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

LENNON RODGERS, MIT
STEPHEN ZOEPF, MIT
JOHANN PRENNINGER, BMW

mobil.TUM 2014

BMW GROUP

BMW Field Trails for e-Mobility

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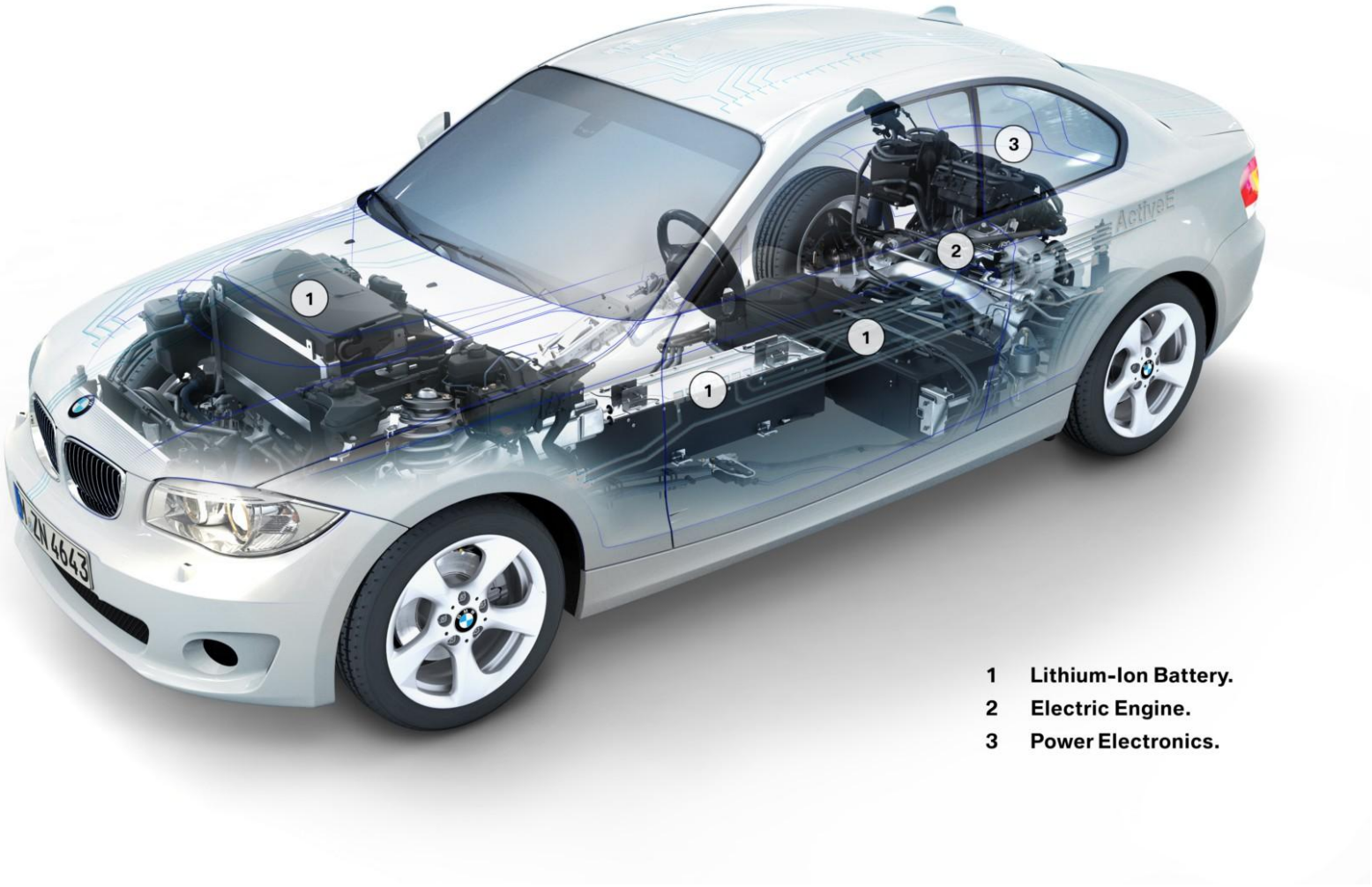
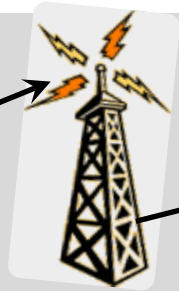
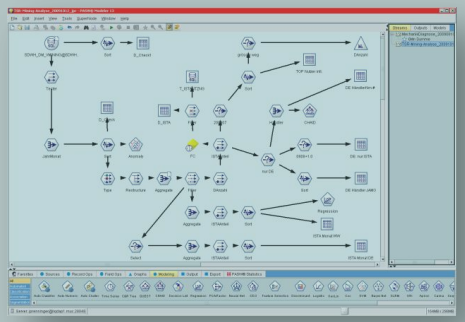


TeleServices are implemented as a communication channel To provide details of usage



Automatic Datamining



a set of analytical apps is provided for in depth analysis

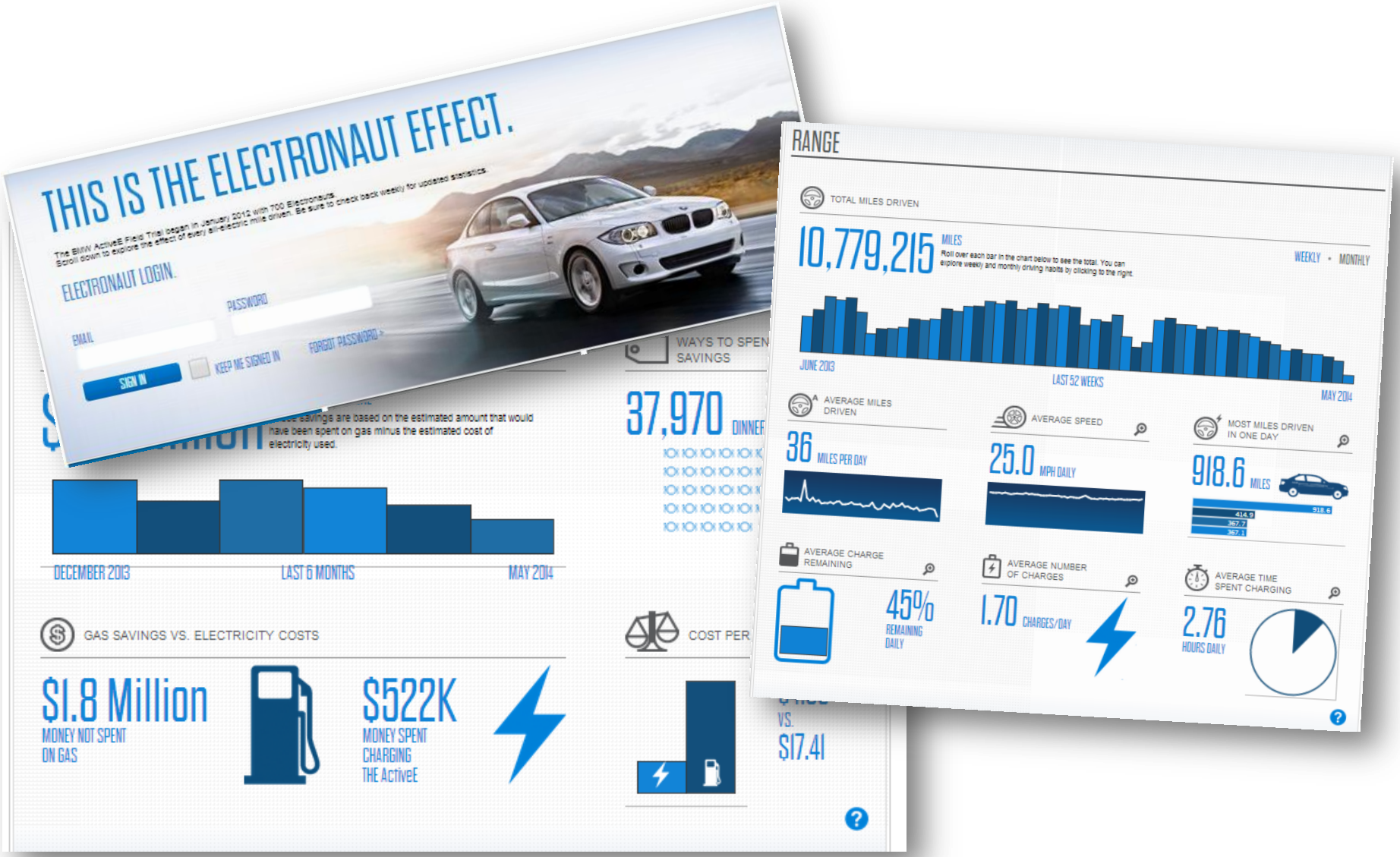
ActiveE-Analytics.qvw
Last Update: 2014-05-12 12:32
view details

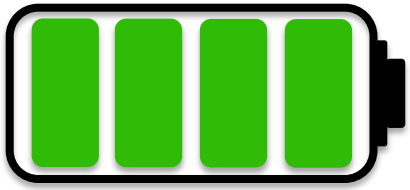
ActiveE-CHARGING_ANALYTICS.qvw
Last Update: 2014-05-12 12:30
view details

E82E_RG.qvw
Last Update: 2014-05-15 06:51
Next Update: 2014-05-16 06:45
view details

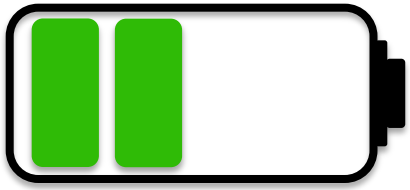
ActiveE_TSR_LADEN.qvw
Last Update: 2014-05-12 12:38
view details

Aggregated data is fed to the drivers via the ActiveE electronaut homepage





4:30 Remaining



2:30 Remaining

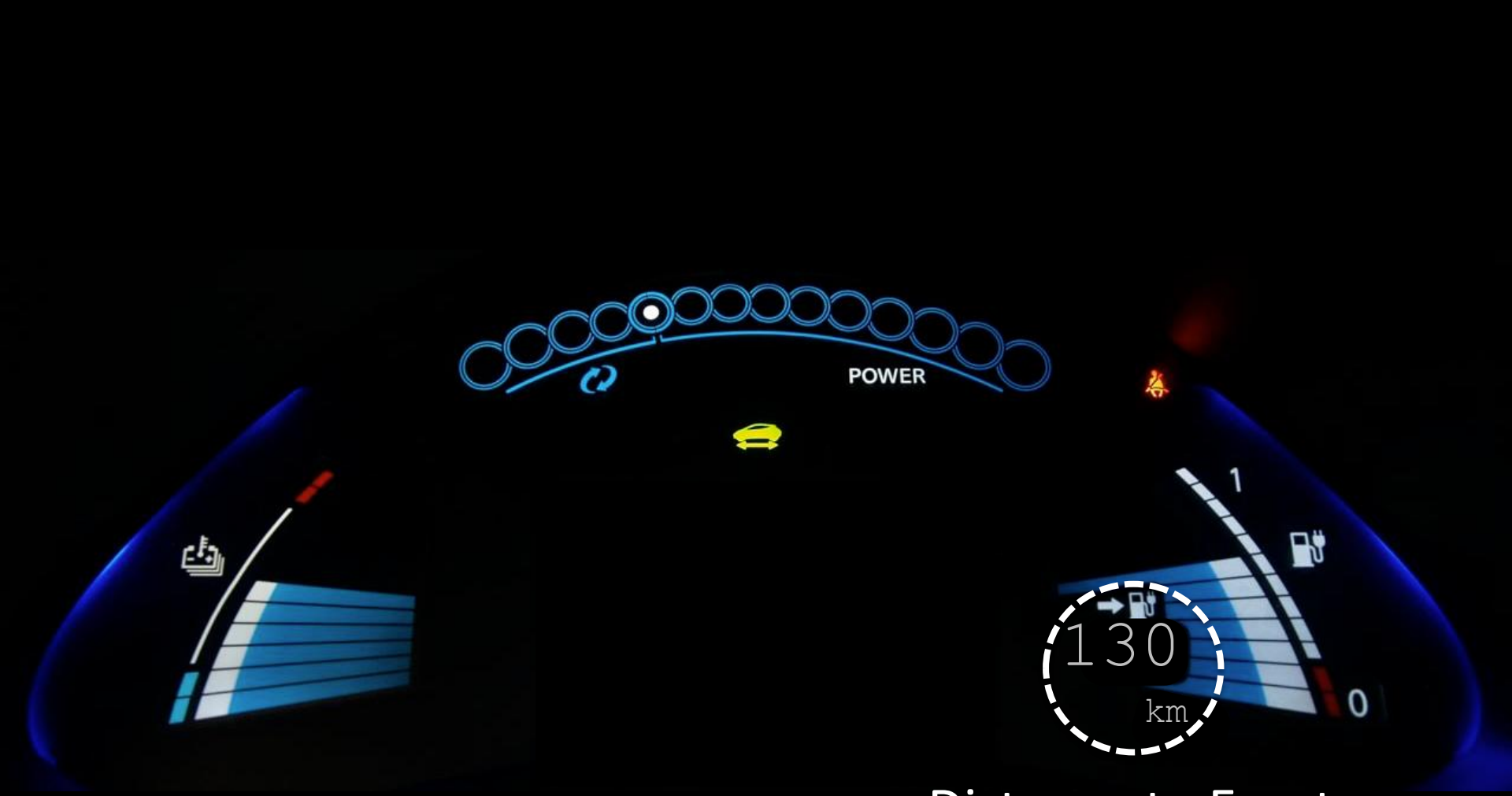
1:00 Remaining

0:03 Remaining

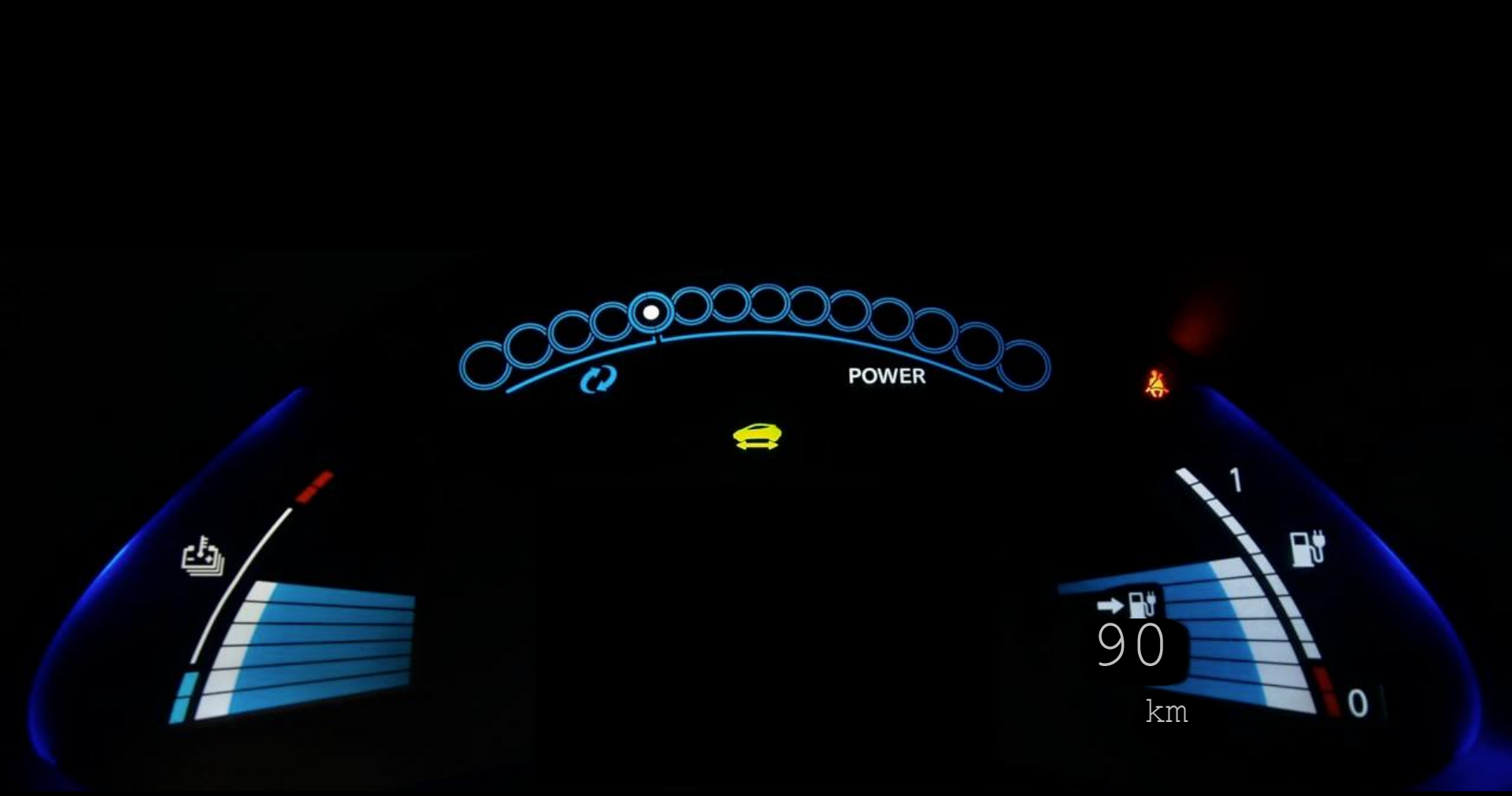
Recharge
Immediately

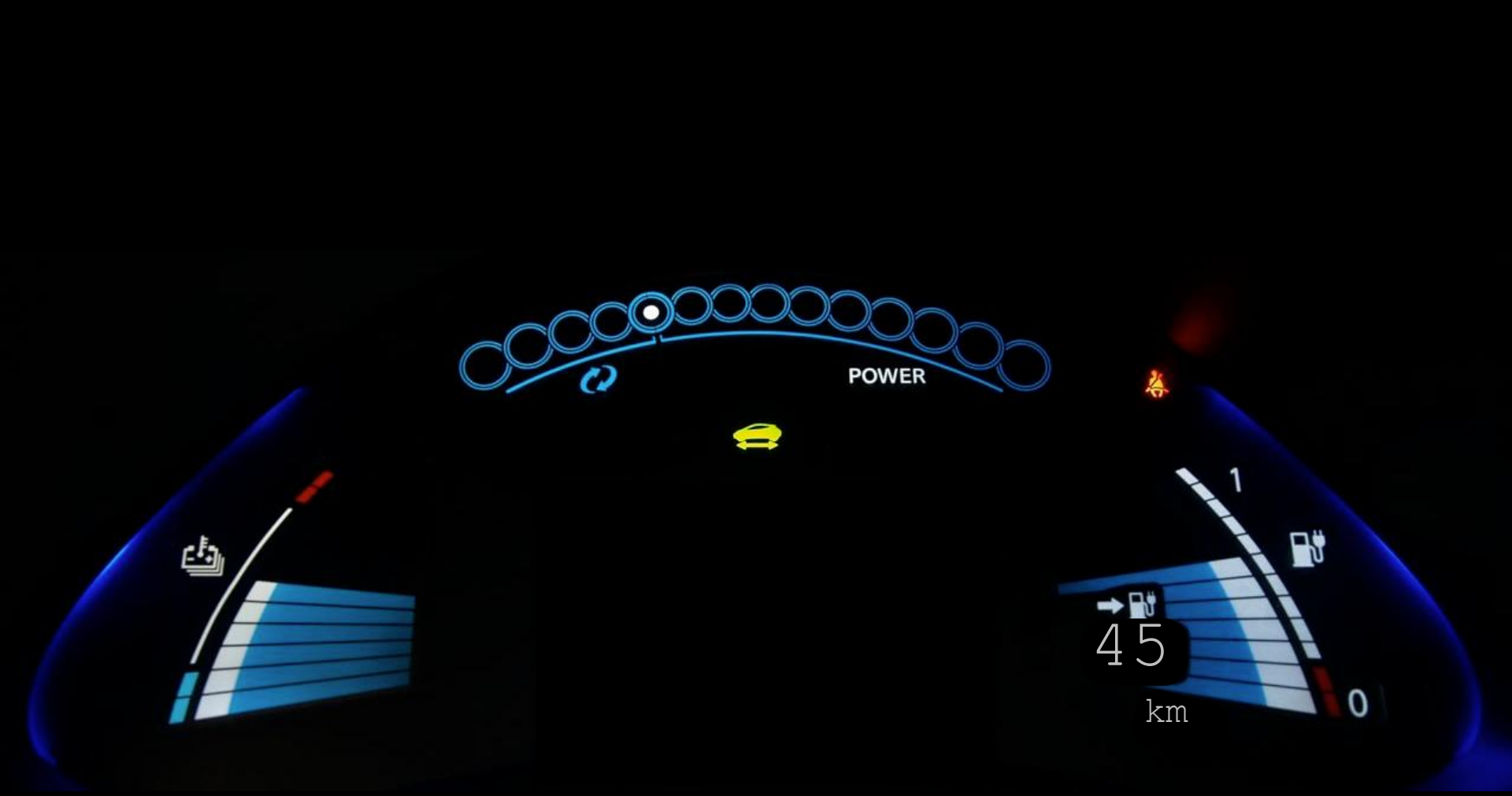
Predicted ≠ Actual

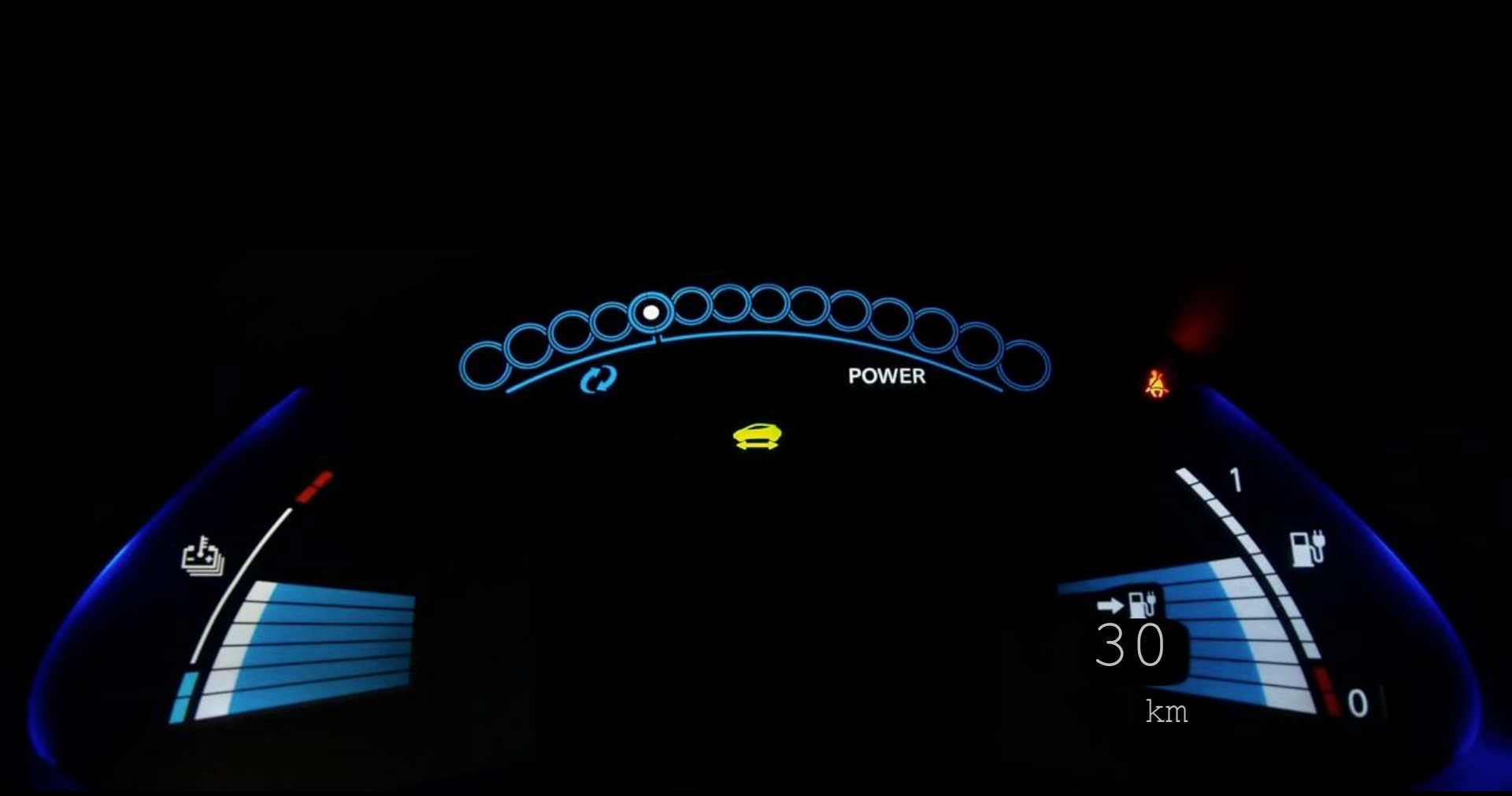
battery use is not constant
and it’s difficult to predict

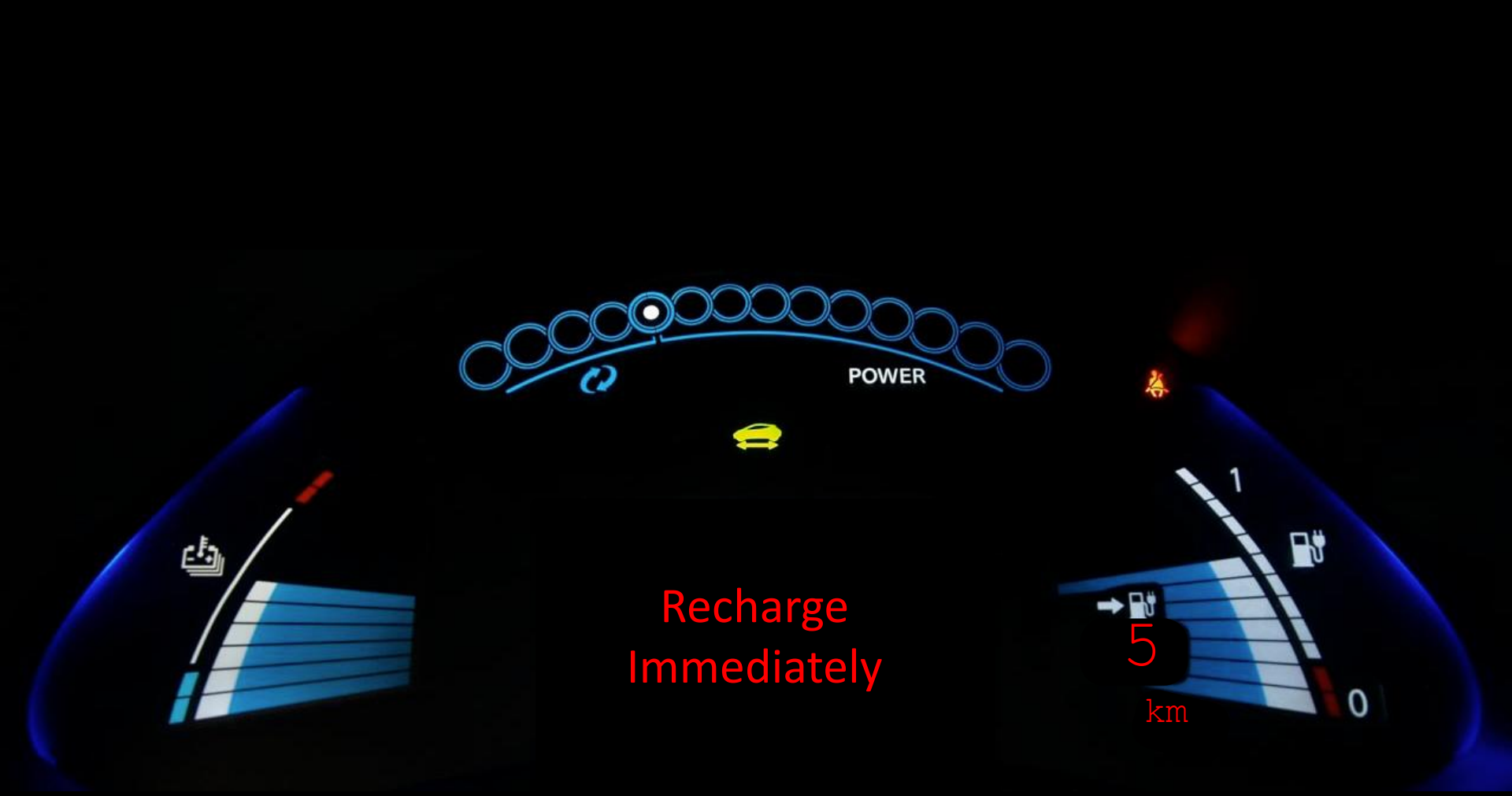


Distance to Empty


POWER
1
0
90
km


POWER
1
0
45
km


POWER
1
0
30
km


POWER
Recharge
Immediately
1
5
km
0

Predicted ≠ Actual

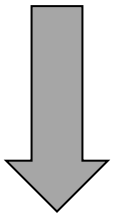
battery use is not constant
and it’s difficult to predict

The New York Times

Stalled Out on Tesla's Electric Highway, 2/8/2013

"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 ≈ future**
- Real world data: cannot always rely solely on past driving data to estimate the future

2nd Important Concept:

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

Battery energy remaining

$$D_{TE}(t) = \frac{E_b(t)}{\bar{p}_f(t)} \quad \begin{matrix} \text{Wh} \\ \text{Wh/km} \end{matrix}$$

Future average energy use

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

$\approx$

$\bar{p}_{past}$ [Wh/km]

Past Driving

? ? $\bar{p}_f$? ?

Future Driving

? ? ? ?

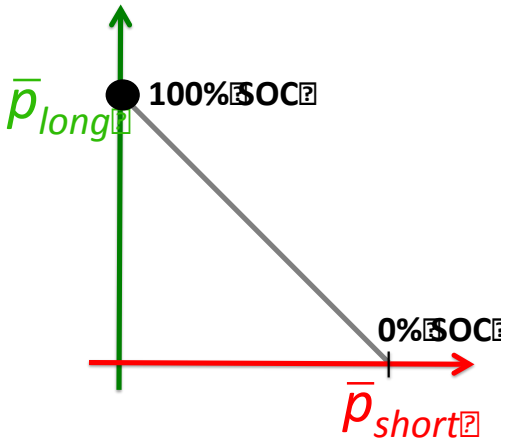
Present

2nd Important Concept:

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

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

$\approx$



$\bar{p}_{long}$ [Wh/km]

300 km

?

$\bar{p}_{short}$

30 km

Past Driving

Present

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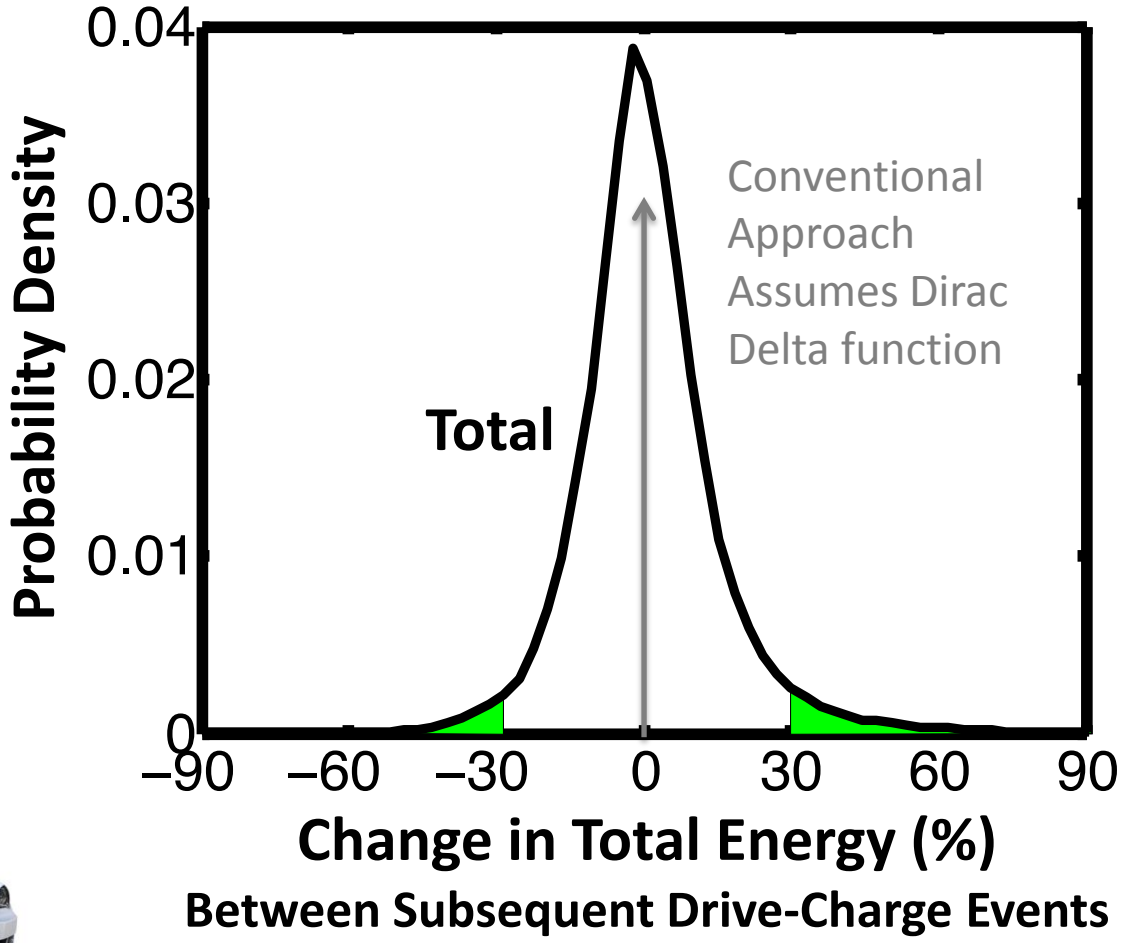
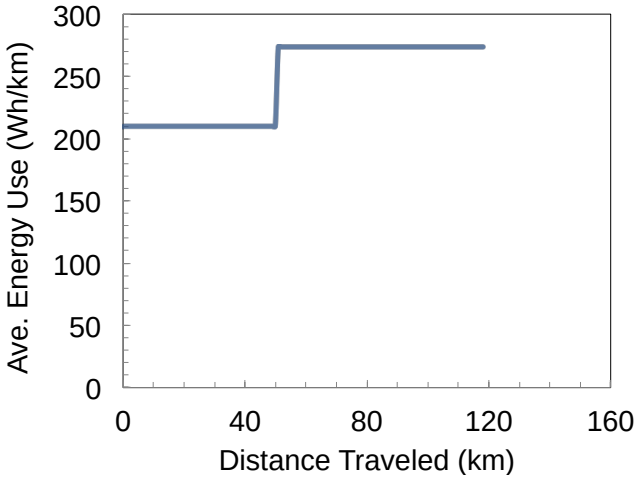
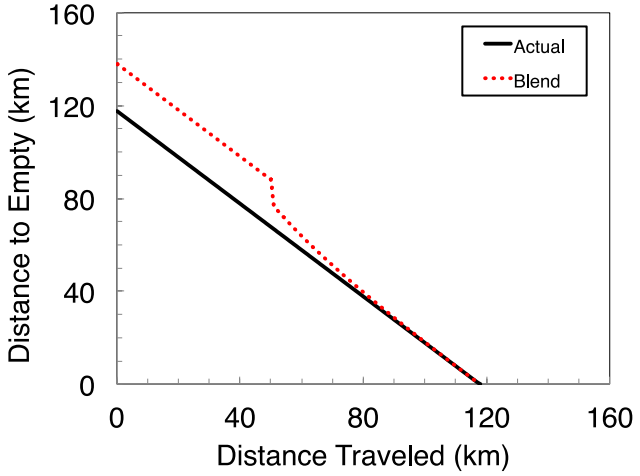
Real world insight: there's a high probability that average energy use (Wh/km) will change by 30% or more between the past and future

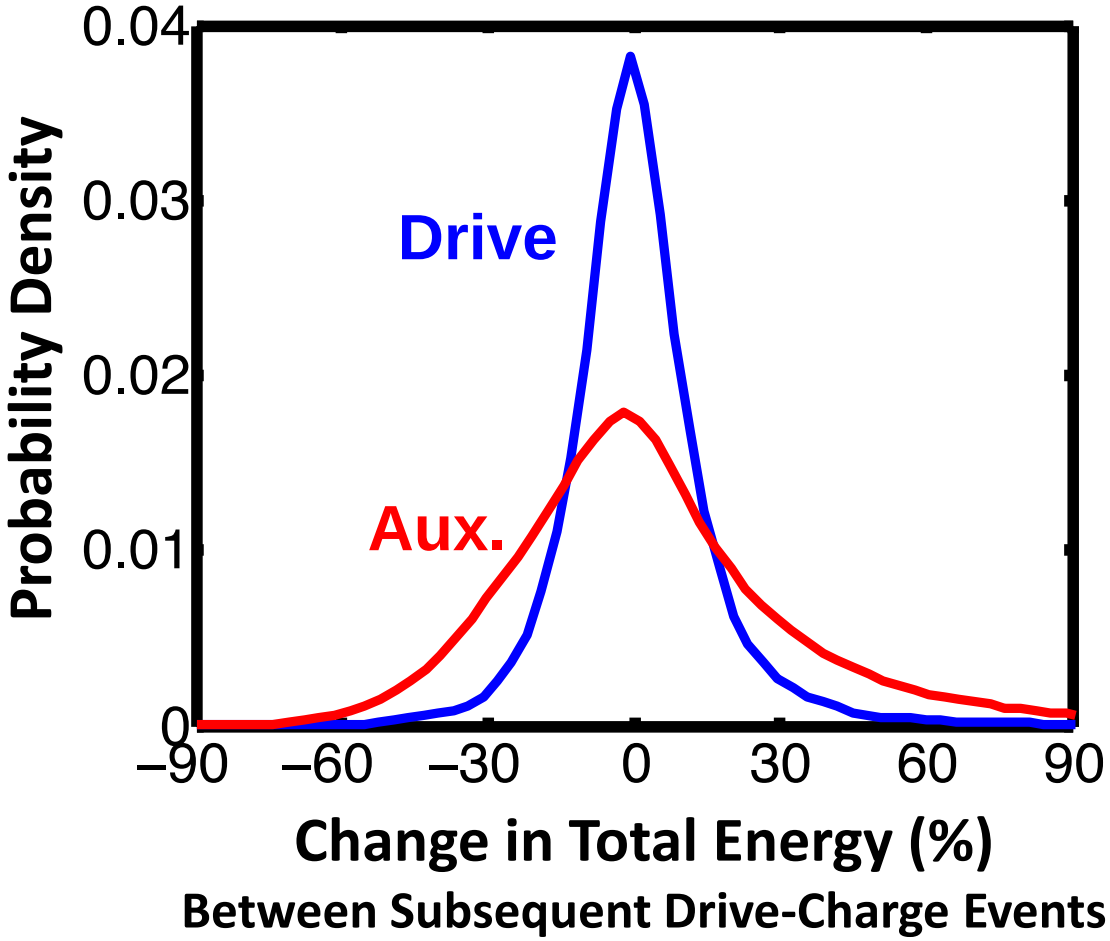


Simulation: when energy consumption changes by 30% mid-drive, conventional methods yield D_{TE} estimation error of ~17-30%

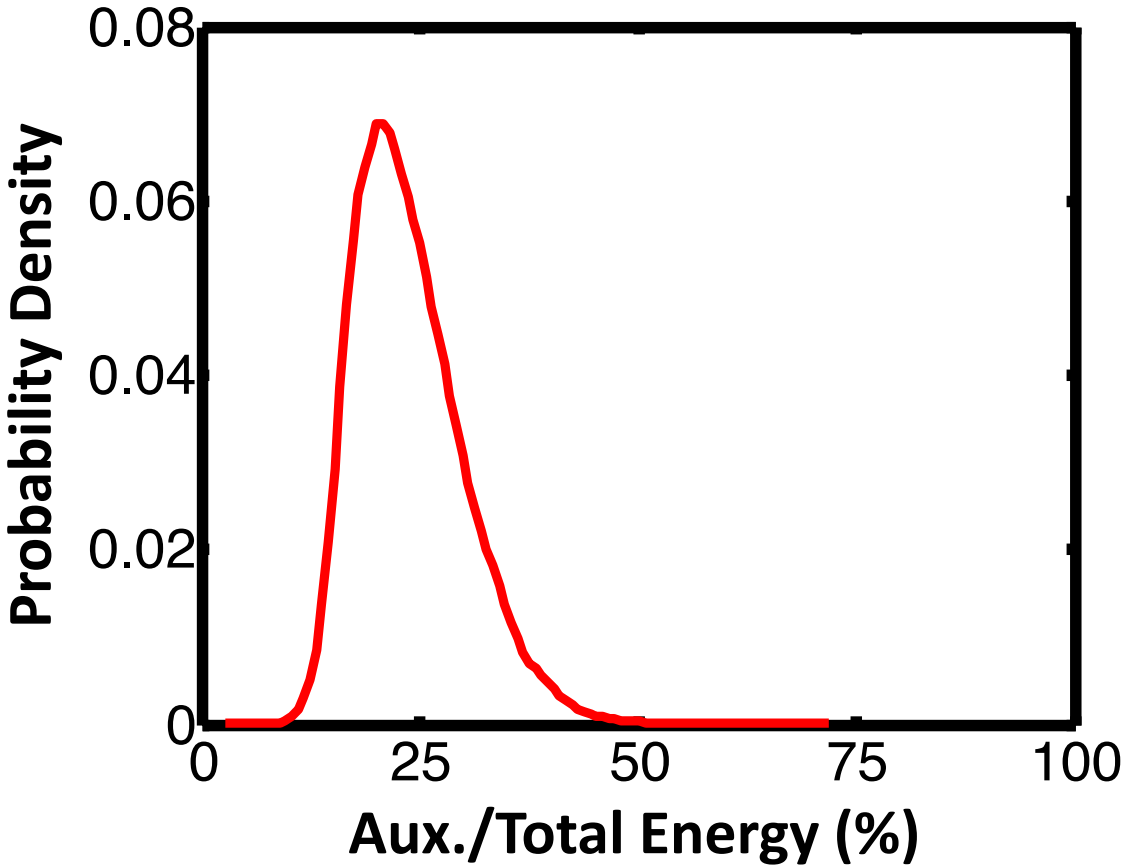




ActiveE dataset shows that auxiliary energy use is the largest source of variation in energy use



ActiveE dataset confirms that auxiliary loads are significant



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0:03 Remaining

Recharge
Immediately

Thank you very much for your attention!
Any questions?