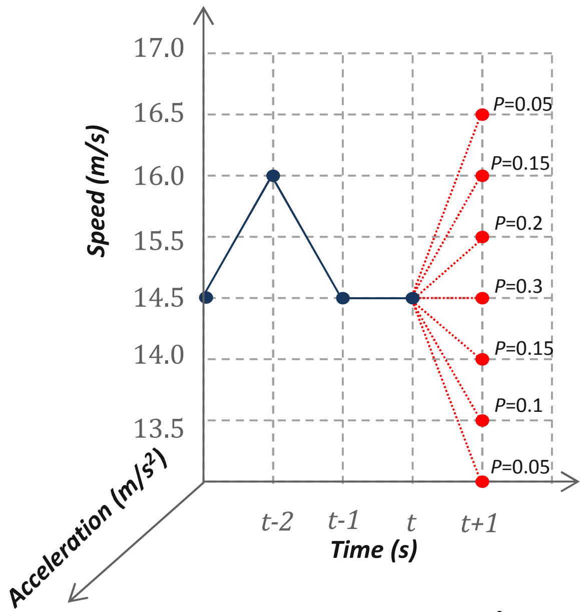
Trip Prediction

Modeling Vehicle Speed with Markov Chains

- What is a Markov chain?
  - Collection of random variables $\{X_1, X_2, \dots, X_p\}$
  - **Memoryless**: the future only depends on the present, not the past

$$P(X_{k+1} = j \mid X_1 = i_1, X_2 = i_2, \dots, X_k = i_k) = P(X_{k+1} = j \mid X_k = i_k) = P_{i,j}$$

  - 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:

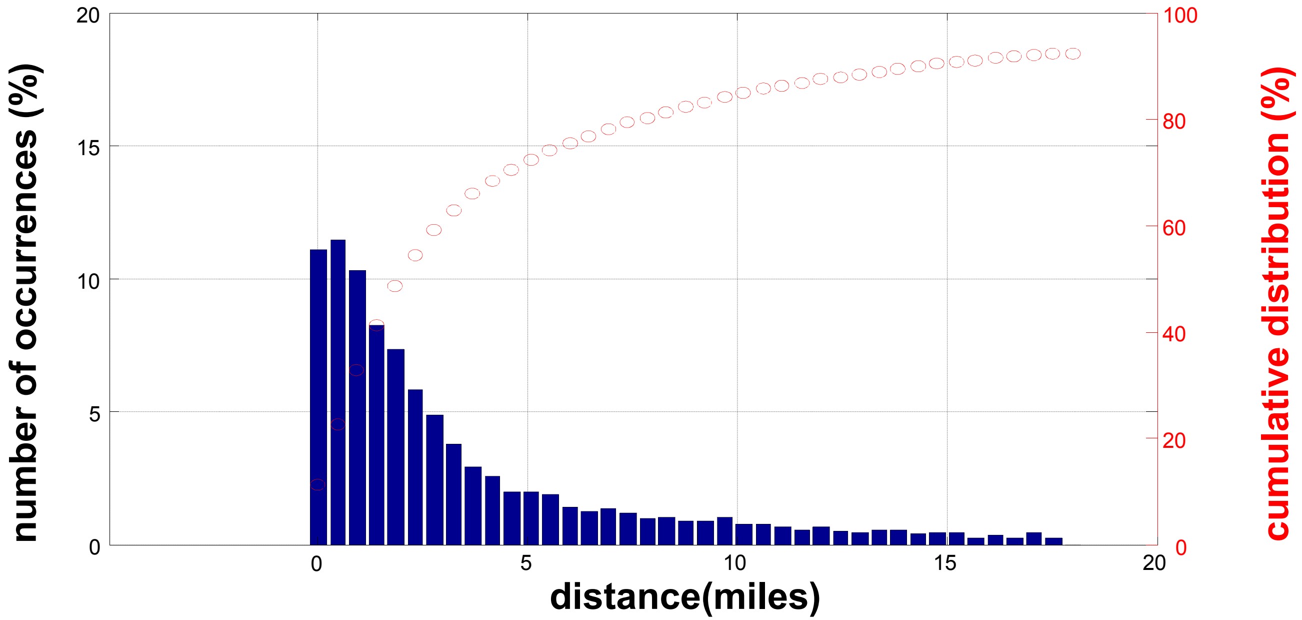
    Speed at time t+1 depends on speed and acceleration at time t

- The Markov chain is defined by a **T**ransition **P**robability **M**atrix (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

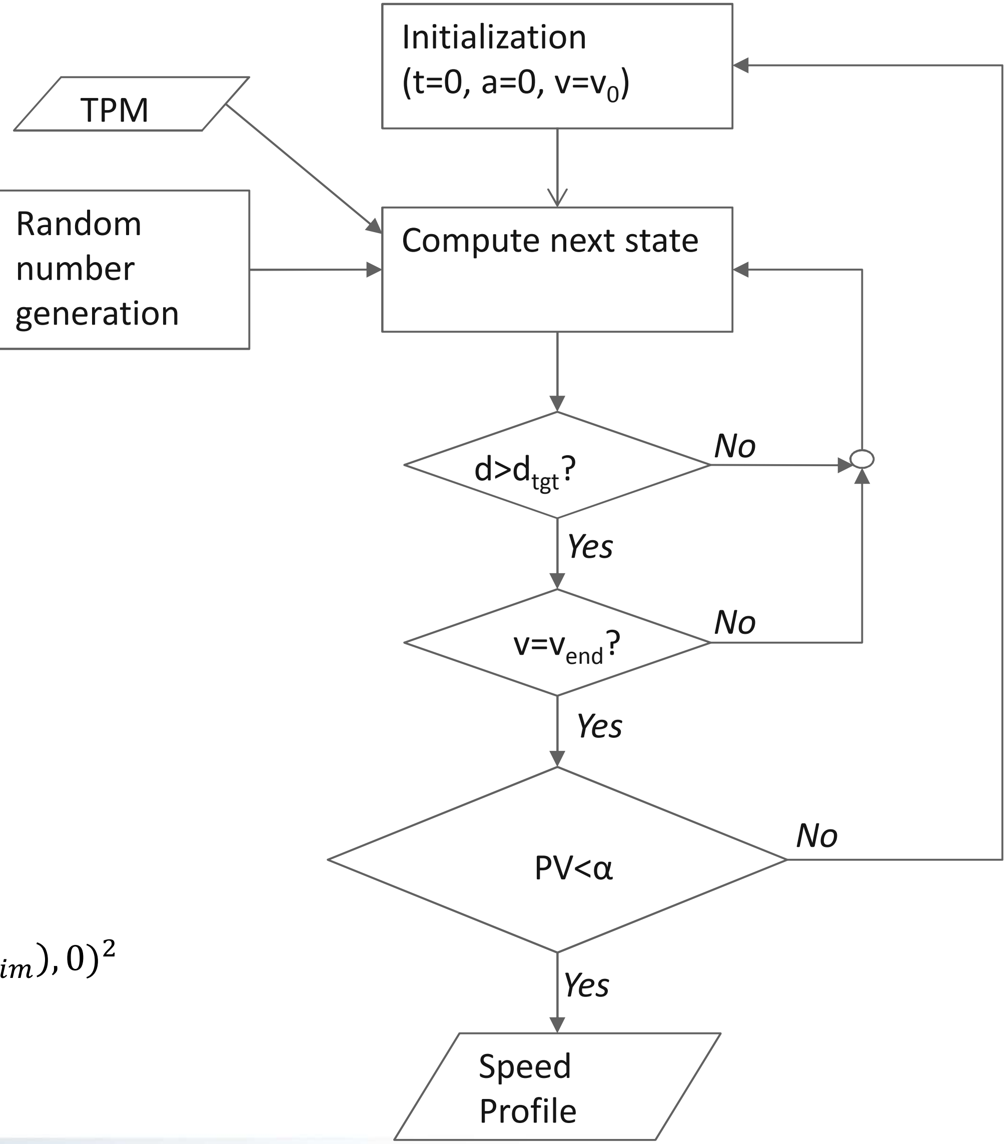
- From the CMAP Database:
  - CMAP = Chicago Metropolitan Agency for Planning
  - Data acquired as part of a comprehensive travel and activity survey for northeastern Illinois in 2007-2008
- 9000+ trips / 400+ drivers / 6,000,000 data points
- Data filtered to remove outliers and unrealistic trips



Constraining the Markov Chain to the Characteristics of a Given Segment

- Target segment defined by representative variables:
  - Average speed V_{tgt}
  - Distanced_{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:

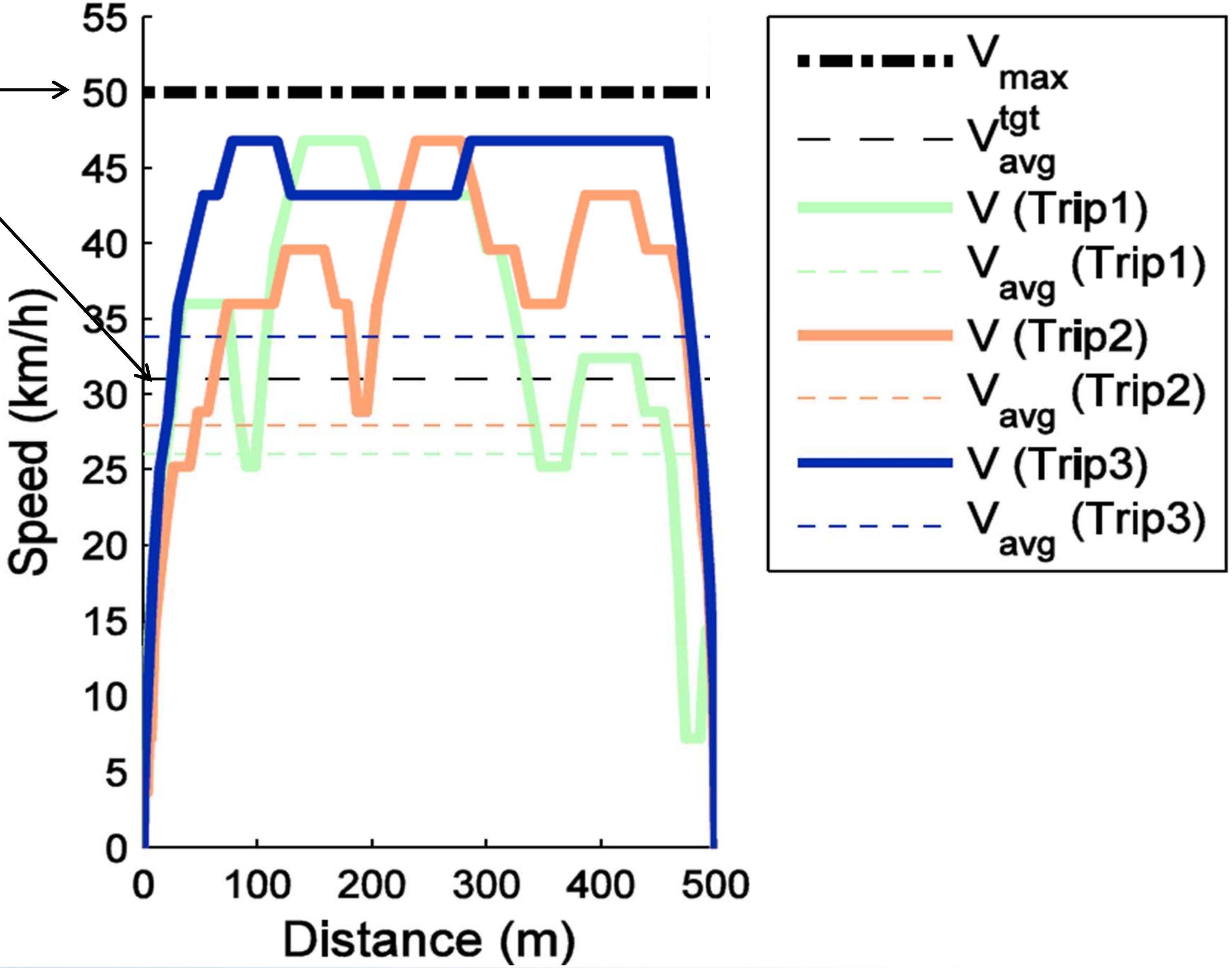
$$PV = w_1 \frac{|V_{avg} - V_{tgt}|}{V_{tgt}} + w_2 \frac{N_{stop}}{d_{seg}} + w_3 \sum_{t=t_1 \dots t_2} \max((V(t) - V_{lim}), 0)^2 + w_4 \frac{|d_{seg} - d_{tgt}|}{d_{tgt}}$$



Example of Segment

Speed Limit
50 km/h

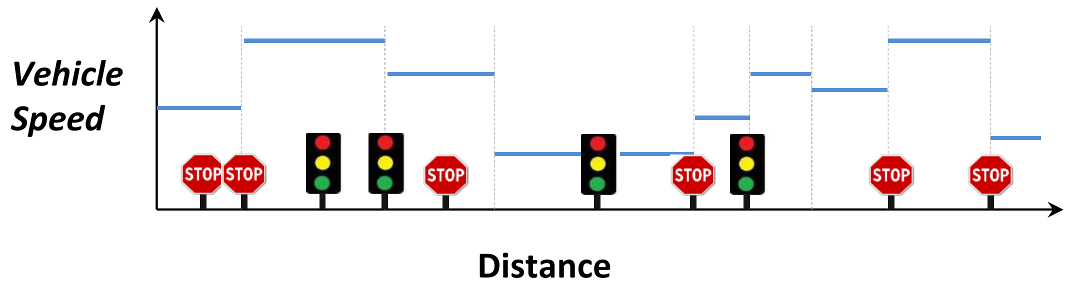
Target Speed
32 km/h



Combining Markov Chains and Geographical Information

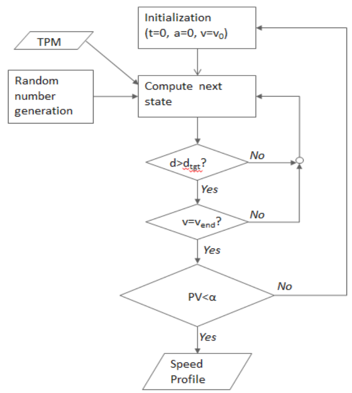
Itinerary in GIS (ADAS-RP)

Raw Data Formatting + Segmentation



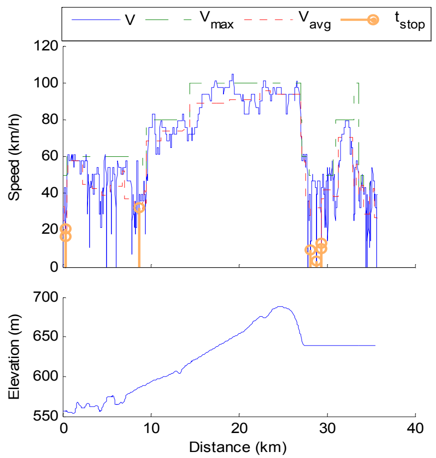
Iterative Stochastic Generation for each Segment

for segment= 1 to n

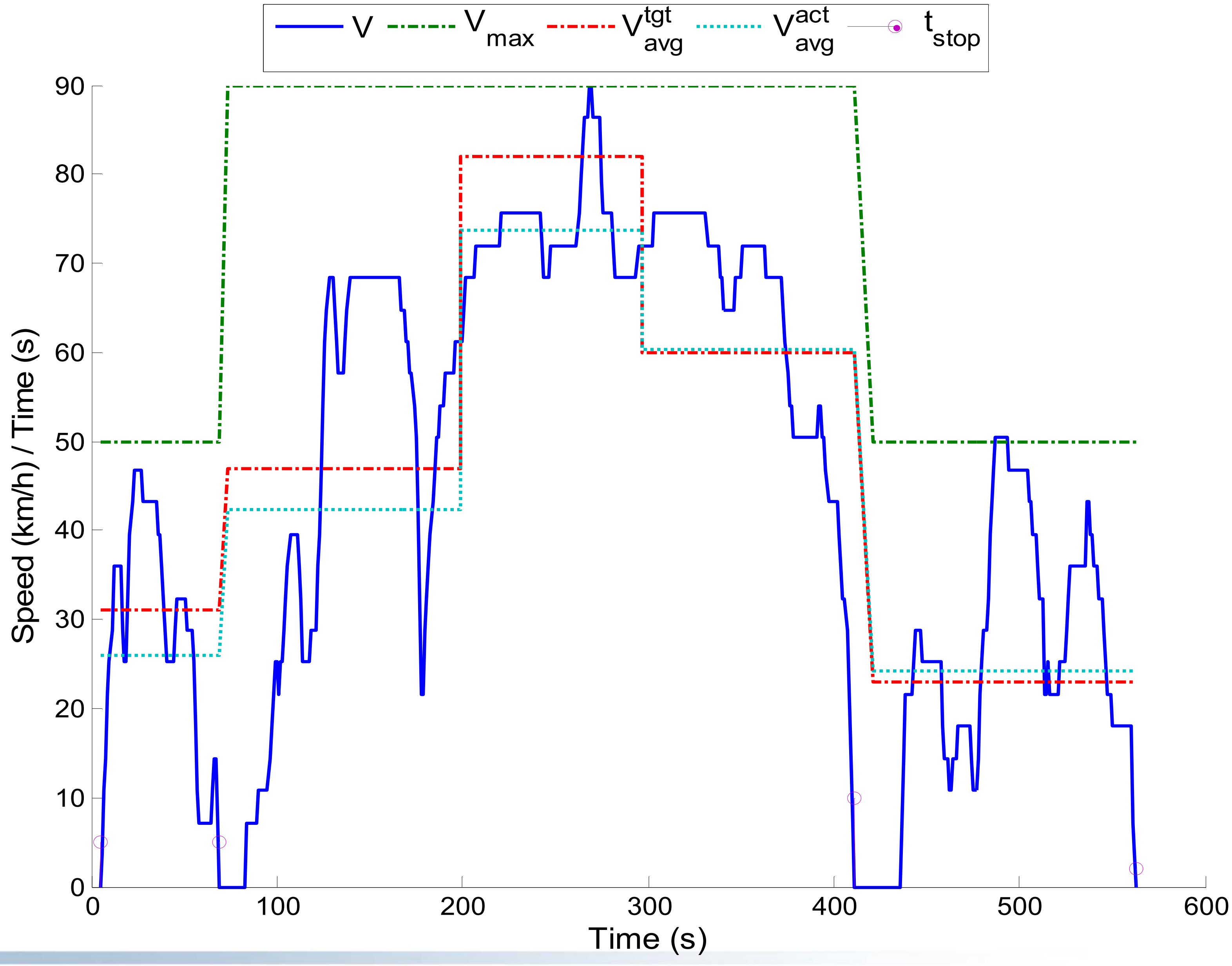


end

Synthesized Trip



Example of Entire Trip

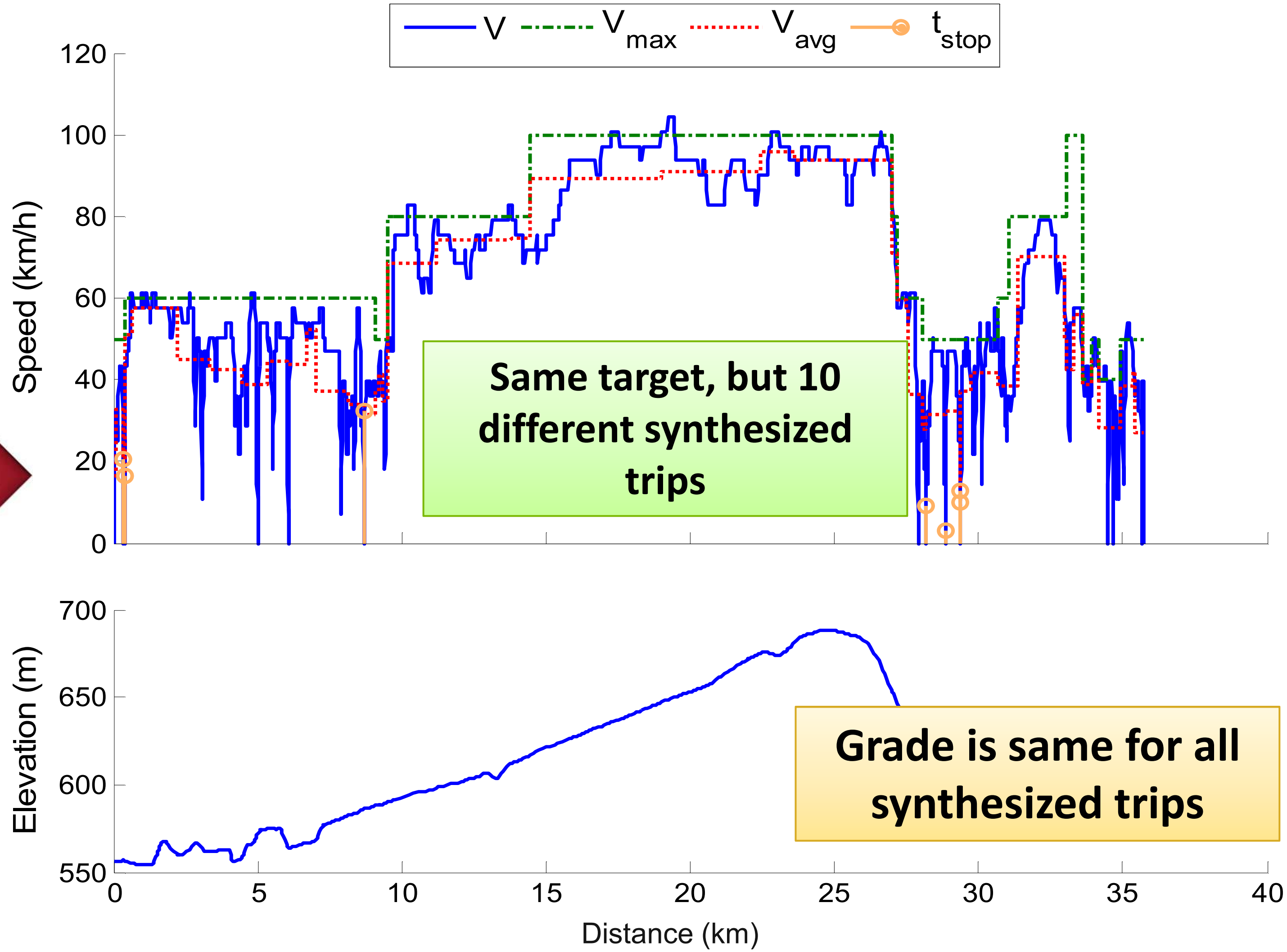


Itinerary Used for Study on Control

Munich area

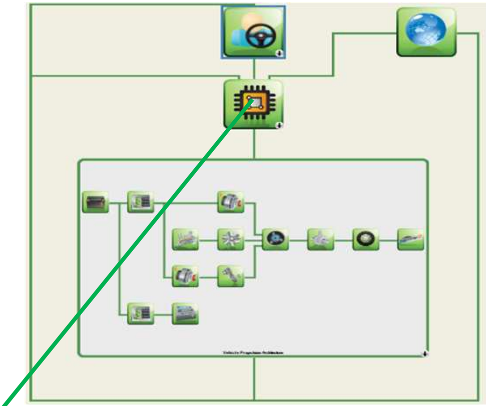
~ 36 km

Speed limited to 100 km/h



Optimal Control

Definition of the Problem



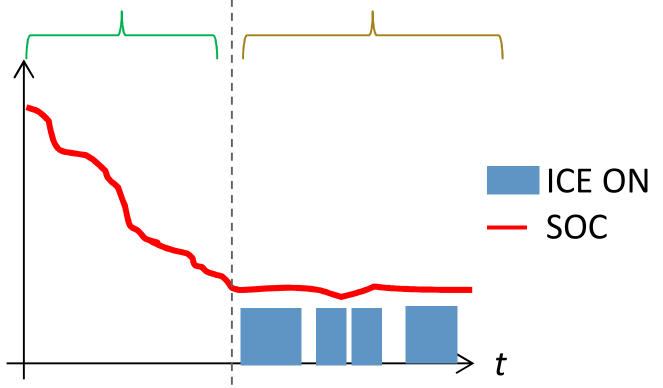
- Simulation environment: Autonomie, forward-looking
- ~ Prius 2012 PHEV:
  - Battery: 4 kWh, 200 V, Li-ion
  - Rated all-electric range: 26 km
  - Top EV speed = 100 km/h

AUTONOMIE

Baseline Control Strategy

EV

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



1 itinerary, 10 different trips

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:

Hamiltonian

$$P_b^* = \underset{P_b}{\mathrm{argmin}}\left(\overbrace{P_f(P_b) + \boldsymbol{r}(\boldsymbol{t})\theta(P_b)P_b}^{\text{Hamiltonian}} \right)$$

Fuel Power
Function of P_b through optimal operation maps

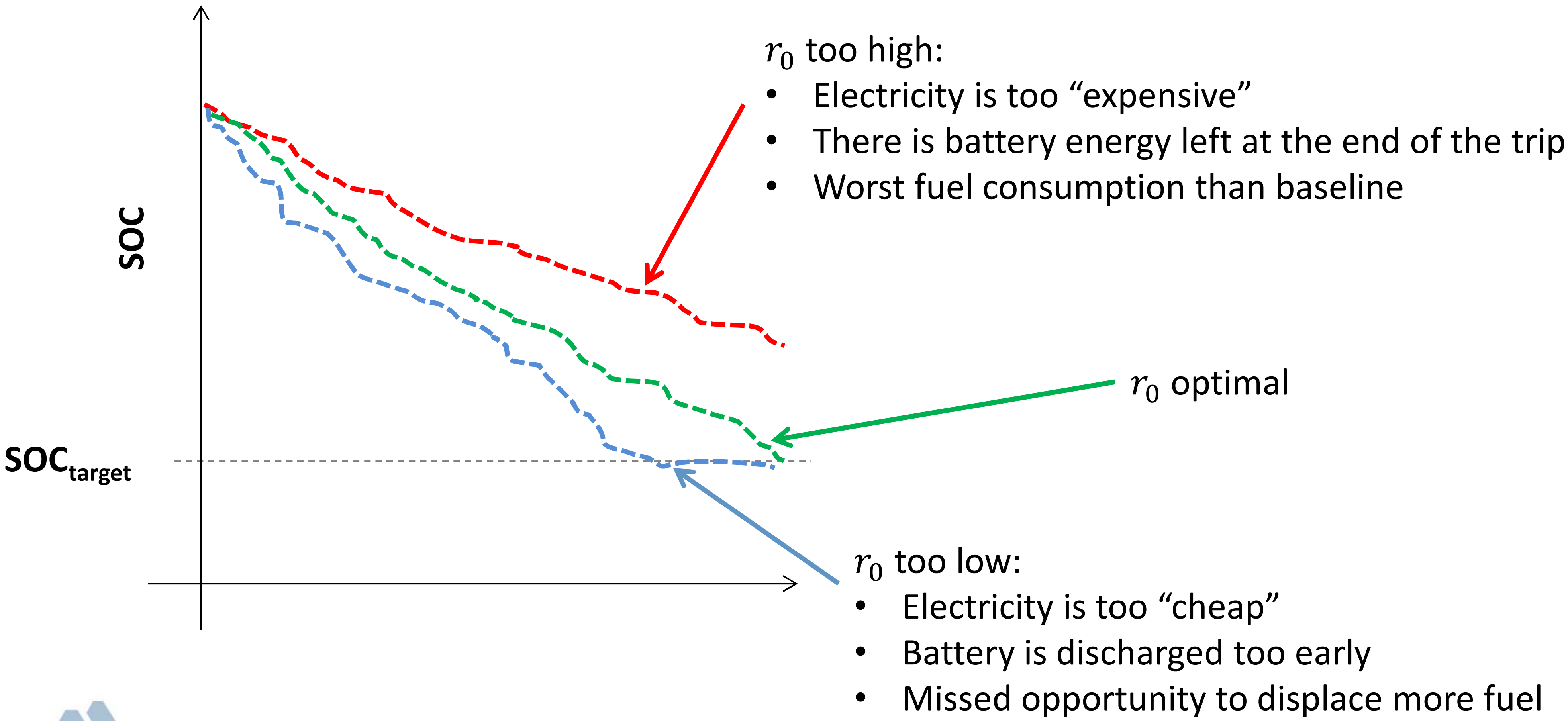
Equivalence Factor

Term close to 1

Battery Power Command

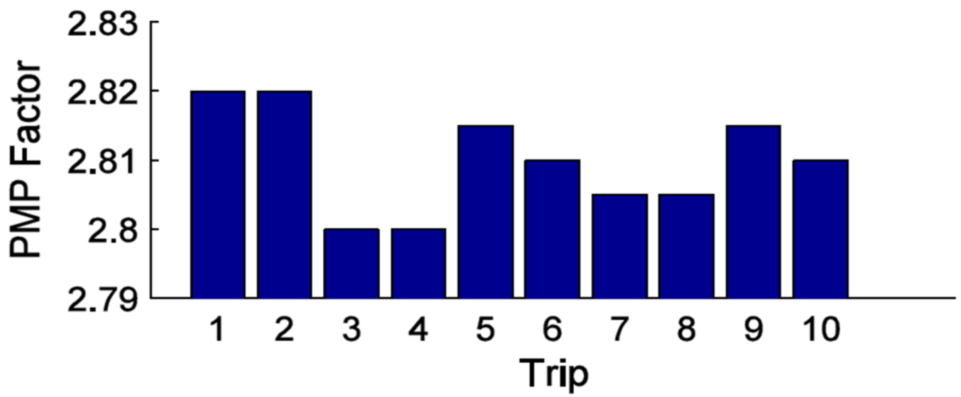
- In our study we make the assumption that $r(t) = r_0$
- PMP only in Charge-depleting mode, then baseline Charge-Sustaining mode control

The Challenge of PMP: the Equivalence Factor Depends on the Trip!

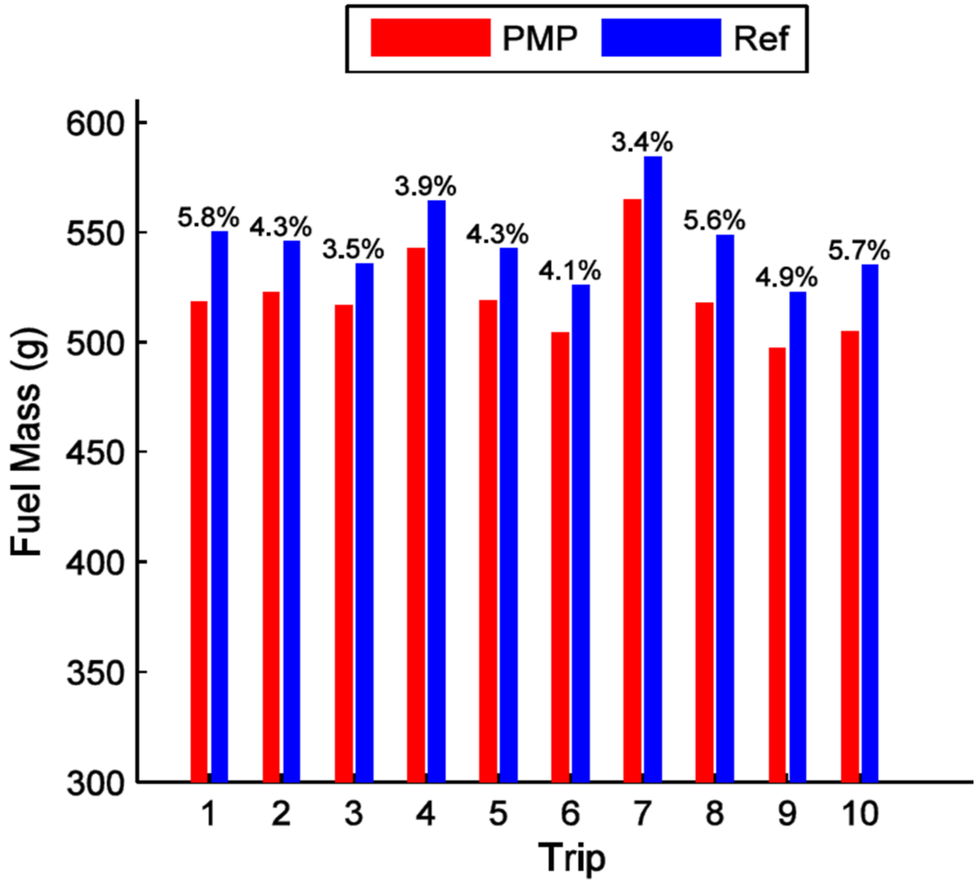


Case 1: Equivalence Factor Is Optimal for each Trip

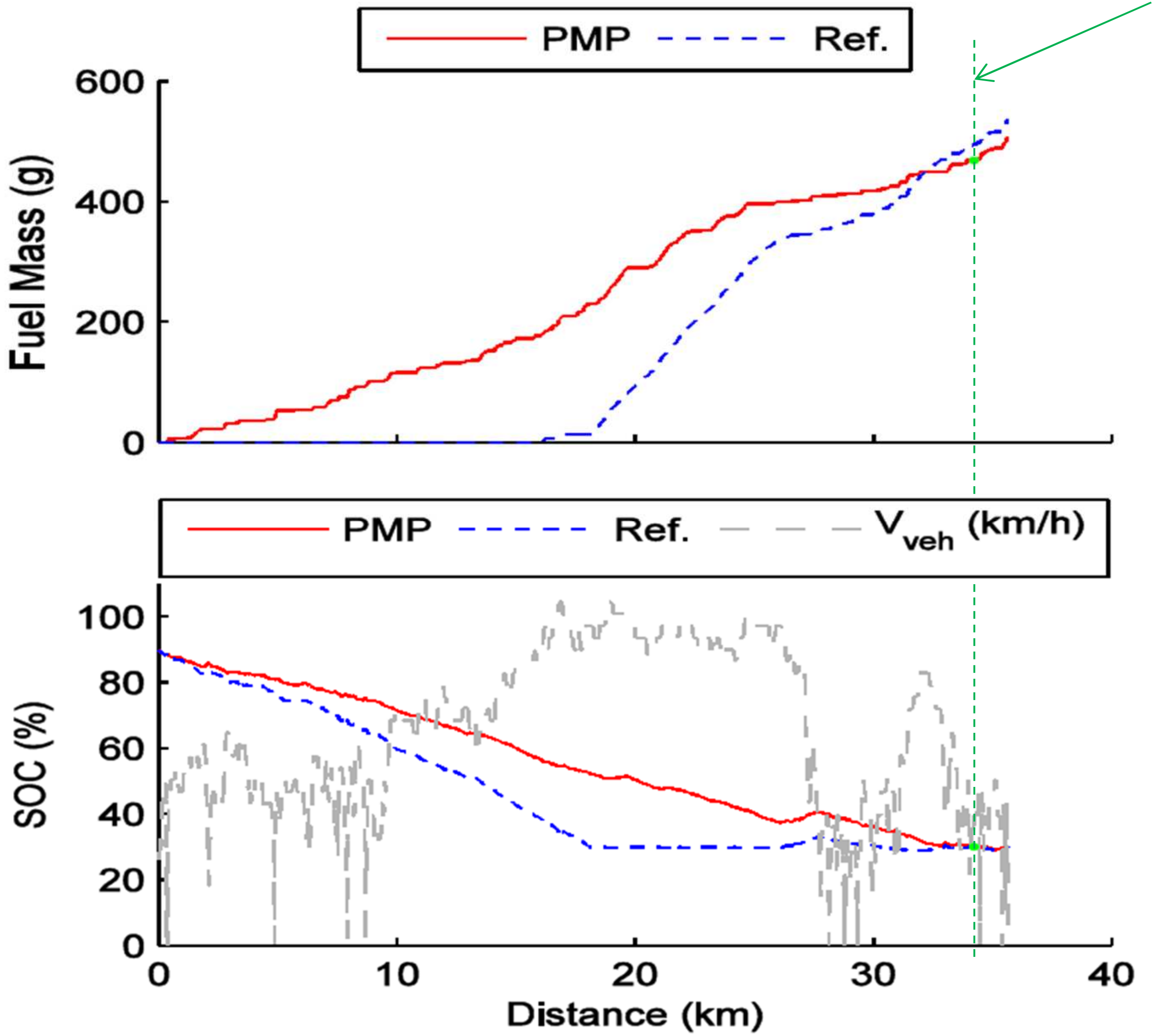
- Equivalence factor optimal for each trip = > best case scenario
- Different eq. factor for each trip



- Fuel savings: 3.5 to 5.7 % , 4.6% on average

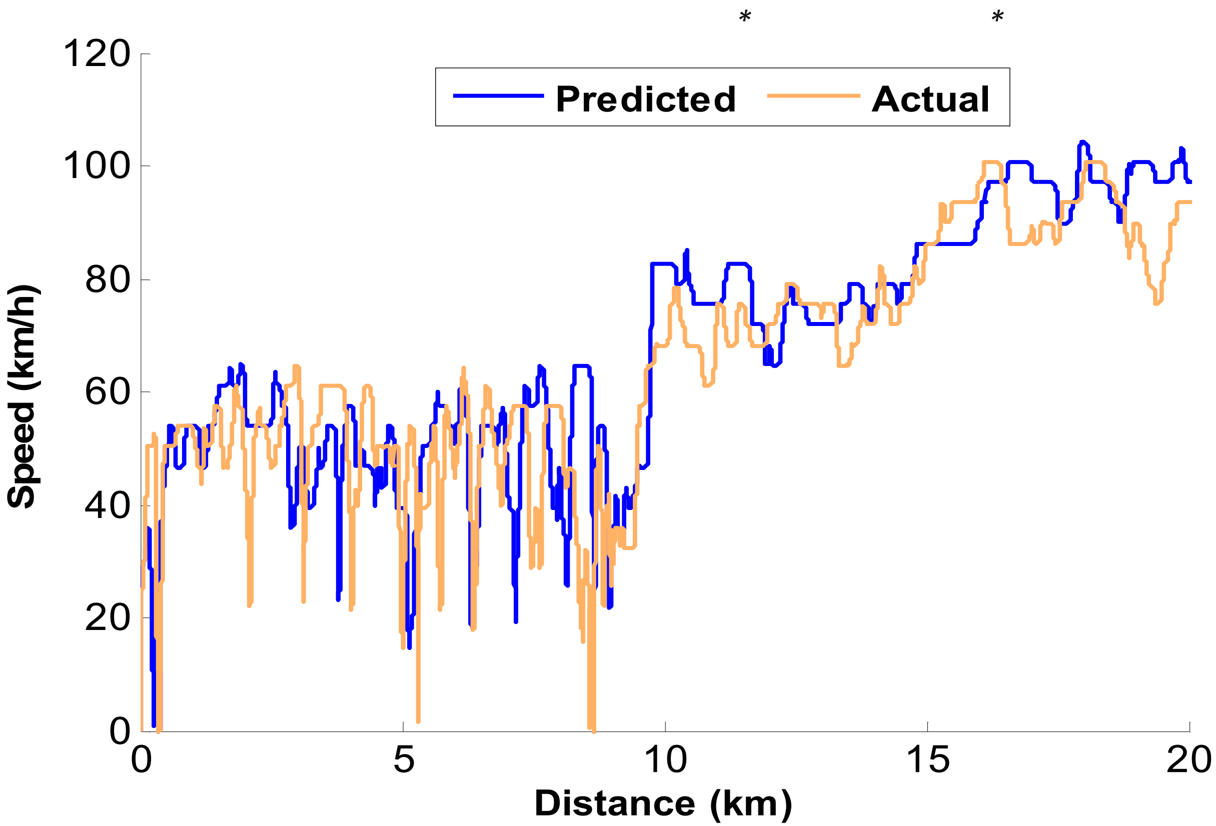


Operations with Optimal Control



After this point, control switches to CS mode

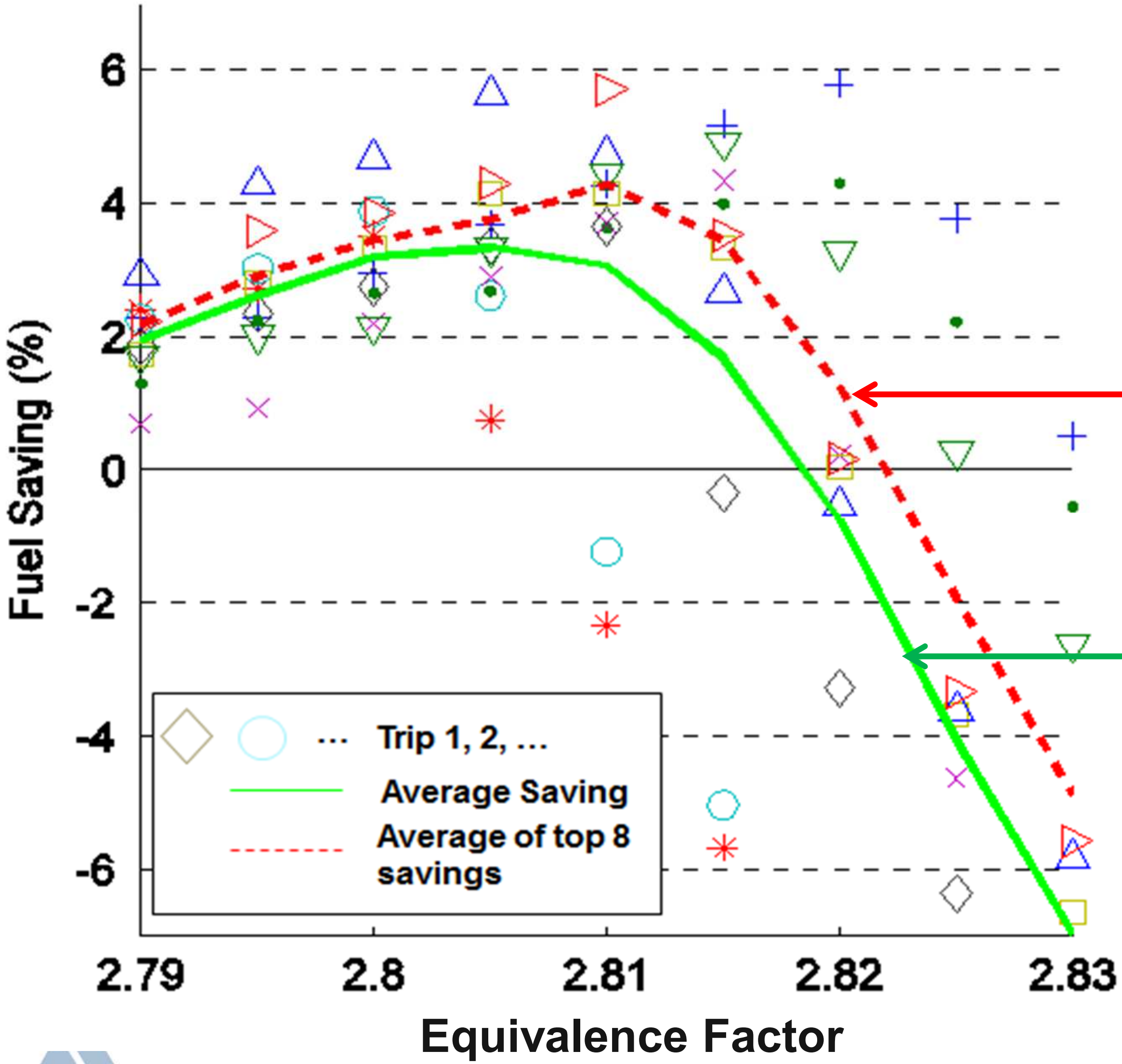
In Real-World, the Exact Speed Profile Is not Known!



- 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

Acknowledgement

HERE (formerly NAVTEQ) provided free license for ADAS-RP

U.S. Department of Energy
Energy Efficiency and Renewable Energy
Bringing you a prosperous future where energy is clean, abundant, reliable, and affordable

Work funded by the US Department of Energy Vehicle Technology Office;
Program managers**: David Anderson**, **Lee Slezak**

Contact

Dominik Karbowski (Principal Investigator): dkarbowski@anl.gov / 1-630-252-5362

Aymeric Rousseau (Systems Modeling and Control Manager): arousseau@anl.gov

See also www.autonomie.net

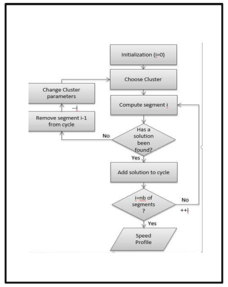
AUTONOMIE

Backup Slides

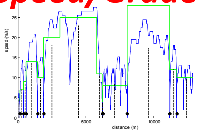
From Itinerary Definition to Simulation of Optimal Control

Define Itinerary in GIS (ADAS-RP)

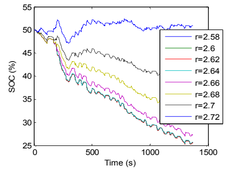
Generate Speed Profile Using Markov Chains



Speed/Grade

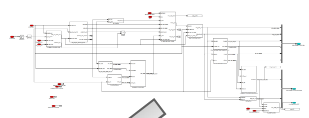


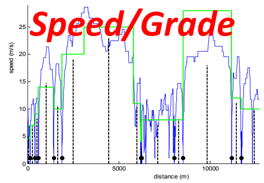
Compute Controller Optimal Tuning

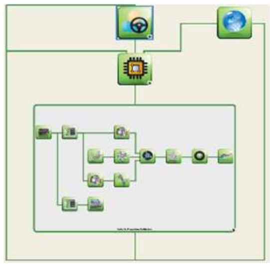


r_0

Optimal Controller







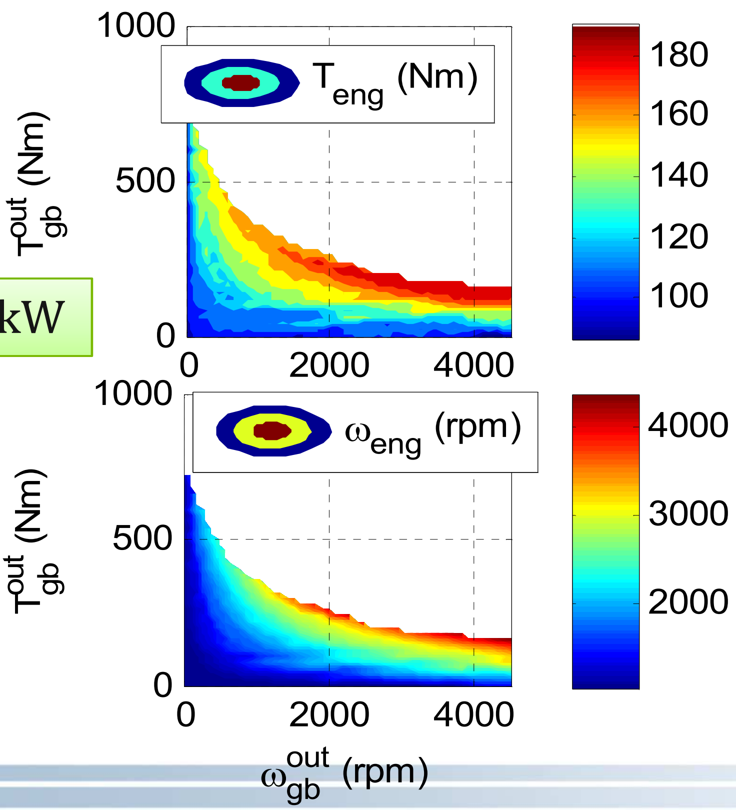
Simulate in a Forward-Looking Model (Autonomie)

- Our approach:
  - Work on both optimal control and prediction
  - Propose implementable solutions

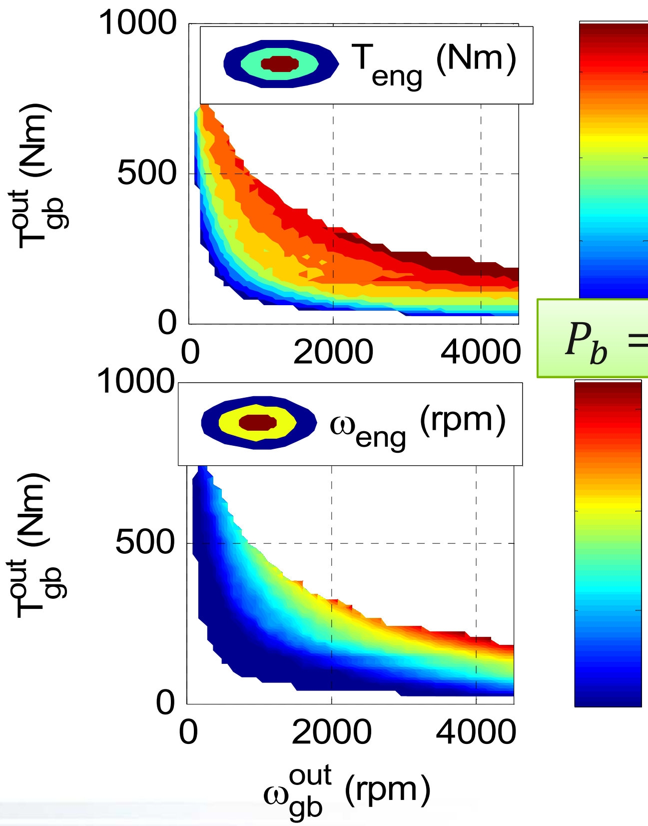
Operating the Powertrain Optimally (with a few Givens) Requires Optimal Operation Maps

- 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

$P_b = -10\ \mathrm{kW}$



$P_b = 7\ \mathrm{kW}$



Argonne Published Work

- Adaptive control:
  - P. Sharer, A. Rousseau, et al., ***Plug-in Hybrid Electric Vehicle Control Strategy: Comparison between EV and Charge-Depleting Options,*** SAE paper 2008-01-0460, SAE World Congress, Detroit, April 2008
- Dynamic Programing:
  - D. Karbowski, A. Rousseau, et al., ***Plug-in Vehicle Control Strategy: From Global Optimization to Real Time Application,*** 22th International Electric Vehicle Symposium (EVS22), Yokohama, October 2006
  - D. Karbowski, K.-F. Freiherr von Pechmann, et al**.,** ***Comparison of Powertrain Configurations for Plug-In Hybrid Operation Using Global Optimization,*** SAE paper 2009-01-1334, SAE World Congress, Detroit, April 2009
  - Pagerit, S., Rousseau, A., Sharer, P., ***Global Optimization to Real Time Control of HEV Power Flow: Example of a Fuel Cell Hybrid Vehicle***, EVS 21, Monaco, April 2005.
- PMP / ECMS:
  - N. Kim and A. Rousseau, "**A Sufficient Condition of Optimal Control for Hybrid Electric Vehicles**," *IMechE Part D: J. Automobile Engineering*, accepted.
  - N. Kim, S. W. Cha, and H. Peng, "**Optimal Equivalent Fuel Consumption for Hybrid Electric Vehicles**," *IEEE Trans. Control Syste. Technol.*, vol. 20. no. 3, May 2012, pp. 817-825. [link]
  - N. Kim, A. Rousseau, and D. Lee, "A Jump Condition of PMP-based Control for HEVs," *J. Power Sources*, vol.196, no.23, Dec. 2011, pp. 10380-10386*.* [link]
  - N. Kim, S. W. Cha, and H. Peng, "**Optimal Control of Hybrid Electric Vehicles Based on Pontryagin's Minimum Principle**," *IEEE Trans. Control Syste. Technol.*, vol. 19, no. 5, Sept. 2011, pp. 1279-1287.
- Trip prediction:
  - D. Karbowski, S. Pagerit, A. Calkins, "**Energy Consumption Prediction of a Vehicle along a User-Specified Real-World Trip**”, EVS26, May 2012, Los Angeles