ANALYZING THE ENERGY CONSUMPTION OF THE BMW ACTIVEE FIELD TRIAL VEHICLES WITH APPLICATION TO DISTANCE TO EMPTY ALGORITHMS

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mobil. TUM 2014
BMW Field Trails for e-Mobility
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1 Lithium-Ion Battery.
2 Electric Engine.
3 Power Electronics.
TeleServices are implemented as a communication channel to provide details of usage.

A set of analytical apps is provided for in-depth analysis:

- ActiveE-Analytics.qwv
  Last Update: 2014-06-12 12:32
  view details

- ActiveE-CHARGING_ANALYTICS.qwv
  Last Update: 2014-06-12 12:30
  view details

- E32E_RG.qwv
  Last Update: 2014-06-18 06:51
  Next Update: 2014-05-19 08:45
  view details

- ActiveE_TSR_LADEN.qwv
  Last Update: 2014-06-12 12:38
  view details
Aggregated data is fed to the drivers via the ActiveE electronaut homepage
0:03 Remaining

Recharge
Immediately
Predicted ≠ Actual

battery use is not constant and it’s difficult to predict
Distance to Empty

130 km
Recharge Immediately

5 km
Predicted ≠ Actual

battery use is not constant and it’s difficult to predict
“Nearing New York, I made the first of several calls to Tesla officials about my creeping range anxiety.”

-J. Broder

~15 - 35% Error in $D_{TE}$
Range Anxiety

Survey of EV users: A more accurate Distance to Empty estimate may be more valuable than increasing the size of the battery pack

Franke, et al, August 2011
Can we use the ActiveE driving data to better understand why Distance to Empty is so difficult to predict?
Introduction to $D_{TE}$ Estimation

- The objective is to estimate the future energy use.
- Conventional $D_{TE}$ algorithms assume past $\approx$ future.
- Real world data: cannot always rely solely on past driving data to estimate the future.
2nd Important Concepts:

- The objective of a $D_{TE}$ algorithm is to estimate the future average energy use.

\[
D_{TE}(t) = \frac{E_b(t)}{\bar{p}_f(t)} \quad \text{Wh/km}
\]

Battery energy remaining

Future average energy use
\[ \hat{D}_{TE}(t) = \frac{E_b(t)}{\hat{\rho}_f} \]

\( \rho_{past} \) [Wh/km]

Past Driving

Present

\( \rho_f \)

Future Driving
2\textsuperscript{nd} Important Concept:

- Conventional methods only use past driving information to estimate $\bar{p}_f$

\[ \hat{D}_{TE}(t) = \frac{E_b(t)}{\hat{\bar{p}}_f} \]

- Past Driving
  - $\bar{p}_{long}$: 300 km
  - $\bar{p}_{short}$: 30 km

- Present
  - $\bar{p}_{long}$: 100% SOC
  - $\bar{p}_{short}$: 0% SOC

$\approx 300 \text{ km}$
Introduction to $D_{TE}$ Estimation

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- Conventional $D_{TE}$ algorithms assume past $\approx$ future

- Real world data: cannot always rely solely on past driving data to estimate the future
Real world insight: there’s a high probability that average energy use (Wh/km) will change by 30% or more between the past and future.
Simulation: when energy consumption changes by 30% mid-drive, conventional methods yield \( D_{TE} \) estimation error of \(~17\text{-}30\%\)
ActiveE dataset shows that auxiliary energy use is the largest source of variation in energy use.

![Probability Density Curve]

- **Drive**
- **Aux.**

Change in Total Energy (%)

Between Subsequent Drive-Charge Events
ActiveE dataset confirms that auxiliary loads are significant
Introduction to $D_{TE}$ Estimation

✔️ The objective is to estimate the future energy use.

✔️ Conventional $D_{TE}$ algorithms assume past $\approx$ future.

✔️ Real world data: cannot always rely solely on past driving data to estimate the future.
0:03 Remaining

Recharge immediately
Thank you very much for your attention! Any questions?