Generating realistic data for developing artificial neural network based SOC estimators for electric vehicles

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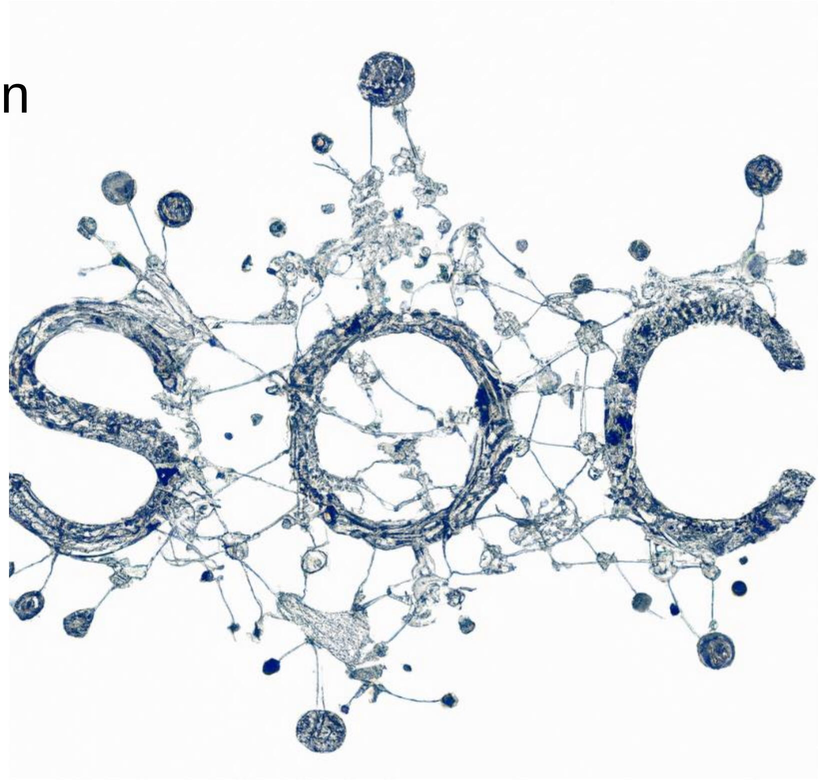
Motivation

- ANN: Powerful tool for SOC Estimation
- The Achilles' Heel: Data Dependency
- Data must be:
  - Adequate & Accurate
  - Representative
  - Disjoint for training and testing



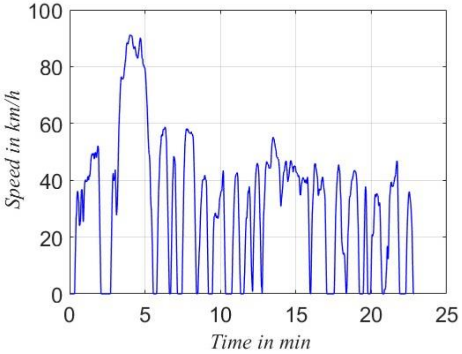
Our Data Sources for SOC Estimation

- Real driving data [1]
- Online databases
- Battery or cell testing with
  - Standardized Driving Profiles

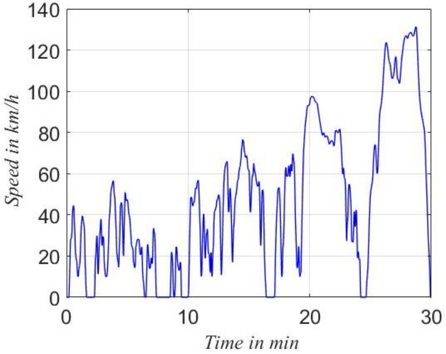
[1] D. Jimenez-Bermejo, J. Fraile-Ardanuy, S. Castano-Solis, J. Merino, and R. Alvaro-Hermana, “Using dynamic neural networks for battery state of charge estimation in electric vehicles,” Procedia Computer Science, vol. 130, pp. 533–540, 2018.

Standardized Driving Profiles

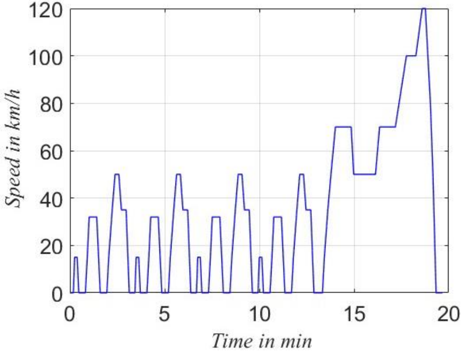
UDDS



WLTP



NEDC



Designed

Speed

Current

Convert

Repeat

Objective

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Tests with Standardized Driving Profiles

(+) cost effective
(+) reproducibility

(-) speed profiles
(-) representability

Tests with realistic profiles

(+) cost effective
(+) load oriented
(+) reproducibility
(+) representability

(-) inaccuracies
(model, data etc…)

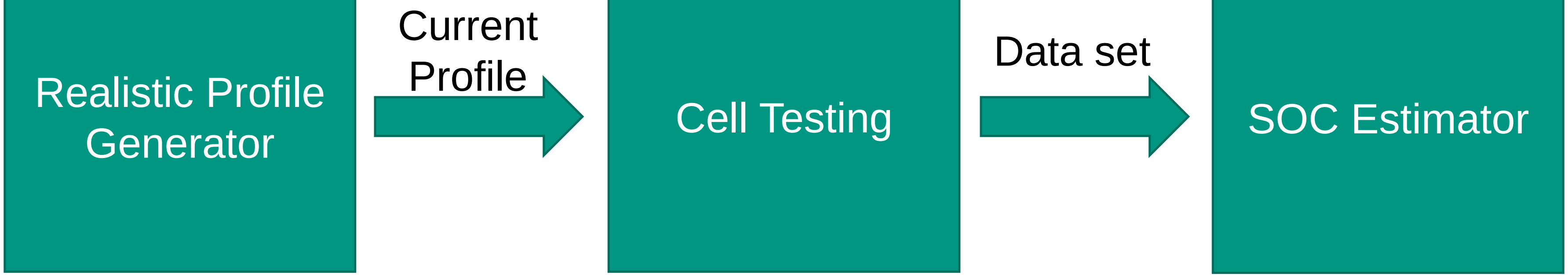
Real driving experiments

(+) real life cond.
(+) load oriented

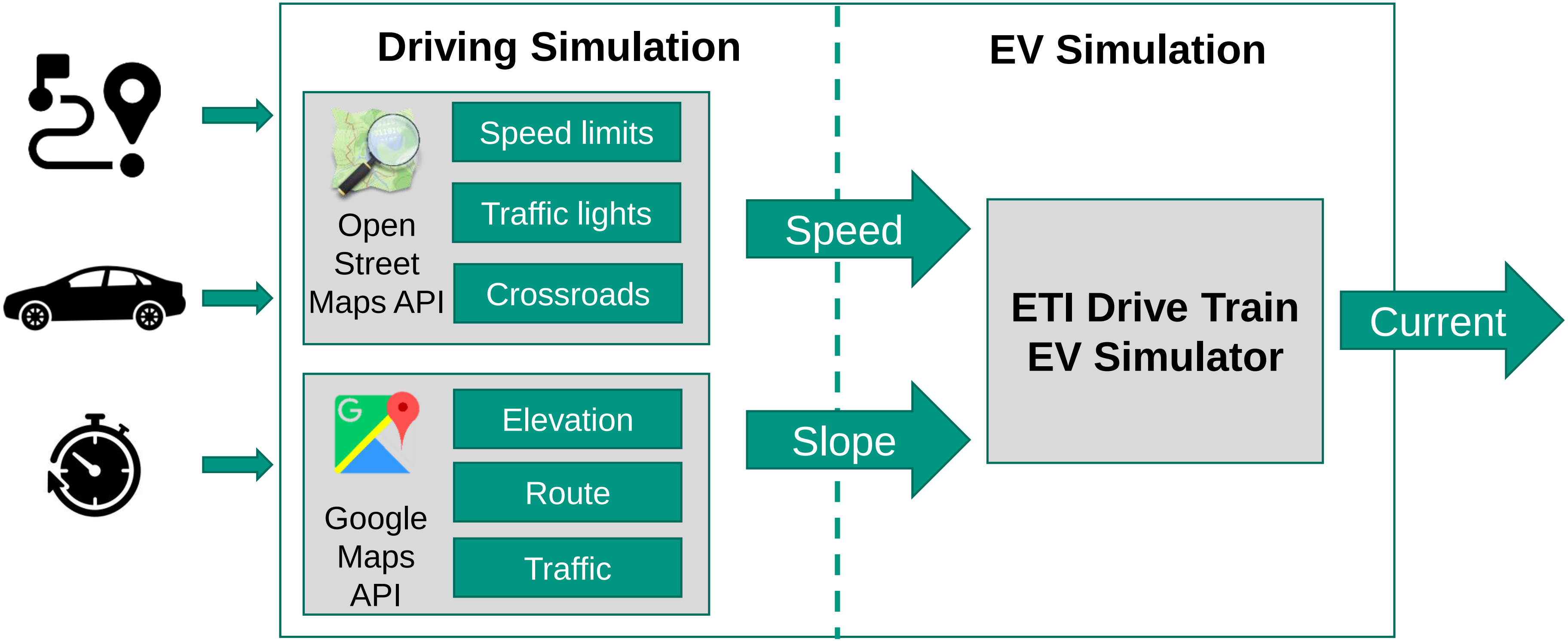
(-) time consuming
(-) expensive

cost & representativeness

Overview of Proposed Method



Design of Realistic Profile Generator

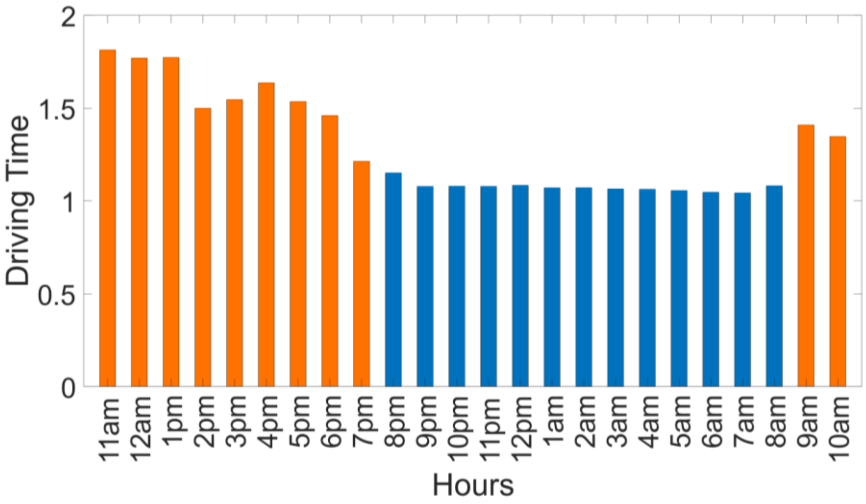


Driving Simulation - Average Speed

- Real time average speed in traffic

$$v_{av} = \begin{cases} \dfrac{l_{seg}}{t_{traffic}} \quad , & v_{av} \leq v_{lim} \\ v_{lim} \quad , & v_{lim} \leq v_{av} \end{cases}$$

- 24h analysis of driving duration:
  - Karlsruhe → Stuttgart
  - 19.08.2022 Friday 11:00 -
    20.08.2022 Saturday 10:00



Driving Simulation - Speed Deviation

- Oscillation model of speed fluctuations [2]

Low-Frequency Noise (LF)	Medium-Frequency Noise (MF)	High-Frequency Noise (HF)
• traffic congestion • speed limits • construction areas	• road topology • traffic flow • driving behavior	• road conditions • lane changes • rapid driving maneuvers • Spontaneous reactions

$$v_{dev}(t) = A_{HF}\sin(\omega_{HF}\,t + \varphi_{HF}) + A_{MF}\sin(\omega_{MF}\,t + \varphi_{MF})$$

$$v_{rel,1} = v_{av} + v_{dev}$$

[2] V. Schwarzer and R. Ghorbani, “Drive cycle generation for design optimization of electric vehicles,” IEEE Transactions on Vehicular Technology, vol. 62, no. 1, pp. 89–97, 2013..

Driving Simulation: Evolution of Speed Profile

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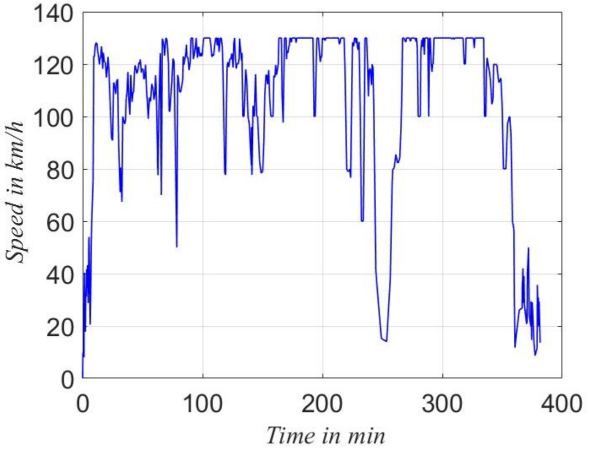
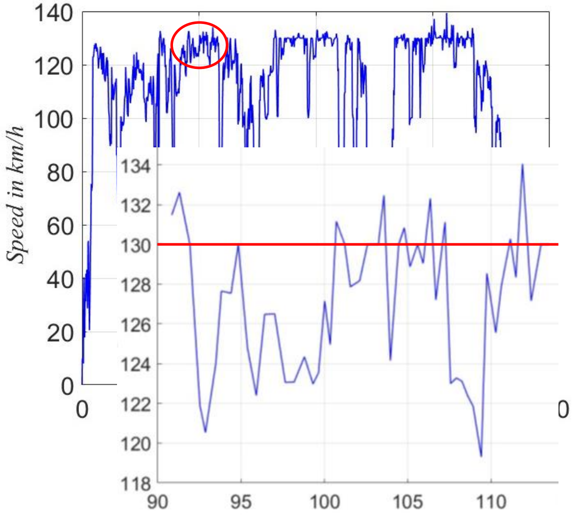
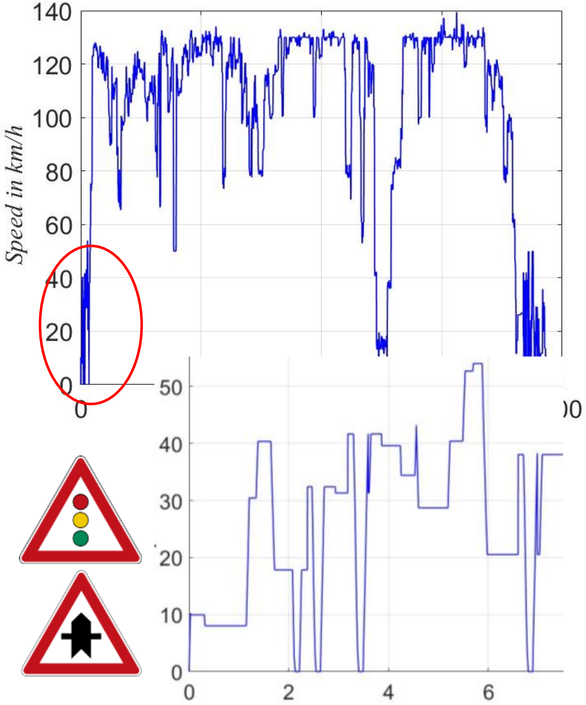
v_{av}



$v_{rel,1}$



v_R



Road: Karlsruhe – Berlin
Departure Time: 05.02.2023 at 21:47
Distance: 683 km (424 miles)
Duration: 6h 25 min.

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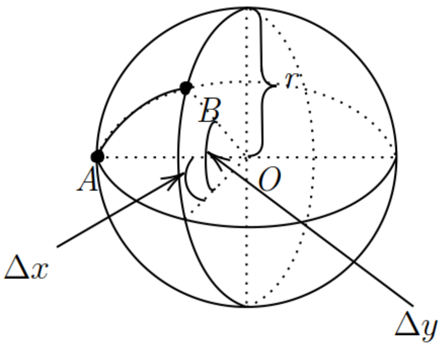
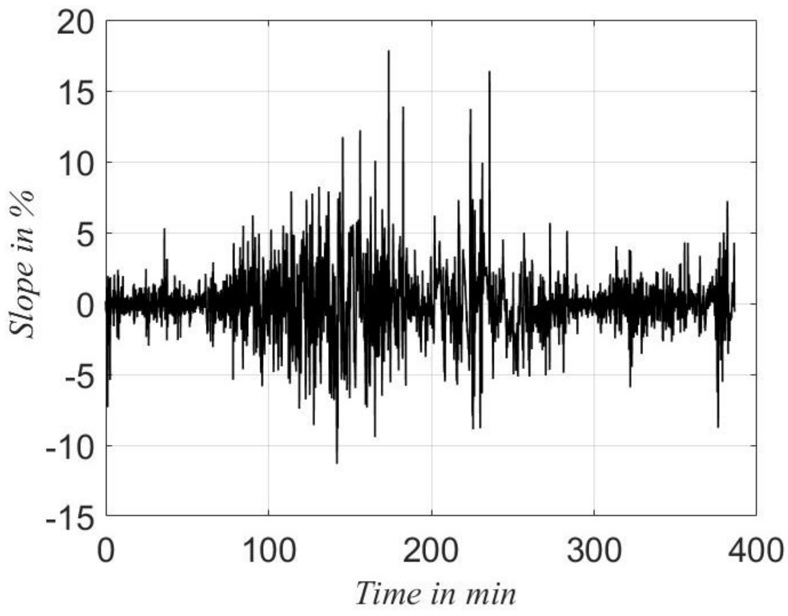
Generating Slope Profile

- Impact on load and recuperation
- Google Maps API: Coordinates
- Haversine Formula for ΔL_p
- Google Elevation API: ΔH_p



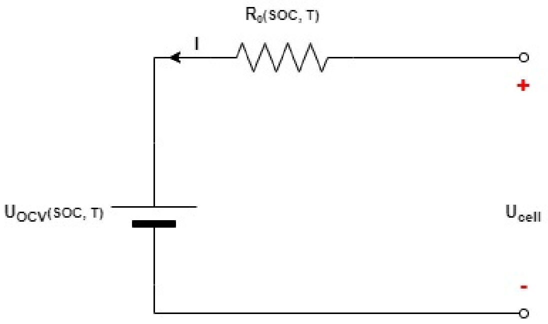
$$\delta_p = \frac{\Delta H_p}{\Delta L_p} = \tan(\alpha_p)$$

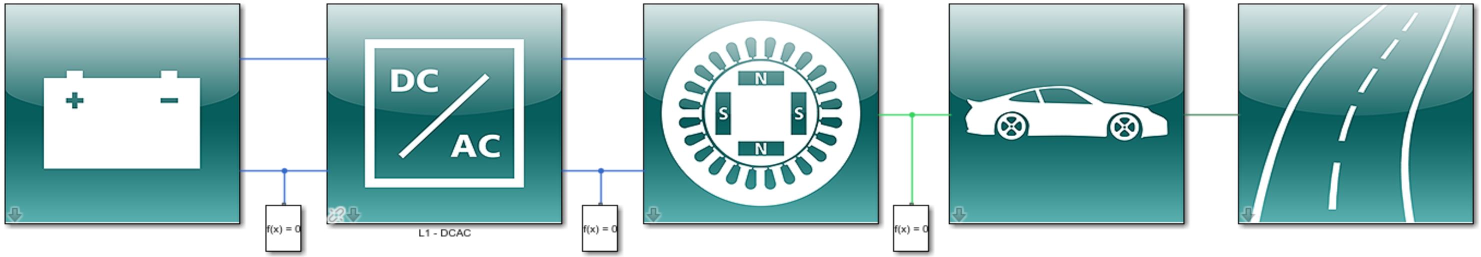


Slope profile for Karlsruhe – Berlin

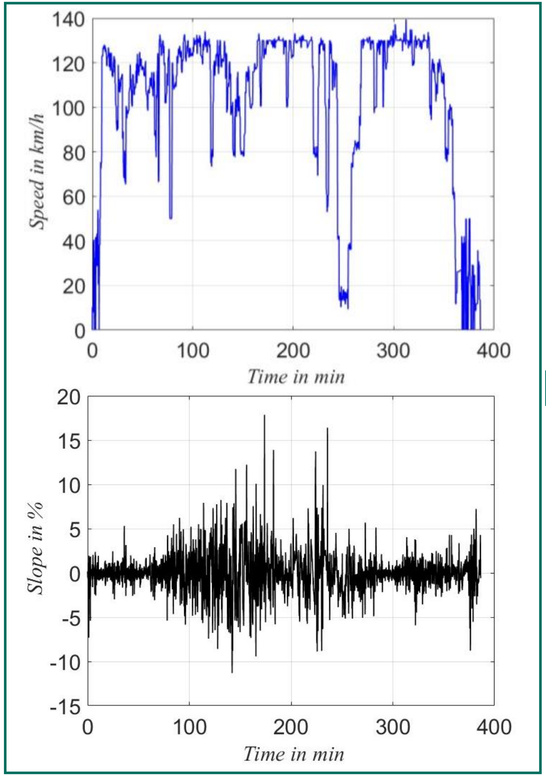
EV Simulation - ETI Drive Train Model

- In House developed EV Simulator
  - Speed- and slope profile
  - Battery: 400 V / 40 kWh with Rint Model
  - Motor: 100 kW / 220 Nm (PMSM)
  - Weight: 1400 kg
  - Drag coef.: 0,29



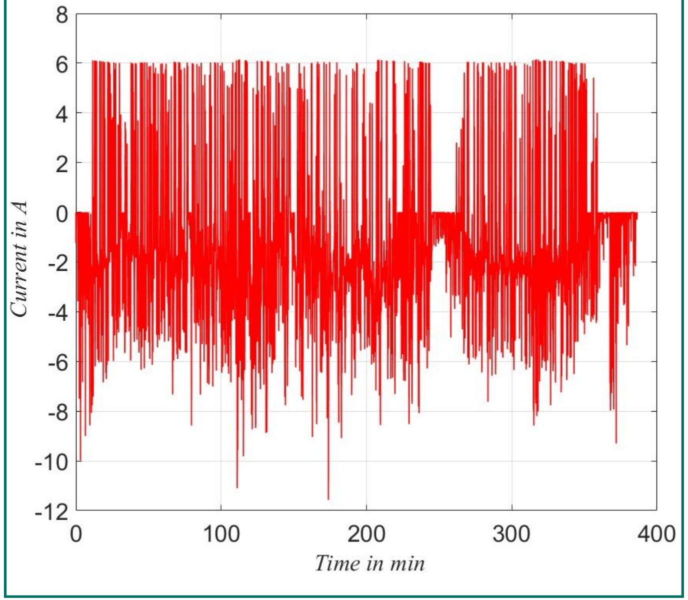


Workflow for EV Simulation



ETI Drive Train Model

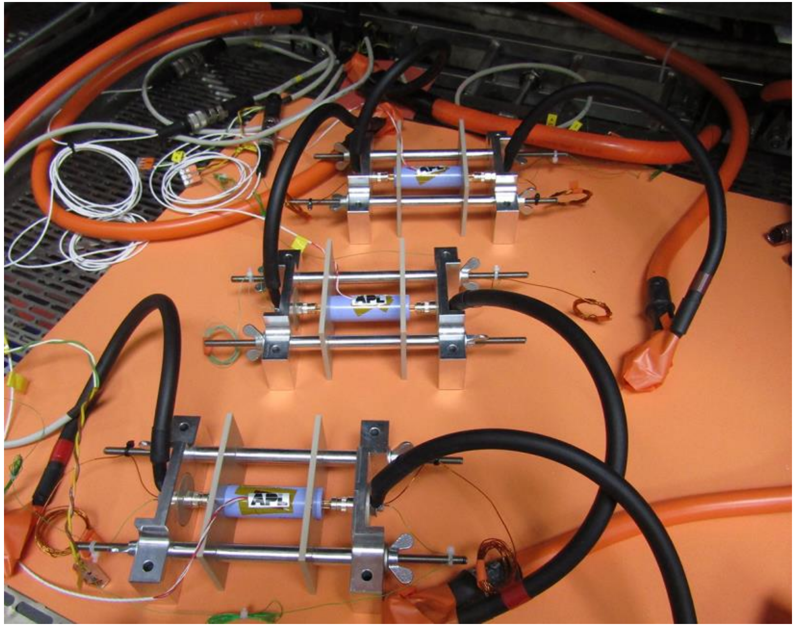
Realistic Current Profile



Exemplary case: Karlsruhe – Berlin

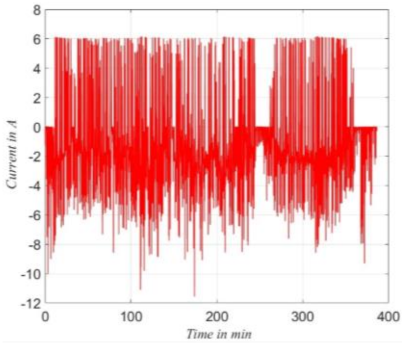
Cell Testing

- Cell-Testing at APL Group
  - 25°C at Temperature chamber
  - Voltage accuracy: $\pm 1mV$
  - Current accuracy: $\pm 0,05\%$
  - Temperature accuracy: $\pm 1K$



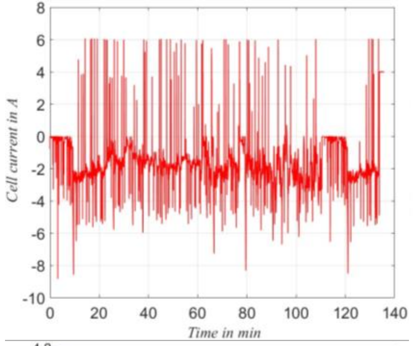
Workflow for Cell Testing

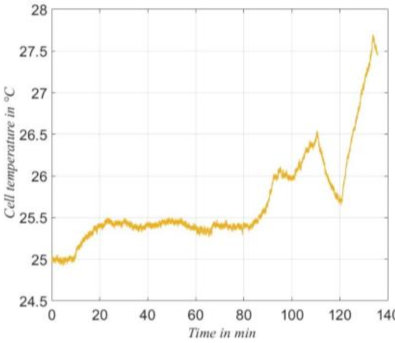
Current Profiles

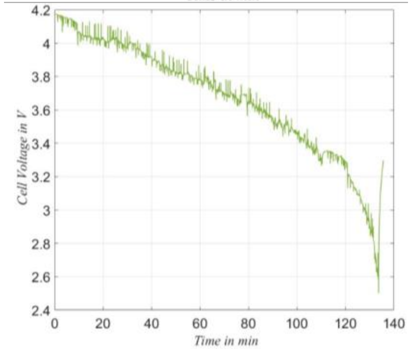


Tester

Data set







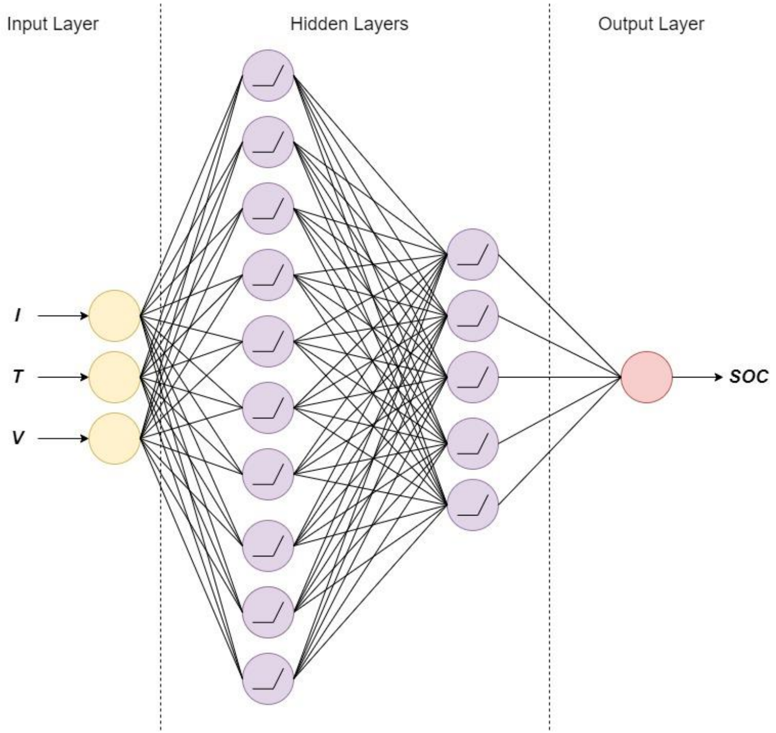
SOC
SOH

Tested cell:
Samsung INR21700-40T
Nom. Capacity: 4Ah
Nom. Voltage: 3,6 V

ANN based SOC Estimator

- Multi Layer Perceptron (MLP)
- ReLU Activation Functions in HLs
- Linear Activation Functions in OL
- Loss function mean squared error

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (SOC_i - \widehat{SOC_i})^2$$



Performance Analysis of SOC Estimator

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- Estimator trained with WLTP data set
- Testing with realistic data sets and NEDC
- Root mean squared error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(SOC_i - \widehat{SOC_i}\right)^2}$$

- Relative estimation error:

$$REE = \frac{RMSE_{TP} - RMSE_{WLTP}}{RMSE_{TP}} \times 100\%$$

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Results: Generated realistic driving profiles

- 10 driving profiles: 1.321 km (820 miles), 15 h
- Highway & City Driving
- Rush-hour & off-peak periods

TABLE III
GENERATED REALISTIC DRIVING PROFILES

No.	Origin - Destination	Departure Time	Duration	Length	$\overline{v}$	v_{max}
1.a	Berlin, Mitte - Berlin, Neukölln	06.02.2023 (Mon) 00:53	27.8 min	16.15 km	34.3 km h^{-1}	80.9 km h^{-1}
1.b	Berlin, Mitte - Berlin, Neukölln	08.02.2023 (Wed) 15:58	56.8 min	16.15 km	17.2 km h^{-1}	80.4 km h^{-1}
2.a	Frankfurt, Innenstadt - Frankfurt, Nieder-Erlenbach	05.02.2023 (Sun) 22:12	22.8 min	14.53 km	38.5 km h^{-1}	113 km h^{-1}
2.b	Frankfurt, Innenstadt - Frankfurt, Nieder-Erlenbach	06.02.2023 (Mon) 17:13	32.2 min	14.53 km	27.4 km h^{-1}	109.4 km h^{-1}
3.a	Frankfurt, West - Frankfurt, Mitte-Nord	05.02.2023 (Sun) 22:14	13.3 min	4.9 km	22 km h^{-1}	50 km h^{-1}
3.b	Frankfurt, West - Frankfurt, Mitte-Nord	06.02.2023 (Mon) 17:19	16 min	6.1 km	22 km h^{-1}	60 km h^{-1}
4	Karlsruhe - Berlin	05.02.2023 (Sun) 21:47	386 min	677.5 km	104 km h^{-1}	139 km h^{-1}
5.a	Frankfurt - Würzburg	08.02.2023 (Wed) 01:23	78.8 min	119.86 km	89.2 km h^{-1}	122.7 km h^{-1}
5.b	Frankfurt - Würzburg	09.02.2023 (Thu) 01:58	77.8 min	119.86 km	91.3 km h^{-1}	128.4 km h^{-1}
6	Karlsruhe - Zugspitze	05.02.2023 (Sun) 08:30	207.7 min	332.2 km	95.2 km h^{-1}	136.2 km h^{-1}
	WLTP		30 min	23.1 km	46.3 km h^{-1}	131.3 km h^{-1}
	NEDC		19.7 min	11 km	33.6 km h^{-1}	120 km h^{-1}

Results: Performance of SOC Estimator

Test Profile	RMSE	Rel. Error
WLTP	1,31%	-
NEDC	1,44%	9,03%
1.a (City)	1,91%	31,45%
1.a (City)	1,92%	31,77%
2.a (City)	1,97%	33,5%
2.a (City)	1,86%	29,57%

Test Profile	RMSE	Rel. Error
3.a (City)	1,95%	32,82%
3.a (City)	2,18%	39,91%
4 (Highway)	1,74%	24,71%
5.A (Highway)	1,95%	32,82%
5.B (Highway)	1,70%	22,94%
6 (Highway)	1,87%	29,95%

Mean Error: 33,17% in “City” | 27,60% on “Highway“ | 30,94% Overall

Summary & Outlook

- Real or realistic data is crucial for accurate performance analysis of SOC Estimators.
- Realistic data can improve the generalization capabilities.
- The proposed approach is able to generate realistic data sets in a cost efficient way.
- Future steps include generating a more extensive set of profiles for training.
- Conducting long-term tests to study the impact of various driving scenarios on battery degradation.

Thank you for your kind attention!

APL Group

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