AVL List GmbH (Headquarters)

# AVL

# Extending Battery Life of Electric Vehicle Fleets

**The Battery – Dead or Alive**

**Dr. Veronika Obersteiner**

Public

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# ABOUT US

# AVL - Enterprise Development Automotive

AVL is the world's largest independent company for development, simulation and testing technology of powertrains (hybrid, combustion engines, transmission, electric drive, batteries, fuel cell and control technology) for passenger cars, commercial vehicles, construction, large engines and their integration into the vehicle.

The headquarter of AVL is in Graz, Austria.

**EXPERIENCE**
**>70** years !

**5** powertrain elements

**RESEARCH 10%**
of turnover in-house R&D

**INNOVATION 1,500**
granted patents

**STAFF**

**11,500** employees

**65%** engineers and scientists

**GLOBAL FOOTPRINT**

**45** engineering locations

- **>220** testbeds
- Global customer support network

# AVL Battery Activities

AVL

## Instrumentation for Service and Work shops

AVL DiTest

Pack Validation Production Signoff

## Instrumentation for System Development & Optimization

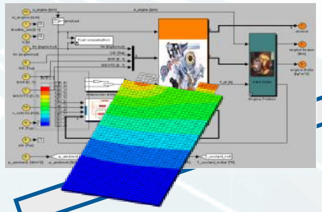
Business Unit ITS

HIL DEVELOPMENT

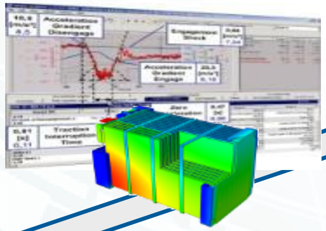
BATTERY E-STORAGE TESTER™

POWERTRAIN TESTBED

Battery Cell Simulation



Module Simulation



Cell Testing / HIL

Module Testing / HIL

Pack Testing / HIL

Vehicle Integration

Business Unit PTE

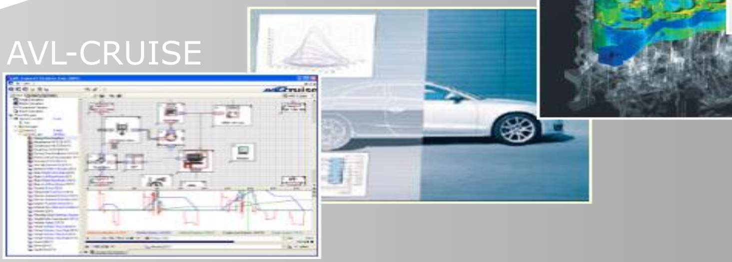
AVL-CRUISE

AVL-CRUISE M

AVL-FIRE

AVL-CAMEO

AVL-DRIVE



AVL FIRE™

AVL CRUISE™

AVL CRUISE™ M

Business Unit AST

## Software Tools for Powertrain System Development & Optimization

# Extending Battery Life for Electric Vehicle Fleets

## The Battery Value Chain
From raw materials to recycling

## Why Do Batteries Die?
Cell chemistry, Battery design, Operation strategy, Thermal management, Driver usage

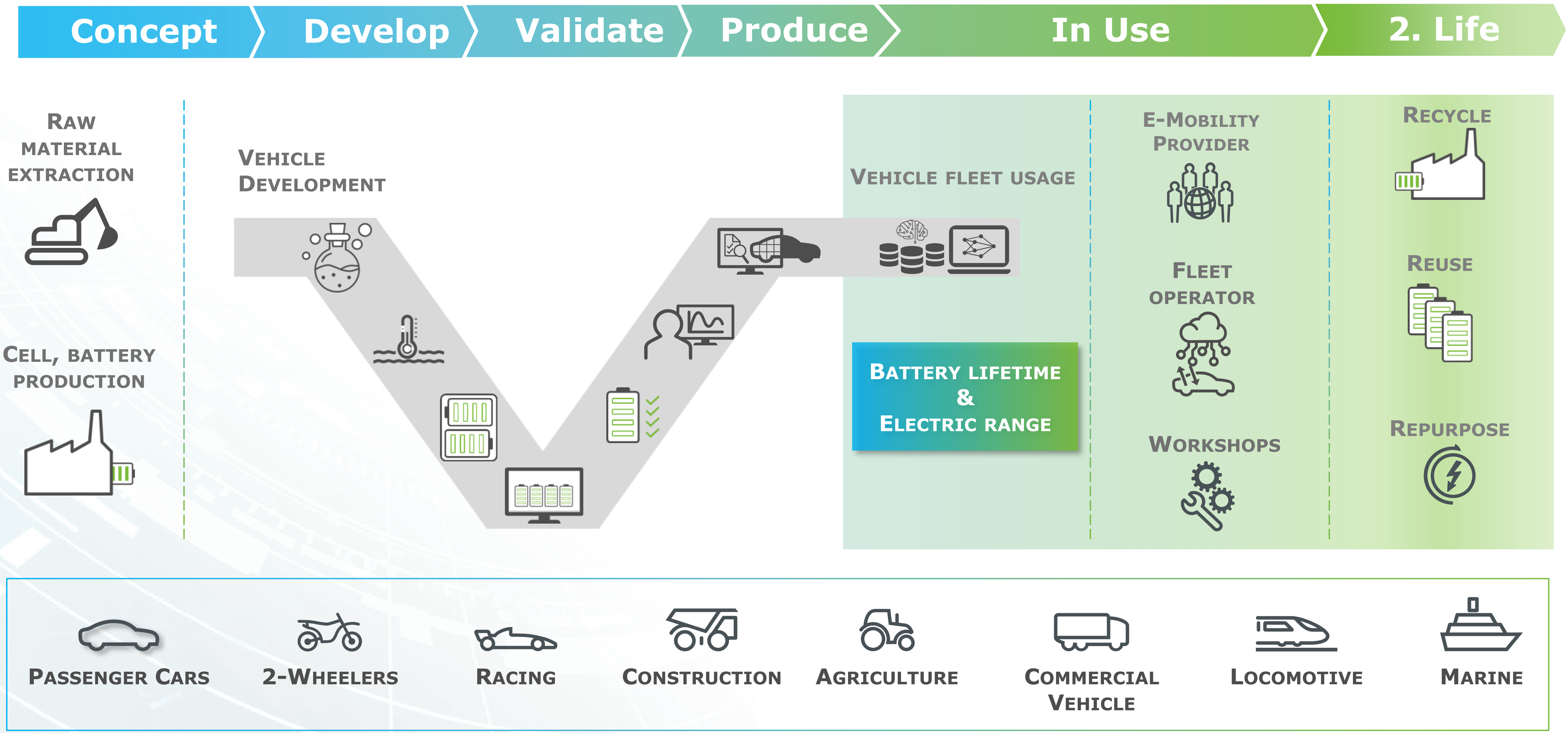
## Battery Testing, Simulation and Lifetime Prediction
Aging model parametrization

## In-use Fleet Monitoring to Extend Battery Life
Fleet monitoring, Update over the Air, Advanced Predictive Maintenance

## Project References & Key Messages

# The Battery Value Chain

# Battery Lifecycle Management



# Battery Lifecycle Management

## Challenge

Different parties involved

Data tracking needed along whole value chain needed

No standard for battery state of health or remaining battery value


## Questions

How long can I use my battery in my application ?

Why do my batteries die?

How can I choose the best cell, pack and operation strategy?

Can I optimize my operation strategy to maximize lifetime?

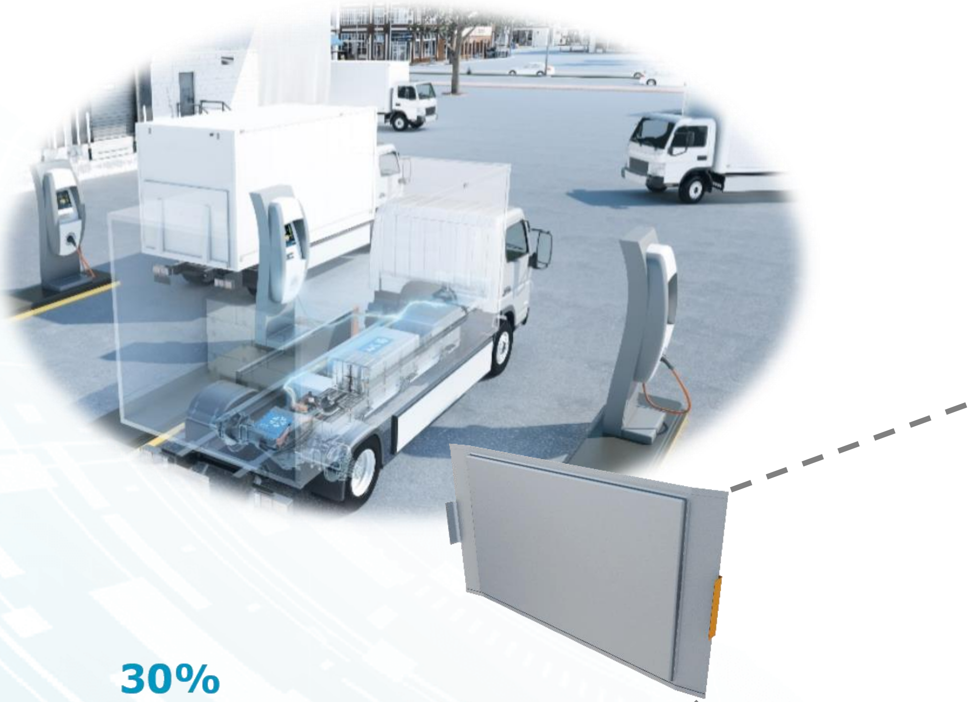
## Solution & Answers

AVL provides technology to increase battery life of electric vehicle fleets

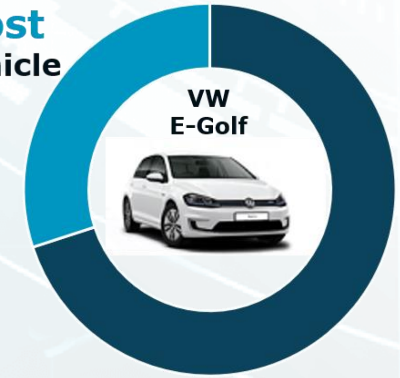
# Why Do Batteries Die?

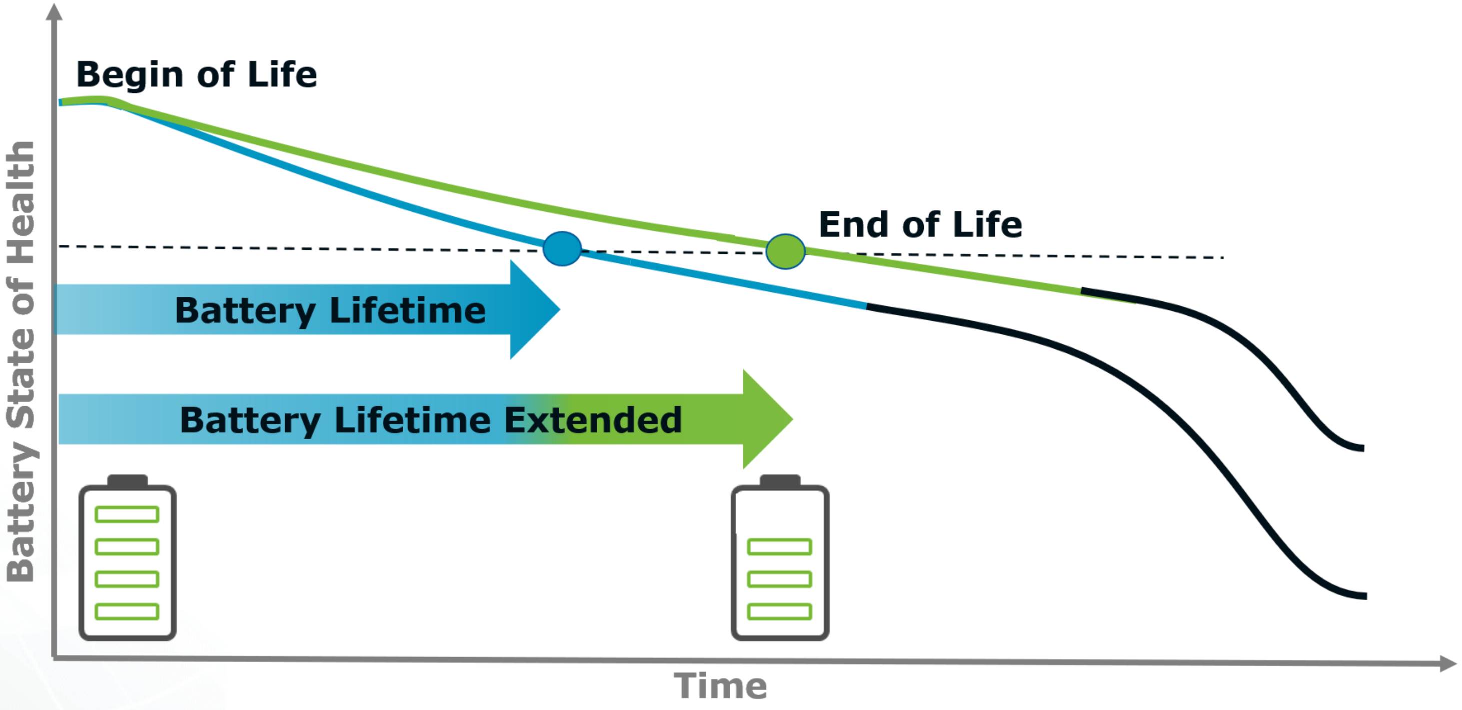
# The Lifetime of a Battery

- Battery is key component & most expensive part in xEV
- Battery ages over time depending on driver usage, decreasing electric range, performance and safety

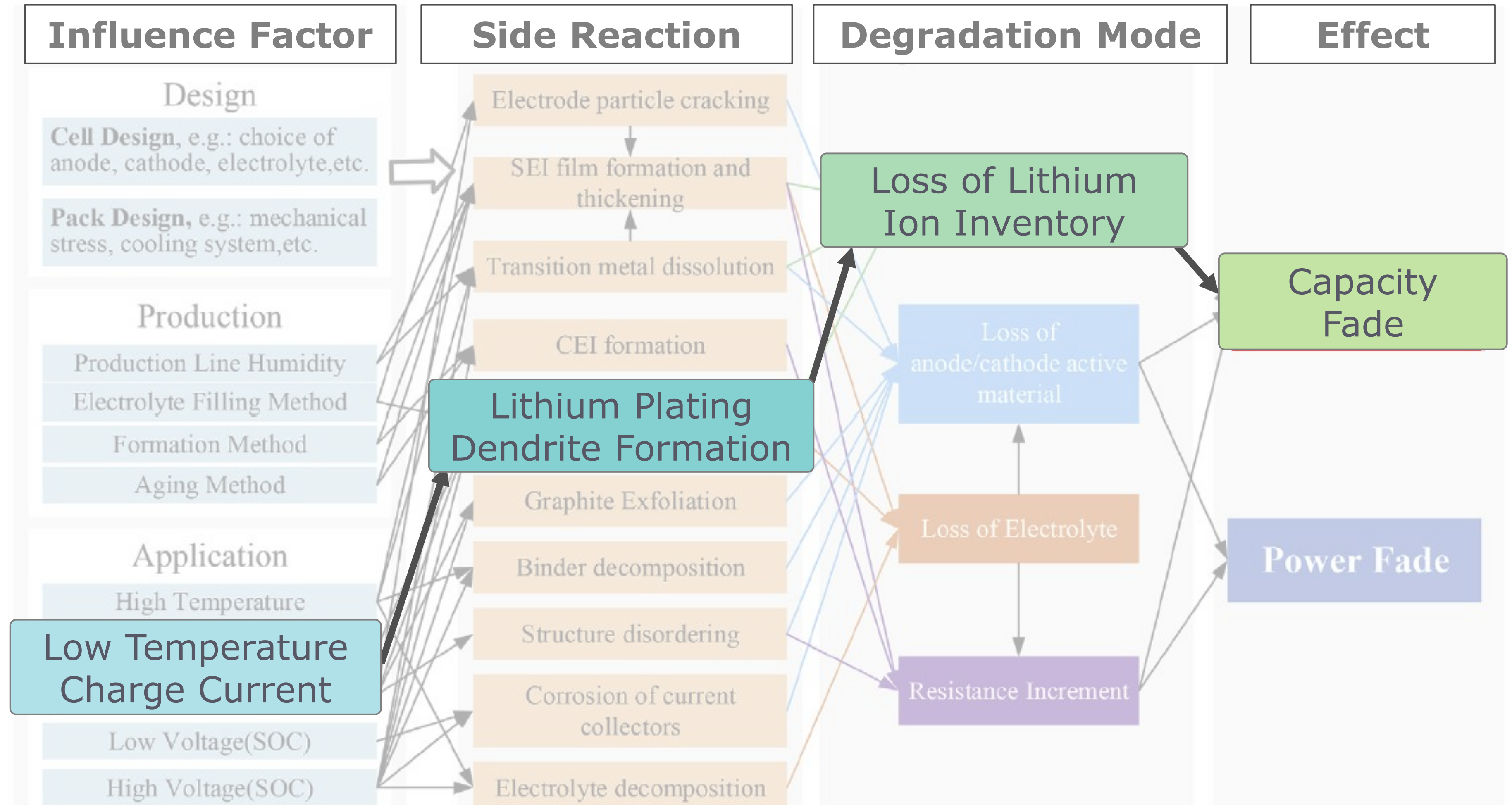


**30%**
**Battery Cost**
**as Part of Vehicle Net Cost**



# Why Do Lithium-Ion Batteries Die?




Adapted from Han, Xuebing, et al. *eTransportation* 1 (2019): 100005

# Ageing Influences

Ageing has various influence factors

- some can be controlled
- some can't

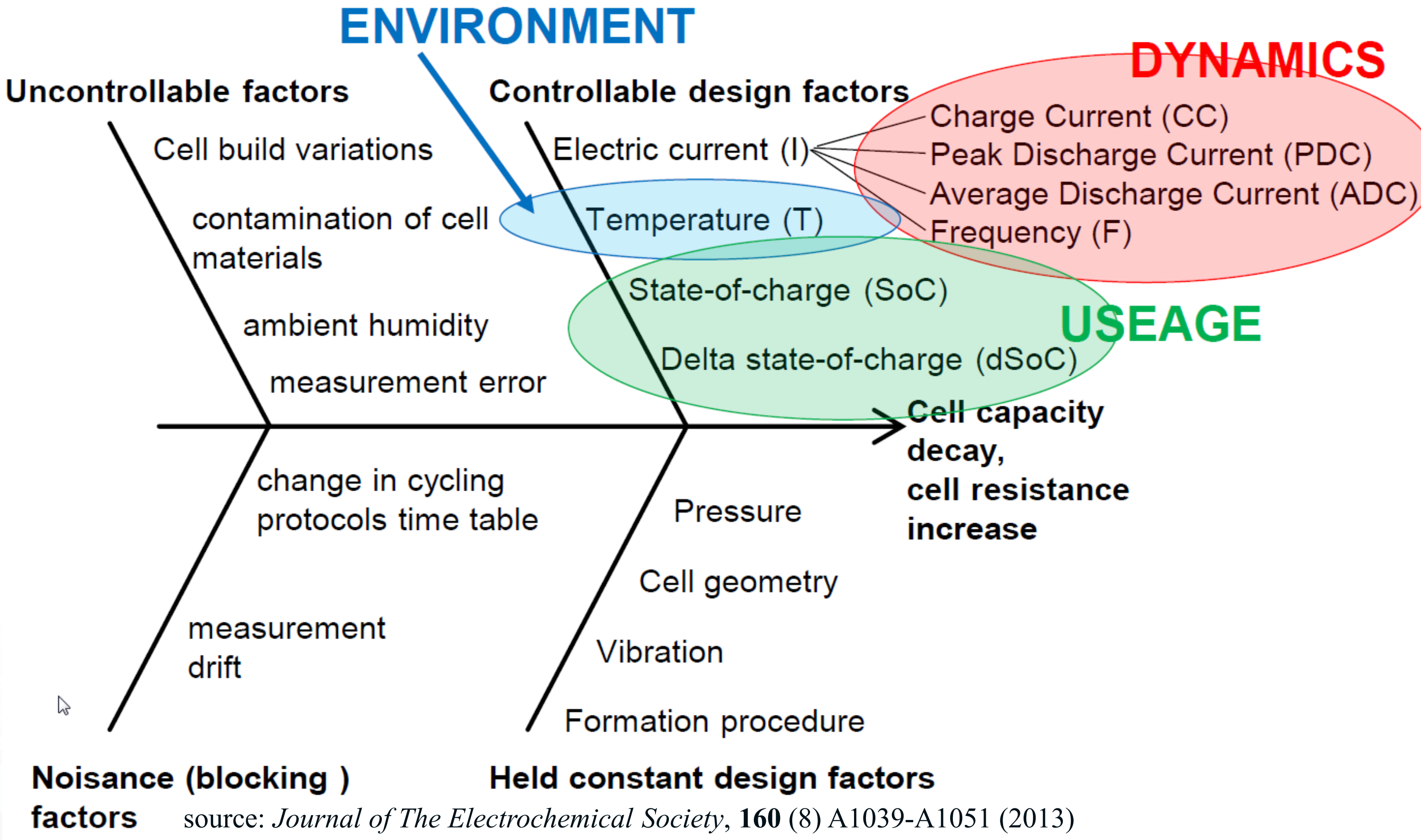
The factors also influence each other

**T, SoC and dSoC** are long-term influences

they can be addressed in the usage profile and with the BTMS (Battery Thermal Management System)

**Current**-related influences effect short-term

they can be addressed in the BMS operation strategy (Battery Management System)




source: *Journal of The Electrochemical Society*, **160** (8) A1039-A1051 (2013)

# Battery Temperature

## Trade-off between Safety, Performance & Lifetime

Battery Temperature

-20°C | 0°C | 20°C | 40°C | 60°C | 80°C

Little power

High internal resistance

High degradation
at high currents & low
temperatures due to
lithium plating

Low efficiency

High power

Low internal resistance

Ideal battery temperature

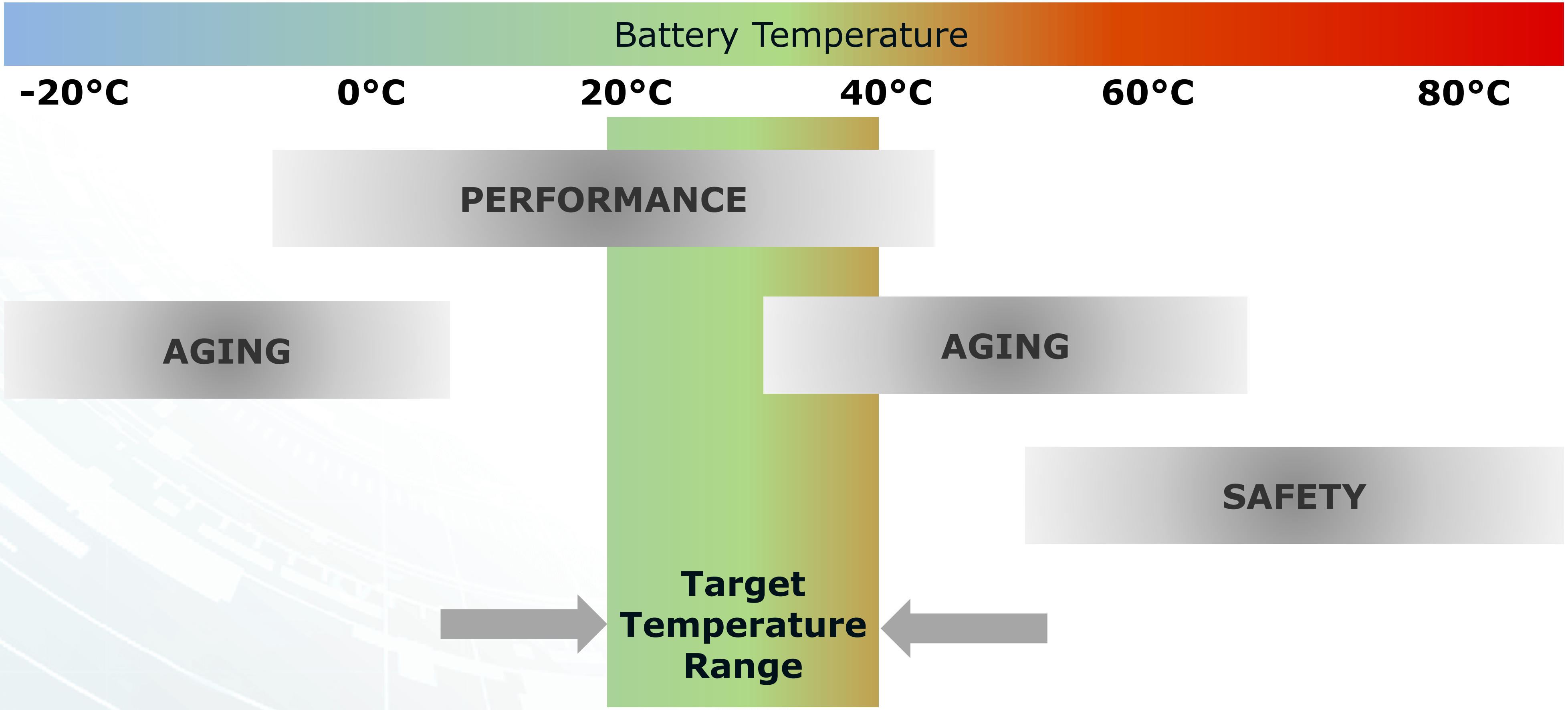
High efficiency

High battery degradation

Risk for thermal runaway

High efficiency

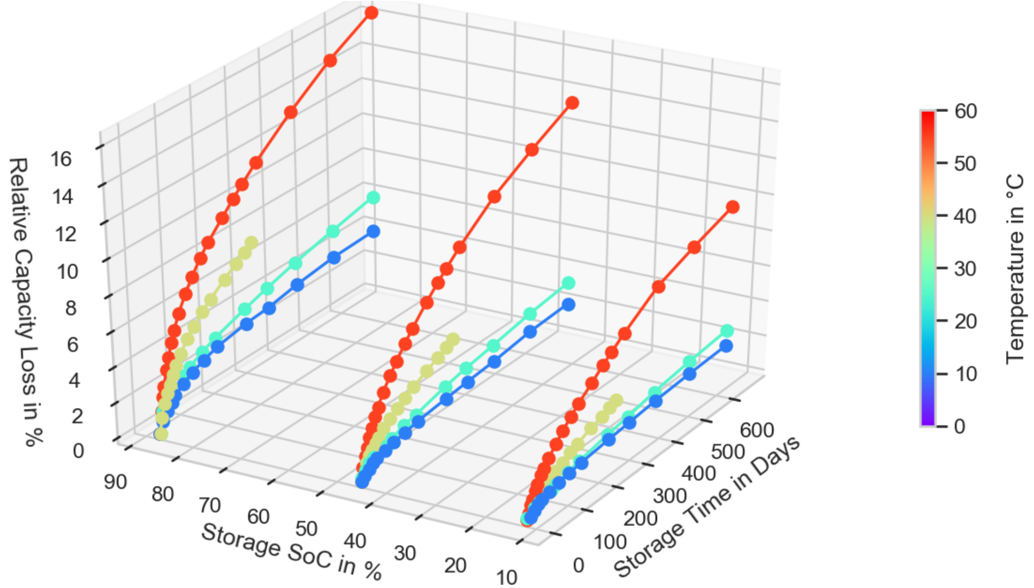
# Battery Temperature
## Trade-off between Safety, Performance & Lifetime



# Effect of Temperature on Cell Aging

- Temperature is one of the most important drivers for cell degradation
- Chemical side reaction rate increases with temperature
- Charging at very low temperature can lead to lithium plating

→ Ensuring battery in temperature interval (~ 15-35°C) is key to improving battery life




*From "Aging of Lithium-Ion Batteries in Electric Vehicles", Peter Keil, 2017*

# How to Increase Battery Life

- **Cell Design and Chemistry**

  Material degradation, chemical reactions

- **Battery Pack Design**

  Cooling system, electrical connection, mechanical load

- **Environment**

  Road profile, climatic condition

- **Vehicle Operation Mode**

  Driving, parking, charging

**Significant impact on battery aging from in-use phase**



# Battery Testing, Simulation & Lifetime Prediction

# How can Battery Aging be Modeled?

**AVL is working on different modeling approaches:**

TEST DATA AMOUNT

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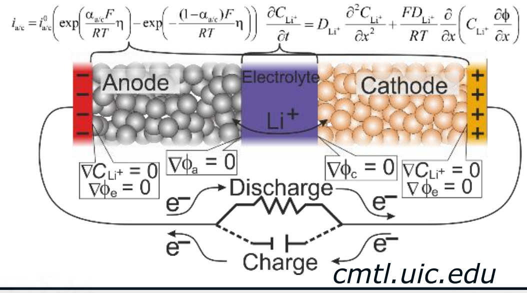
### Physics - Based Model

- Physical, chemical, biological laws
- No aging experiments
- Electro-chemical modeling

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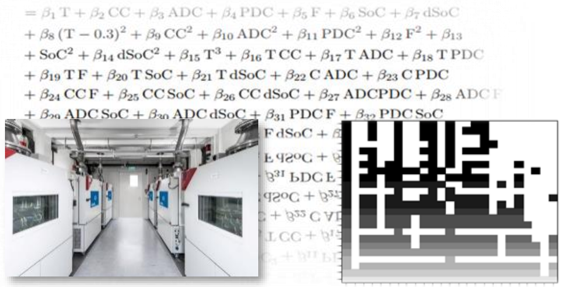
- Based on aging experiments
- Statistical methods



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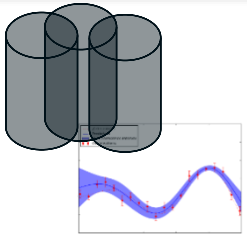


$$y = X\beta + Zu + \epsilon$$

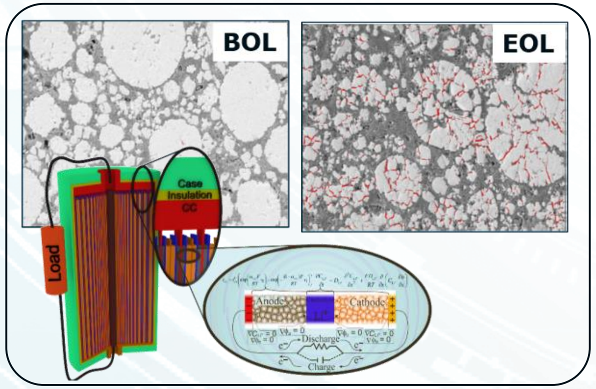
ACCURACY

COMPLEXITY

# Battery Testing and Vehicle Fleet Data

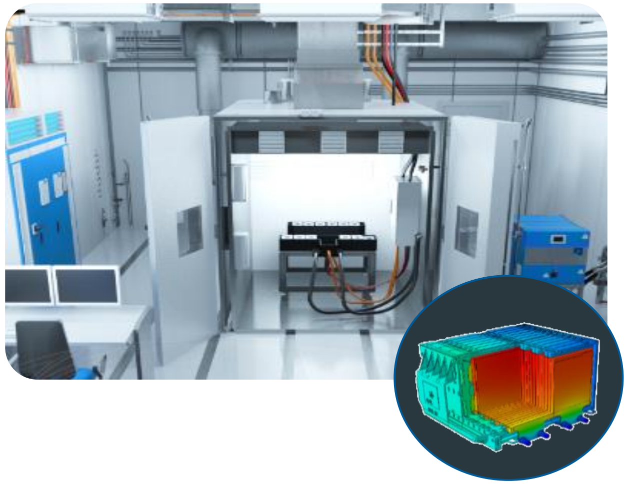
**AVL is using different testing approaches as well as fleet data to parametrize models**

**Battery Sub Cell Testing / Analysis**




**Battery Cell Testing**

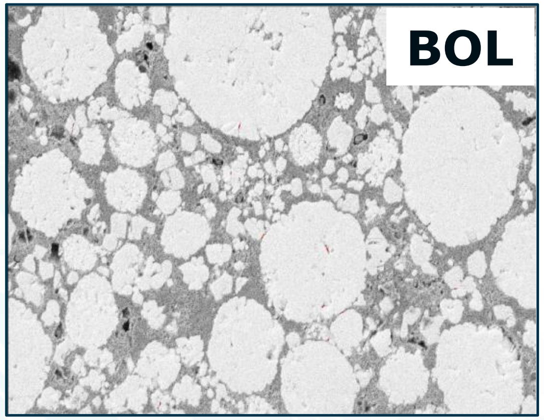
**Battery Module/Pack Testing**

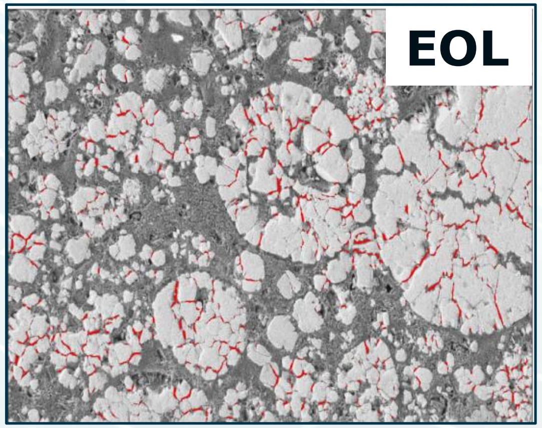


**xEV Testing & In-Use**

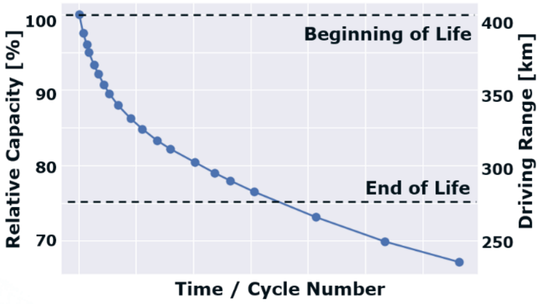
# Battery Testing and Vehicle Fleet Data

## Post-Mortem Analysis

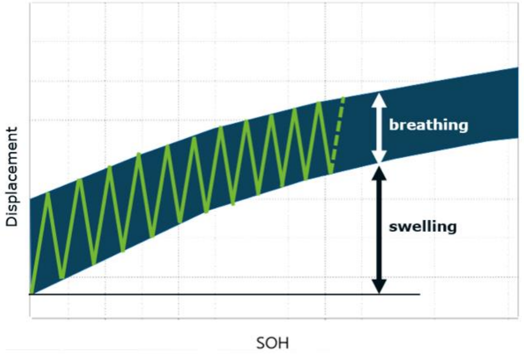


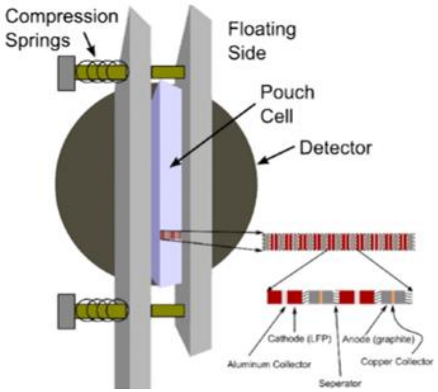




## Capacity, Resistance, Impedance in RPT

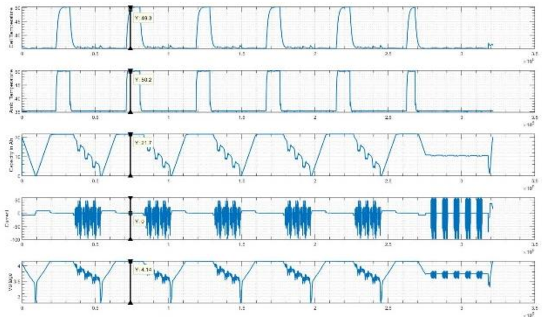



## Cell Swelling, Mechanical Pressure




## Vehicle Data Logging

# How can Battery Aging be Modeled?

**AVL is working on different modeling approaches:**

TEST DATA AMOUNT

PHYSICAL CHEMICAL DETAILS

### Physics - Based Model

- Physical, chemical, biological laws
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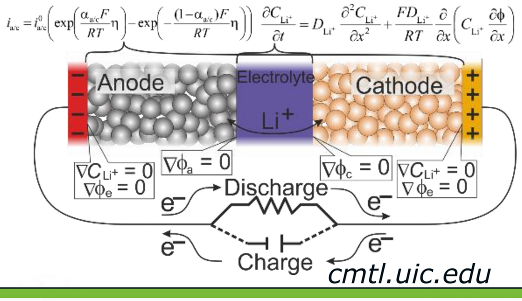
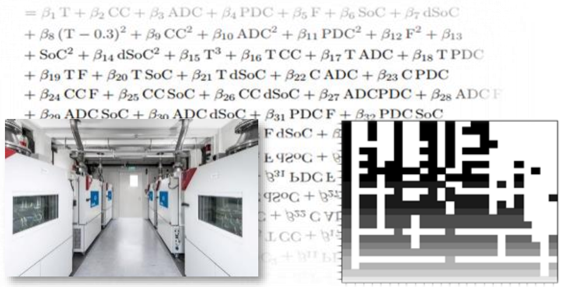
- Electro-chemical modeling




### Half - Empirical Model

- Half-empirical data driven model
- Based on aging experiments
- Statistical methods



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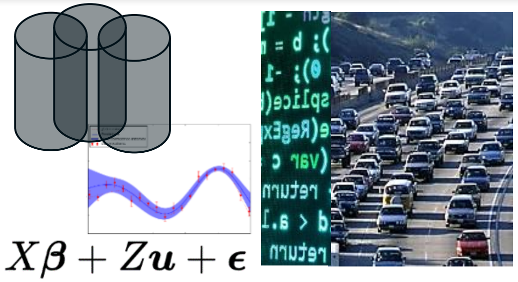


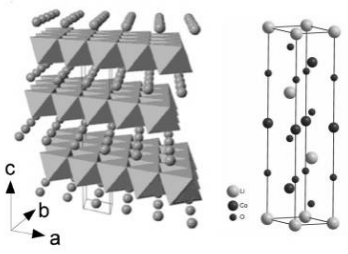
$$y = X\beta + Zu + \epsilon$$

ACCURACY

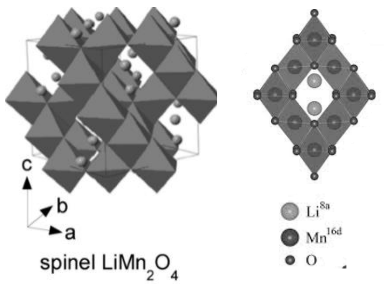
COMPLEXITY

# Physics-Based Model

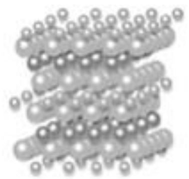
## Electro-chemical Model, Sensitivity Study




layered $LiCoO_2$




spinel $LiMn_2O_4$



Layer structure (NMC*)
Lithium: Metal: Oxygen:

### LCO
### **L**ithium **C**obalt **O**xide

| Material parameters | | | | Geometric parameters | | | | Transport parameters | | |
|---|---|---|---|---|---|---|---|---|---|---|
| film resistance | A | | C | Thickness | A | S | C | solid diffusion coefficient | A | C |
| columbic capacity of material | A | | C | Thickness of current collector | A | | C | conductivity of matrix | A | C |
| capacitance | A | | C | initial stoichio-metric parameter | A | | C | rate constant for bulk reaction | A | C |
| density of insertion material | A | S | C | radius of particles | A | | C | rate constant side reaction 1 | A | C |
| density of current collector | A | | C | volume fraction of electrolyte | A | S | C | rate constant side reaction 2 | A | C |
| density of electrolyte | A | S | C | volume fraction of polymer | A | S | C | rate constant side reaction 3 | A | C |
| density of polymer material | A | S | C | volume fraction of inert filler | A | | C | *+ other parameters* | | |
| density of inert filler | A | S | C | volume fraction of active material | A | S | C | | | |

### LMO
### **L**ithium **M**anganese **O**xide

| Material parameters | | | | Geometric parameters | | | | Transport parameters | | |
|---|---|---|---|---|---|---|---|---|---|---|
| film resistance | A | | C | Thickness | A | S | C | solid diffusion coefficient | A | C |
| columbic capacity of material | A | | C | Thickness of current collector | A | | C | conductivity of matrix | A | C |
| capacitance | A | | C | initial stoichiometric p. | A | | C | rate constant for bulk reaction | A | C |
| density of insertion material | A | S | C | radius of particles | A | | C | rate constant side reaction 1 | A | C |
| density of current collector | A | | C | volume fraction of electrolyte | A | S | C | rate constant side reaction 2 | A | C |
| density of electrolyte | A | S | C | volume fraction of polymer | A | S | C | rate constant side reaction 3 | A | C |
| density of polymer material | A | S | C | volume fraction of inert filler | A | | C | *+ other parameters* | | |
| density of inert filler | A | S | C | volume fraction of act.material | A | S | C | | | |

### NMC
### Lithium **N**ickel **M**anganese **C**obalt Oxide

| Material parameters | | | | Geometric parameters | | | | Transport parameters | | |
|---|---|---|---|---|---|---|---|---|---|---|
| film resistance | A | | C | Thickness | A | S | C | solid diffusion coefficient | A | C |
| columbic capacity of material | A | | C | Thickness of current collector | A | | C | conductivity of matrix | A | C |
| capacitance | A | | C | initial stoichiometric p. | A | | C | rate constant for bulk reaction | A | C |
| density of insertion material | A | S | C | radius of particles | A | | C | rate constant side reaction 1 | A | C |
| density of current collector | A | | C | volume fraction of electrolyte | A | S | C | rate constant side reaction 2 | A | C |
| density of electrolyte | A | S | C | volume fraction of polymer | A | S | C | rate constant side reaction 3 | A | C |
| density of polymer material | A | S | C | volume fraction of inert filler | A | | C | *+ other parameters* | | |
| density of inert filler | A | S | C | volume fraction of act.material | A | S | C | | | |

| Very important | Important | Might be important | Not important |
|---|---|---|---|

Investigate sub-cell structures, materials, design on battery cell aging

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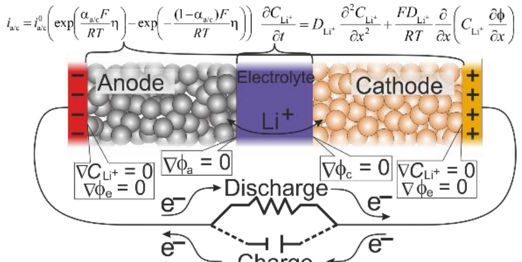


cmtl.uic.edu

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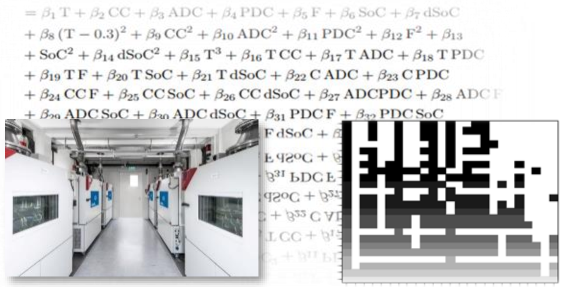

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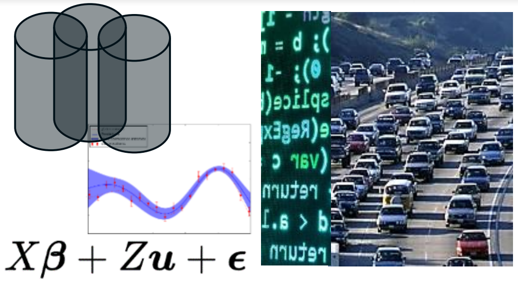


$$y = X\beta + Zu + \epsilon$$

ACCURACY

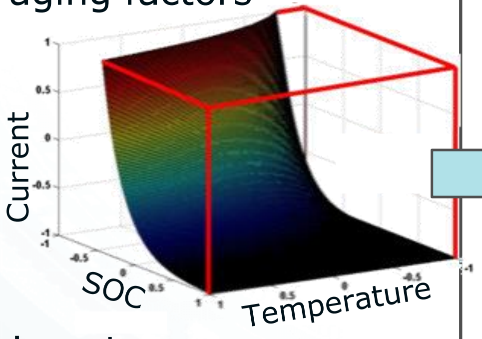
COMPLEXITY

# Half-Empirical Model
## Statistical Lifetime Prediction

### I. Cell testing

- Design of Experiment **DOE**
- On basis of aging factors

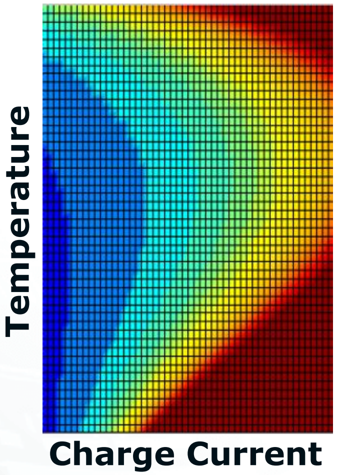
T, SOC, ΔSOC, CC, ADC, PDC

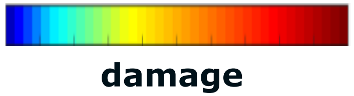



- Aging experiments
- 30-90 tests, 6 months to 2 years

### II. Mathematics & Statistics

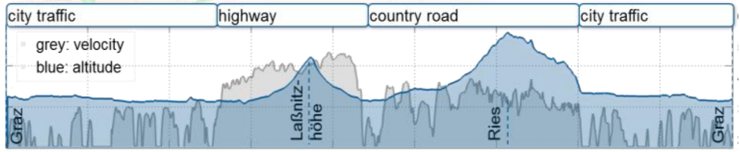
- Input: **Cell tests**, capacity fade, resistance increase, impedance change
- Output: Mathematical **model** for time until EOL & damage




$$t_{EOL} = \sum_j \beta_j x_j$$
$$= \beta_1 T + \beta_2 CC + \beta_3 ADC + \beta_4 PDC$$
$$+ \beta_8 (T - 0.3)^2 + \beta_9 CC^2 + \beta_{10} ADC^2$$
$$+ SoC^2 + \beta_{14} dSoC^2 + \beta_{15} T^3 + \beta_{16} T$$
$$+ \beta_{19} T F + \beta_{20} T SoC + \beta_{21} T dSoC +$$
$$+ \beta_{24} CC F + \beta_{25} CC SoC + \beta_{26} CC d$$
$$+ \beta_{29} ADC SoC + \beta_{30} ADC dSoC + \beta$$
$$+ \beta_{33} PDC dSoC + \beta_{34} F SoC + \beta_{35} F$$

### III. Lifetime Prediction


Input: driving profile, battery temperature, statistical model

Output: **Lifetime**, distance until EOL, Detect parts of a driving profile that constitute the largest **damage**

**Optimization** of **driving, cooling, charging** strategy

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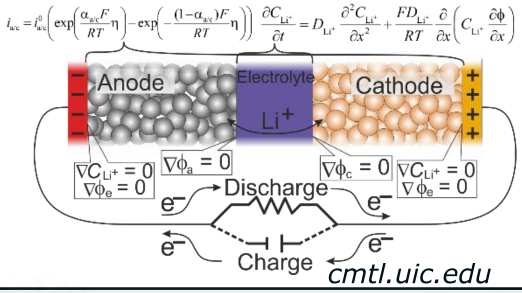


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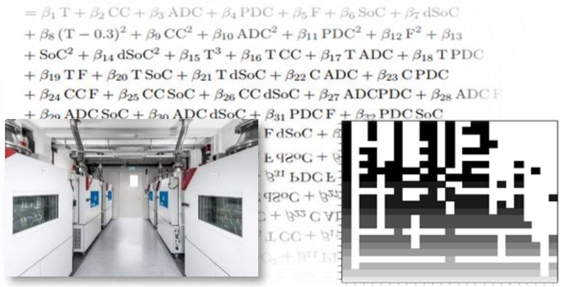

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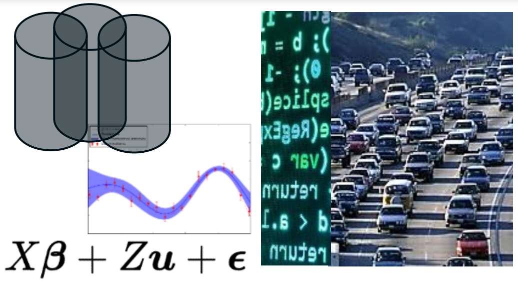
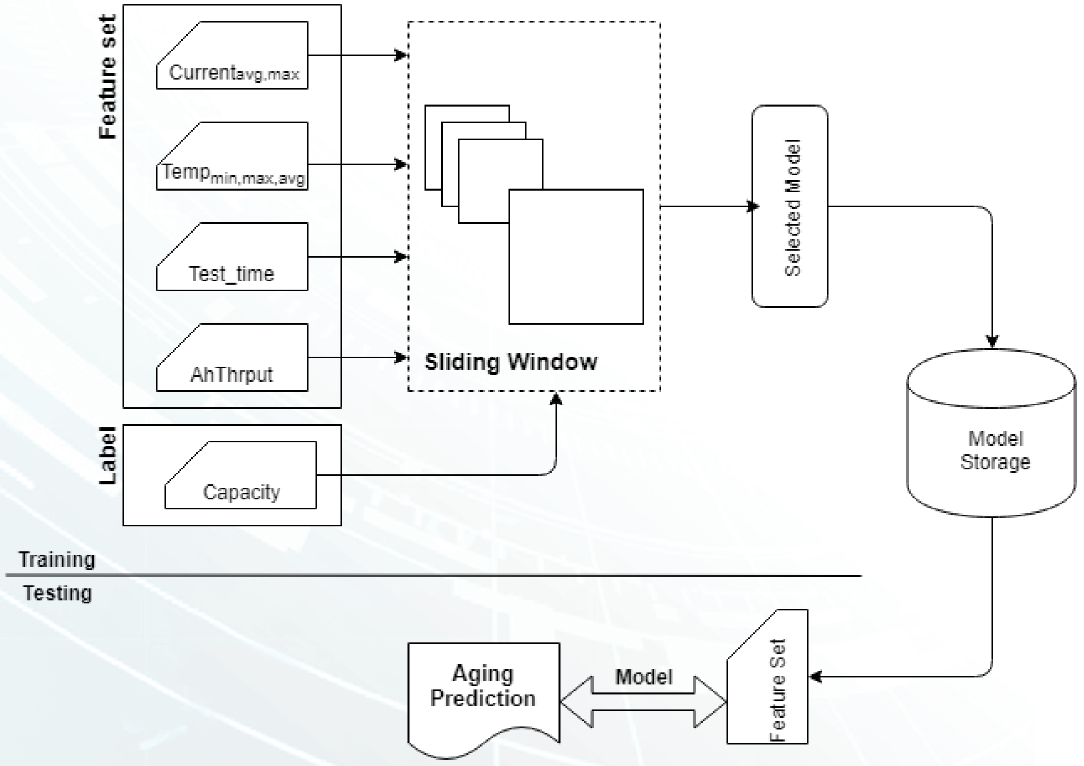
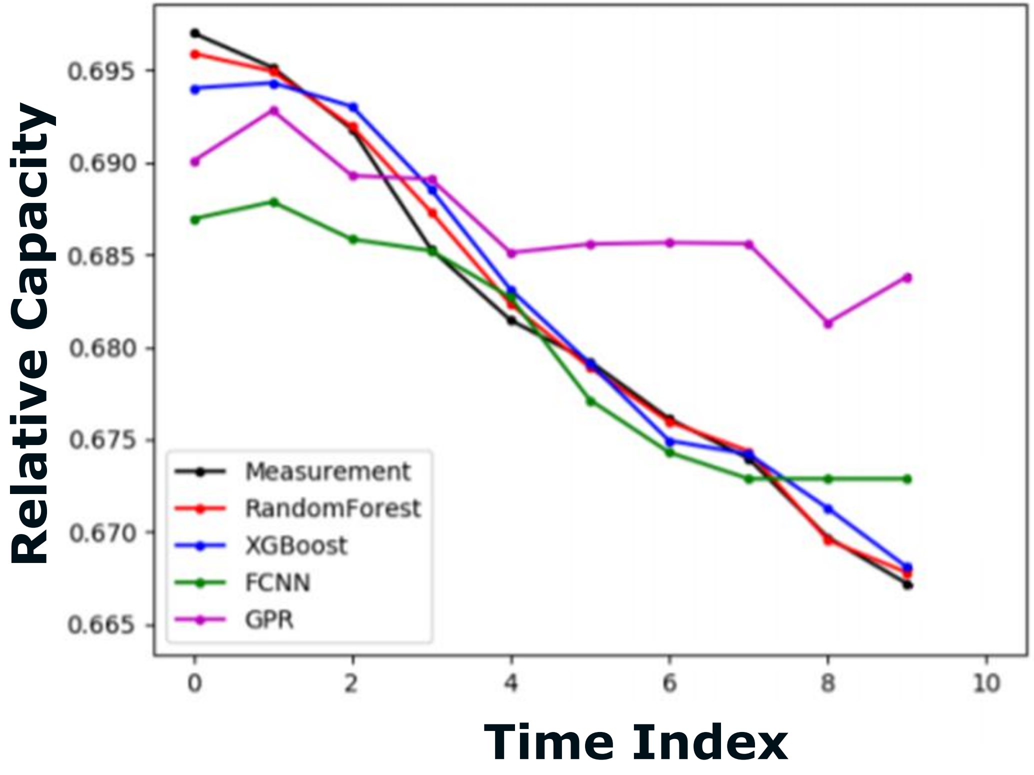


$$y = X\beta + Zu + \epsilon$$

# Data-Driven Models
## Machine Learning Methodologies

- NMC battery type
- ~80 Cell measurement data from 13-month experiments.
- Random Forest, XGBoost, FCNN, GPR methods



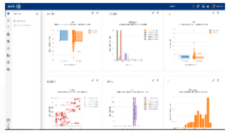
# In-use Fleet Monitoring to Extend Battery Life

# AVL Solution

## Extending Battery Life of Electric Vehicle Fleets

### Fleet Monitoring & Analytics Platform

Monitor battery condition
Analyze data



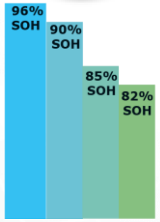
### Digital Twin

Real-time simulation based on vehicle signals

### Data Collection

Secure data transfer

### Battery Lifetime Methodology




KPI Generation
Battery State of Health
Battery Degradation
Battery Remaining Value

- ✓ Improve **battery value** & profitability
- ✓ Optimize **charging strategy**
- ✓ Increase **workshop efficiency**
- ✓ Reduce **total cost of ownership**
- ✓ Optimize **warranty** claim process
- ✓ Cost-efficient battery **replacements**

# Data Collection & Fleet Monitoring

Fleet **Data Collection**

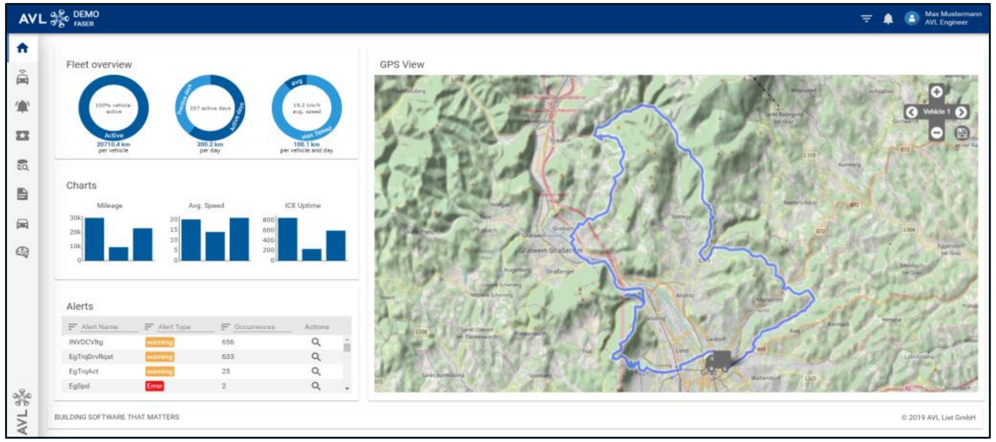
GPS, BMS data (T, I, U, SOC), environmental temperature, on-board data

**Data Integration** into Analytics Platform

Data import, quality check, visualization, report generation

**Data Analysis**

Driving behavior, battery usage, charging strategy, statistics

# Digital Twin & Battery Lifetime Methodology

**Digital Twin** of Vehicle / Battery

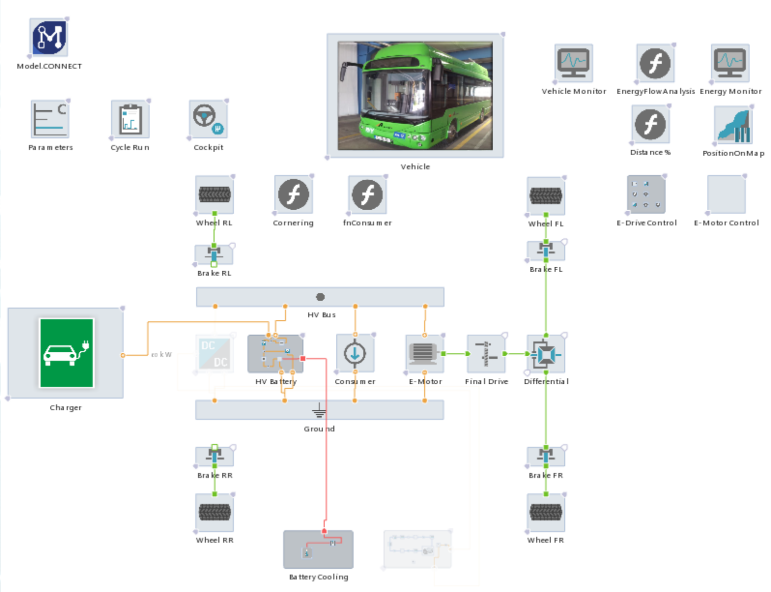
Model parametrization from component and/or fleet data; real-time digital twin

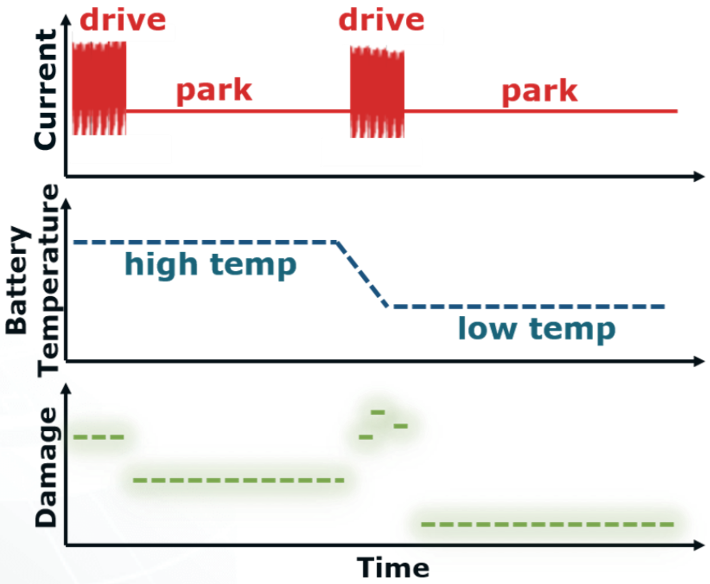
Battery **Condition Monitoring**

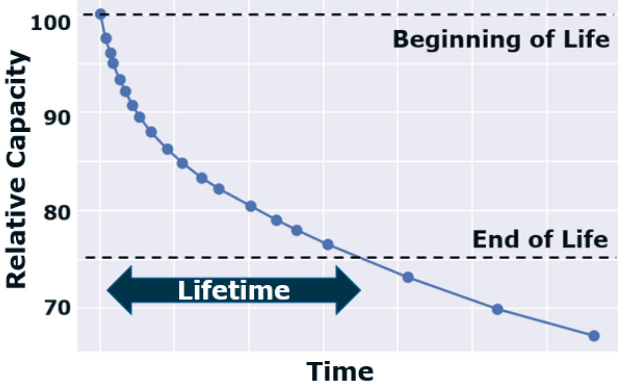
Battery damage, optimize routes & charging strategy, predictive maintenance

Battery **Lifetime Prediction**

Based on customer usage predict battery end of life, battery remaining value

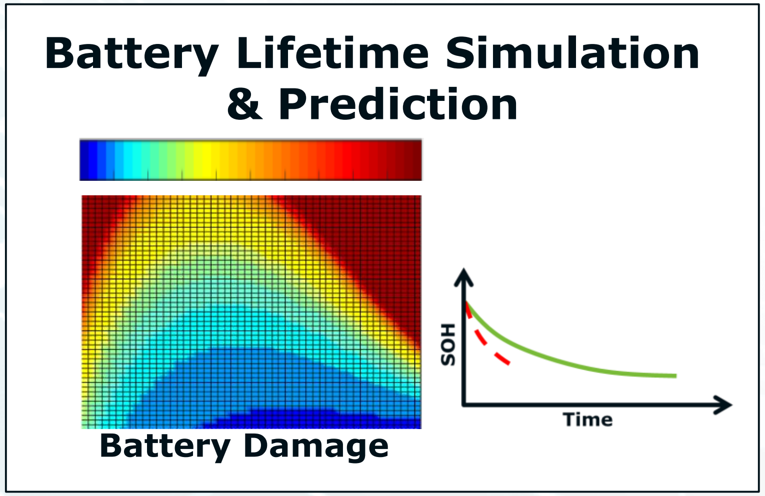


# Project References & Key Message

# Customer Reference - Premium OEM
## Project: Battery Lifetime Simulation


### Battery Lifetime Simulation

**Project description**

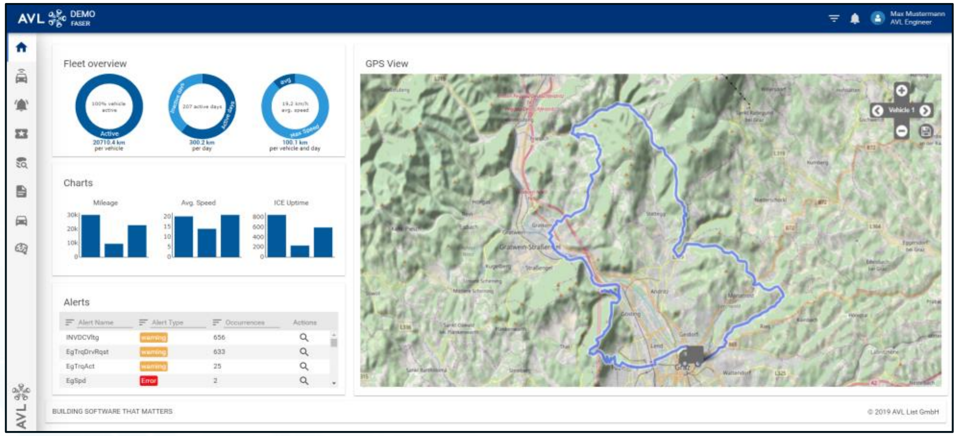
Battery Lifetime Prediction for Customer Usage Driving Profiles

- Battery cell aging testing
- Battery cell aging model parametrization
- Customer driving profile generation
- Battery lifetime simulation and prediction for different customer profiles

**Targets / AVL Tasks**

- Design of experiment DoE method for battery tests
- Execution of battery testing and data evaluation
- Creation, testing and validation of battery lifetime model
- Tool generation to set up customized driving profiles
- Comparison of predicted battery lifetime for various customer profiles

# Customer Reference - Premium OEM
## Project: Real-time Battery Data Monitoring of E-Scooter Fleet





### E-Scooter Fleet Monitoring

**Project description**

E-Scooter Fleet Testing & Monitoring of Battery Condition

- E-scooter fleet test plan
- 24/7 real-time monitoring of entire battery management system, GPS and ambient conditions for 2 years
- Fleet data analysis

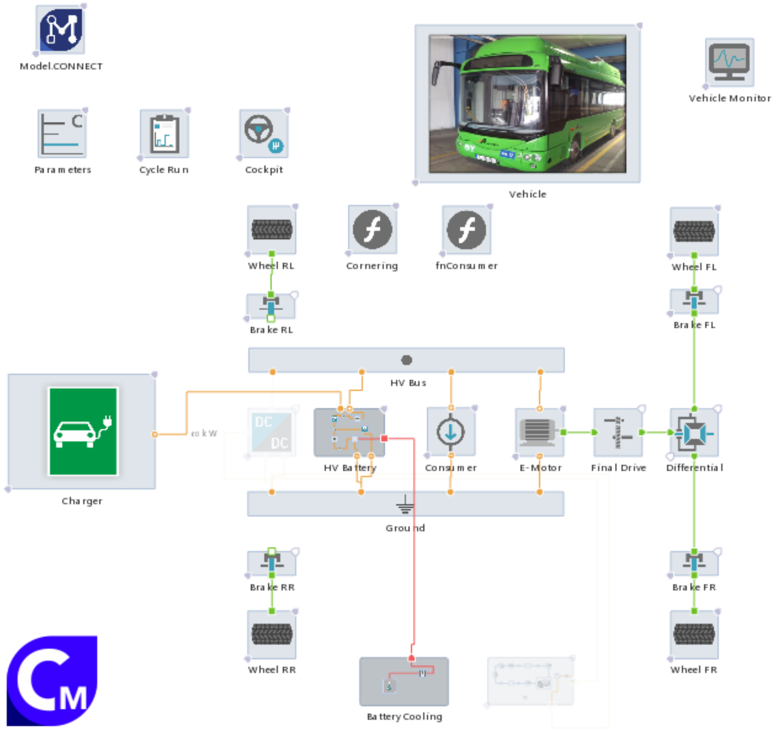
**Targets / AVL Tasks**

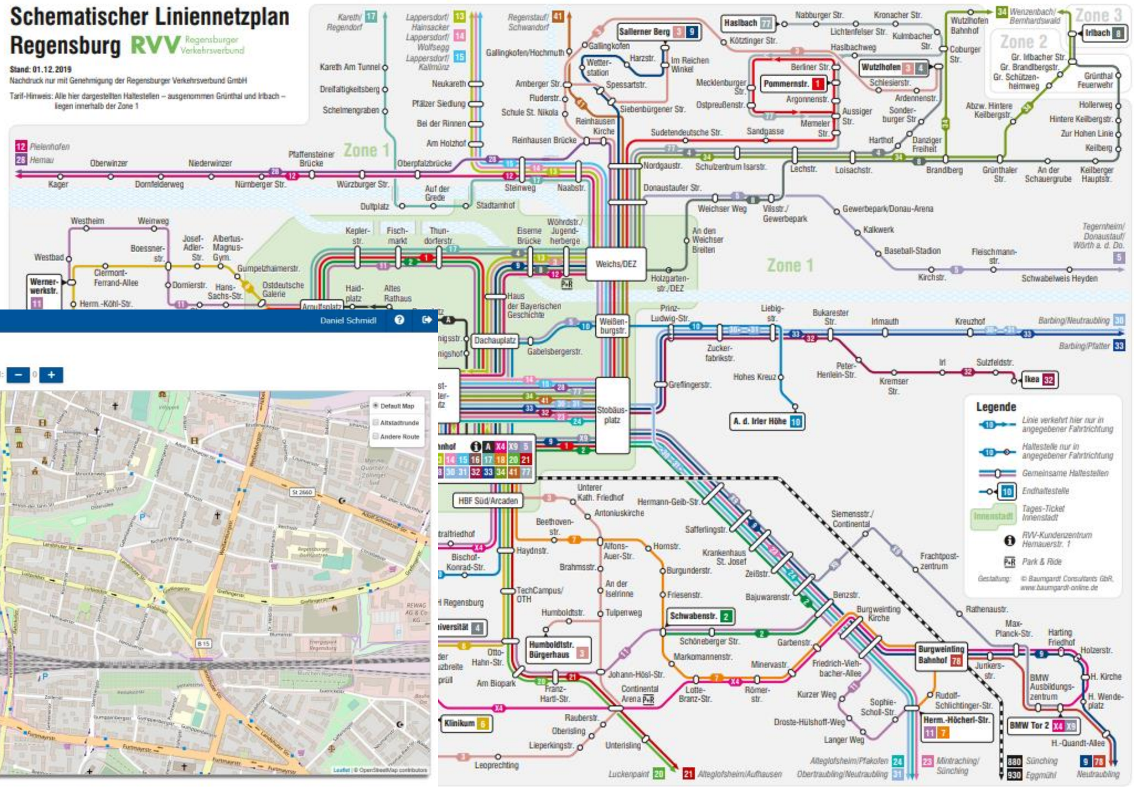
- Installation of data logger on E-Scooter fleet
- Secure data transfer to AVL fleet analytics platform
- Customized data analysis on platform
- Data observation and analysis for 2 years

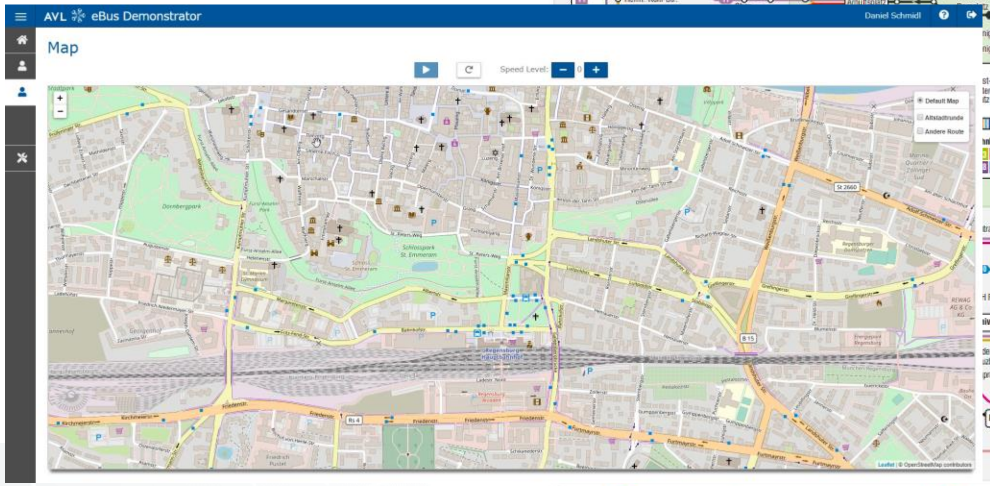
# AVL Methodology References

## E-Bus Fleet Management

- Virtual electric bus parametrized from real E-Bus data and driven in virtual environment
- Several routes in City of Regensburg, Germany
- Optimization of operation strategy, planning of charging infrastructure as an input e.g. for cities.

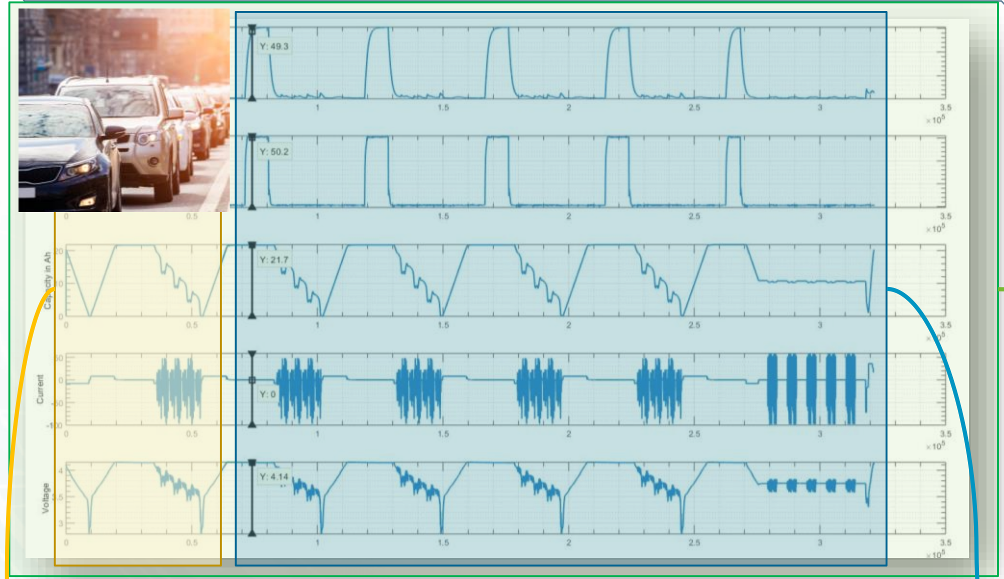


# AVL Methodology References

## Aging Model Parameterization from Fleet Data

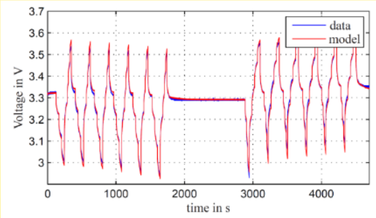


Ageing Model Identification purely done from fleet data measurements

- No additional testing effort for BOL/EOL system characterization
- Empirical ageing modelling approach for generic use-case
- Improved remaining lifetime prediction using identified ageing model

Nonlinear system identification using multiple model networks, using Beginning of Life measurements from fleet

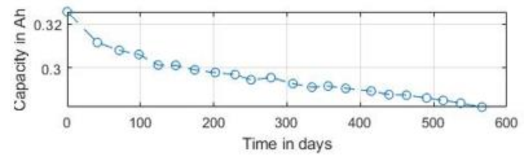

Global model based on weighted aggregation of linear U/I models




Combined SOC/SOH estimation using U/I model to identify capacity and resistance change over lifetime

U, I, T → **SOC/SOH Observer** → SOC, Ah, R

Observer output is used to train the ageing model



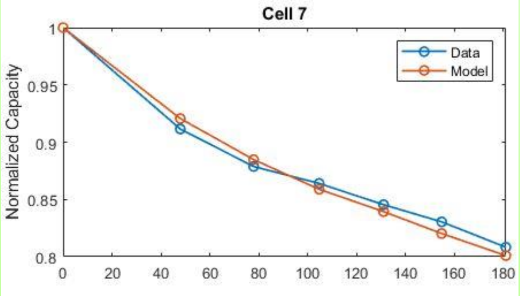

Incremental Ageing Model formulation

$$\Delta\hat{Q} = f(X|\theta)$$

$$\hat{Q}_k = \sum_{i=1}^{k} \Delta\hat{Q}_i$$

and identification by minimizing the error

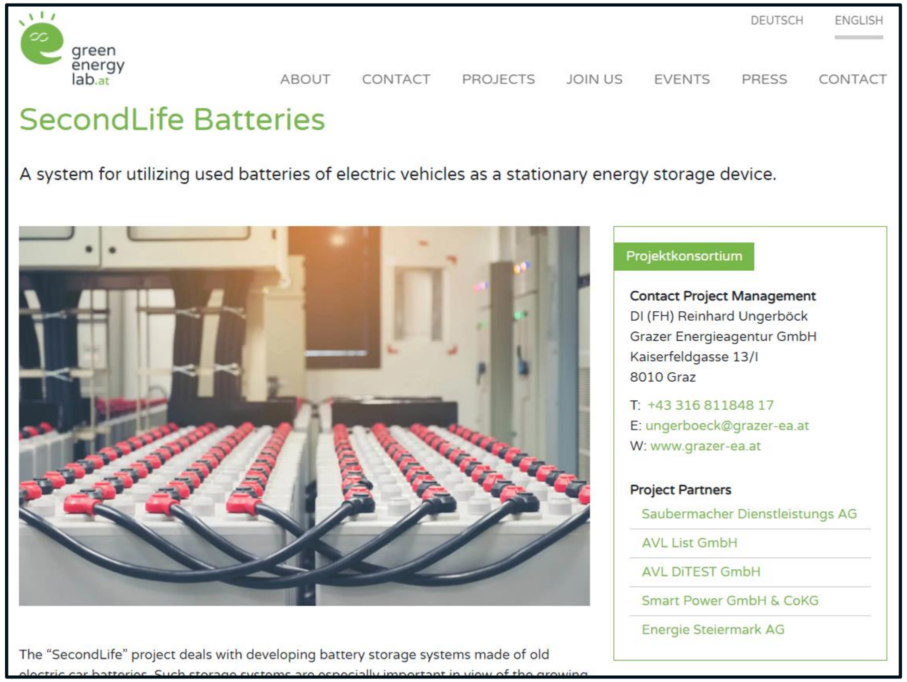
$$\min_{\theta} \|\Delta Q - X\theta\|_1 + \lambda\|\theta\|_1$$



# AVL Methodology Reference
## Remaining Battery Value

AVL

- AVL is part of research project "Second Life Batteries"
- One focus area is the development of a tool for the complete analysis of the **remaining value** of a battery after usage in the vehicle




**BATTERY PACK after USAGE in VEHICLE**

**BATTERY REMAINING VALUE**

REUSE
- **Historical battery data**
- **SOH (>80%), failure probability**
- **Raw material**
- **Pack disassembly ability to module level**

REPURPOSING
- **Historical battery data**
- **SOH (<80%-e.g.60%), failure probability**
- **Raw Material**
- **Pack disassembly ability to module level**

RECYCLING
- **Raw Material**
- **Pack disassembly ability to module level**

https://greenenergylab.at/en/projects/secondlife-batteries/

# Extending Battery Life of Electric Vehicle Fleets

AVL provides technology to

**INCREASE BATTERY LIFE**

of electric vehicle fleets

**HOW**

Real-time battery data collection in the field

Battery aging testing, simulation, lifetime prediction

Customized fleet analytics platform & recommendations

**WHY**

Improve battery value & profitability

Enable operation & charging strategy optimization

Save time, cost with predictive maintenance

# Contact

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# Thank You

www.avl.com