Accurate Remaining Range Estimation for Electric Vehicles

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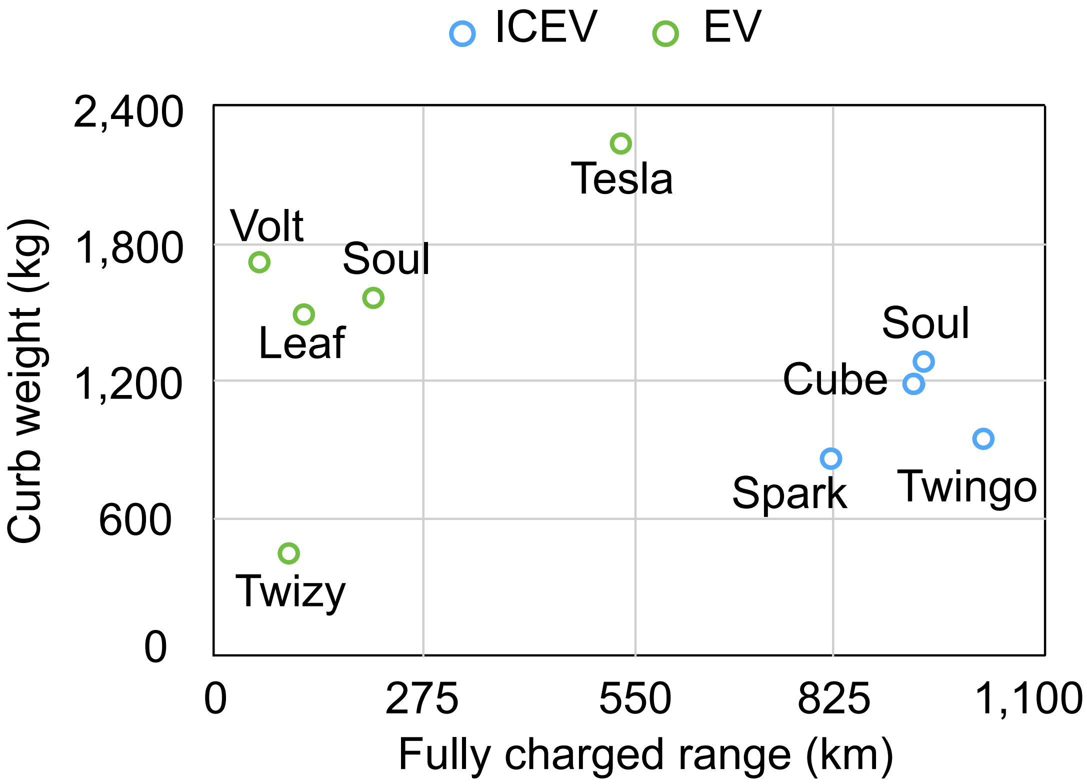
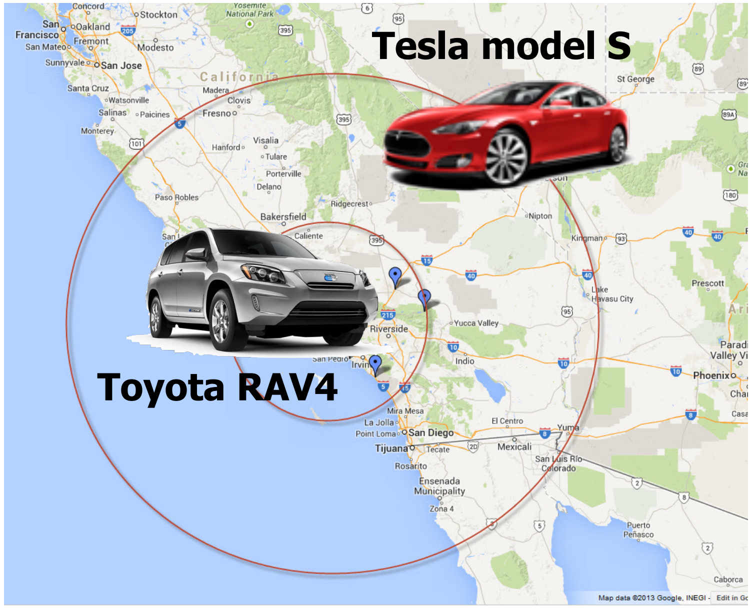
Outline

- **Motivation: Remaining range estimation**
- Related works
- Our framework
- Experiment
- Conclusion

Fully Charged Ranges of EV

- Electric vehicles are emerging with their great advantages, but EV drivers suffer from the short driving range
- EV have 5X shorter fully charged ranges than that of ICEV (Internal Combustion Engine Vehicles)





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Range Anxiety

- Range anxiety is the fear that a vehicle may not have sufficient energy to reach its destination
- The range anxiety comes from the uncertainty of the remaining range
- Modern fuel gauges show the remaining range but it’s only based on the driving history (past fuel consumption)

Range Anxiety in EV

- Most of the electric vehicle drivers always suffer from the range anxiety
  - Limited EV charging facilities, long charging time
  - Running out of battery while driving gives the same inconvenience as the vehicle breakdown

Range Anxiety in EV

- The statistics says that most of the EV drivers attempt only 70% of the estimated driving range with confidence
- The range anxiety in EV make the effective driving range of the EV even shorter
- Efforts to mitigate range anxiety
  - More EV charging facility, higher density batteries, fast charging, and range extender
  - Above solutions are time consuming or high cost

Rav4 EV
112 km **160 km**

Model S
300 km **420 km**

Twingo
1000 km

Paper Contribution

- In this paper, we provide accurate range estimation
- It mitigates the uncertainty of the driving range alleviates the range anxiety
- It restores the reserved range and extend the effective driving range
- Same effect of extended range without increasing the battery capacity

Case 1

Case 2

Outline

- Motivation
- **Related works**
  - **History based RR**
  - **Model based RR**
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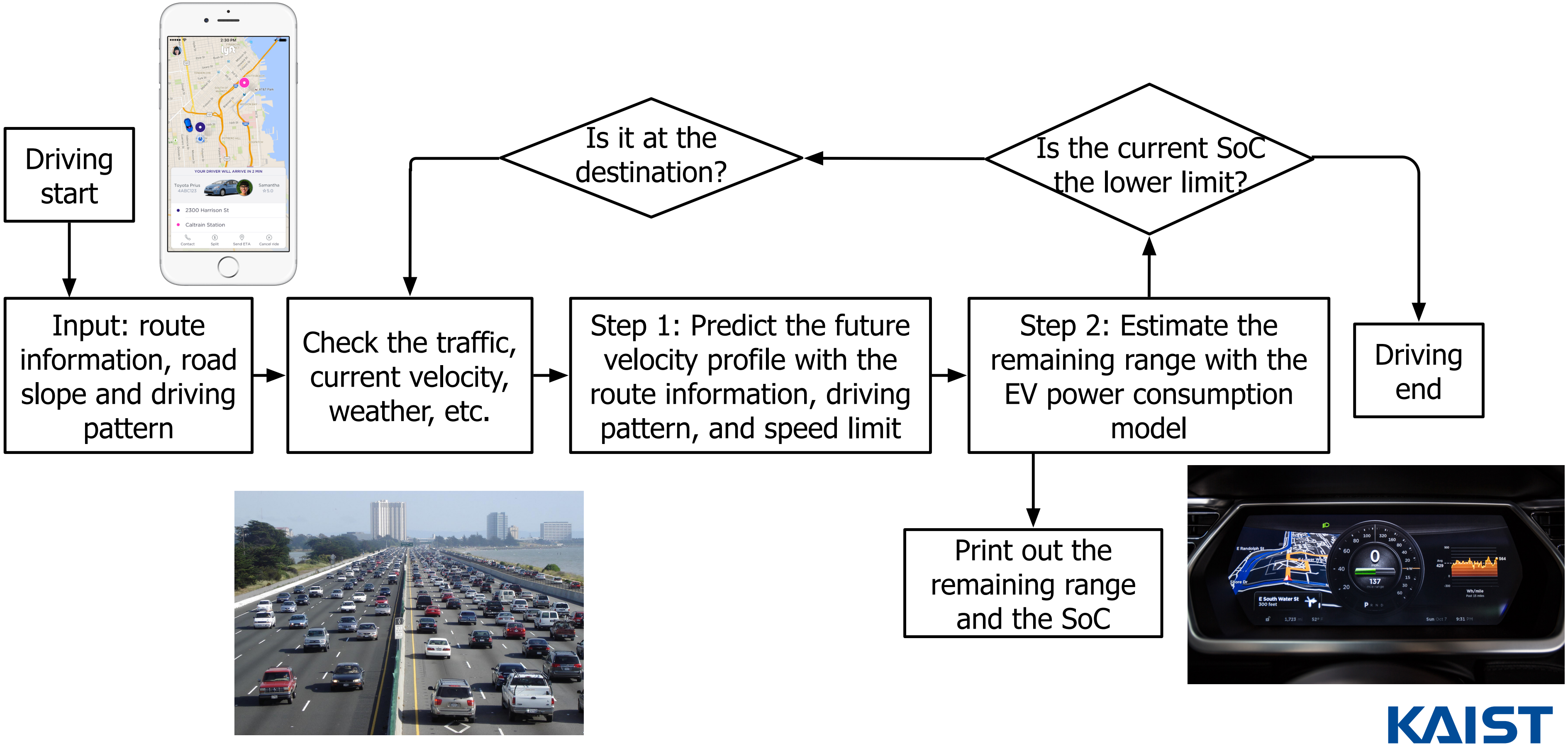
RR Estimation Framework

- The general remaining range framework can be simplified as following figure



Driving start

Input: route information, road slope and driving pattern

Check the traffic, current velocity, weather, etc.

Step 1: Predict the future velocity profile with the route information, driving pattern, and speed limit

Step 2: Estimate the remaining range with the EV power consumption model

Is the current SoC the lower limit?

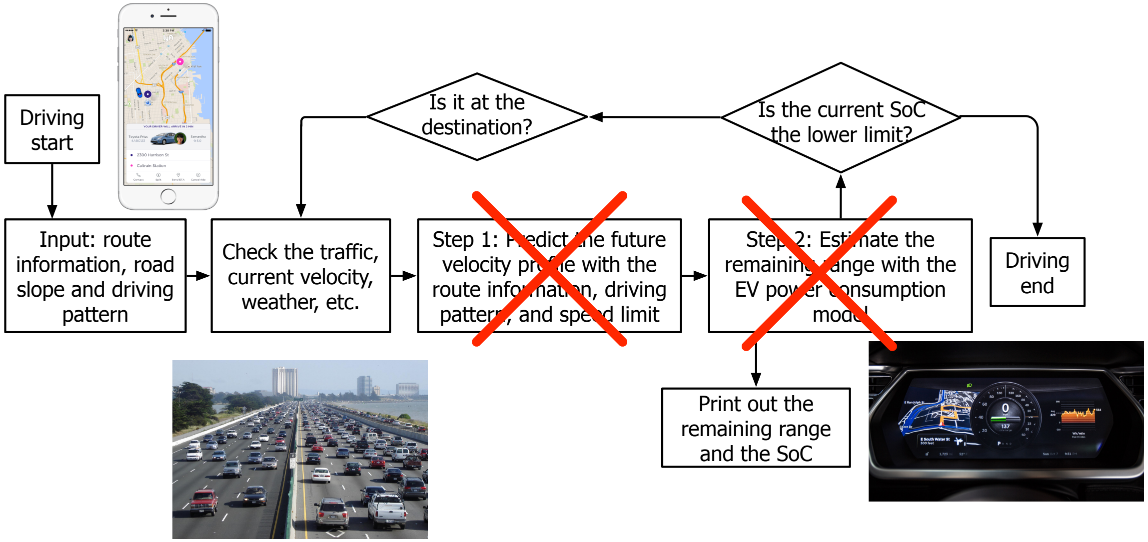
Is it at the destination?

Print out the remaining range and the SoC

Driving end

History Based RR

- History based remaining range estimation assumes the future power consumption is the same as the past power consumption



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Is the current SoC the lower limit?

Is it at the destination?

Driving end

Print out the remaining range and the SoC

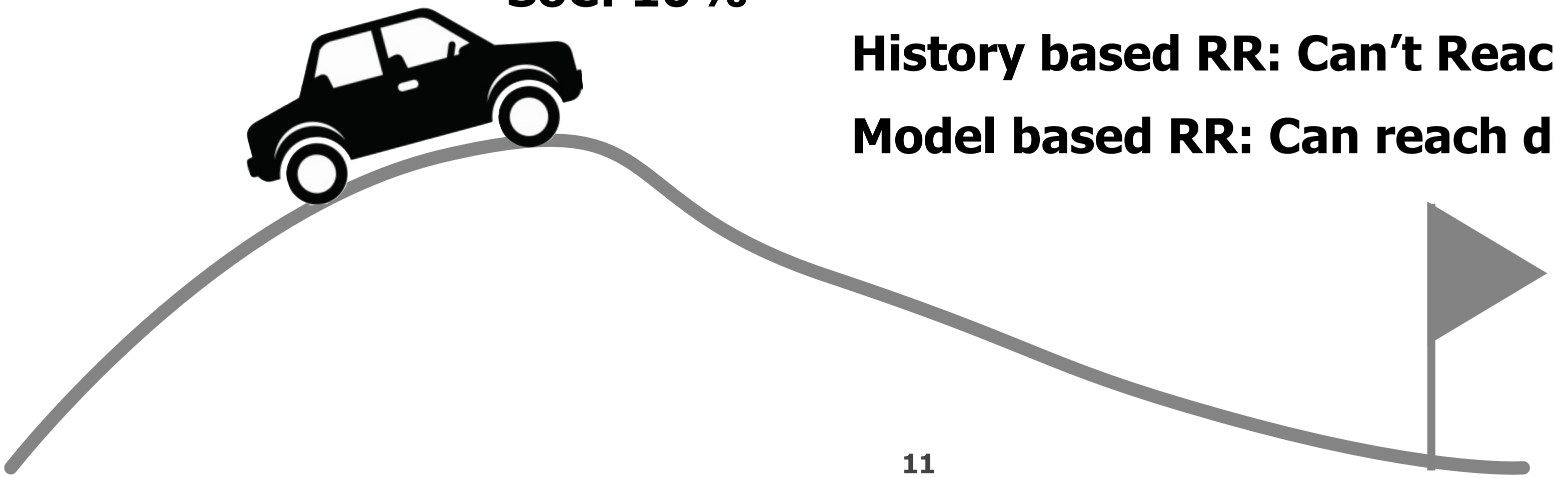
$$\hat{\bar{p}}_{future}(x) \approx \bar{p}_{past}(x)$$

- Some works used regression based algorithm to improve the estimation accuracy

$$\hat{\bar{p}}_{future}(x) = \hat{y}(x) * \bar{p}_{Long}$$

Model Based RR

- Model based remaining range estimation is naturally more accurate than the history based estimation
- There are some works about the model based range estimation
- They focused on predicting the future driving profile, but left the power model simplified



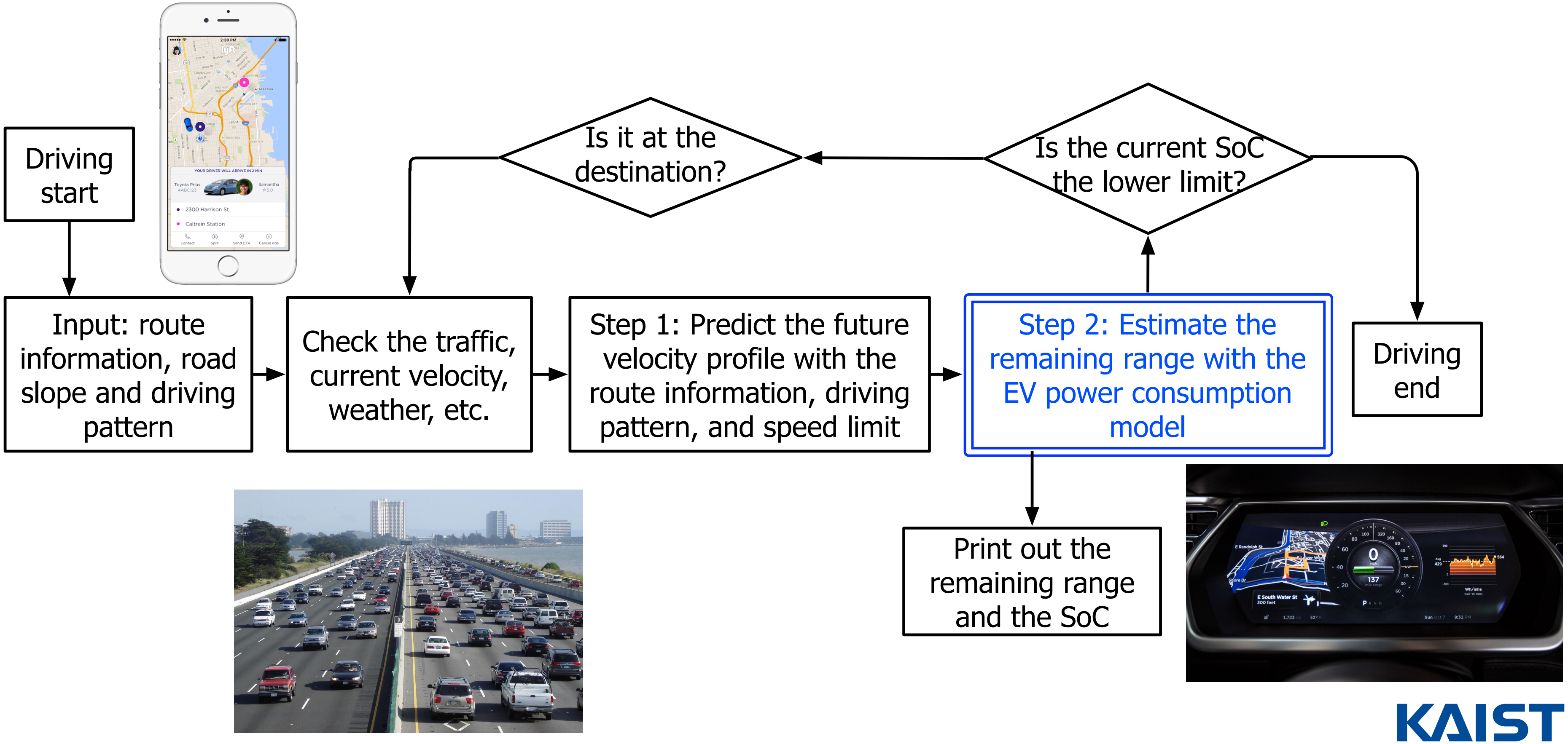
SoC: 10%

History based RR: Can't Reach destination

Model based RR: Can reach destination

Paper Contribution

- In this paper, we focus on an accurate EV power model to achieve an accurate remaining range estimation



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- Related works
- **Our framework**
    - **Remaining range estimation**
    - **EV power model**
- Experiment
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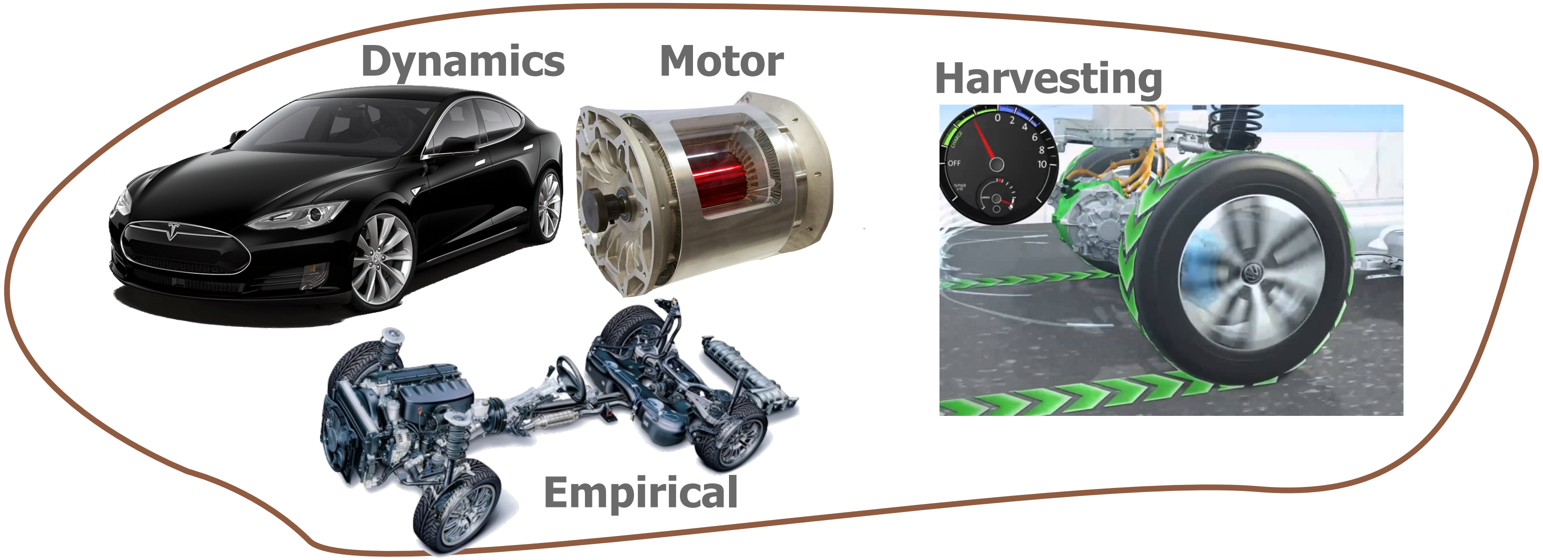
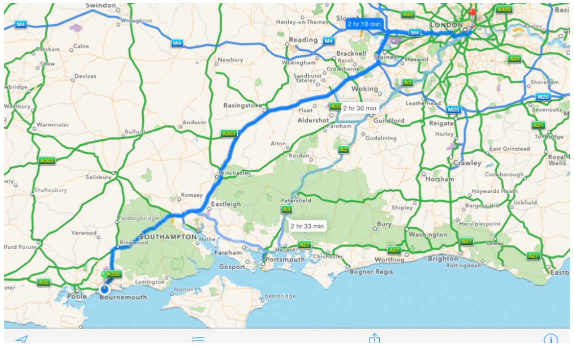
Proposed Range Estimation

- We start with a basic assumption that the future driving profile is given

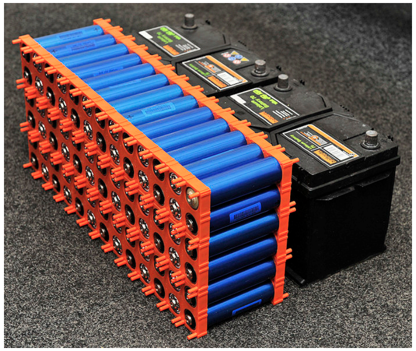
EV Power Model



Future driving profile



Battery model

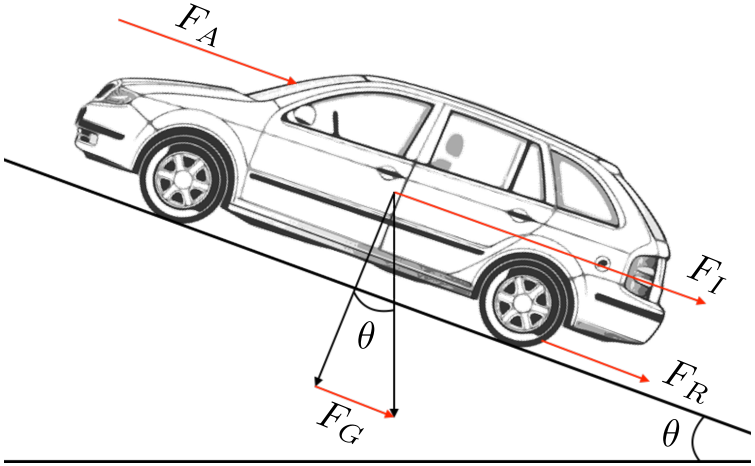


Remaining Range

Vehicle Dynamics Model

- Widely used vehicle power consumption model

$$\begin{aligned} P_{dynamics} &= F\frac{ds}{dt} = Fv \\ &= (F_R + F_A + F_G + F_I + F_B)v \\ &\approx (F_R + F_G + F_I)v \\ &\approx (\alpha + \beta sin\theta + \gamma a)mv, \end{aligned}$$



$$F_R(rolling\ resistance) \sim C_{rr}W$$

$$F_G(gravitational\ resistance) \sim W\sin\theta$$

$$F_I(inertial\ resistance) \sim ma$$

$$F_A(aerodynamic\ resistance) \sim \frac{1}{2}\rho C_d A v^2$$

Proposed Advanced Dynamics Model

- Motor efficiency actually differs dynamically according to the operating status

$$\eta = \frac{P}{P + k_i\omega + k_w\omega^3 + k_cQ^2 + C}$$

$$F_i(Iron\ and\ friction\ loss) \sim k_i\omega$$

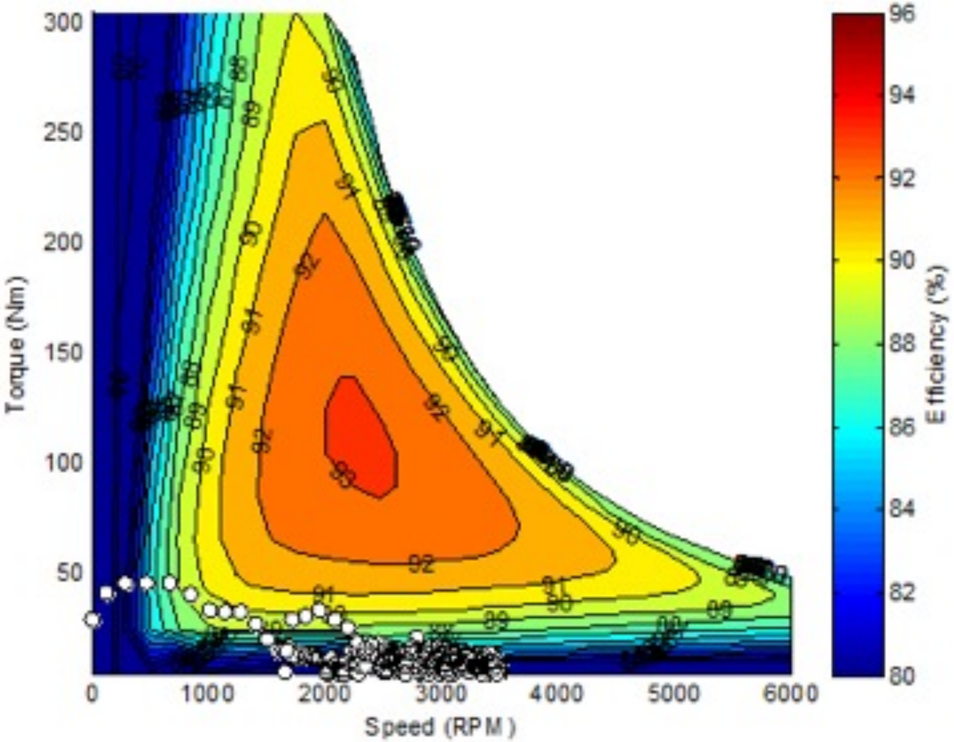
$$F_w\ (Windage\ loss) \sim k_w\omega^3$$

$$F_c\ (Copper\ loss) \sim k_cQ^2$$

$$Constant\ loss \sim C$$

$$T = P/v = (\alpha + \beta sin\theta + \gamma a)m$$

$$P_{advanced} = Tv + C_0 + C_1v + C_2T^2$$



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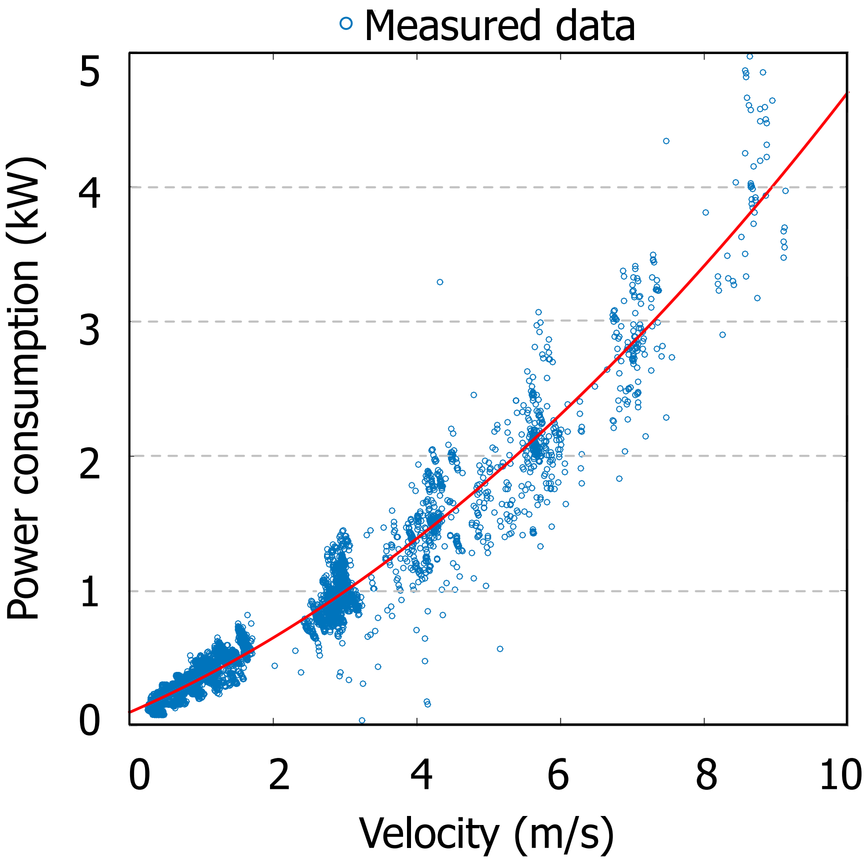
Proposed Hybrid Power Model

- Advanced dynamics model ignores the drivetrain and ancillary losses in the estimation
- A pilot experiment to verify the adequacy of the advanced dynamics model
- Finally, we propose the **hybrid power model** including the quadratic term from empirical data



$$T = P/v = (\alpha + \beta sin\theta + \gamma a)m$$

$$P_{hybrid} = Tv + C_0 + C_1 v + C_2 v^2 + C_3$$

Regenerative braking model

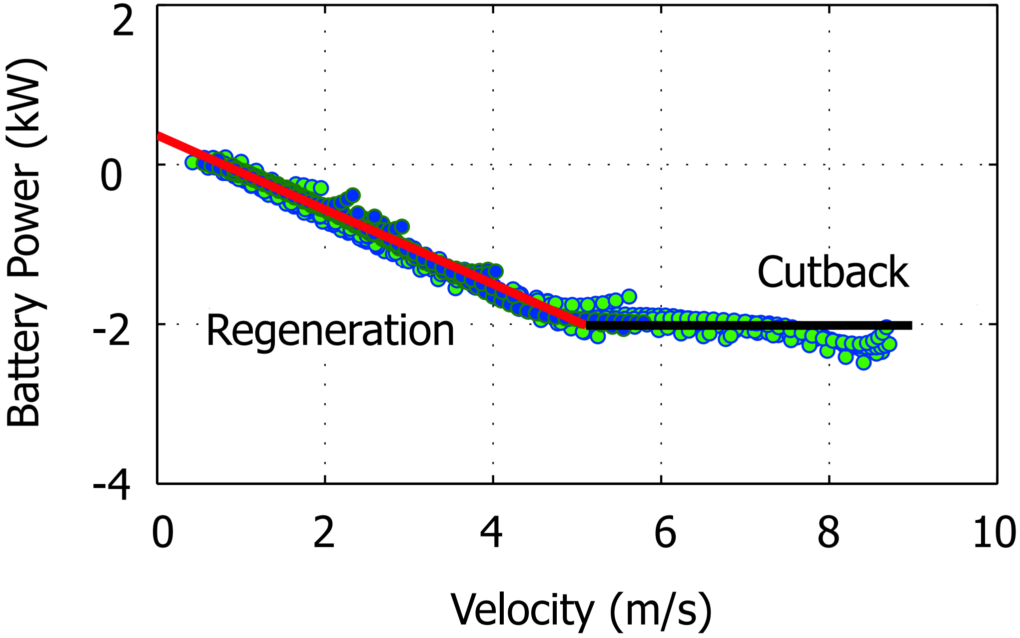
- One of the most commonly used energy harvesting methods in the EV is regenerative braking

- The regenerative braking comes from the electromagnetic induction

$$P_{induction} \propto \omega$$

- Regenerative power can be modeled as follows

$$P_{regen} = \delta v - \epsilon$$
$$= (460.53\ J/m)v - (333.92\ J/s)$$



Power Models

- Vehicle dynamics model

$$P_{vehicle} = (\alpha + \beta sin\theta + \gamma a)mv$$

- Advanced dynamics model

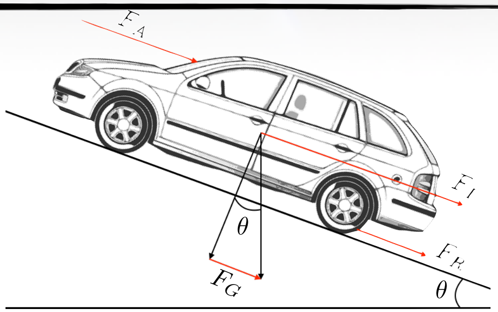
$$T = P/v = (\alpha + \beta sin\theta + \gamma a)m$$

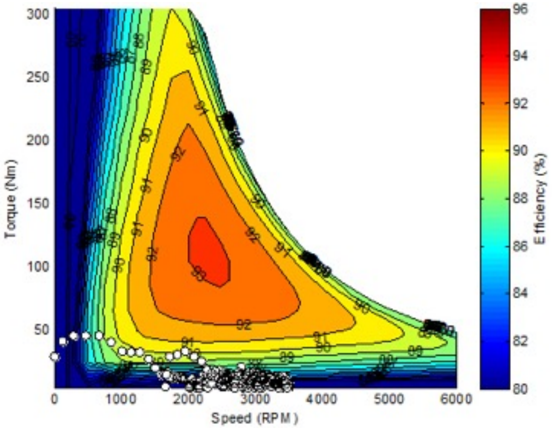
$$P_{advanced} = Tv + C_0 + C_1 v + C_2 T^2$$

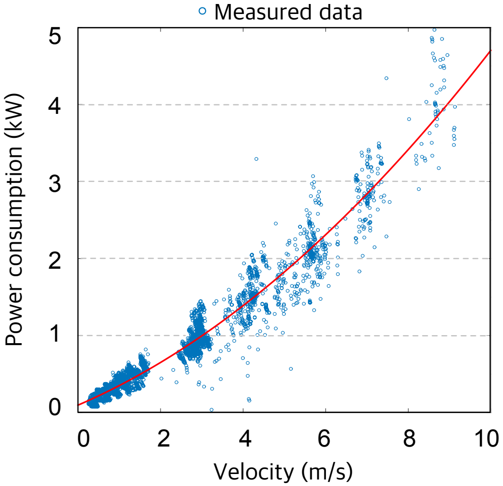
- Hybrid power model

$$T = P/v = (\alpha + \beta sin\theta + \gamma a)m$$

$$P_{hybrid} = Tv + C_0 + C_1 v + C_2 v^2 + C_3 T^2$$





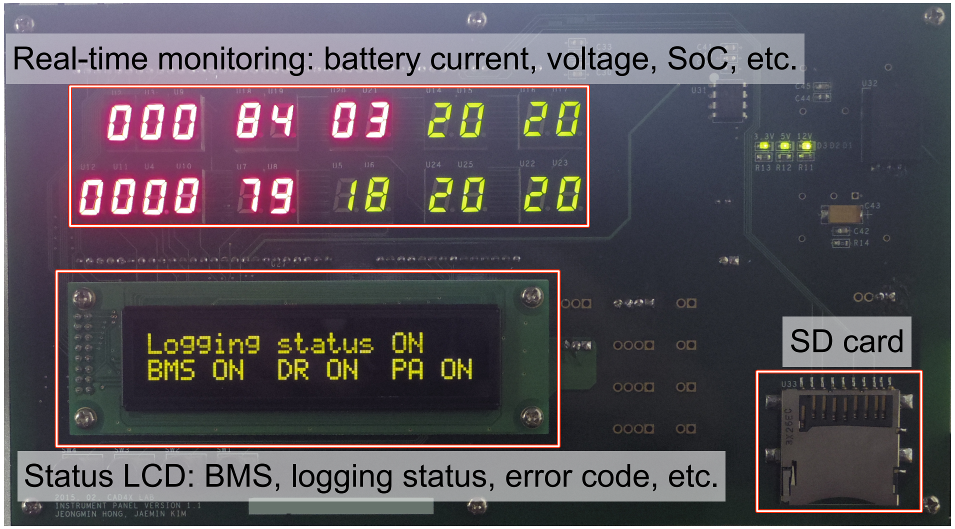


Outline

- Motivation
- Related works
- Our framework
- **Experiment**
    - **Power modeling and validation**
    - **Remaining range estimatio**
- Conclusion

Specification of the target vehicle

- We use a light-weight custom EV to verify the accuracy of power modeling and remaining range estimation
- Specification
  - Curb weight: 481 kg
  - Maximum velocity: 35 km/h
  - 76.8 V, 48 Ah LiFePO4 battery pack

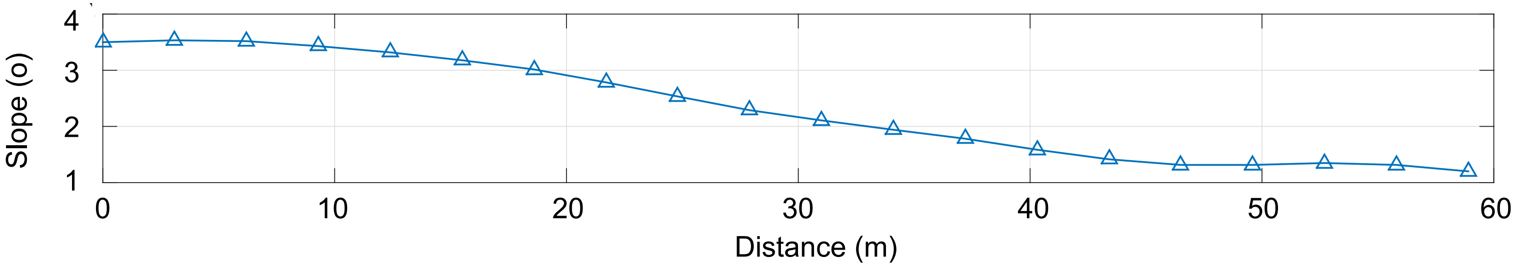

Real-time monitoring: battery current, voltage, SoC, etc.

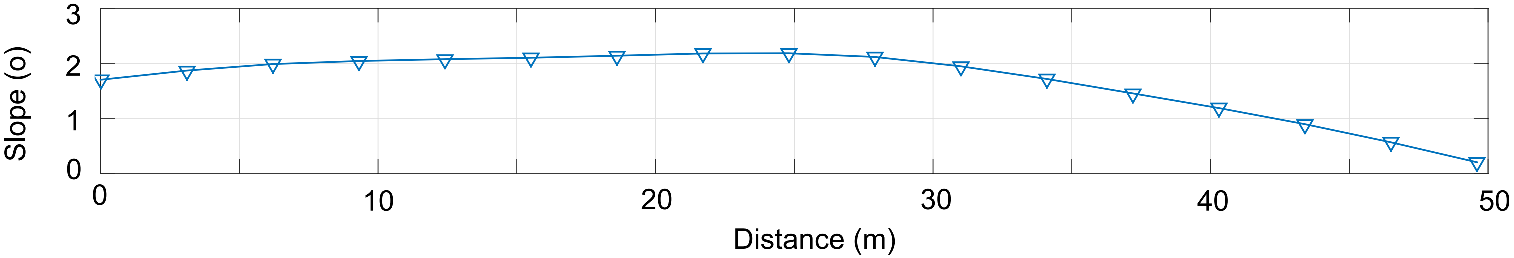
Status LCD: BMS, logging status, error code, etc.

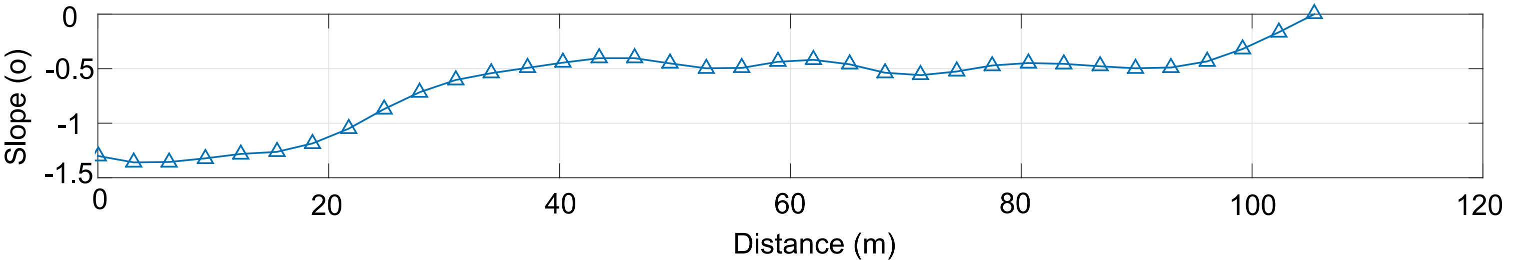
SD card

Data logging

- We chose a regression based approach for the modeling
- For the model fidelity, we collect 6000s of driving data from various routes







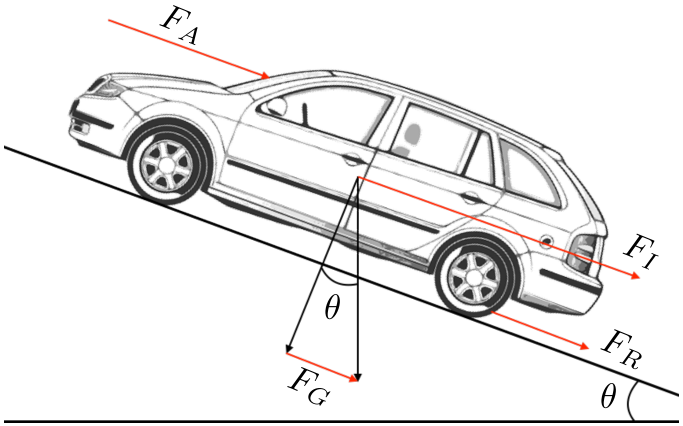
Power consumption model

- Vehicle dynamics model

$$T = (\alpha + \beta sin\theta + \gamma a)m,$$

$$P_{dynamics} = Tv$$

$$\alpha = 0.59, \beta = 12.63, \gamma = 1.46.$$



- Advanced vehicle dynamics model

$$P_{advanced} = Tv + C_0 + C_1 v + C_2 T^2,$$

$$\alpha = 0.33, \beta = 10.70, \gamma = 1.09,$$

$$C_0 = 5.28, C_1 = 118.55, C_2 = 0.0017.$$

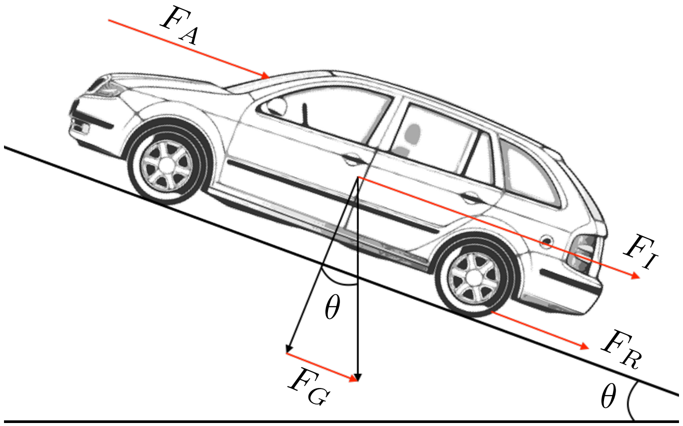
Power consumption model

- Vehicle dynamics model

$$T = (\alpha + \beta sin\theta + \gamma a)m,$$

$$P_{dynamics} = Tv$$

$$\alpha = 0.59, \beta = 12.63, \gamma = 1.46.$$



- Hybrid power model

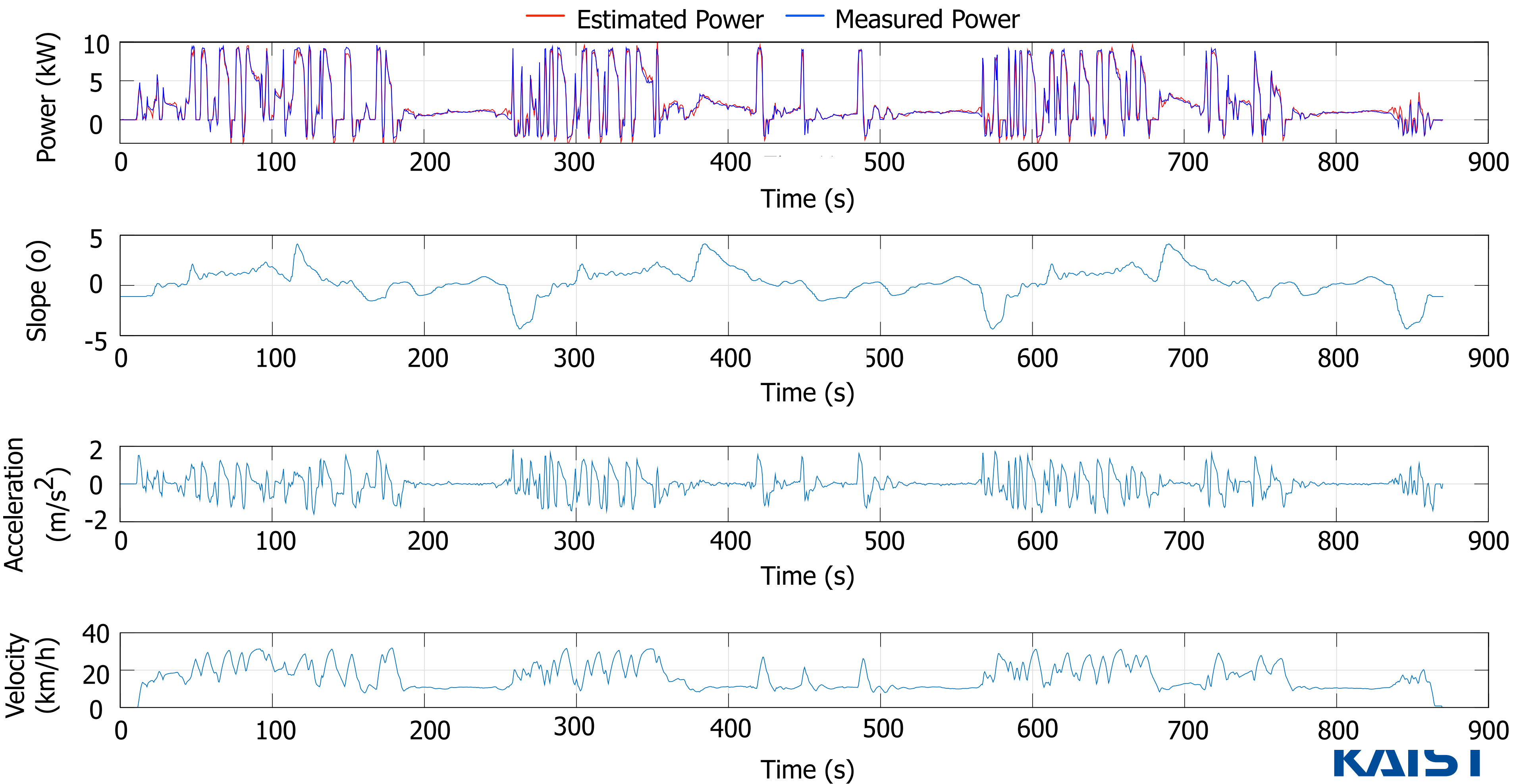
$$P_{hybrid} = Tv + C_0 + C_1 v + C_2 v^2 + C_3 Q^2,$$

$$\alpha = 0.32, \beta = 10.11, \gamma = 1.08,$$

$$C_0 = 5.28, C_1 = 7.39, C_2 = 20.62, C_3 = 0.0019.$$

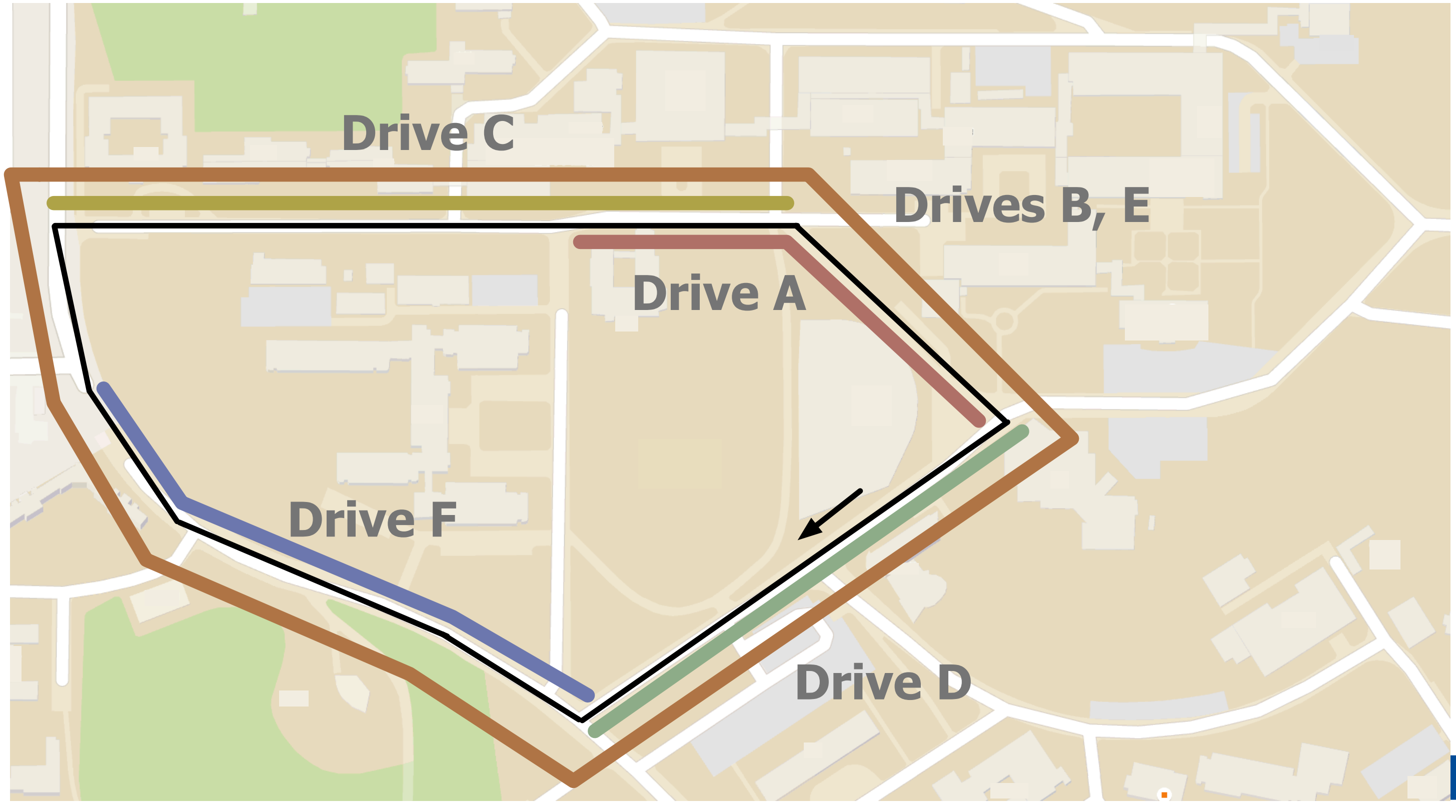
Model validation result

- Hybrid power model yield only 3.78 % error

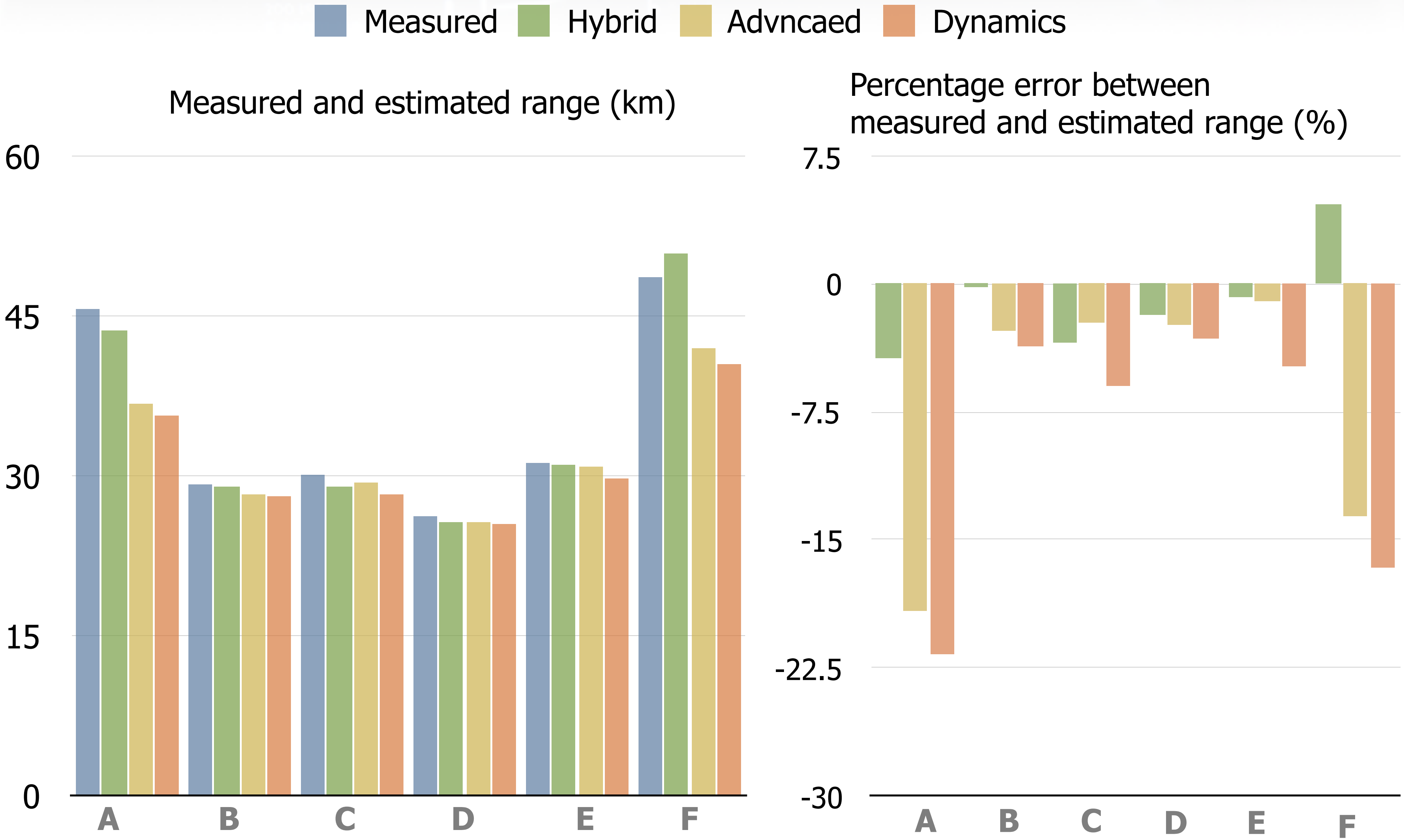


Test bench drives

- We perform 6 test bench drives for the remaining range estimation
- Each drives were performed in different driving manner



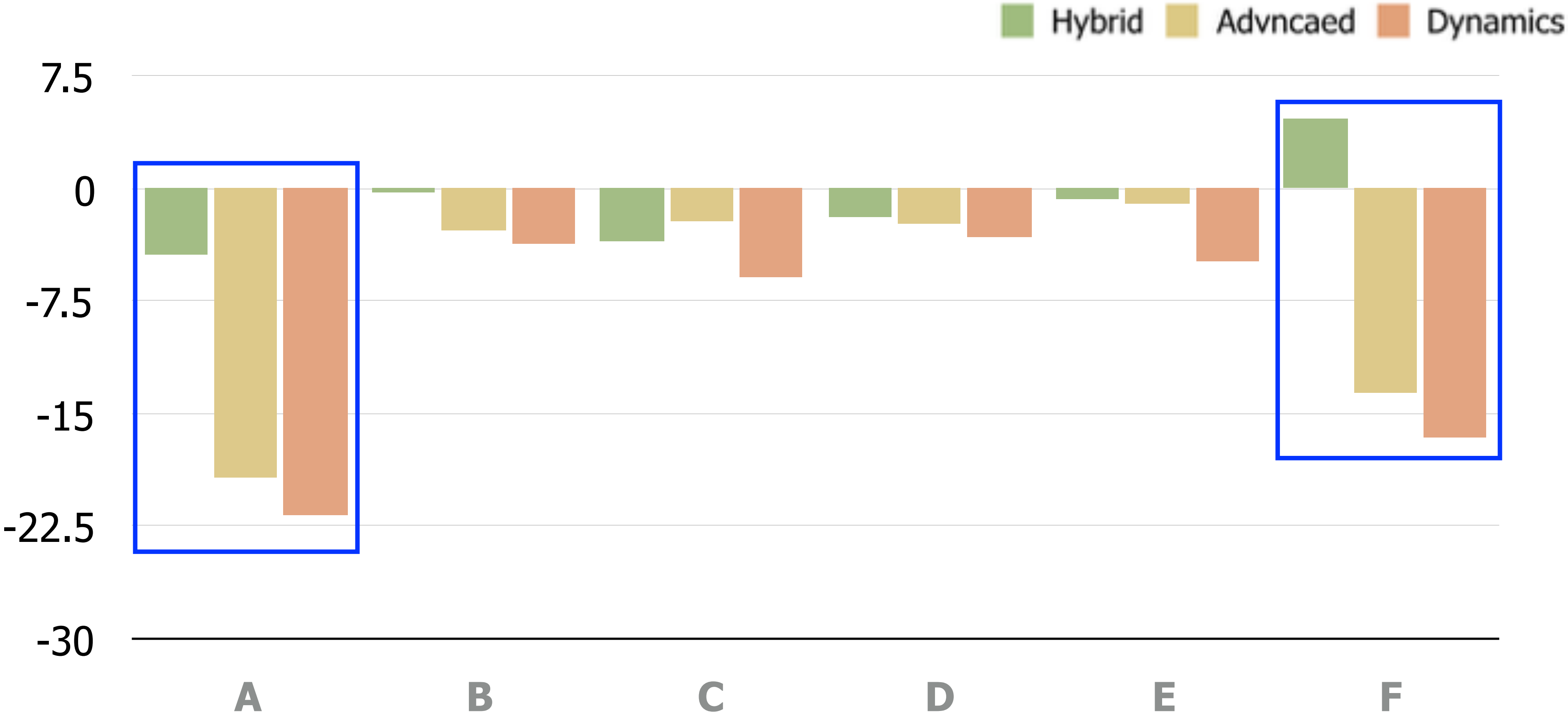
Remaining range estimation


Measured and estimated range (km)

Percentage error between measured and estimated range (%)

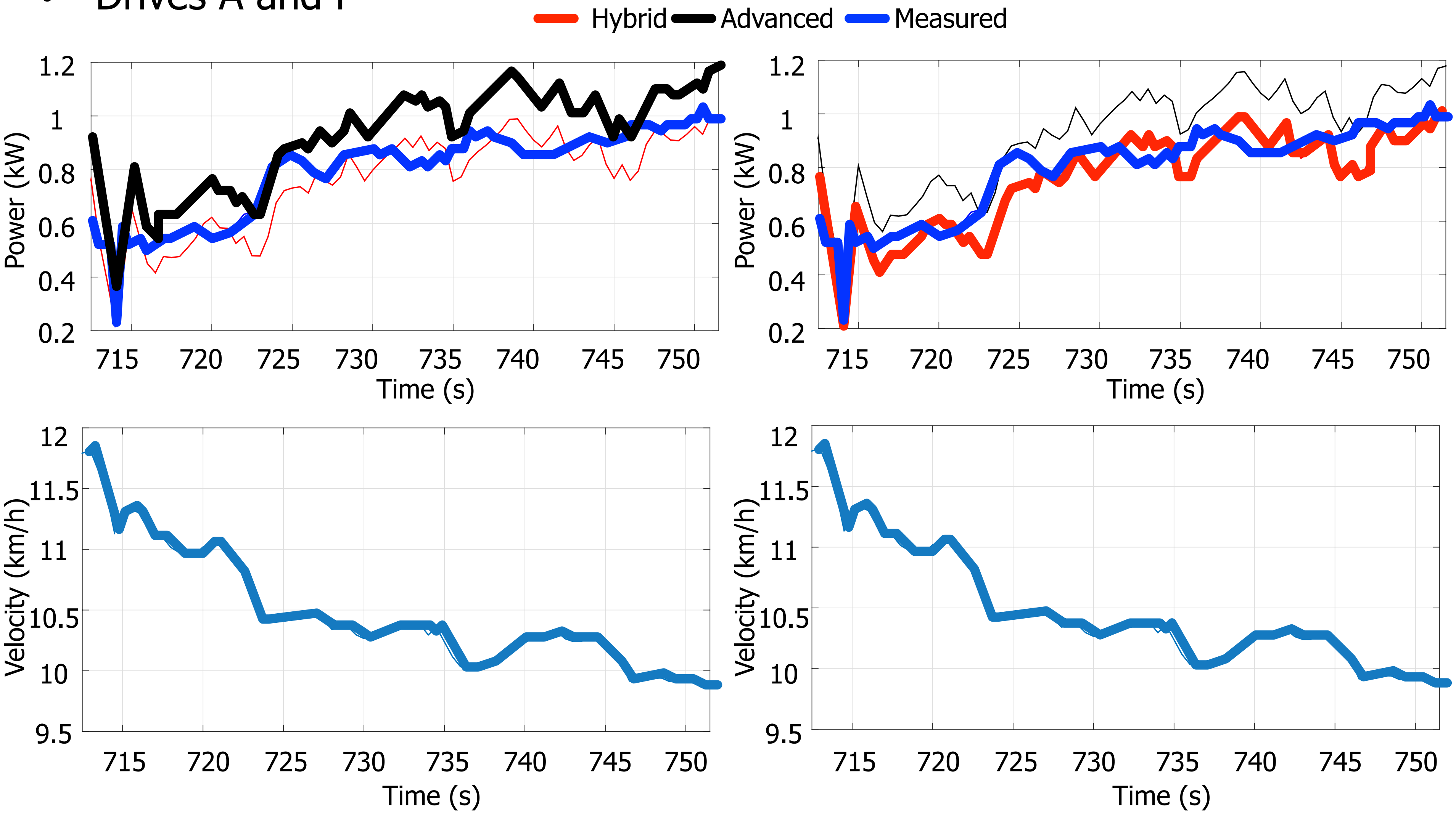
Remaining range estimation

- Drives A and F
    - Speed range: bellow 11.5 km/h
    - Degree range from -0.6° to 0.9°



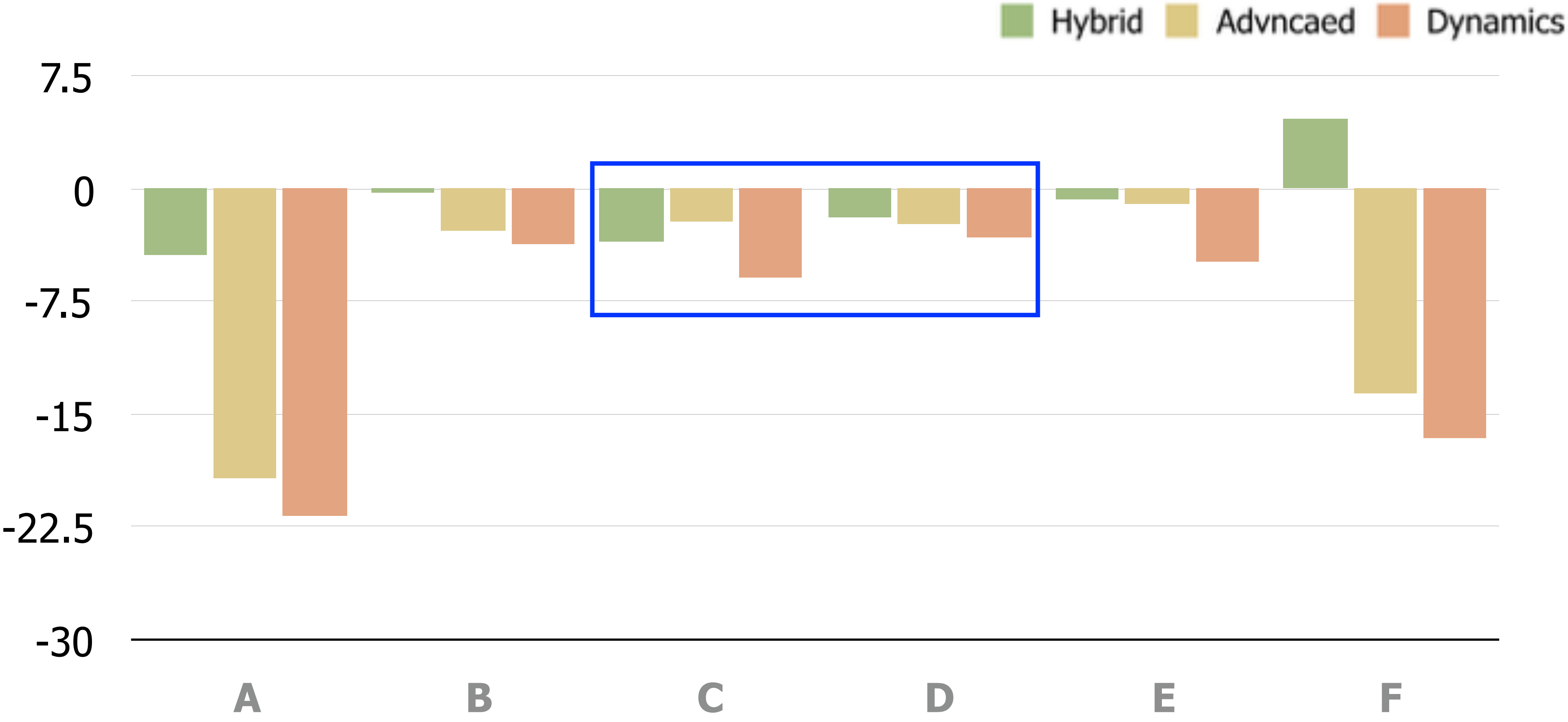
Remaining range estimation

- Drives A and F



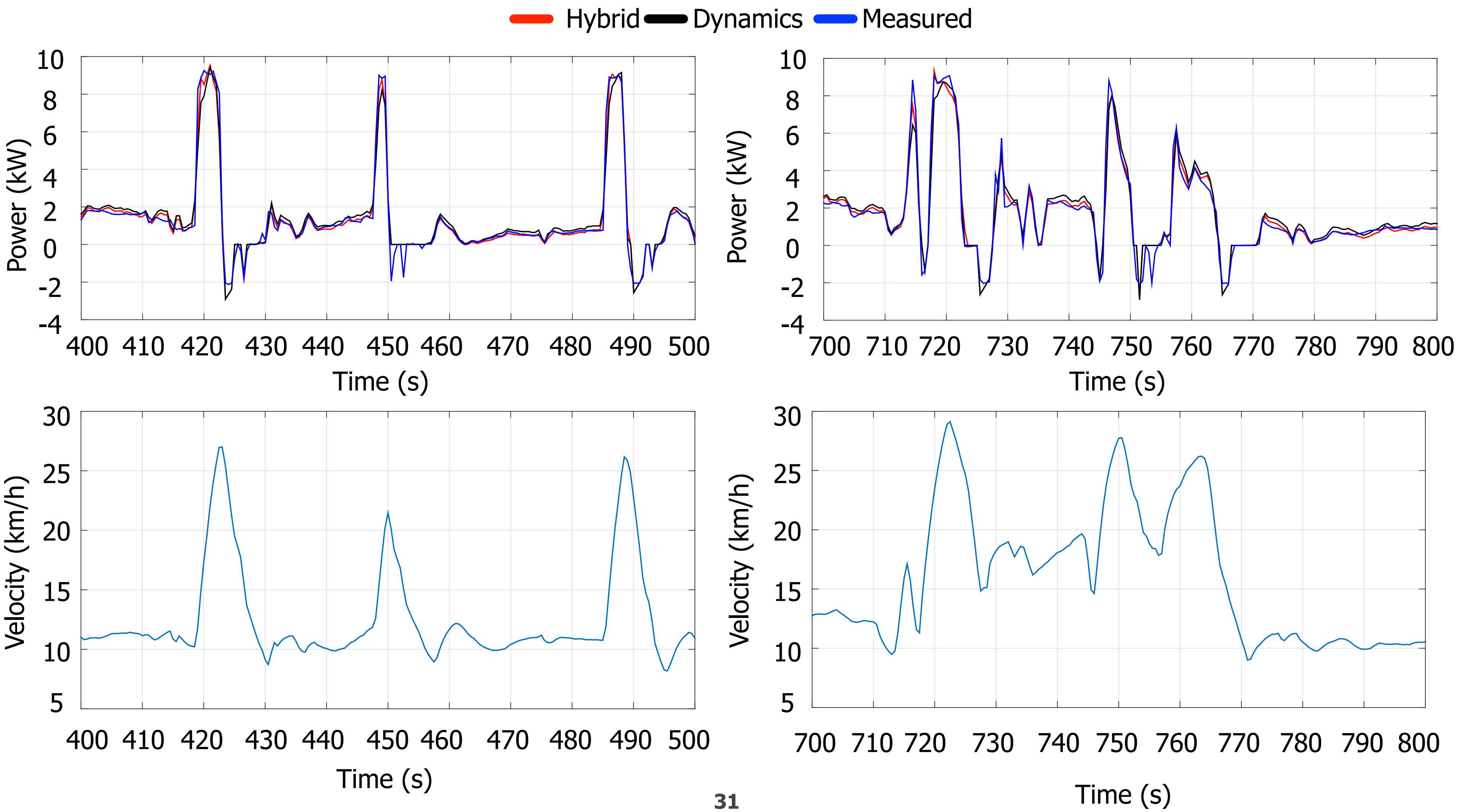
Remaining range estimation

- Drives C and D
  - Speed range: 5 km/h to 32 km/h
  - Degree range: -0.6° to 0.85°



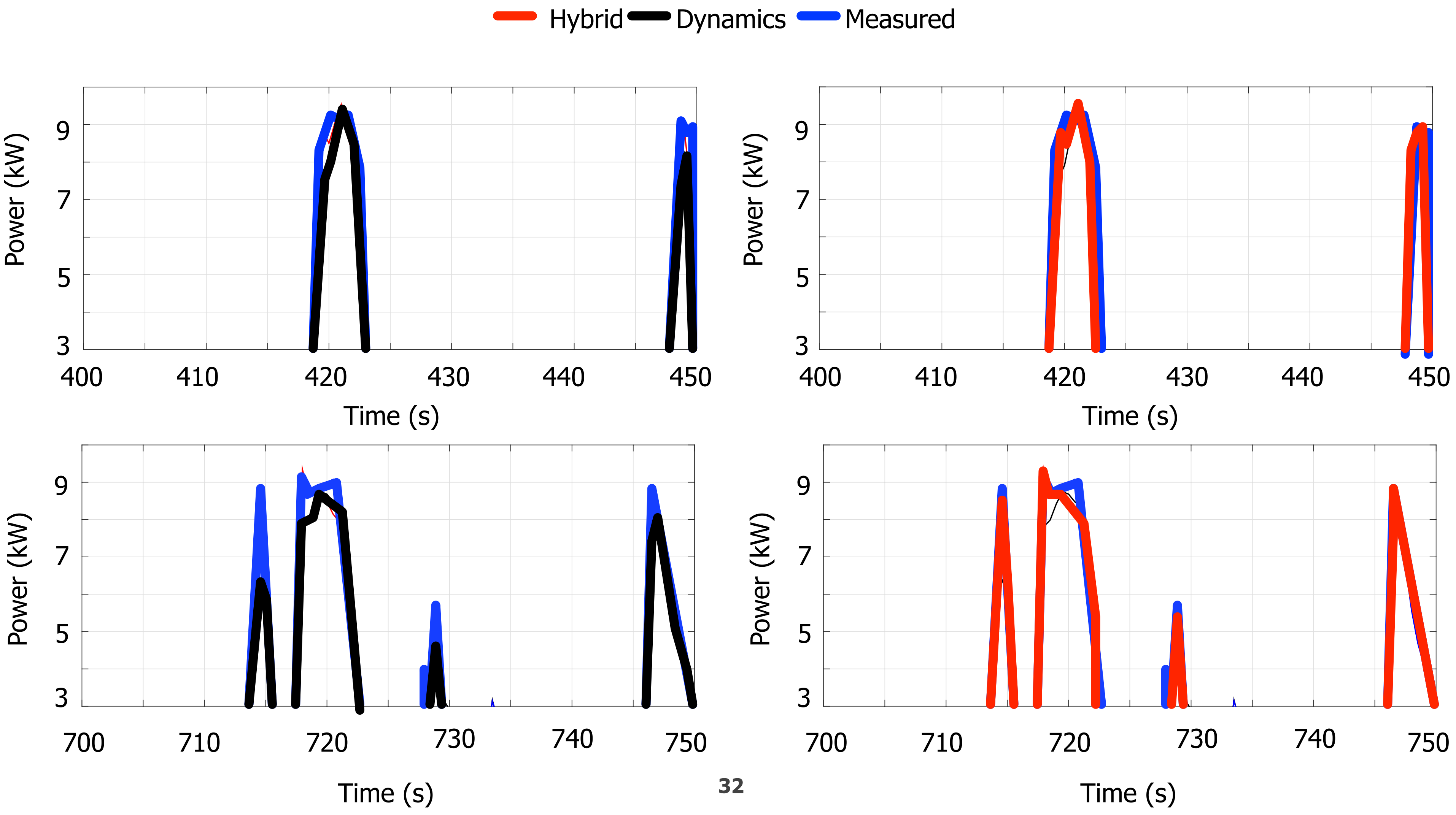
Remaining range estimation

- Drives C and D



Remaining range estimation

- Closer look at drives C and D



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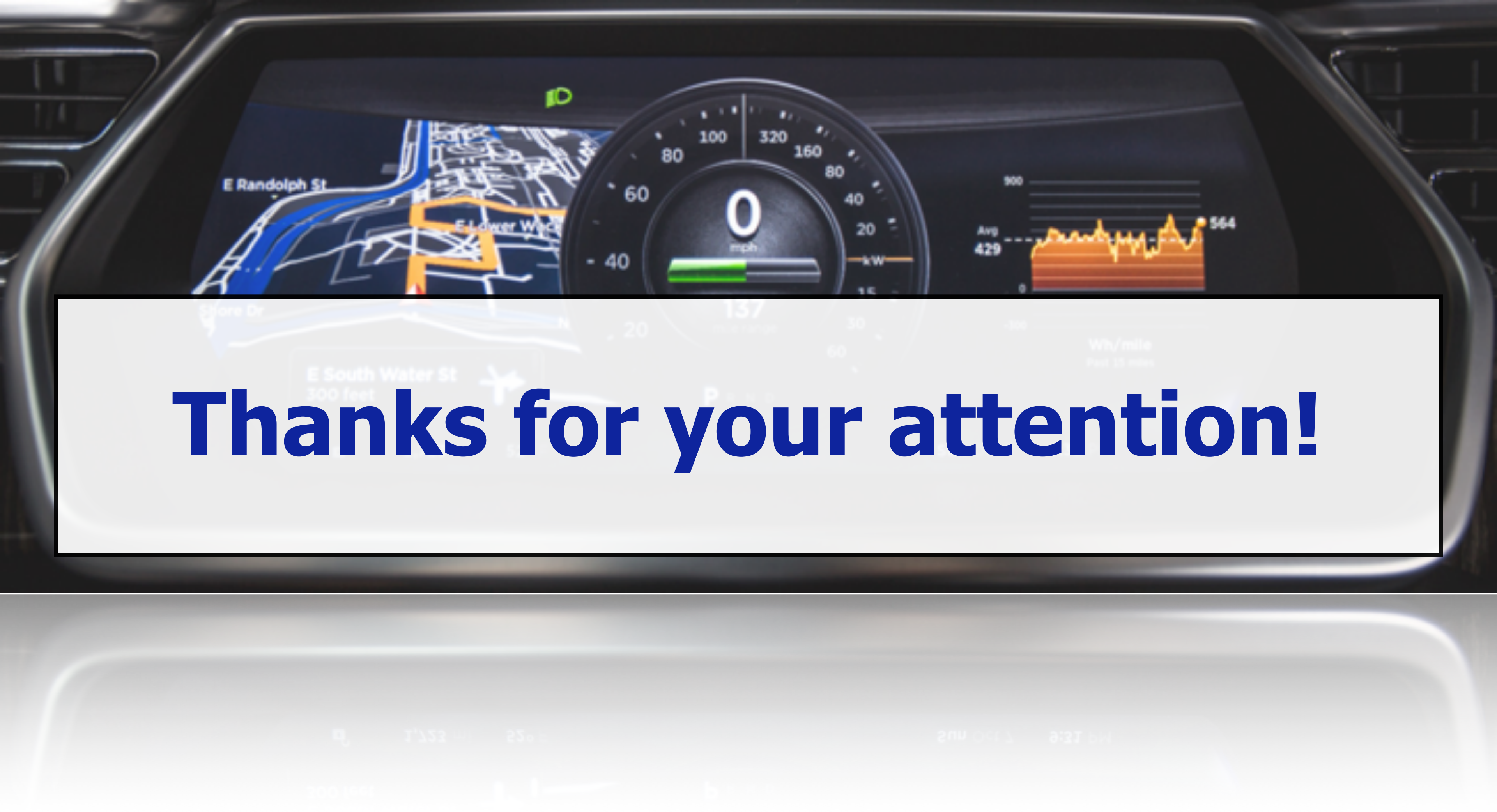
Conclusions

- We achieve higher remaining range accuracy
- The absolute average errors for **hybrid power model**, advanced dynamics model, and vehicle dynamics model are **2.52%**, 6.85%, 9.33% respectively
- The hybrid power model shows increased estimation accuracy not only in the total remaining range, but also in the instantaneous power estimation



Thanks for your attention!

Electric conversion

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High speed custom EV