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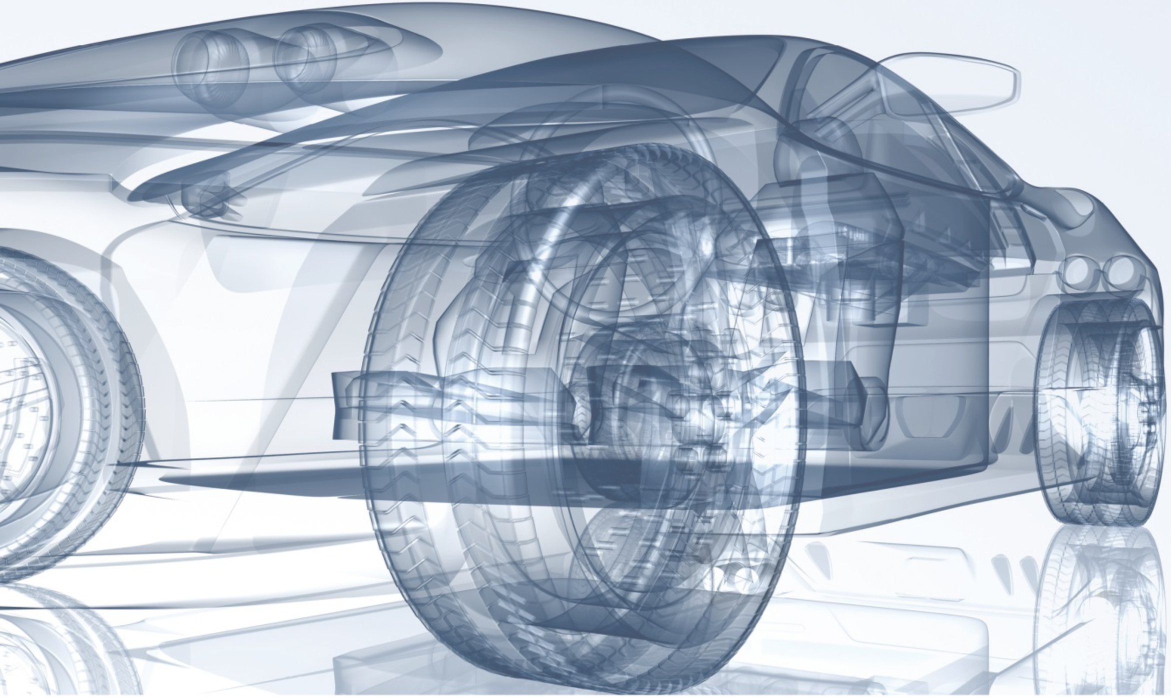

The 30th International Electric Vehicle Symposium & Exhibition

October 9–11, 2017

Messe Stuttgart, Germany

www.evs30.org

Battery Health Monitoring and Degradation Prognosis in Fleet Management Systems

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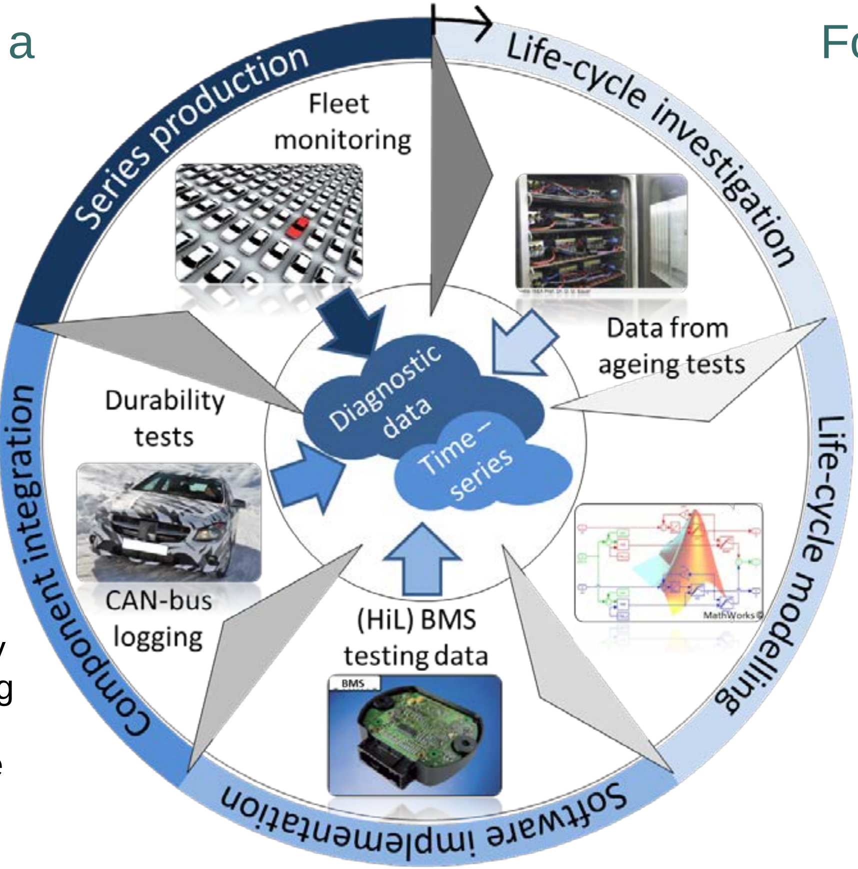
Introduction and Overview

Motivation

Development cycle for a lithium-ion battery

- Battery fade is a complex phenomenon provoked by environmental conditions and utilization modes
- A life-cycle investigation is performed by applying duty cycles on single cells as the first step of the development cycle
- The ageing model supports the product development by interpolating or extrapolating the data from ageing tests as not every utilization case can be measured



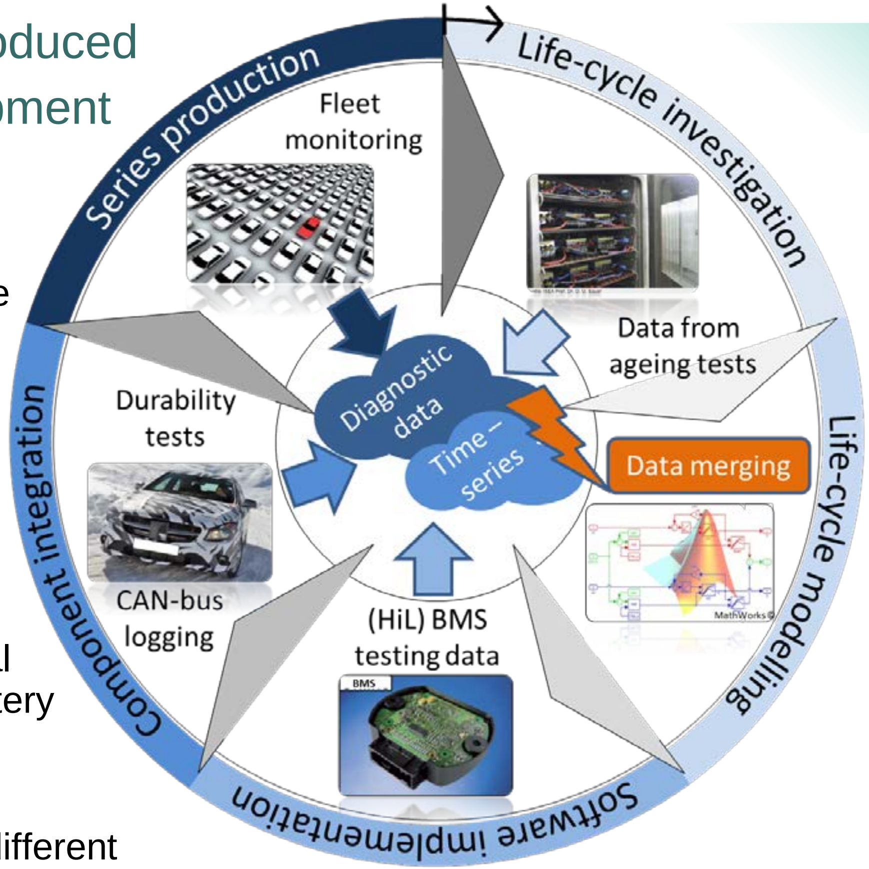
Following questions arise during development:

- Do the chosen duty cycles represent the real-world utilization?
- How can the ageing model be continuously improved at each single development step?
- Is there a convenient type of an ageing model which supports the fleet monitoring in performing degradation prognosis as well as an on-board health monitoring?

Objective

Merging of all data produced during battery development

- The ageing model can achieve a significant improvement if available ageing data from each single development step is considered during the modelling process
- Such an improved model integrated into a fleet management system is able to identify a potential failure of each single battery



Problem:

- The gathered data is of different type – time-series and diagnostic data

Targets to be achieved:

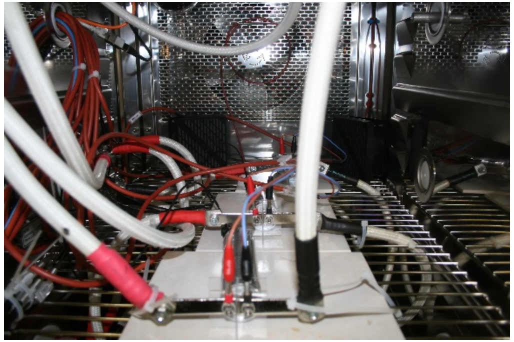
- Unified treatment of all available data as input for the ageing model
- Development of a model especially adapted for usage in a fleet management system
- Derivation of an on-board capable and self-adapting health monitoring algorithm to track the individual degradation of a particular battery

Overview

Life-cycle investigation of lithium-ion cells and batteries

Test objects and procedure

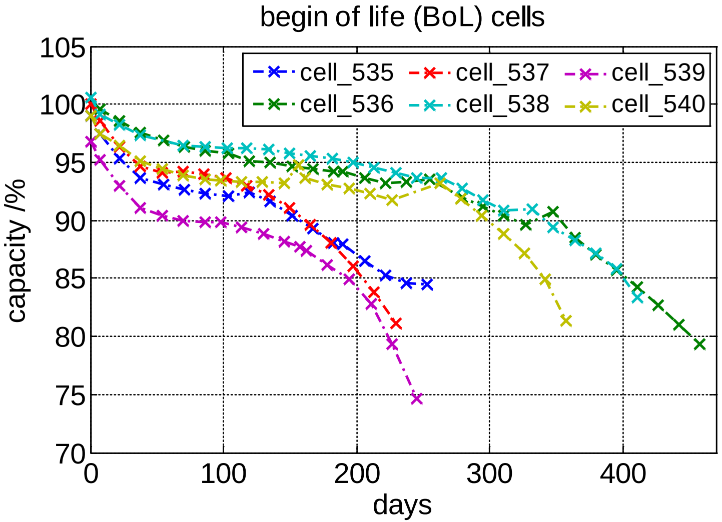
- Two batteries and twelve high-power lithium-ion cells were experimentally investigated
- Six of them experienced a cyclically repeated real-world current profile at room temperature, starting at BoL with two different levels of SoCs for each pair of three cells **(the “life-cycle” dataset)**
- Further six cells with different SoH stages were exposed to much more varying real-word current and temperature profiles as well as several SoC levels **(the “durability test” dataset)**
- One new and an already deteriorated battery were stressed by a captured real-word profile under laboratory conditions by considering identical operating conditions as they were integrated in vehicles (battery cooling etc.) **(this 70 cells represent a “fleet” of 70 vehicles for validation purposes later on)**

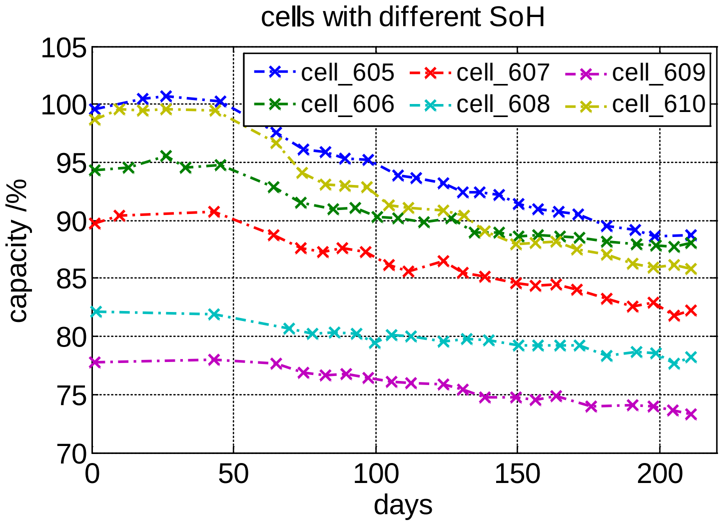


Life-cycle investigation of lithium-ion cells and batteries

Test results and observations

- A higher operating SoC applied on three BoL cells during cycling reduces their lifespan by half
- The real-world testing profile affects the cells with different SoH unequally; newer cells deteriorate faster
- The capacity loss of the 70 cells from the two tested batteries is quite similar to cells starting at BoL in the right figure





Overview

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Empirical modelling of the ageing behavior

Time-series analysis

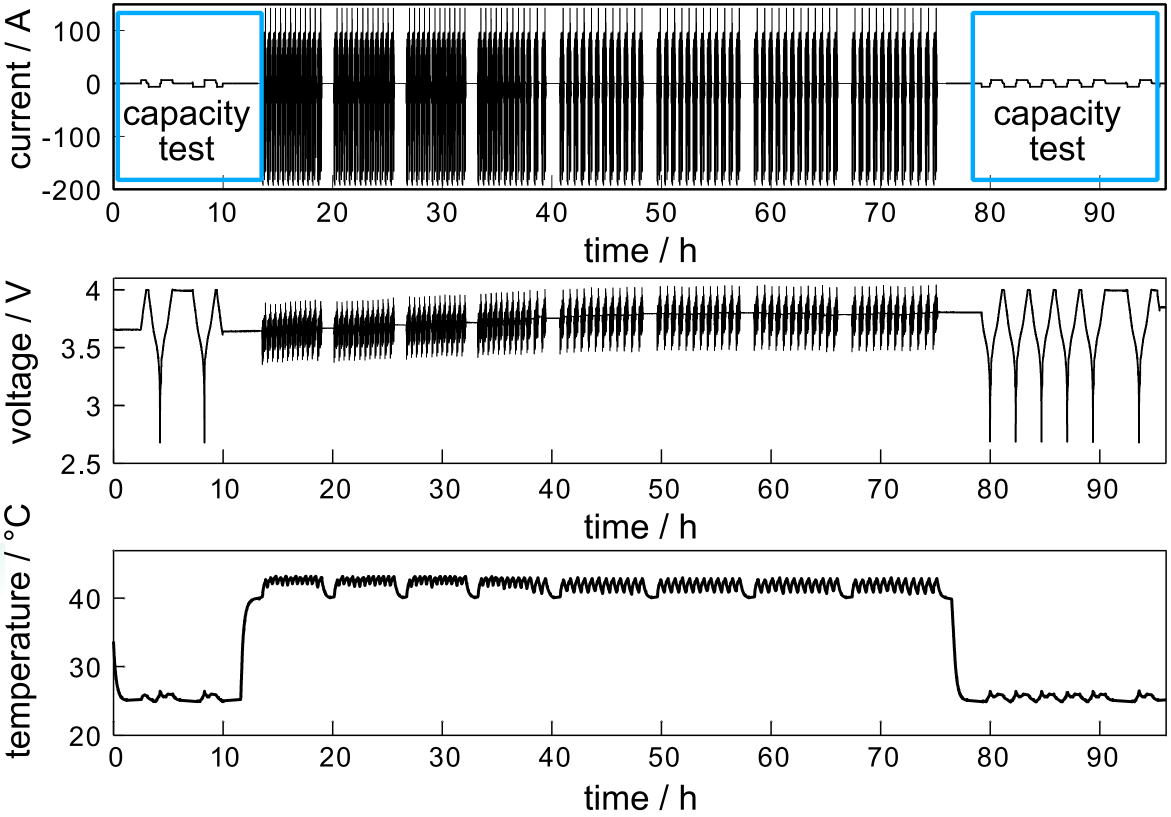
- An empirical model involves the current, the voltage, the temperature and the SoC as the model input whereas the capacity decrease is its output

Problem:

- A time-series between two capacity values can contain several million of measured data points

→Data reduction to one single (multidimensional) data point

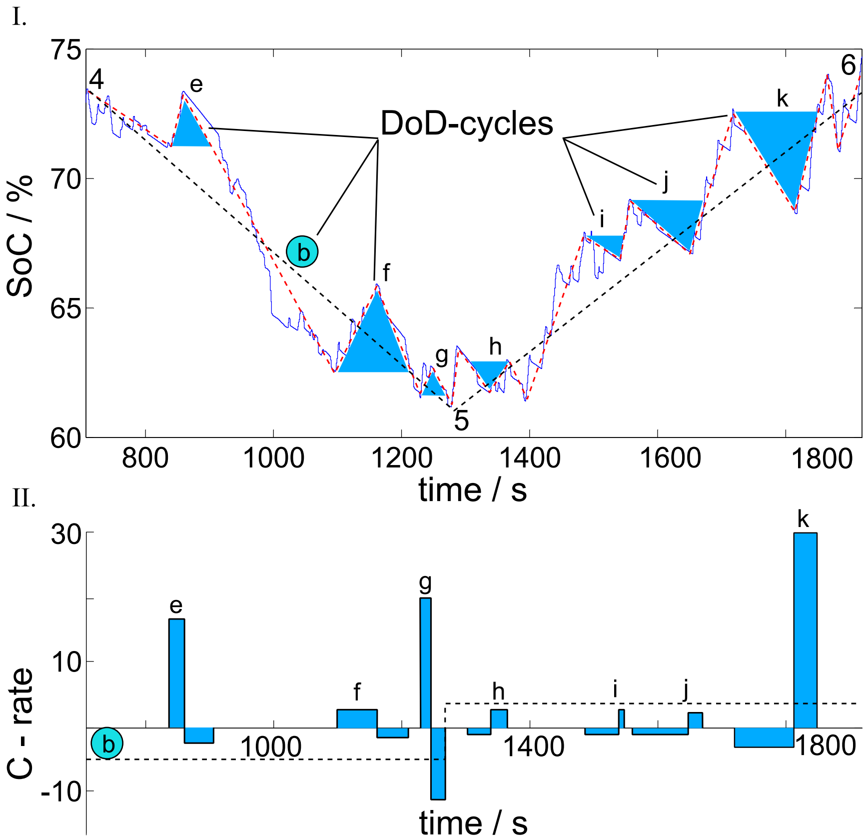
→How to “cut” a long time-series into segments?



Empirical modelling of the ageing behavior

Time-series segmentation

- The well known rainflow-counting algorithm from machinery is used for counting depth-of-discharges (DoD) in the SoC trend
- Each found DoD-cycle in the SoC trend represents a single time-series segment
- The temperature an voltage trends can be segmented on the same way according to the time span of a particular DoD-cycle
- As the current may vary in a high-frequent manner during a DoD-cycle, an approximation of its trend is appropriated
- Every DoD-cycle can be approximated by a constant charging and discharging C-rate

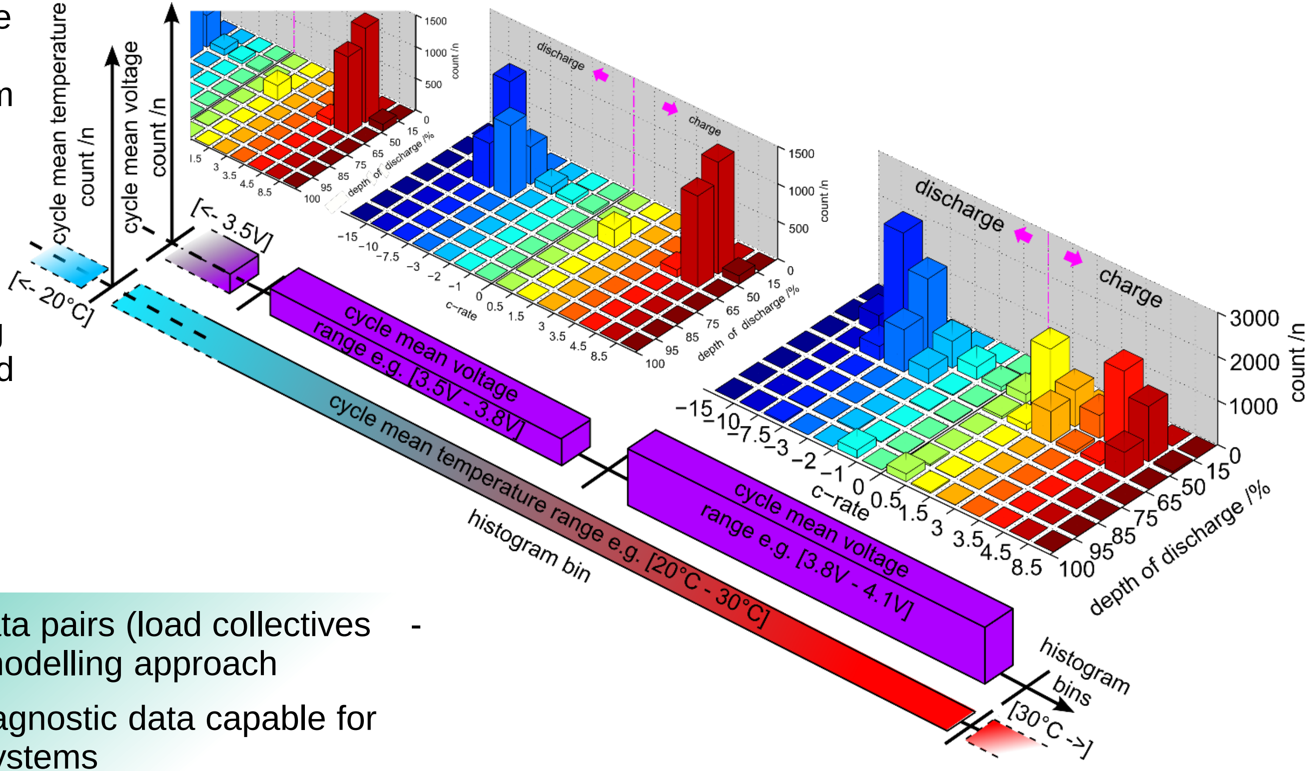


A. Nuhic et.al., A Health-Monitoring and Life-Prediction Approach for Lithium-Ion Batteries Based on Fatigue Analysis, Advanced Automotive Battery Conference Europe 2013 , 2013.

Empirical modelling of the ageing behavior

Histogramming time-series segments into “nested“ load collectives

- At first, every found DoD-cycle is classified by its mean temperature in a 1D-histogram
- Every bin of this histogram contains a further 1D-histogram for mean voltage of the found DoD-cycle
- A 2D-histogram for classifying the found cycle by its DoD and corresponding charge- and discharge-rate is contained in every bin of the mean voltage histogram



→Preparation of input-output data pairs (load collectives - capacities) for the empirical modelling approach

→Converting time-series into diagnostic data capable for usage in fleet management systems

Empirical modelling of the ageing behavior

”Course of dimensionality“

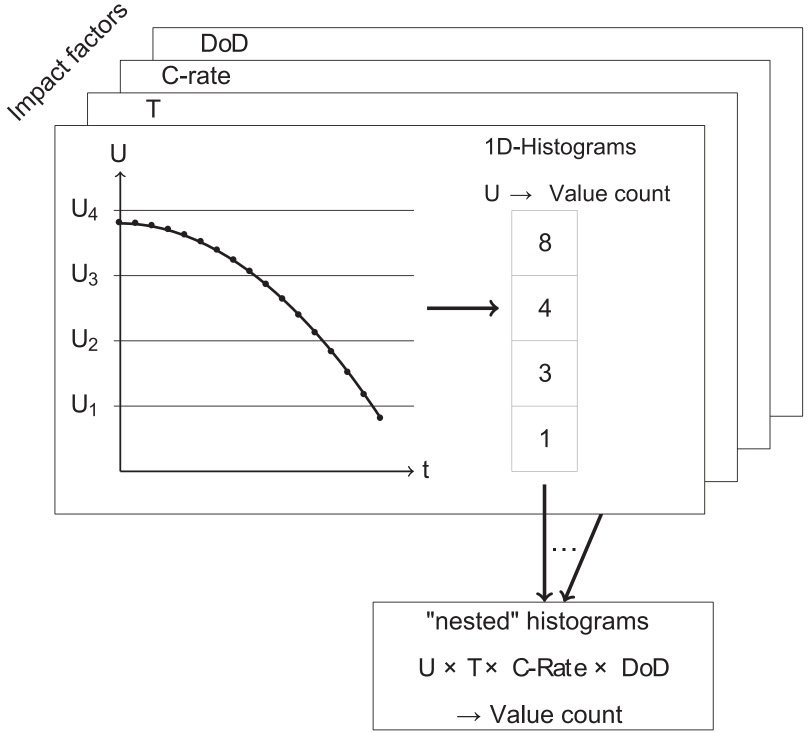
- Sample calculation:

  - 14-bin voltage histogram
  - 12-bin temperature histogram
  - 14-bin C-rate histogram
  - 7-bin DoD histogram

→**Results in 16464 counted values or so called “features”**

- Taking the central moments of a histogram like the mean, variance, kurtosis, skewness reduces the amount of features
- Performing a so called “feature selection” reduces the features to the most relevant by eliminating irrelevant or redundant features

→**Determining the features that affect the ageing most**



Empirical modelling of the ageing behavior

Statistical learning methods for regression

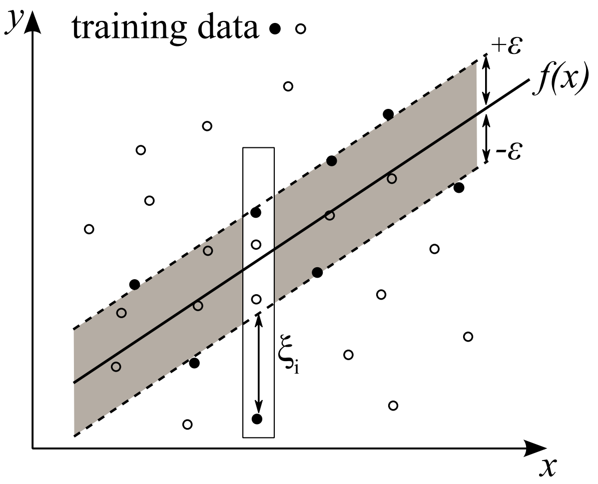
- Two powerful data-driven methods for learning non-linear models have been employed

→*Support vector regression:*

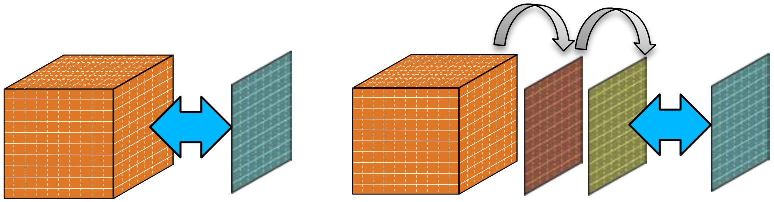
$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) k(x_i, x) + b$$

→*Relevance vector regressio*

$$f(x) = w_0 + \sum_{i=1}^{n} w_i \psi_i(x) = w^T \psi(x)$$



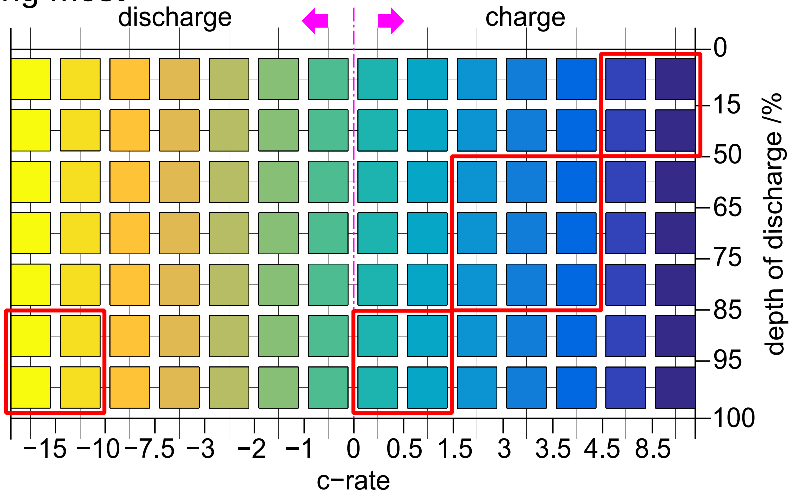
- The training process can either be performed with the whole data set at once **(batch-form)** or **incrementally** whenever a new data point is available
- Only the support or relevance vectors chosen from the training data determine the regression function

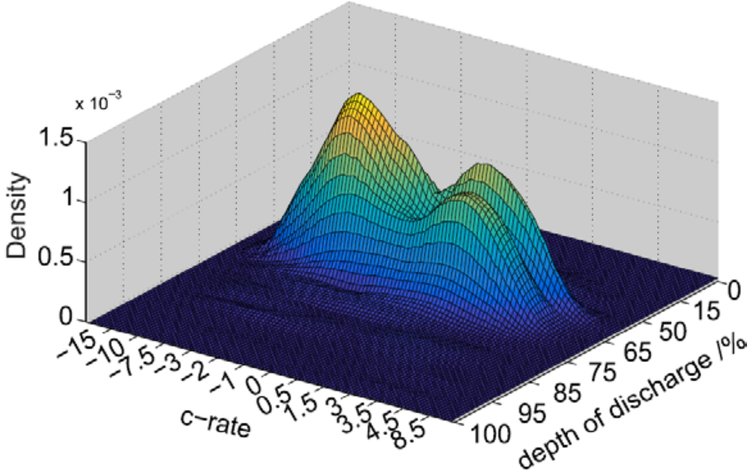


Empirical modelling of the ageing behavior

Degradation prognosis approach by extrapolating the load collectives

- Discrete points of a histogram need to be converted into a continuous probability density, e.g. by kernel estimators
- Each bin is extrapolated depending of its probability density, so bins with higher probabilities have more counts
- The variability in load collectives can be modelled individually by defining "damage" regions with physical background
- Choosing different bandwidth for the kernel in this regions results in a histogram extrapolation that affects the ageing most

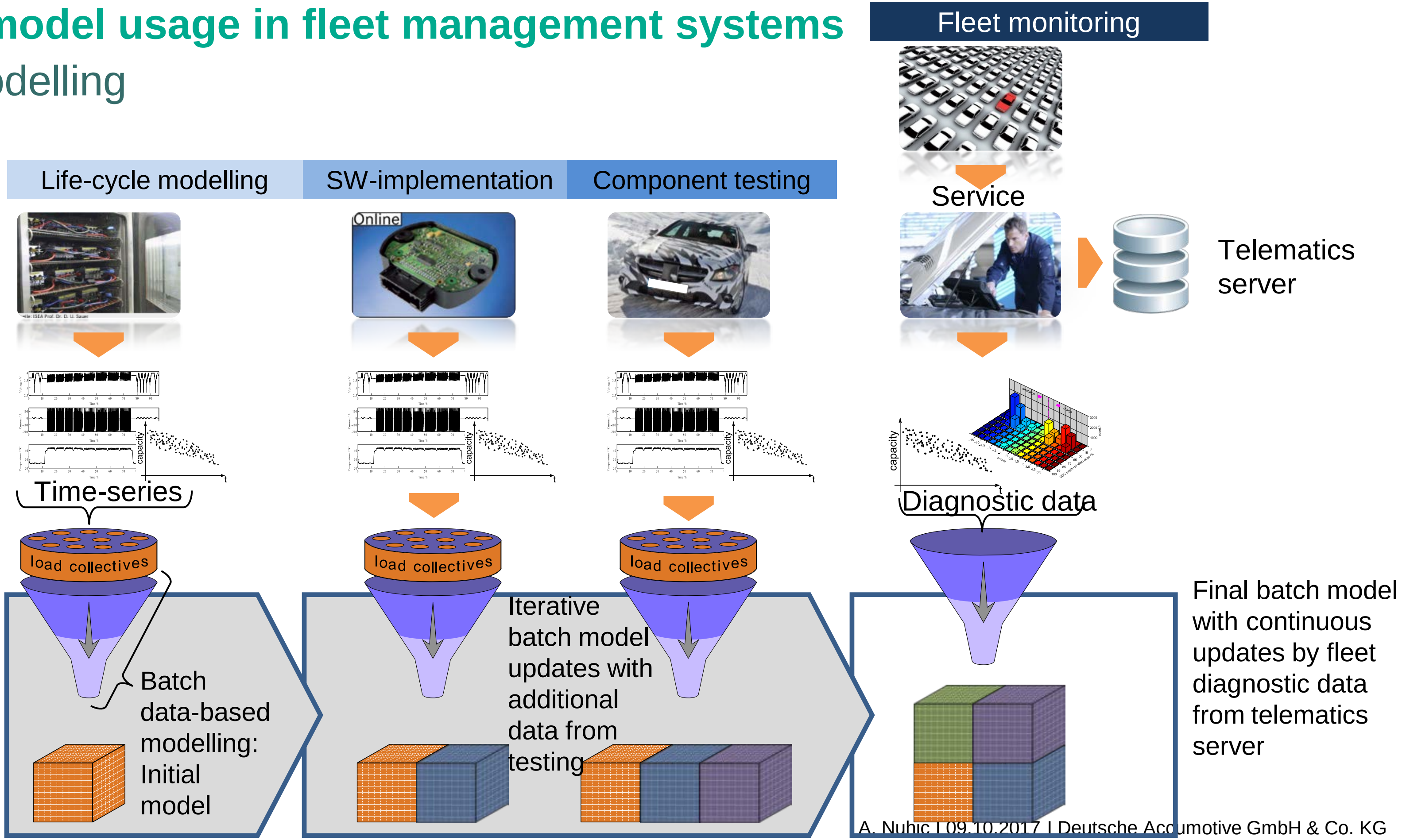




Overview

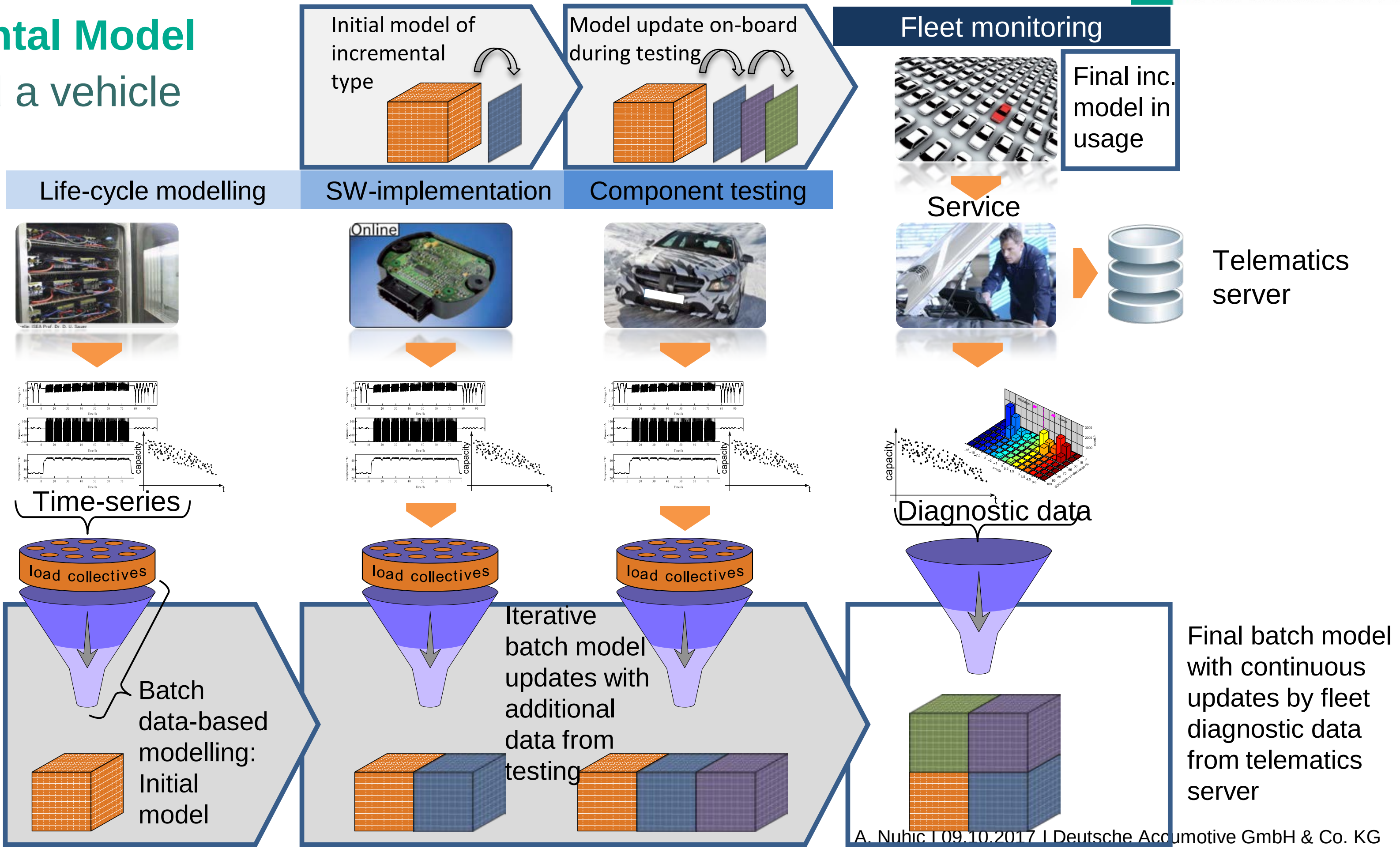
Ageing model usage in fleet management systems

Batch modelling



Incremental Model

On-board a vehicle

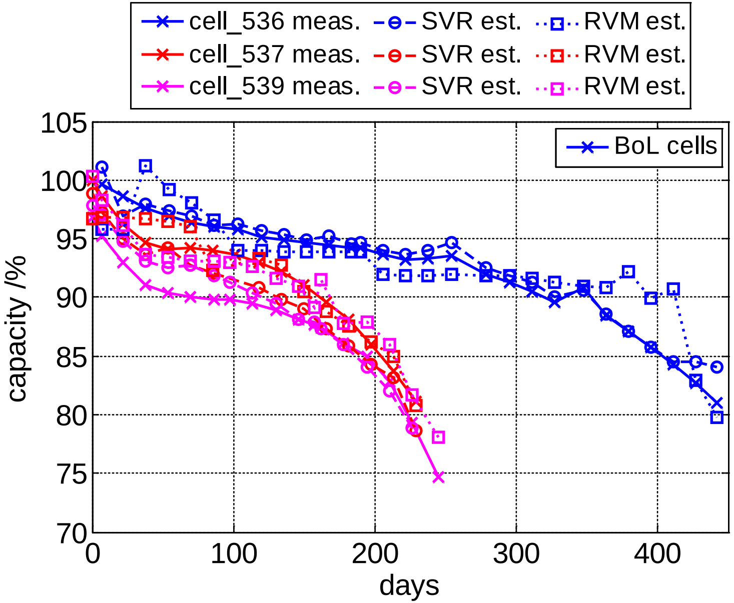


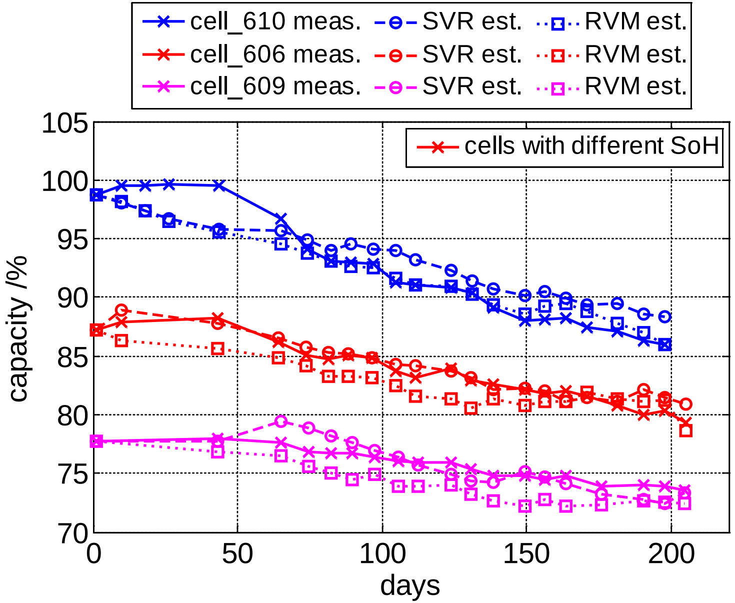
Overview

Results

Batch model

- Model results of SVR and RVM validated on data only from life-cycle measurements with BoL cells (left graph)
- Model validation on an updated dataset by measurements from durability tests (“life-cycle” + “durability test” datasets)

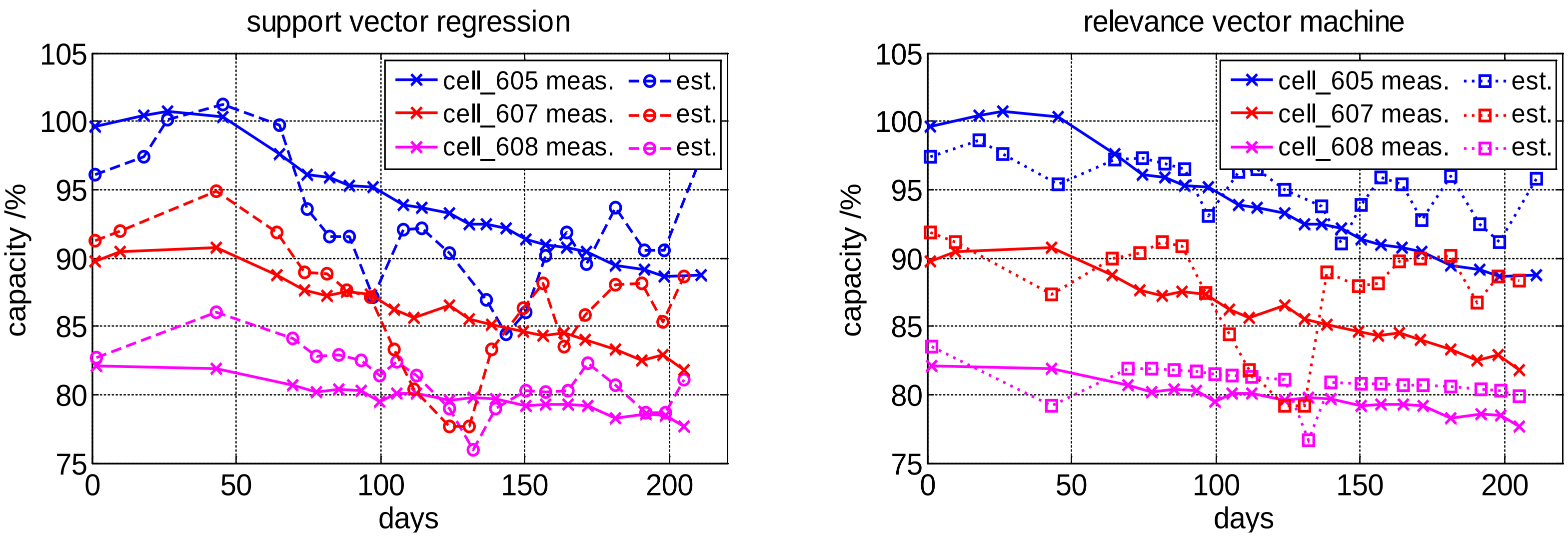




Results

Batch model validation on unseen data

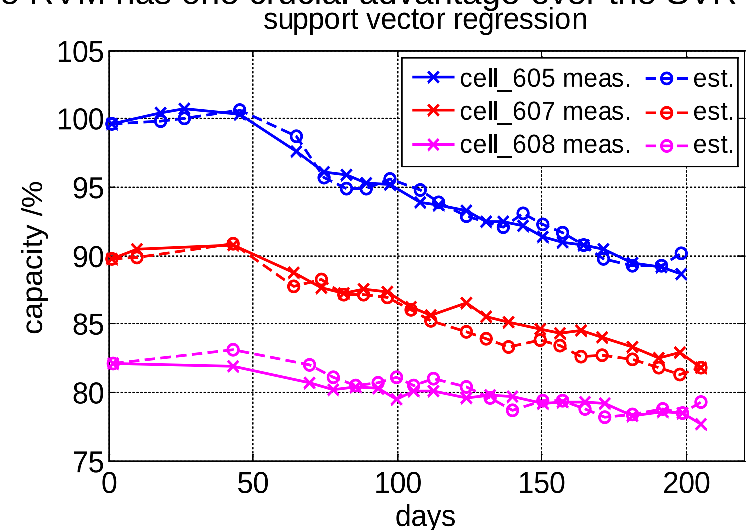
- The prognosis of the capacity degradation is not satisfactory when applied to the “durability tests” dataset if the batch model is build upon only the “life-cycle” dataset
- A possible explanation could be a vague duty cycle used in the laboratory investigation which does not represent the variability of a real-world battery utilization

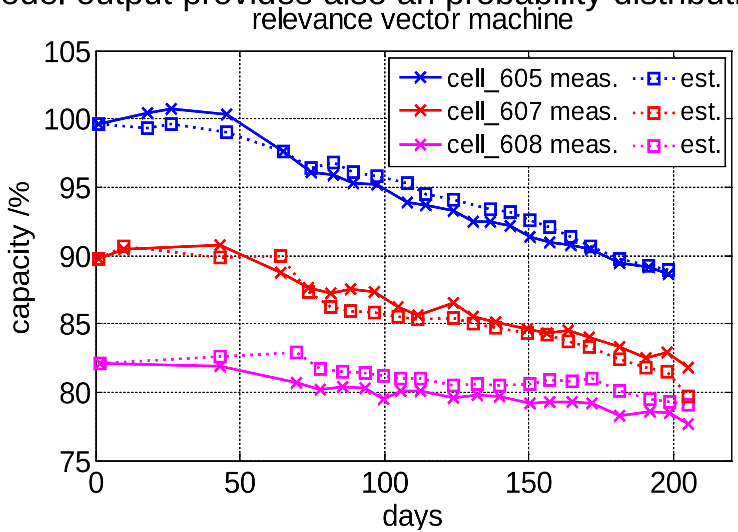


Results

Incremental model

- An on-board incrementally updated batch model, either of SVR or RVM type, is able to track the capacity very precisely
- A such updated data-based model is in the best position to perform a accurate degradation prognosis as they incorporate the “knowledge” about the degradation behavior from the life-cycle investigations on
- The RVM has one crucial advantage over the SVR – its model output provides also an probability distribution





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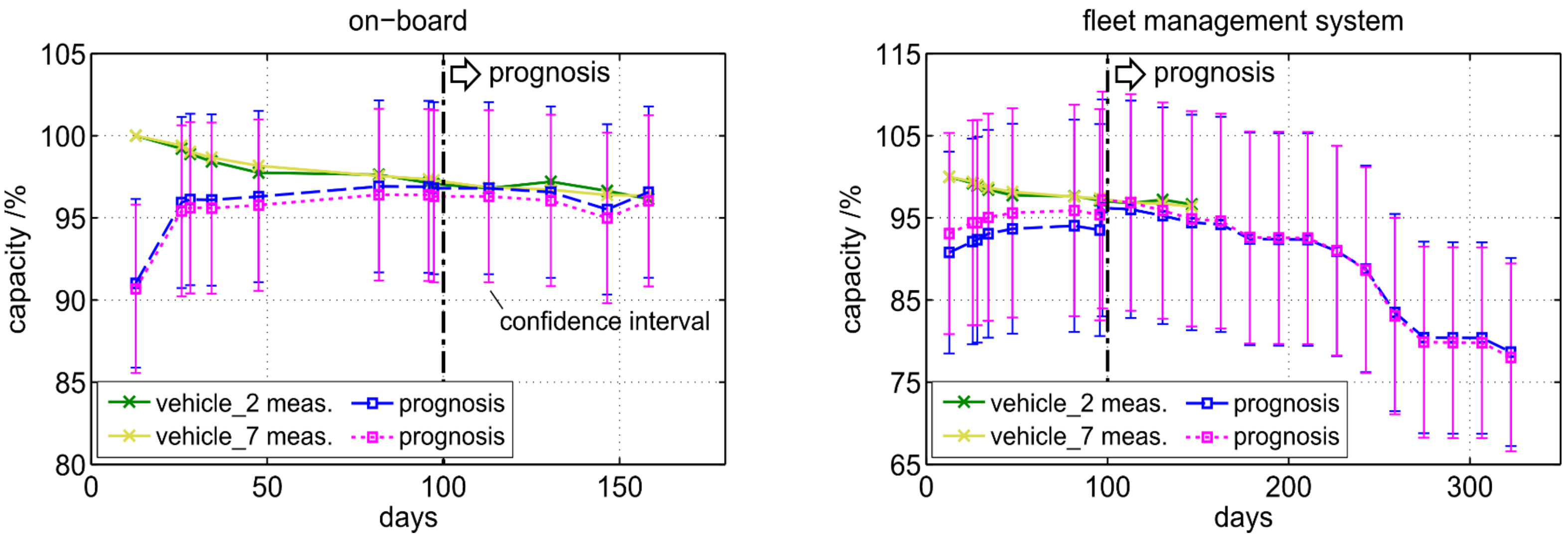
Results

On-board and fleet management prognosis

- Two cells of a batch from 70 cells of the two tested batteries are chosen randomly to represent vehicles with lithium-ion batteries to demonstrate the prognosis capabilities of the developed approach
- The prognosed capacity degradation for the next 50 to 200 days seems quite realistic by considering the results from life-cycle investigation where the cells deteriorated to their end-of-life within a period of one year



Summary

1 Development of an novel battery health and degradation prognosis approach especially adapted for usage in fleet management systems

2 Realisation of a large scale life-cycle investigation of automotive lithium-ion cells as well as batteries for the creation of diverse datasets required for the data-based modeling approach

3 First introduction of an “nested” load collective for data reduction and conversion of time-series to diagnostic data

4 Extrapolation of load collectives with kernel methods for prognosis purposes

5 Implementation of two statistical learning methods – the support vector regression and the relevance vector regression – in their batch form as well as an incremental type of them

6 Both methods showed promising results in battery degradation prognosis

Thank you for your attention