Machine Learning for Battery Management Systems

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Overview

- Motivation and typical applications
- Non invasive measurement by means of impedance spectroscopy
- Implementation Hardware of the BMS with built-in impedance spectroscopy functionality
- New Software Algorithms of the BMS
- Summary

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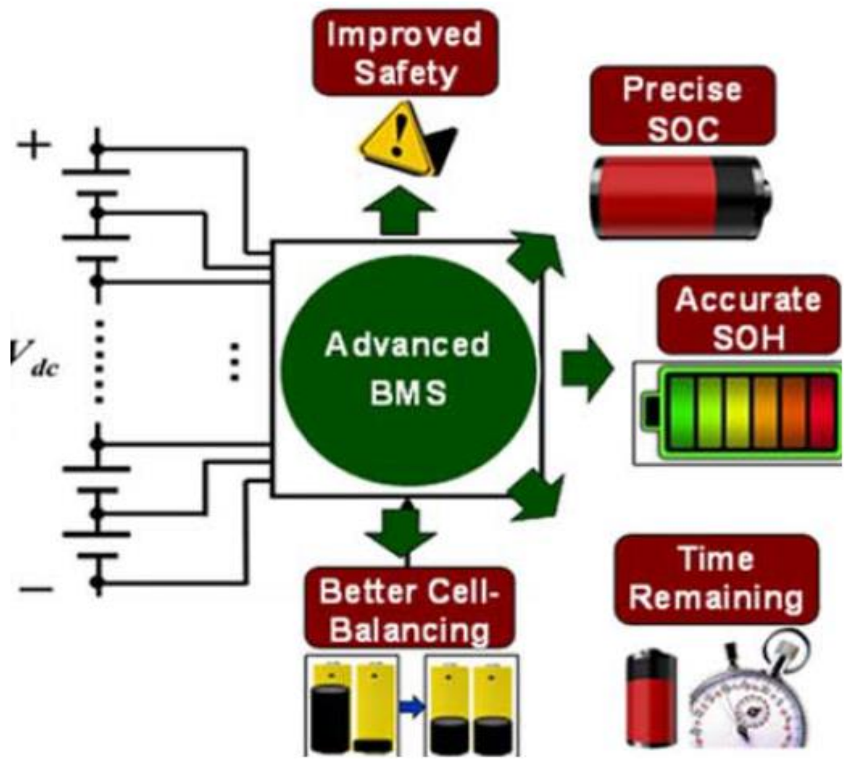
Motivation

- Necessary Requirement: Monitoring of voltages, temperatures and currents of **each cell**
- Important quantities for a save and reliable operation of the battery management systems: **State of Charge (SoC)** and the **State of Health (SoH)** of each cell of the complete battery system



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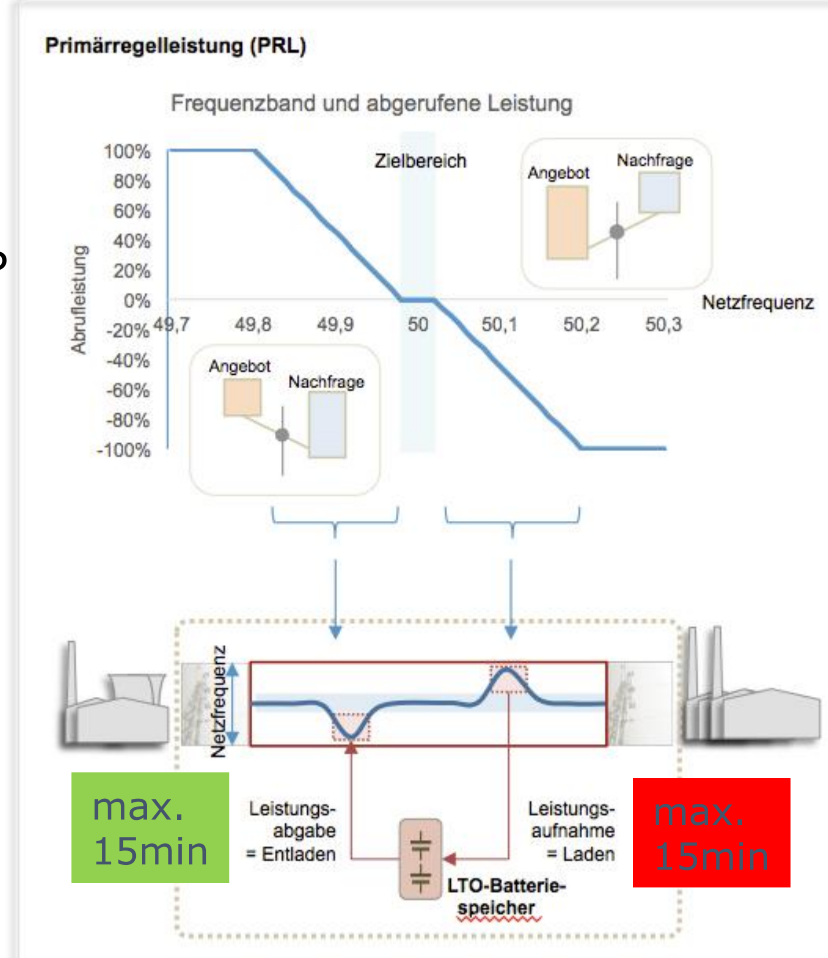
Typical Application

- Prequalified providers of primary balancing power (PBP) apply for an auction every week
- Requirement: Minimum 1MW PBP
- Service is automatically dependent on the grid frequency
- PBP delivered within 30 seconds and up to 15min.
- State of the art: For each MW PBP approx. 2MWh of battery capacity is necessary.
- <u>Diagnostic features like the SoC</u> for 24h/7d- operation are essential!



Source: www.liacon-batteries.de

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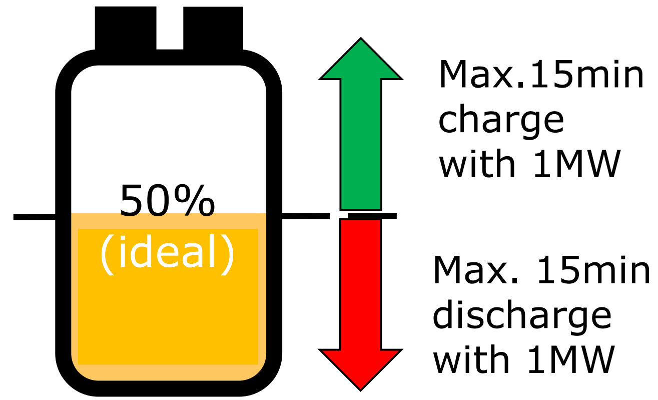
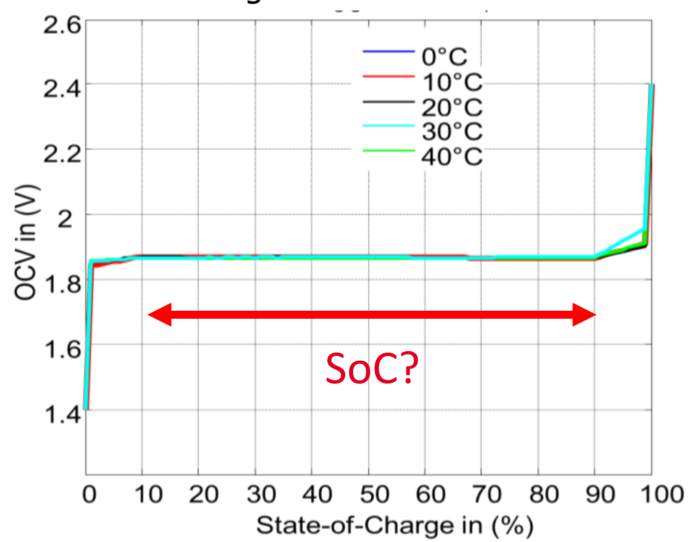
Diagnostic problems with LTO-Cells

- Bidirectional PBP requires an average SoC at 50% with high swings towards 100% and 0%.
- Permanent cycling of the battery requires high reliability of the complete system and an exact Determination of the SoC



- Problem :
  SoC-Estimation
  by open circuit voltage
  is impossible for LTO-cell technology

Open Circuit Voltage of a LTO-cell over SoC und T



Standard methods like voltage referencing or coulomb counting will not work out!

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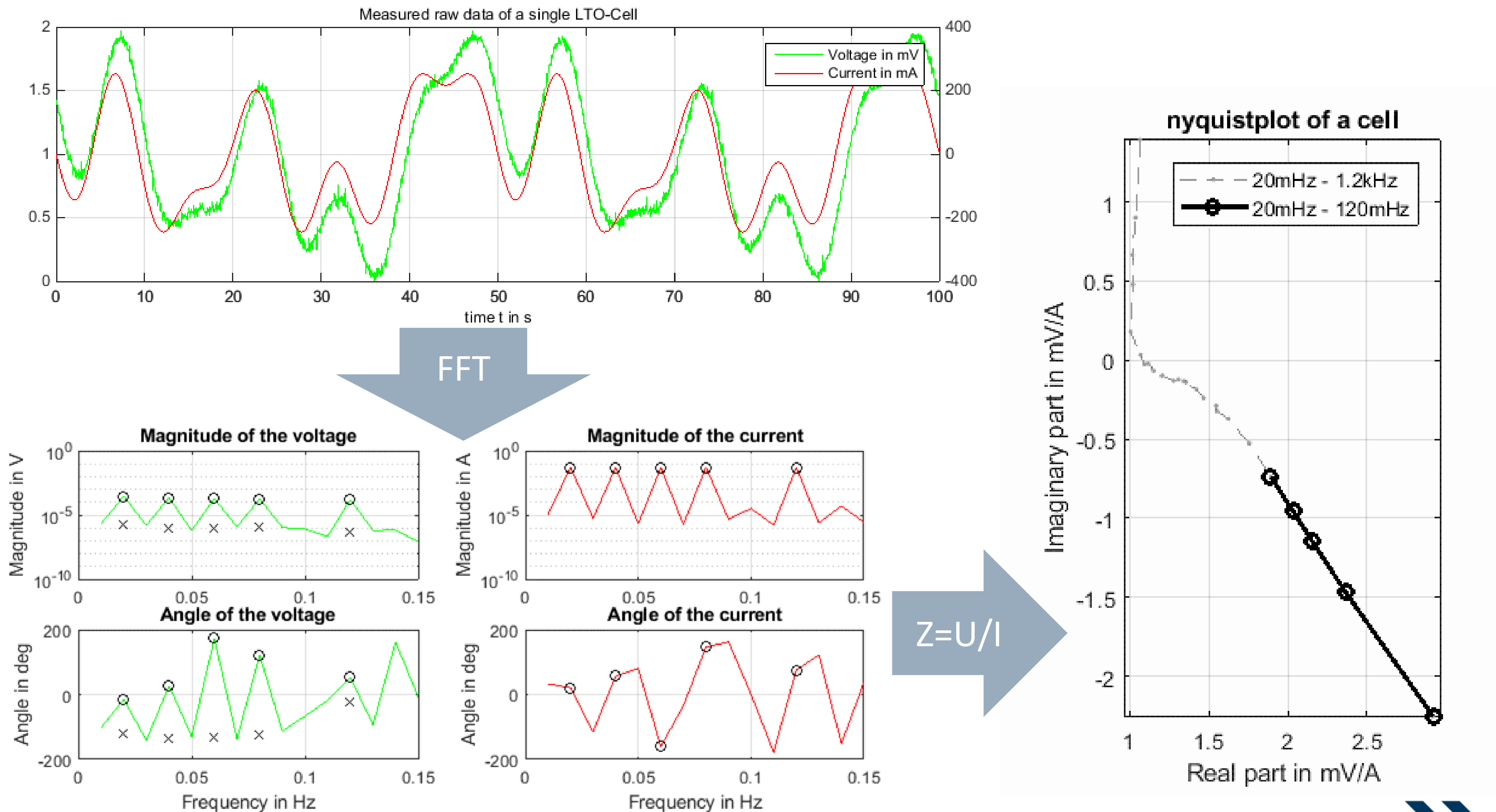
Impedance spectroscopy



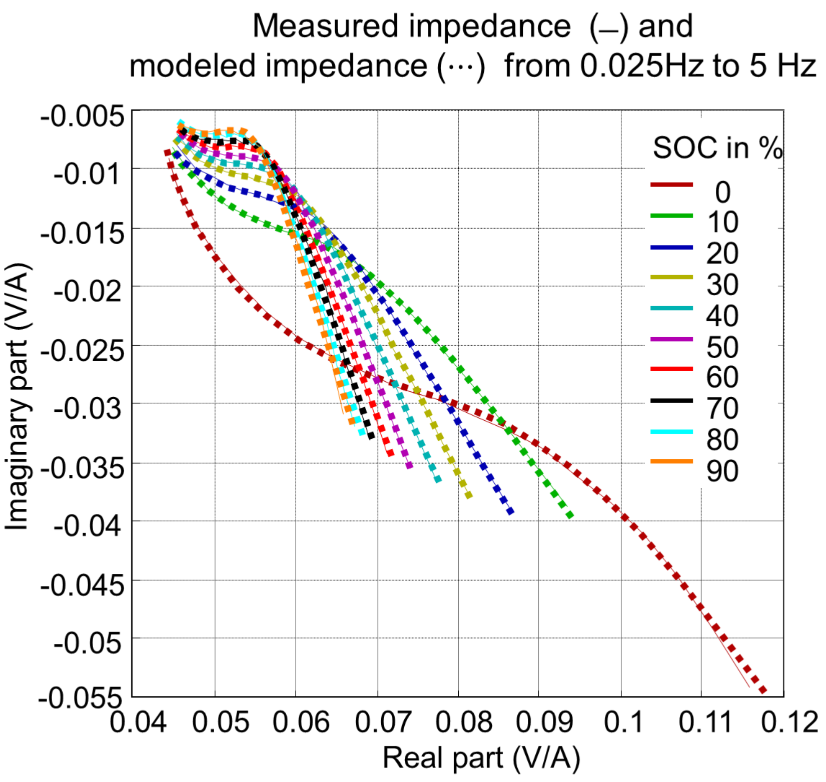
Impedance spectroscopy

Impedances of several frequency sweeps at different SoC in % show a distinctive behavior especially at low frequencies!

Further impact on the impedance:

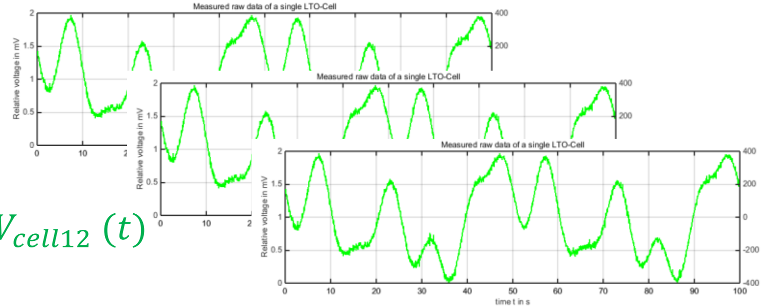
Temperature, current history and age.

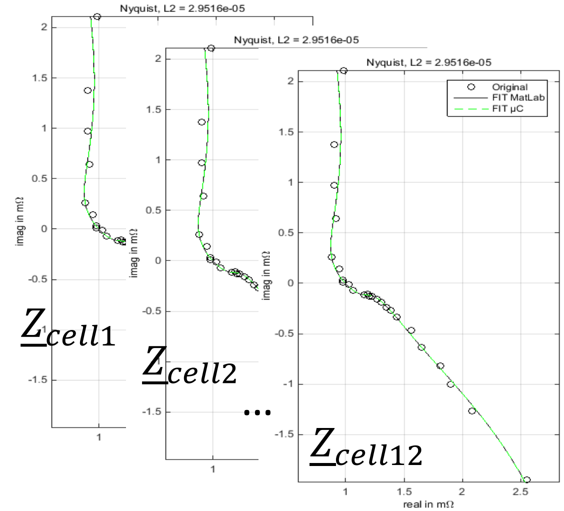
SoC of a cell is highly dependent on **the operation point!**



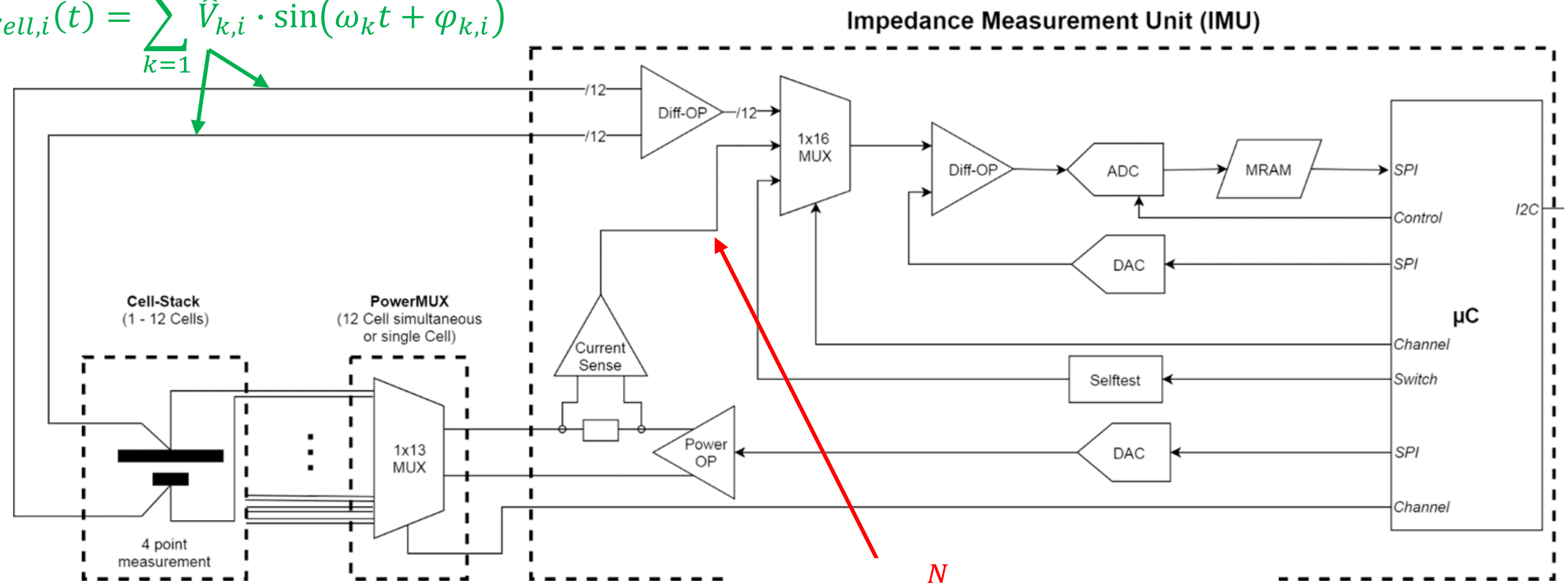
Hardware of the BMS

$V_{cell1}\ (t)$
$V_{cell2}\ (t)$
...
$V_{cell12}\ (t)$





$$V_{Cell,i}(t) = \sum_{k=1}^{N} \hat{V}_{k,i} \cdot \sin(\omega_k t + \varphi_{k,i})$$



$$I_{exc}(t) = \sum_{k=1}^{N} \hat{I} \cdot \sin(\omega_k t + \varphi_k)$$

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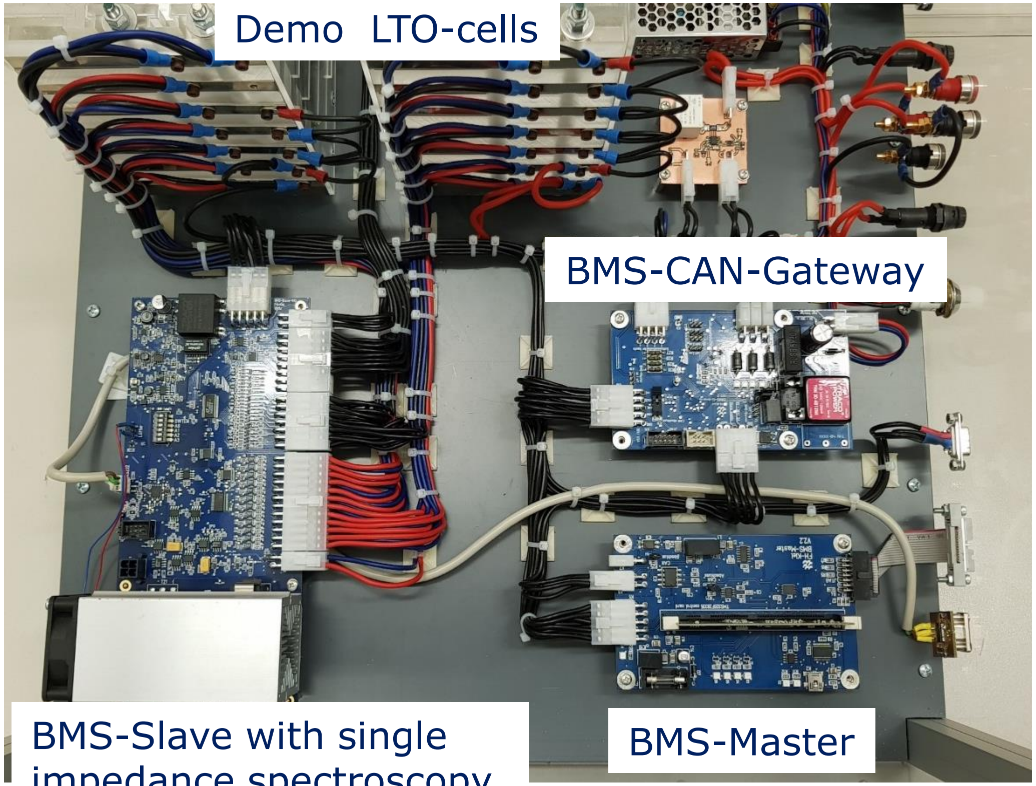
Hardware of the BMS

- **BMS-Slave for 12 cells**:
  I) Limit monitoring: Cell Temperatures, voltages, string current
  II) Impedance spectroscopy functionality for each cell
  III) Modular concept for additional cells
- **BMS-Gateway:**
  Communication between one BMS-Master and several BMS-Slaves
- **BMS-Master:**
  I) Intelligent data collection unit
  II) Decision about limits
  III) Estimation of SoC and SoH



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Software algorithm for SoC

- Since the SoC is heavily dependent on the operation point impedance spectroscopy is not sufficient!

- Representative features are needed to estimate the cell individual SoC

- Solution:
  I) Supervised machine learning with suitable features
  II) Generation of an adequate training data set

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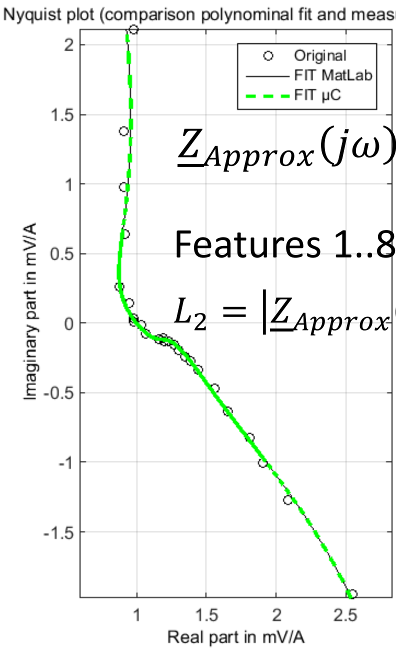
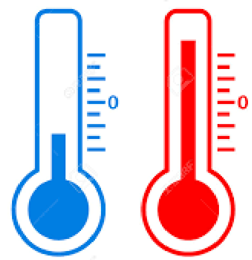
Software algorithm on the BMS



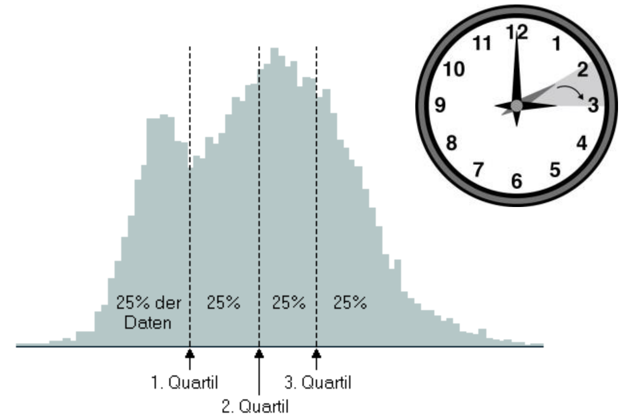
$$\underline{Z}_{Approx}(j\omega) = \sum_{k=0}^{7} \underline{c}_k \omega^k$$

Features 1..8: $\underline{c}_0 \dots \underline{c}_7$

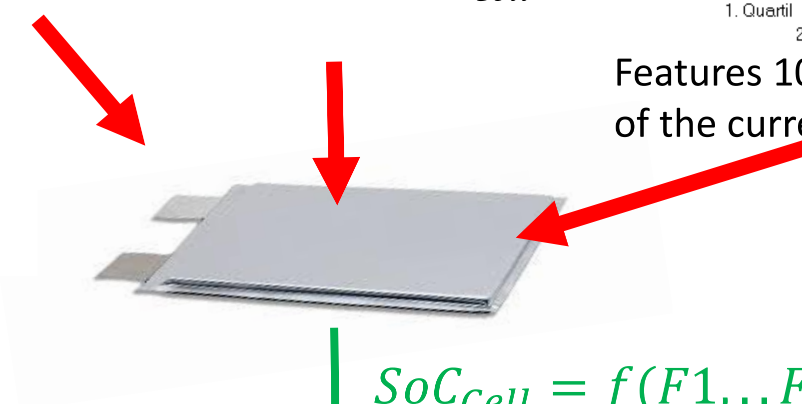
$$L_2 = \left|\underline{Z}_{Approx}(j\omega) - \underline{Z}_{Meas}(j\omega)\right|$$



Feature 9: T_{Cell}



Features 10 and 11: $1.\,and\ 3.\,Quartil$ of the current flow of the past 1h



$$SoC_{Cell} = f(F1,..F11)$$

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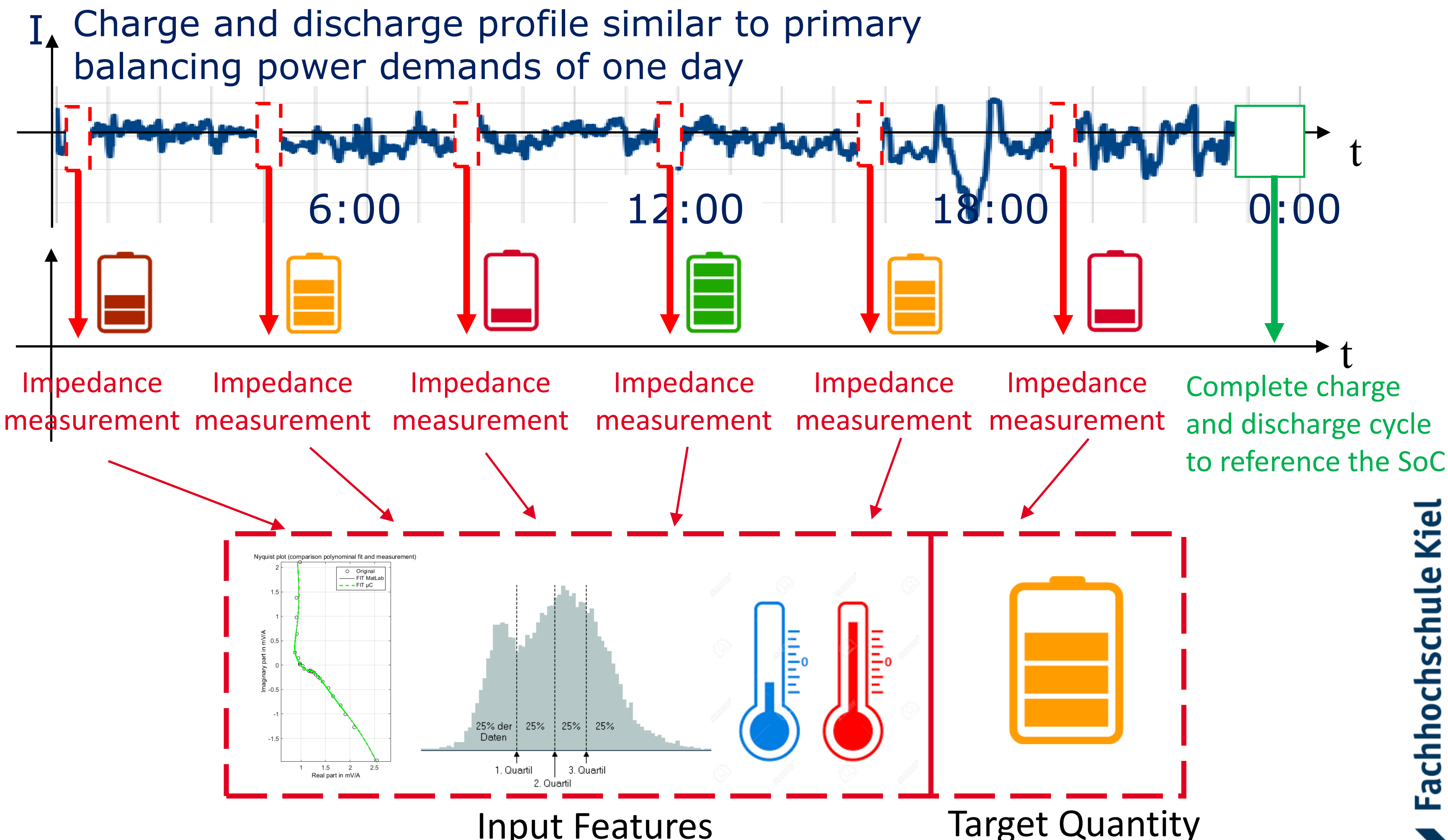
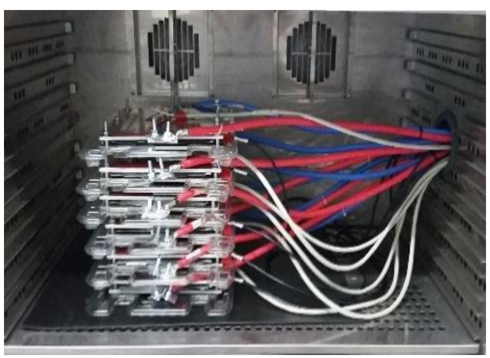
Software algorithm on the BMS

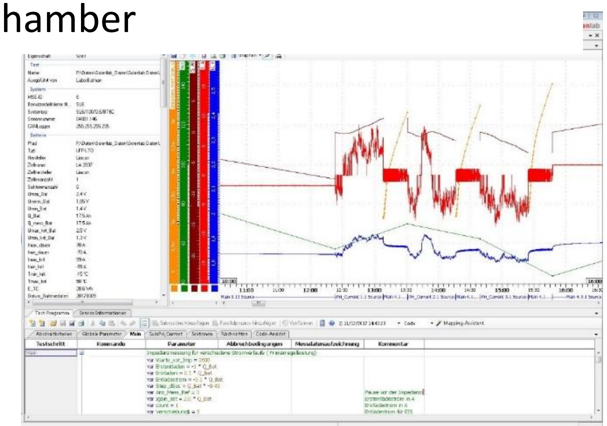


Software algorithm on the BMS

Complete setup: Battery tester and climate chamber



6 LTO-Cells in a climate chamber



Control software for data generation

6 Channel: Battery tester (with impedance spectroscopy)

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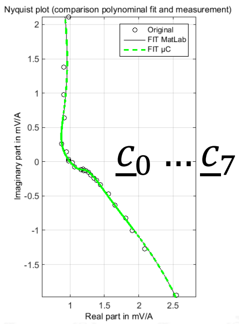
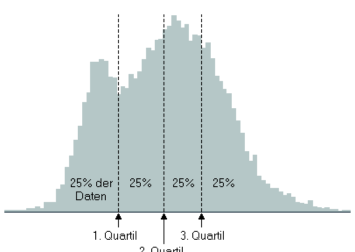
Software Algorithm on the BMS

Features

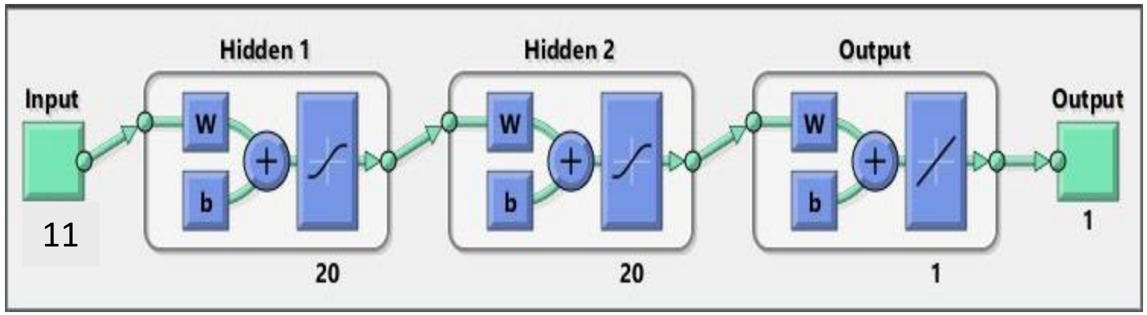


$\underline{c}_0 \dots \underline{c}_7$

T_{Cell}



$1. and\ 3. Quartil$



SoC

- Supervised machine learning procedure
  2500 training and 500 test data sets
- Modell represents a feed forward artificial network
- Different combinations of input data sets and number of neurons in hidden layers were tested during the training process
- Best results are achieved with 20 neurons in 2 hidden layers and with all 11 given features.

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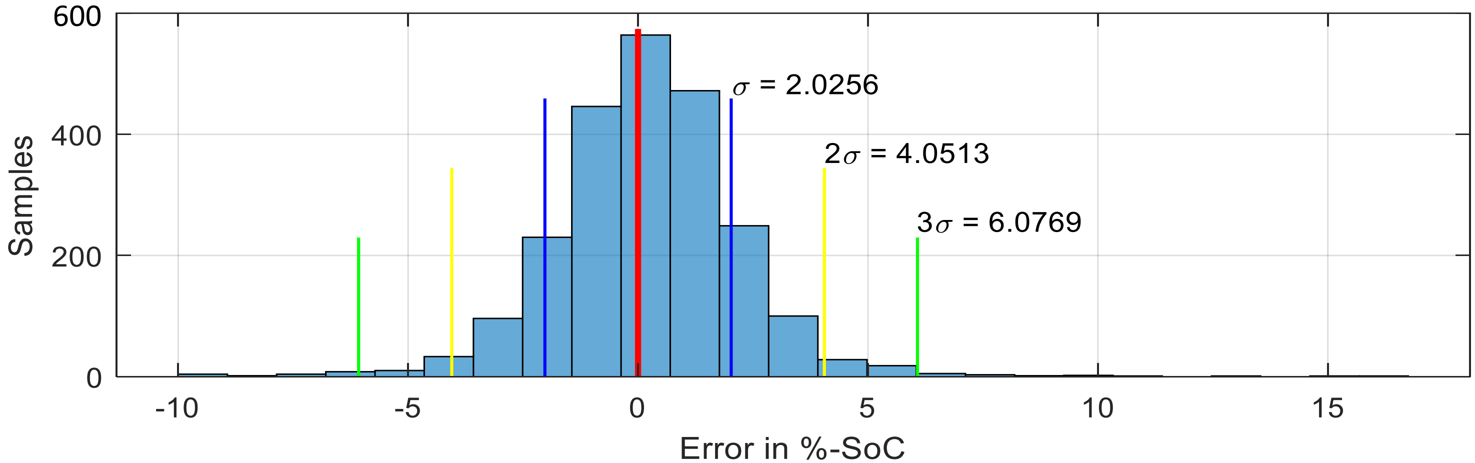
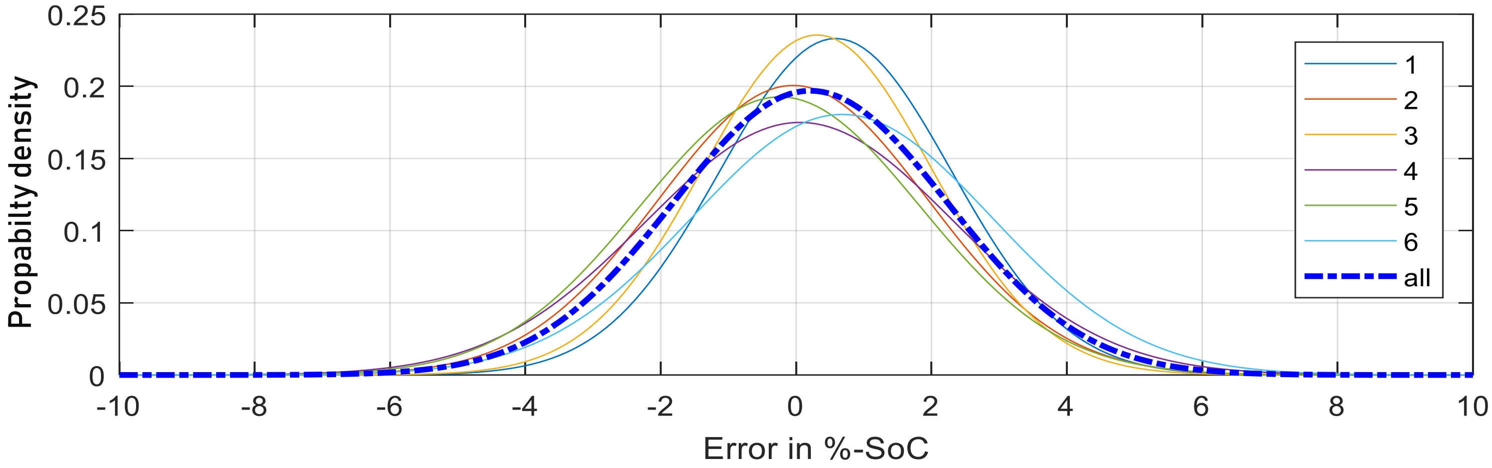
Software algorithm on the BMS



- Overall accuracy: 99% of all samples show an error less than **+/-5%** of the correct SoC.

Software algorithm on the BMS



- Variances in the process quality of the cells show, that the SoC of some cells (e.g. cell 1 and 3) can be better estimated than others (e.g. cells 2 and 6).
- Determined model keeps the relative error of the SoC within an acceptable +/-5% SoC-error

Summary

- Supervised machine learning methodology can be successfully applied to BMS in order to improve the overall diagnostic functionality for the determination of **SoC** of Lithium-Ion Cells.

- **Artificial neuronal networks** can be easily implemented in BMS-Master-Units with **low computational resources**.

- The same methodology can be applied to estimate the **SoH after the production of cell** or **during the operation** of complete battery systems:
  This is part of a new research project funded by the BMBF (Federal Ministry of Education and Research in Germany)

- All methods are **non destructive** and **non invasive**, so **no sensors** have to be integrated in the cells, which would cause complications on the electro-chemical behavior.

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