GENERATING SYNTHETIC CUSTOMER DRIVING DATA FOR DATABASED AGEING PREDICTION OF 48V LI-ION BATTERIES

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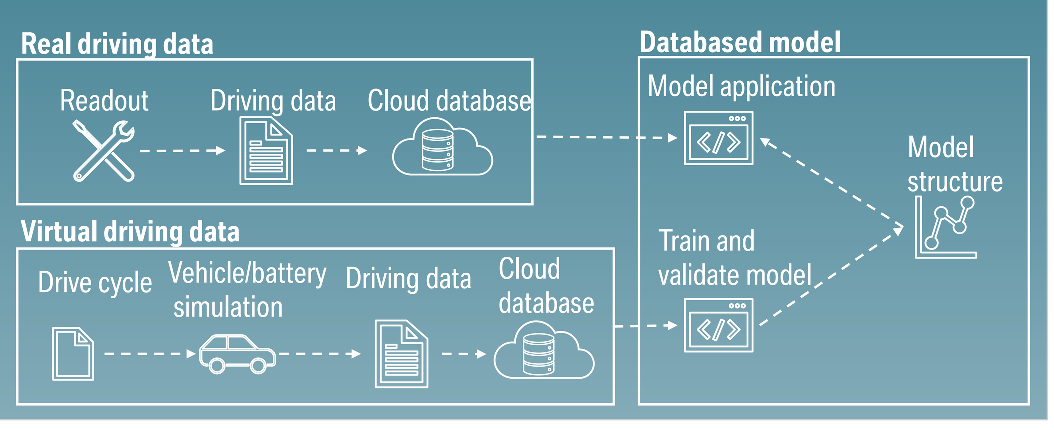
Abstract

Serial production cars happen to have different software versions depending on their state of production. Monitored aggregated customer data thus includes state of health (SOH) values generated by different algorithms. To ensure comparability over the collected data, databased models are needed which can be applied on selected input variables. For this purpose a simulation toolchain has been created to generate virtual customer driving data using stochastic customer driving profiles. Synthesizing aggregated driving data requires vehicle simulation and battery ageing models to compute ageing factors caused by the given driving profiles.



Conclusion

A simulation toolchain to synthesize virtual customer data offers manifold opportunities as a starting point for databased ageing analysis of Li-Ion batteries in vehicle applications. In regards to state prediction it serves as a data generator to provide software status independent SoH values for training and validation purposes. Hence, a databased model can be trained on the data created by the toolchain and after successful validation applied on the actual driving data.

From a forecasting perspective the toolchain acts as a reference model to assess the estimation performance of already trained databased models. In the context of battery development, the toolchain can be applied for lifecycle prediction once an underlying ageing model has been parametrized from laboratory data.

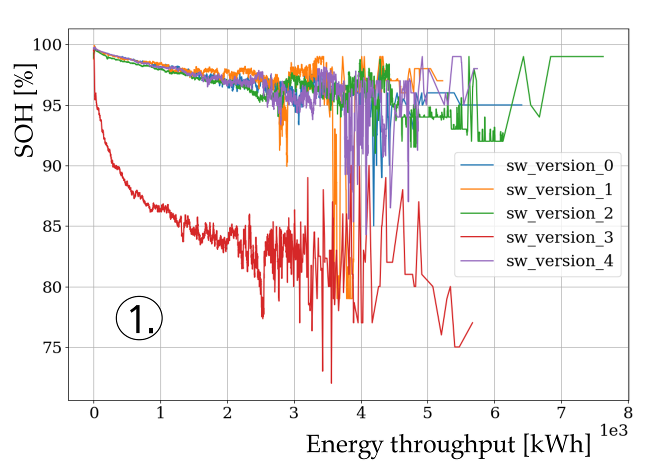
Real Driving Data

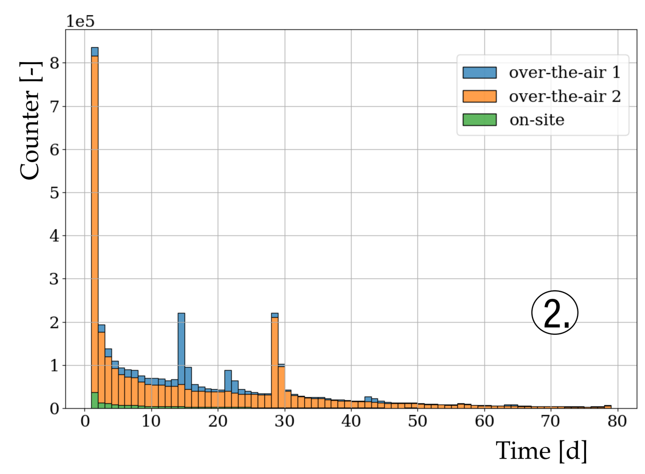
Real Driving Database contains BMS memory variables and consists of three tables:

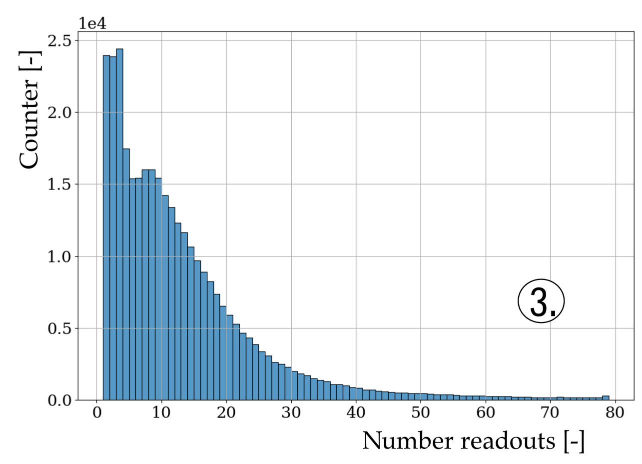
- **Single Values**: Min/Max values (current, voltage, temperature); SoH; Counters (energy throughput, ampere hour)
- **Histogram Values**: Counters (time in SoC/temperature, (dis-)charge in temperature)
- **History Values**: Historic values of Single Values

Stats Database

num vehicles	~350k
num readouts	~8M
Ø num readouts /vehicle	~23
start date	11/2019

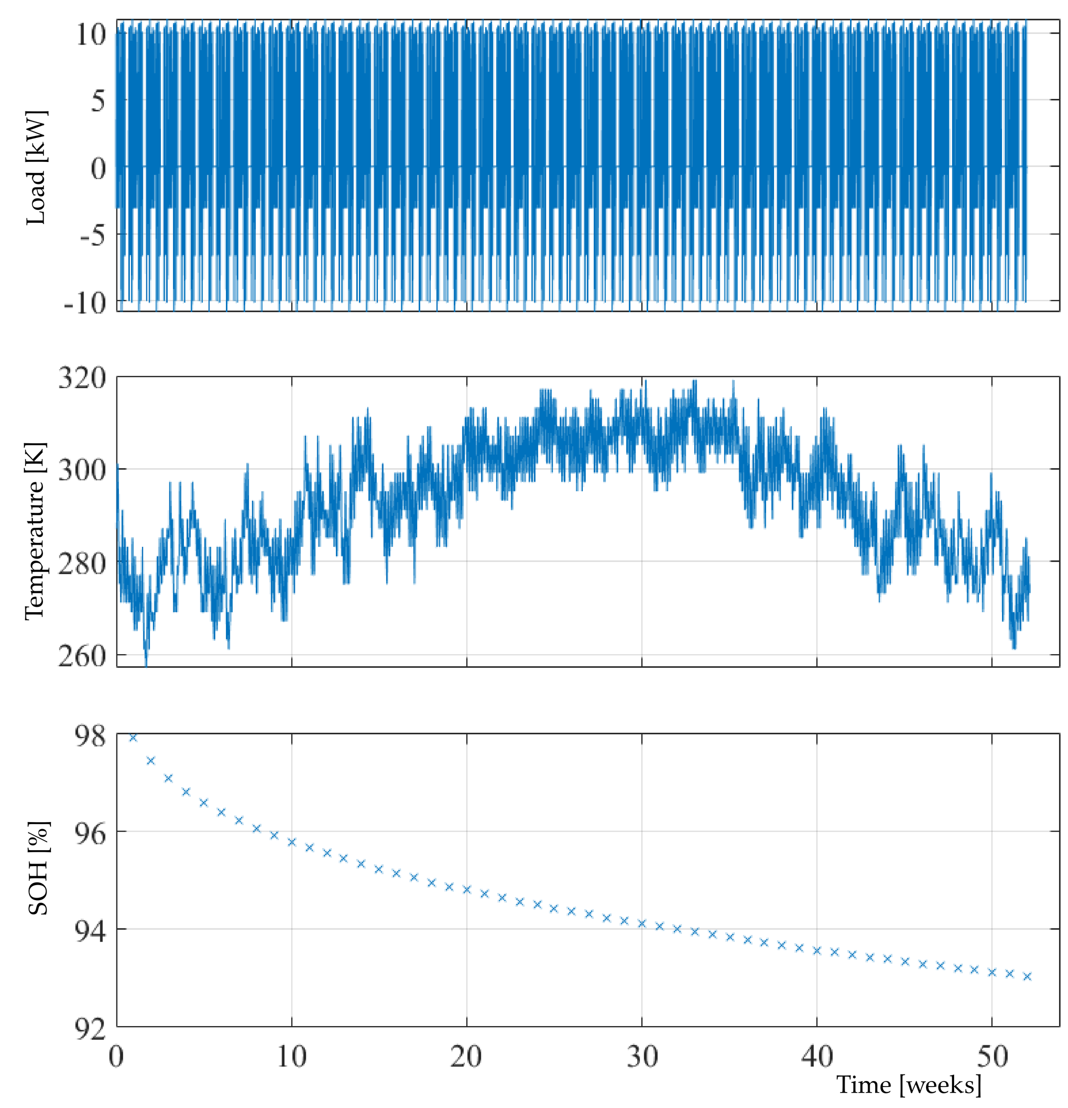






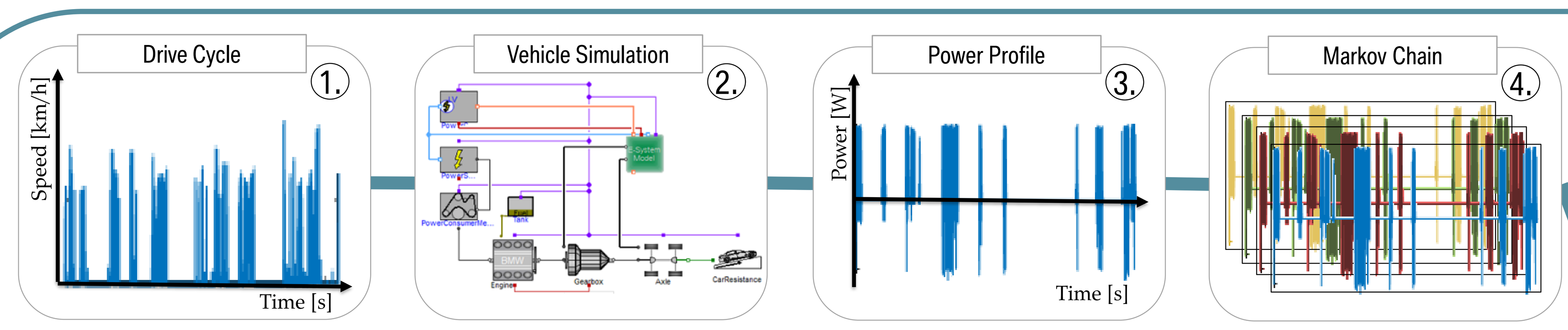
1. SoH predictions from different software versions but same cell chemistry; necessity for independent monitoring model given due to significant inconsistency among models
2. Readout intervals vary with readout type; over-the-air systems have regular readout times
3. Number of readouts per vehicle exponentially decreases

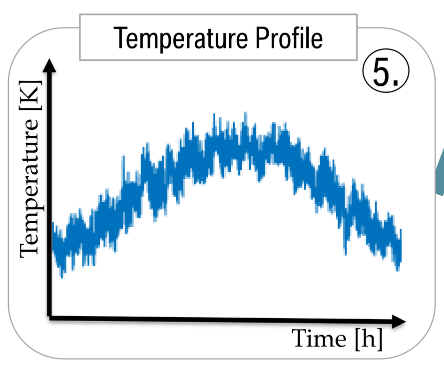
Virtual Driving Data

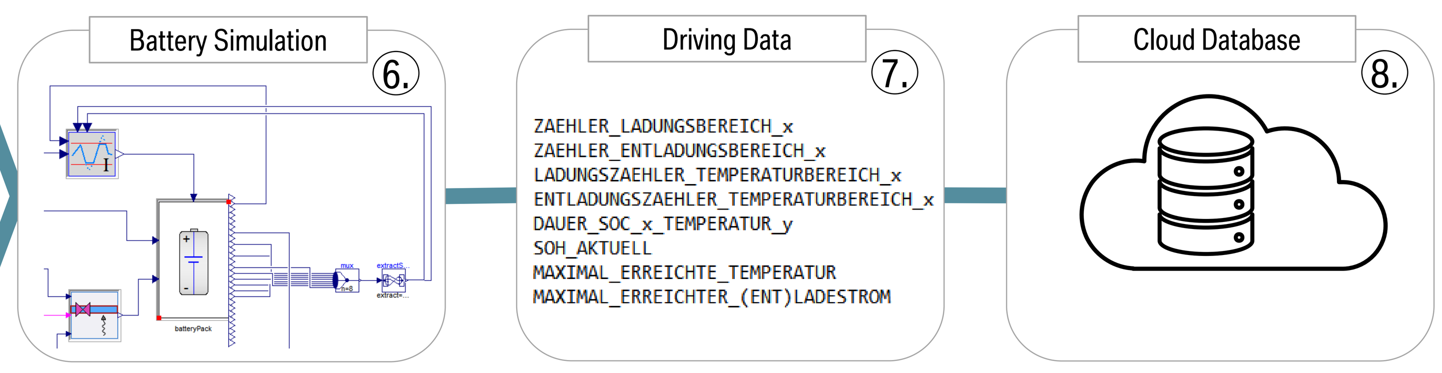


Battery ageing simulation over 52 weeks; weekly load profile gets repeated, from the temperature profile the current week is selected; at the end of every week the semi-empirical ageing model generates the battery SoH value

Tool Chain







1. Customer **driving week profile**; sampling time: 1s
2. **Vehicle simulation model** containing mechanical and electric subsystems; simulation time: ~48h → time consuming
3. **48V load profile** resulting from eBoost, recuperation and load point shifting; max. ~11kW
4. Synthesizing additional load profiles using a **Markov Chain**; discretization intervals: 5W
5. Inhouse **year temperature profile**, sampling time: 1h
6. Electrical and thermal **battery simulation model** with semi-empirical ageing model
7. Create **driving data variables**
8. Upload simulated data into **cloud database**

Stats Simulation*

time vehicle simulation	~ 48h
time Markov Chain	~ 1min
time battery simulation	~12min

* for a one-week profile