Vehicle Propulsion Systems
Energy Management

Case Study: AHEAD

Dec. 8th, 2016
Introduction

Hybrid Electric Bus
Operating Modes
Energy Management

Vehicle Model
Chassis
Traction Motor
Supercaps
EGU
DC-Link

Component Sizing
Sizing Problem
Vehicle Model
Control Problem
Algorithms
Results

Energy Management
Driver Prediction
Control Problem
Algorithm
On-Road Test
Realistic Operation
Outlook
Introduction

**Goal:** 25% lower fuel consumption than a Diesel bus
Vehicle Topology

Serial Hybrid Electric Bus:

Length: 12m  Electric Motor: 280kW = 375hp
Capacity: 85 Pas.  Diesel engine: 6.7l, 184kW
Weight: 13.5t  Supercaps: 300kW

625Wh ≈ $E_{\text{kin}}^{60\text{km/h}}$
Operating Modes

- Pure electric
- Pure Diesel-electric
- Recharge
- Boost
Operating Modes

- Pure electric
- Pure Diesel-electric
- Recharge
- Boost
Operating Modes

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Operating Modes

- Pure electric
- Pure Diesel-electric
- Recharge
- Boost
Energy Management

Controlled by Driver

Controlled by Energy-Management

Control: Provide $P_{req}$

Optimization: and use minimum amount of fuel
Outline of Talk

1. Introduction
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4. Energy Management
5. Conclusion
Chassis Model

The figure shows the comparison between measured (blue line) and modeled (green line) speed profiles for different time intervals. The equation for speed as a function of time is given by:

\[ v(t) = \int_{0}^{t_f} \sum \frac{F(t)}{m} dt \]

The friction coefficients are:

- Rolling: 0.65 %
- Aerodynamic: 0.90 [-]
Chassis Model

![Graph showing vehicle model parameters over distance](image)

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**Component Sizing**

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Traction Machine

\[ P_{em} = f(T_{em}, \omega_{em}) \]
Traction Machine

\begin{figure}
\centering
\begin{subfigure}{\textwidth}
\includegraphics[width=\textwidth]{fig1}
\end{subfigure}
\caption{Comparison of measured and modeled traction machine performance under varying operating conditions.}
\end{figure}
**SuperCaps Model**

\[
Q_{sc}(t) = Q_{sc}(0) + \int_{0}^{t} I_{sc}(t) dt
\]

\[
U_{sc}(t) = C_{sc} \cdot Q_{sc}(t) - R_{sc} \cdot I_{sc}(t)
\]
SuperCaps Model

Spec-sheet:
\[ C_{sc} = 63 \text{ F} \]
\[ R_{sc} = 18 \text{ m}\Omega \]

Identified:
\[ C_{sc} = 60 \text{ F} \]
\[ R_{sc} = 17 \text{ m}\Omega \]
Engine-Generator Unit

Rotational speed is a degree of freedom!

Control unit tasks:
Given a requested electric output power $P_{g,\text{req}}$

- define a valid rotational speed setpoint $\omega_g$
- using torque of engine and generator
  - control speed to setpoint
  - control output power to setpoint

Optimization task (offline):
- find optimal speed for each possible value of $P_{g,\text{req}}$
  - static optimization problem
Optimal operation of EGU

EGU efficiency \( \eta_g = \frac{P_g \Delta t}{H_{lHV} \dot{m}_f \Delta t} = \frac{\text{electric energy generated}}{\text{fuel energy used}} \)

\[ \eta_g = 100 \times \frac{P_g}{H_{lHV} \dot{m}_f} \]

![Graph showing EGU efficiency vs. electric power](image_url)

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Engine-Generator Unit

\[
\eta_g \text{ [%]} \quad \text{Torque [Nm]} \quad \text{Speed [rpm]}
\]

- 1000 1500 2000
- 165 kW
- 120 kW
- 90 kW
- 50 kW
- 20 kW
- 0 kW

\[\text{dc converter frequency switch}\]
Engine-Generator Set

\[ \int_0^t \dot{m}_{f,\text{CAN}} \, dt = \int_0^t \dot{m}_{f,AIC} \, dt \]
DC-link = tiny capacity.
DC-Link

- DC-link = tiny capacity
- Con-/Inverters deliver/remove energy to/from DC-link
- Energy in DC-link: \( E_{DC} = \frac{1}{2} CU^2 \)
- Goal is to keep DC-link voltage constant
- Each Con/Inverter is P-controlled, deadband = priority

![DC-Link Diagram]

- Controller output
  - Performance limits of component
  - Demand value
  - Dead zone (width proportional to priority)
  - Control deviation of DC-Link voltage
Outline of Talk

1. Introduction
2. Vehicle Model
3. **Component Sizing**
4. Energy Management
5. Conclusion
Optimization Task during the Design-Phase

Given a bus line, find the fuel-optimal sizing of power-train components.
SuperCap Sizing
Fuel consumption is influenced by sizing **AND** energy management

- Sub-optimal control
- Apparent optimum

**Problem**

Fuel consumption is influenced by sizing **AND** energy management.
Fuel consumption is influenced by sizing AND energy management.
Theoretical optimal performance serves as a benchmark.
Vehicle Model

State variables: \( x_k = [E_{sc,k}, n_g] \in X \)
Control variable: \( u_k = P_{g,k} \in U \)
Disturbances: \( w_k = P_{req,k} \in W \)

Model:
\[
\begin{align*}
x_{k+1} &= f(x_k, u_k, w_k) \\
m_{f,k} &= g(u_k)
\end{align*}
\]
Optimal Control Problem

Minimize:

Fuel consumption \( \left( \sum_{k=0}^{N} \dot{m}_{f,k} \right) \)

subject to:

- driver demand \( P_{\text{req}} \)
- system dynamics and constraints

for all time instances \( k \) along the bus line.
Algorithms

- Dynamic Programming
- Convex Optimization
Algorithms

- **Dynamic Programming**
  - guarantee for optimality
  - standard method to solve sizing problems
    - curse of dimensionality
    - prone to numerical errors (if \( n > 1 \))

Efficient implementation avoiding numerical errors:


- **Convex Optimization**
Algorithms

- **Dynamic Programming**
- **Convex Optimization**
  - guarantee for optimality
  - extremely efficient solvers
  - approximations necessary
  - no binary decision variables (engine on/off, gear shifts,...)

Iterative algorithm to include binary decision variables:

Results

- Graph showing speed (km/h) over time (s)
- Graph showing power (kW) over time (s)
- Graph showing energy (Wh) over time (s)
Dynamic Programming

Driver requests

$P$ [kW]

$E_{sc}$ [Wh]

DP solution

Time [s]
Convex Optimization

![Graph showing speed, power, and energy consumption over time.]

- Speed in km/h
- Power in kW
- Energy in Wh

Convex solution vs DP solution.
Buslines

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<table>
<thead>
<tr>
<th>Speed [km/h] / Altitude [m]</th>
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<tbody>
<tr>
<td>0 1 2 3 4 5 6 7 8 9</td>
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<tr>
<td>0 20 40 60</td>
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<tr>
<td>0 5 10 15</td>
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<th>Distance [km]</th>
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<td>0 1 2 3 4 5 6 7 8 9</td>
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</tbody>
</table>
Results

Line 1

Line 2

Line 3

Line 4

Supercap Capacity [Wh]

Supercap Capacity [Wh]

Energy Management

Driver Prediction

Control Problem

Algorithm

Realistic Operation

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Results

- Line 1
  - \( \frac{l}{100\text{km}} \)
  - \( 500 \) to \( 2000 \) Supercap Capacity [Wh]

- Line 2
  - \( \frac{l}{100\text{km}} \)
  - \( 500 \) to \( 2000 \) Supercap Capacity [Wh]
  - DP solution
  - Convex optimization

- Line 3
  - \( \frac{l}{100\text{km}} \)
  - \( 500 \) to \( 2000 \) Supercap Capacity [Wh]

- Line 4
  - \( \frac{l}{100\text{km}} \)
  - \( 500 \) to \( 2000 \) Supercap Capacity [Wh]
Results

Supercaps cost: Optimal ≈ 72'000 CHF, HESS-Hybrid ≈ 38'000 CHF
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State-of-the Art Method

Equivalent Consumption Minimization Strategy assumptions
- Open-Circuit Voltage constant
- State-constraints neglected

Supercaps:

Non-constant voltage:

\[ V_{oc}(t) = \frac{Q(t)}{C} \]

"Small" capacity:

\[ E_{sc} \approx E_{50km/h}^{kin} \]
(Stochastic) Dynamic Programming

1. $\mathcal{J}_N^o(x_N) = g_N(x_N)$

2. $\mathcal{J}_k^o(x_k) = \min_{\mu_k(x_k)} E \left\{ g(x_k, u_k, w_k) + \mathcal{J}_{k+1}^o(f(x_k, u_k, \bar{w})) \right\}$

- Non-causal!
Driver Analysis

Driver Analysis
Driver Analysis

---

**Graph:**

- Vertical axis: Requested Power [kW]
- Horizontal axis: Speed [km/h]

---

**Table:**

<table>
<thead>
<tr>
<th>Speed [km/h]</th>
<th>Requested Power [kW]</th>
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<tbody>
<tr>
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<td>29 / 59</td>
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Driver Analysis

![Driver Analysis Graph]

- **Speed [km/h]**
- **Requested Power [kW]**

The graph illustrates the relationship between speed and requested power for different driving scenarios. The red line represents a specific driver's pattern, while other lines indicate variations in power demand across different speeds.
Driver Analysis

![Driver Analysis Graph]

- **Requested Power [kW]**:
  - 0
  - 50
  - 100
  - 150
  - 200
  - 250

- **Speed [km/h]**:
  - 0
  - 10
  - 20
  - 30
  - 40
  - 50
  - 60

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Driver Analysis

\[ w_k = w^i \]
Driver Analysis

\[ w_k = w^i \]

\[ \text{possible } w_{k+1} \]

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Driver Prediction
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Idea: Given $w_k = [v_k, P_{req,k}]^T$, the future driver commands $w_{k+1}$ can be predicted by a probability density function:

$$\bar{w}_{k+1} \sim \mathcal{P}(w_k),$$

$\mathcal{P}$ is a Markov-chain!
Stochastic Driver Prediction Model

\[\bar{w}_{k+1} \sim \mathcal{P}(w_k)\]
Stochastic Driver Prediction Model

\[
\bar{w}_{k+1} \sim \mathcal{P}(w_k)
\]

\begin{align*}
&\text{predicted probability distribution} \\
&w_k, \quad w_{k+1} \text{ (actual)}
\end{align*}
Stochastic Driver Prediction Model

\[ P_{\text{req}} \text{[kW]} \]

\[ v \text{[km/h]} \]

-250 -200 -150 -100 -50 0 50 100 150 200 250

0 10 20 30 40 50 60

low probability high probability
Stochastic Driver Prediction Model

\[
\begin{array}{cc}
\text{low probability} & \text{high probability} \\
\end{array}
\]

![Graph showing probability distribution of vehicle speed and power demand](image)

- \( P_{\text{req}} \) [kW]
- \( v \) [km/h]
Stochastic Driver Prediction Model

$v [\text{km/h}]$

$P_{\text{req}} [\text{kW}]$
Stochastic Driver Prediction Model
Stochastic Driver Prediction Model
Stochastic Driver Prediction Model

![Graph showing stochastic driver prediction model with probability distribution for power demand and speed.](graph.png)
Stochastic Driver Prediction Model

\[ P_{\text{req}} \] [kW] vs. \( v \) [km/h]

- Low probability
- High probability
Stochastic Driver Prediction Model

The graph shows the relationship between power required ($P_{\text{req}}$) and speed ($v$) in km/h. The x-axis represents speed, while the y-axis represents power required. The color gradient indicates the probability distribution, with lighter colors representing low probability and darker colors representing high probability.
Stochastic Driver Prediction Model

$v$ [km/h]

$P_{req}$ [kW]

-250 -200 -150 -100 -50 0 50 100 150 200 250

0 10 20 30 40 50 60

low probability

high probability

Stochastic Driver Prediction Model
Stochastic Driver Prediction Model

\[ P_{\text{req}} \text{[kW]} \]

\[ v \text{ [km/h]} \]

- Low probability
- High probability

\[ 0 \quad 10 \quad 20 \quad 30 \quad 40 \quad 50 \quad 60 \]

\[ -250 \quad -200 \quad -150 \quad -100 \quad -50 \quad 0 \quad 50 \quad 100 \quad 150 \quad 200 \quad 250 \]

\[ 0 \quad 10 \quad 20 \quad 30 \quad 40 \quad 50 \quad 60 \]
Stochastic Driver Prediction Model

![Stochastic Driver Prediction Model Graph]

- Low probability
- High probability

\[
P_{\text{req}} \quad [\text{kW}] \quad v \quad [\text{km/h}]
\]

- Probability distribution for required power and speed.
Stochastic Driver Prediction Model

![Graph showing the relationship between power demand \( P_{req} \) and speed \( v \). The graph illustrates low and high probability regions for different speeds.](image)
Stochastic Driver Prediction Model

![Graph showing the relationship between speed (v) and power requirement (P\_req) for low and high probability scenarios. The graph includes a red dot indicating a specific point on the graph.](image-url)
Stochastic Driver Prediction Model

![Graph showing probability distribution for vehicle speed and power demand](image)

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Stochastic Driver Prediction Model

\[ P_{\text{req}} \text{ [kW]} \]

\[ v \text{ [km/h]} \]
Stochastic Driver Prediction Model

![Graph showing the relationship between vehicle speed (v) and required power (P_{\text{req}}) with low and high probability regions.](image_url)
Stochastic Driver Prediction Model

![Graph showing the relationship between vehicle speed (v) and power demand (P_{req}) with low and high probability regions indicated.](image)
Stochastic Driver Prediction Model

![Graph showing stochastic driver prediction model with probability distribution for speed (v [km/h]) vs. power required (P_{req} [kW]).]
Stochastic Driver Prediction Model

The graph shows the relationship between the required power ($P_{req}$) and the speed ($v$) of a hybrid electric bus. The graph is divided into two regions: low probability and high probability. The low probability region is represented by a lighter color, while the high probability region is represented by a darker color.

The x-axis represents the speed ($v$) in km/h, ranging from 0 to 60. The y-axis represents the required power ($P_{req}$) in kW, ranging from -250 to 250. The graph includes several points indicating different combinations of speed and required power.

The title 'Stochastic Driver Prediction Model' is visible at the top of the page.
Stochastic Driver Prediction Model

![Stochastic Driver Prediction Model](image)

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Stochastic Driver Prediction Model

\[ P_{\text{req}} [\text{kW}] \] vs \[ v [\text{km/h}] \]

- Low probability
- High probability
Stochastic Driver Prediction Model

\[ v \text{ [km/h]} \]

\[ P_{\text{req}} \text{ [kW]} \]

(low probability) (high probability)

-250 -200 -150 -100 -50 0 50 100 150 200 250
Stochastic Driver Prediction Model

\[ v \ [\text{km/h}] \]

\[ P_{\text{req}} \ [\text{kW}] \]

Low probability

High probability

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Stochastic Driver Prediction Model

- Low probability
- High probability

![Graph showing probability distribution of driver prediction models with P_{req} in kW and v in km/h.](image)
Stochastic Driver Prediction Model

![Graph showing stochastic driver prediction model with probability distribution for power demand vs. speed.](image)
Stochastic Driver Prediction Model

\[ P_{\text{req}} \quad [\text{kW}] \]

\[ v \quad [\text{km/h}] \]

-250 -200 -150 -100 -50 0 50 100 150 200 250

0 10 20 30 40 50 60

low probability high probability

Stochastic Driver Prediction Model
Stochastic Driver Prediction Model

![Stochastic Driver Prediction Model](image)
Original Optimal Control Problem

Minimize:

\[ J = \frac{E}{\bar{w}} \left\{ \sum_{k=0}^{N} g(x_k, u_k, w_k) \right\} \]

subject to:

\[ x_{k+1} = f(x_k, u_k, w_k) \]
\[ x_{k=0} = x_0 \]
\[ x_{k=N} = x_N \]
\[ x_k \in X_k \]
\[ u_k \in U_k \]
\[ \bar{w}_{k+1} \sim \mathcal{P}_k \]
Adjusted Optimal Control Problem

Minimize:

\[ J = E \left\{ \sum_{k=0}^{\infty} g(x_k, u_k, w_k) \right\} \]

subject to:

\[ x_{k+1} = f(x_k, u_k, w_k) \]
\[ x_{k=0} = x_0 \]
\[ x_{k=N} = x_N \]
\[ x_k \in X_k \]
\[ u_k \in U_k \]

\[ \bar{w}_{k+1} \sim \mathcal{P}(w_k) = \text{stationary PDF!} \]
Adjusted Optimal Control Problem

If

- the PDF of $\bar{w}$ is stationary, and
- the problem horizon is infinitely long

The optimal cost-to-go $J^o$ and the control policy $\mu^o$ are stationary as well!

An infinite horizon approximates a very long mission...
Vehicle Model Revisited

State variables: \[ x_k = [E_{sc,k}, n_g, \vartheta_e] \in X \]
Control variable: \[ u_k = P_{g,k} \in U \]
Disturbances: \[ w_k = [v, P_{req,k}] \in W \]

Model:
\[
\begin{align*}
x_{k+1} &= f(x_k, u_k, w_k) \\
m_{f,k} &= g(x_k, u_k)
\end{align*}
\]
Stochastic Dynamic Programming

Optimal cost-to-go

\[ \mathcal{J}_k^o(x_k, w_k) \]

= min. fuel needed to finish the problem starting from \((x, w)\) at time \(k\).

If the problem lasts infinitely long

\[ \mathcal{J}_{k+1}^o(x_{k+1}, w_{k+1}) = \mathcal{J}_k^o(x_k, w_k) = \mathcal{J}^o(x, w) \]

= the cost-to-go is **stationary**.

The DP iteration reduces to an implicit equation

\[
\mathcal{J}^o(x, w) = \min_{\mu} \left[ g(\mu) + \mathbb{E}\{ \mathcal{J}^o(\tilde{f}(x, \mu, \tilde{w}), \tilde{w}) \} \right]
\]

\[
\tilde{m}_f(\mu)
\]

\[ "x_{k+1}\]
Stochastic Dynamic Programming

Given a sub-optimal \( \mathcal{J} \), define operator \( T \)

\[
T(\mathcal{J}) = \min_{\mu} \left[ g(\mu) + E_{\bar{w}} \{ \mathcal{J}(f(x, \mu, w), \bar{w}) \} \right]
\]

and

\[
T^2(\mathcal{J}) = T(T(\mathcal{J})) \\
T^3(\mathcal{J}) = T(T^2(\mathcal{J})) \\
T^\alpha(\mathcal{J}) = T(T^{\alpha-1}(\mathcal{J}))
\]

then can show that

\[
\lim_{\alpha \to \infty} T^\alpha(\mathcal{J}) = \mathcal{J}^o \quad \text{and thus} \quad T(\mathcal{J}^o) = \mathcal{J}^o
\]

converges towards the optimal solution [Bertsekas 1995].
Stochastic Dynamic Programming

\[ T_\mu(J) = g(\mu) + \mathbb{E}_w\{J(f(x, \mu, w), \bar{w})\} \]

The gradient is:

"influence of \( J \) on \( T_\mu \)"
Stochastic Dynamic Programming

\[ T_\mu(\mathcal{J}) = g(\mu) + E_{\bar{w}}\{\mathcal{J}(f(x, \mu, w), \bar{w})\} \]
Stochastic Dynamic Programming

\[ T_\mu(J) = g(\mu) + E_{\bar{w}}\{ J(f(x, \mu, w), \bar{w}) \} \]
Stochastic Dynamic Programming

\[ T_\mu(J) = g(\mu) + E_{\bar{w}}\{J(f(x, \mu, w), \bar{w})\} \]

\[ T_{\mu_4}(J) \]

45°
Stochastic Dynamic Programming

\[ T(J) = \min_{\mu} \left[ g(\mu) + E_{\bar{w}} \{ J(f(x, \mu, w), \bar{w}) \} \right] \]
Stochastic Dynamic Programming

$$T(J) = \min_{\mu} \left[ g(\mu) + E_{\mu} \{ J(f(x, \mu, w), \bar{w}) \} \right]$$
Stochastic Dynamic Programming

However, for an infinite horizon problem

$$\lim_{\alpha \to \infty} T^\alpha(\mathcal{J}) \to \infty, \text{ for some } (x, w)!$$

Introduce normalization state \((x_n, w_n)\)

$$H(\mathcal{J}) = T(\mathcal{J}) - T(\mathcal{J}(x_n, w_n))$$

= scalar

then the relative optimal cost \(H^o\) can be found

$$\lim_{\alpha \to \infty} H^\alpha(\mathcal{H}) = H^o$$

= additional cost, compared to starting from \((x_n, w_n)\).
Stationary Control Policy

Result is a stationary control policy: \( P_g^o = \mu^o(x, w) \)
Stationary Control Policy: $P_g^o = \mu^o(x, w)$
Stationary Control Policy: \( P_{g,k}^0 = \mu^0(x_k, w_k) \)

\[
\begin{array}{c}
\begin{array}{c}
P_{\text{req}} \text{ [kW]} \\
\end{array}
\end{array}
\begin{array}{c}
\begin{array}{c}
E_{sc} \text{ Full} \\
\end{array}
\end{array}
\begin{array}{c}
\begin{array}{c}
E_{sc} \text{ Empty} \\
\end{array}
\end{array}
\]

\[
\begin{array}{c}
\begin{array}{c}
v \text{ [km/h]} \\
\end{array}
\end{array}
\begin{array}{c}
\begin{array}{c}
0 \quad 10 \quad 20 \quad 30 \quad 40 \quad 50 \quad 60 \\
\end{array}
\end{array}
\begin{array}{c}
\begin{array}{c}
0 \quad -100 \quad -150 \\
\end{array}
\end{array}
\begin{array}{c}
\begin{array}{c}
50 \quad 100 \quad 150 \\
\end{array}
\end{array}
\]

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\end{array}
\begin{array}{c}
\begin{array}{c}
50 \quad 100 \quad 150 \\
\end{array}
\end{array}
\]
Controller Synthesis

Specific Mission Data

Data from many missions

Specific Controller

Baseline Controller

\[ u^\circ = \mu^\circ(x, w) \]

\[ u^\circ = \mu^\circ(x, w) \]
Standardized On-Road Test

SORT1 = heavy   SORT 2 = mixed   SORT 3 = light
Standardized On-Road Test

How to measure *comparable* values for fuel consumption?

Graph taken from "UITP - Project SORT", 2000
SORT 2 - Results with **Baseline Strategy**

Each test cycle needs to be repeated 10 times.
SORT Results - Conventional

![Bar Chart](chart.png)

- **SORT 1**: Conventional
- **SORT 2**: Conventional
- **SORT 3**: Conventional

**Y-axis**: Fuel Consumption [l/100km]

**X-axis**: SORT 1, SORT 2, SORT 3

Fuel Consumption in liters per 100 kilometers for different SORT configurations, with Conventional vehicle performance shown.
SORT Results - HESS Hybrid

<table>
<thead>
<tr>
<th>SORT</th>
<th>Conventional</th>
<th>HESS Hybrid</th>
<th>Fuel Consumption [l/100km]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>-27.5%</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>-22.6%</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

-27.5% on SORT 1
-22.6% on SORT 2
SORT Results - Simulation Model ($\epsilon < 0.5\%$)

![Bar Chart]

- Fuel Consumption [l/100km]
- Conventional,
- HESS Hybrid Simulation,
- SORT 1: -27.5%,
- SORT 2: -22.6%,
- SORT 3:

**Results**

- Conventional HEV vs. Simulation
- Fuel Consumption Reduction
- SORT 1: -27.5%
- SORT 2: -22.6%
- SORT 3: 

**Component Sizing**

- Sizing Problem
- Vehicle Model
- Control Problem
- Algorithms
- Results

**Energy Management**

- Driver Prediction
- Control Problem
- Algorithm
- On-Road Test
- Realistic Operation
- Outlook
SORT Results - Simulation Model ($\varepsilon < 0.5\%$)

![Graph showing fuel consumption comparison between Conventional, HESS Hybrid, and Simulation for SORT 1, SORT 2, and SORT 3. The percentages indicate Fuel Consumption savings: -27.5%, -22.6%, and -17.5% respectively.]

- **SORT 1:** Conventional - 46 l/100km, HESS Hybrid - 37 l/100km, Simulation - 34 l/100km
- **SORT 2:** Conventional - 40 l/100km, HESS Hybrid - 32 l/100km, Simulation - 27 l/100km
- **SORT 3:** Conventional - 35 l/100km, HESS Hybrid - 28 l/100km, Simulation - 24 l/100km

Fuel Consumption [l/100km]
SORT Results - Optimal Performance

<table>
<thead>
<tr>
<th>SORT</th>
<th>Fuel Consumption [l/100km]</th>
<th>Conventional</th>
<th>HESS Hybrid</th>
<th>Simulation</th>
<th>Optimal Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>+3.0%</td>
<td>45</td>
<td>38</td>
<td>35</td>
<td>32</td>
</tr>
<tr>
<td>2</td>
<td>+2.9%</td>
<td>40</td>
<td>34</td>
<td>32</td>
<td>30</td>
</tr>
<tr>
<td>3</td>
<td>+4.7%</td>
<td>45</td>
<td>38</td>
<td>35</td>
<td>32</td>
</tr>
</tbody>
</table>

Fuel Consumption: [l/100km]
Optimality of **Baseline Strategy**

![Bar chart showing relative increase in energy management for different SORT categories.](chart.png)
Optimality of a Mission-Specific Controller

![Bar chart showing relative increase in energy management with baseline and mission-specific controllers for SORT 1, SORT 2, and SORT 3.](image)

- SORT 1: Baseline -1.0% vs. mission-specific -1.0%
- SORT 2: Baseline -1.0% vs. mission-specific -1.0%
- SORT 3: Baseline 4.5% vs. mission-specific 3.4%
Realistic Operation

The SORT test-cycles are synthetic:

► very repetitive
► very distinct
► no altitude variations
► no variation of vehicle weight

How does the controller perform under realistic conditions?
Line 1 in Heidenheim
Fuel consumption reduction

![Fuel Consumption Chart](image)

- April: -29%
- May: -23%
- June: -22%
- July: -27%

<table>
<thead>
<tr>
<th>Month</th>
<th>Conventional</th>
<th>HESS-Hybrid</th>
<th>Fuel Consumption Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>April</td>
<td>35 l/100km</td>
<td>25 l/100km</td>
<td>-30%</td>
</tr>
<tr>
<td>May</td>
<td>35 l/100km</td>
<td>25 l/100km</td>
<td>-30%</td>
</tr>
<tr>
<td>June</td>
<td>35 l/100km</td>
<td>25 l/100km</td>
<td>-30%</td>
</tr>
<tr>
<td>July</td>
<td>35 l/100km</td>
<td>25 l/100km</td>
<td>-30%</td>
</tr>
</tbody>
</table>
Outline of Talk

1. Introduction
2. Vehicle Model
3. Component Sizing
4. Energy Management
5. Conclusion
Stochastic Dynamic Programming

Assuming

- a stationary pdf for the disturbance
- and an infinite horizon

results in a stationary, causal, optimal state-feedback law.

In the case of a serial hybrid electric bus with supercaps, this solution is close to optimal.

Precision depends on discretization, and computational effort scales exponentially with the number of

- state variables
- control inputs
- variables that influence the Markov chain
Predictive Energy Management

- GNSS
- Predicted road profile
- Actual road profile

Introduction
Hybrid Electric Bus
Operating Modes
Energy Management

Vehicle Model
Chassis
Traction Motor
Supercaps
EGU
DC-Link

Component Sizing
Sizing Problem
Vehicle Model
Control Problem
Algorithms
Results

Energy Management
Driver Prediction
Control Problem
Algorithm
On-Road Test
Realistic Operation
Outlook
Prediction of Future Driving Conditions based on Self-Learning Road Maps

Andreas Ritter

Supervision

Philipp Elbert

February 28, 2014
Problem

Raw GPS signals are not sufficient

- Large amount of data.
- Hard to extract precise information.
- Signal combination is complex.
Concept

General structure

Vehicle sensors: GNSS data

- wheel speeds
- axle speed
- motor speed

Kalman filter

- latitude
- longitude
- altitude
- velocity
- direction

Pose estimations

Road map
Algorithm applied to real measurement data

Map section 1
Algorithm applied to real measurement data

Map section 2
Standard deviation is a measure of Uncertainty

Standard deviation indicates **how repetitive** a bus drives on the bus line.

Standard deviation indicates **how confident** we are about the map data.
Retrieve predictive map data

Map building
Case Study
Energy management system

stationary policy
stochastically optimal
future unknown

Case Study
Energy management system

stationary policy
stochastically optimal
future unknown
Case Study

Energy management system

stationary policy
stochastically optimal
future unknown
Reserve capacity to store future braking energy!

\[ E_{res}(t) = f(v(s), P_{req}(s)) \]

Case Study
Energy management system

Up to now:

\[ u^o = f(v, P_{\text{req}}, \text{SOE}, \omega_g, \vartheta_e) \]
Case Study
Energy management system

Up to now:

\[ u^o = f(v, P_{req}, SOE, \omega_g, \vartheta_e) \]

Additional state:

\[ u^o = f(v, P_{req}, SOE, \omega_g, \vartheta_e, E_{res}) \]
Case Study

Evaluation setup

Oktober 31, 2013, Heidenheim, Germany

build map with 15 different trips

save intermediate maps M0, M1, M2, ..., M15
Case Study

Evaluation setup

trip No 4 of November 07, 2013, Heidenheim, Germany

evaluation with the **same trip** on maps M0, M1, M2, . . . , M15

M0

result without prediction

M1

result with data from one trip

M2

result with data from two trips

M15

result with data from 15 trips
Prediction can reduce fuel consumption

Simulation results of case study

SDP controller with energy reserve

additional fuel consumption compared to noncausal [%]

maps

- prediction with map (online)
- perfect prediction (offline)
- SDP without prediction

M0 M5 M10 M15
Prediction can reduce dissipated braking energy

Simulation results of case study

SDP controller with energy reserve

- prediction with map (online)
- perfect prediction (offline)
- optimal solution (noncausal)
- SDP without prediction

braking energy dissipated in braking resistor [kWh]

maps

M0 M5 M10 M15
Outlook

Still running in Heidenheim.
Thank you for your attention!
Credits

Supervision
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▶ Lino Guzzella
▶ Chris Onder

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▶ Dieter Flubacher

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▶ Tobias Nüesch

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▶ Andreas Ritter
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▶ Manuel Kant
▶ Ismail Abou-Zeid
▶ Raphael Schär
▶ Michael Gugger
▶ Dmitri Karpatchev
▶ Stijn van Dooren
▶ Christian Hohl
▶ Nico Geiser
▶ Duwei Chen
▶ Xinlei Qiu