

The Impact of AI on EV Battery Applications

Dr. Gerald Sammer

AVL List GmbH (Headquarters, Integrated and Open Development Platform)

Impact of AI on Engineering

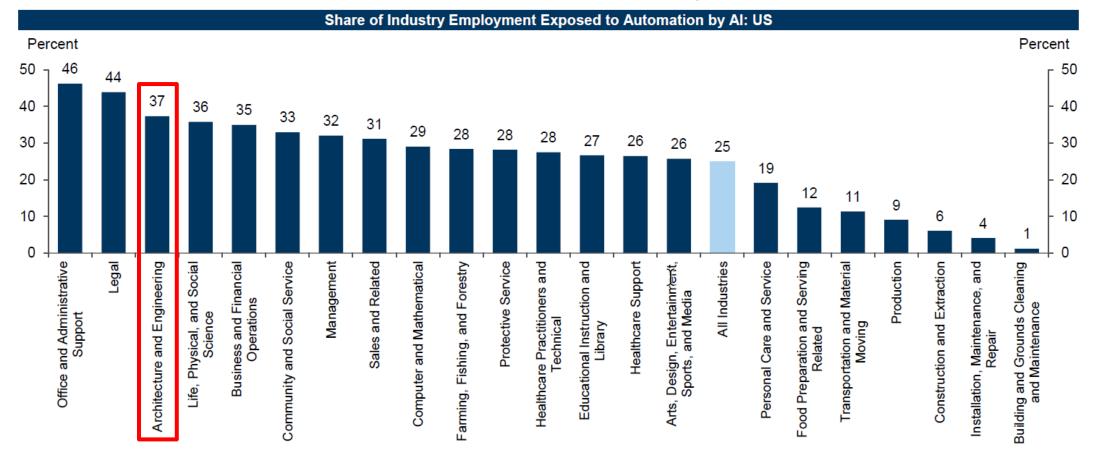


Exhibit 5: One-Fourth of Current Work Tasks Could Be Automated by AI in the US and Europe

Source: Goldman & Sachs

Today's Presenter



Dr. Gerald Sammer

Principal Business Field Owner, Battery & BEV.

M.Sc. in computer science and a Ph.D. in economics.

30+ years professional experience in computer science.

25+ years experience in automotive technologies.

AVL representative in the technical steering committee of the ASAM standardization group for automotive standards.

Public

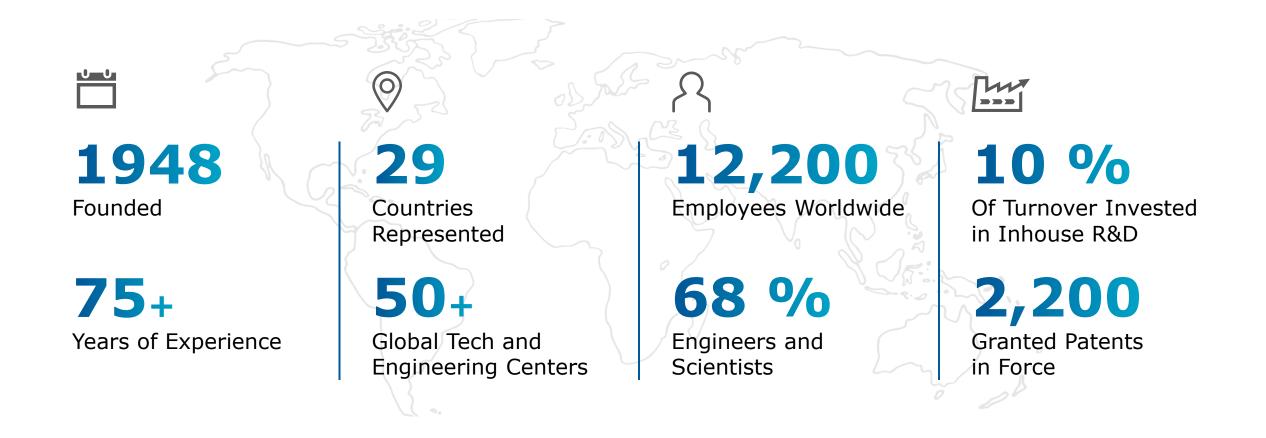
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About Us

At AVL, we are one of the world's leading mobility technology companies for development, simulation and testing in the automotive industry, and in other sectors such as rail, marine, and energy. Based on extensive in-house research activities, we deliver concepts, technology solutions, methodologies, and development tools for a greener, safer, better world of mobility and beyond.





AVL Software, AI and Data Intelligence

Application Know-How

Propulsion systems

Next generation vehicles

Automated and connected mobility

Electrification of functions

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Embedded Software Development

- E/E platforms and integration
- Advanced Driver Assistance Systems (ADAS) and Automated Driving (AD)
- Functional safety and cybersecurity
- ASPICE compliant development

Cloud Software Development

- Customized data pipelines
- Scalable analytics
- Automated CI/CD pipelines

Simulation, Test Software and Methodology

- Design and simulation solutions
- Functional testing (MiL, HiL, SiL)
- Lab and process management
- Test automation and virtualization

Artificial Intelligence Solutions

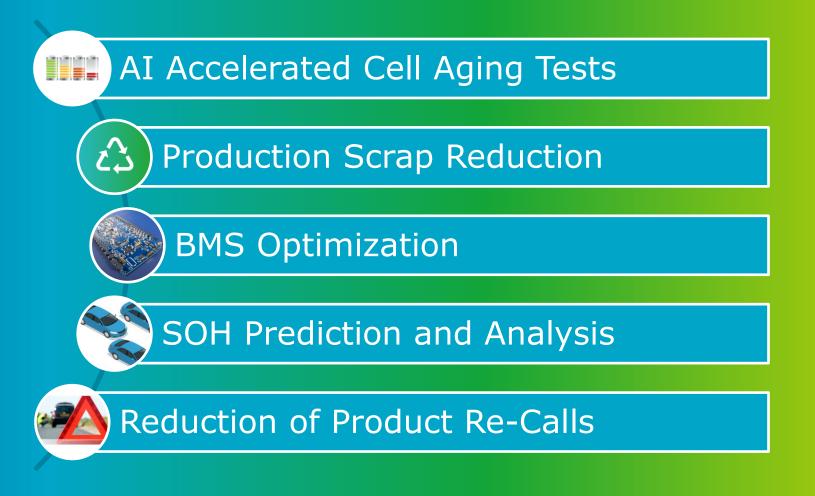
- LLM utilization for Requirements
- Data analytics for development and fleet data
- Anomaly Detection
- Failure prediction
- Root Cause Analysis

All software solutions contain our innovation, engineering legacy and application insight.



AGENDA

Dr. Gerald Sammer

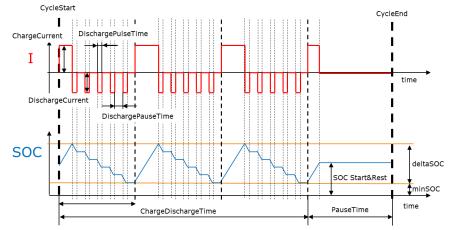


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AI Accelerated Cell Aging Tests

Influencing Factors on Cell Ageing

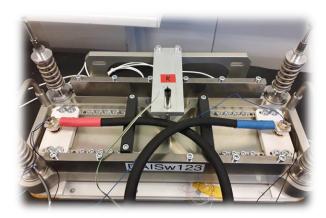




Temperature



Calendaric aging / resting Resting time length Resting time frequency Resting SOC level **Mechanical Stress**



Discharge Current Charge Current DeltaSOC SOC Min / Max



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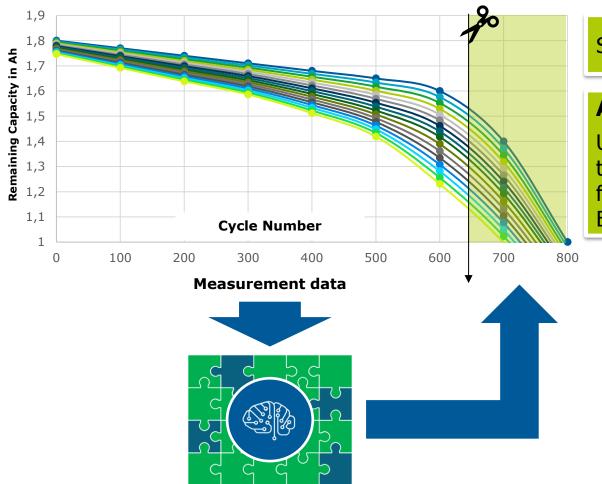
And each parameter variation takes months to measure!

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AI Accelerated Cell Aging Tests

Target: Capacity loss until EOL (e.g. 80% SOH)



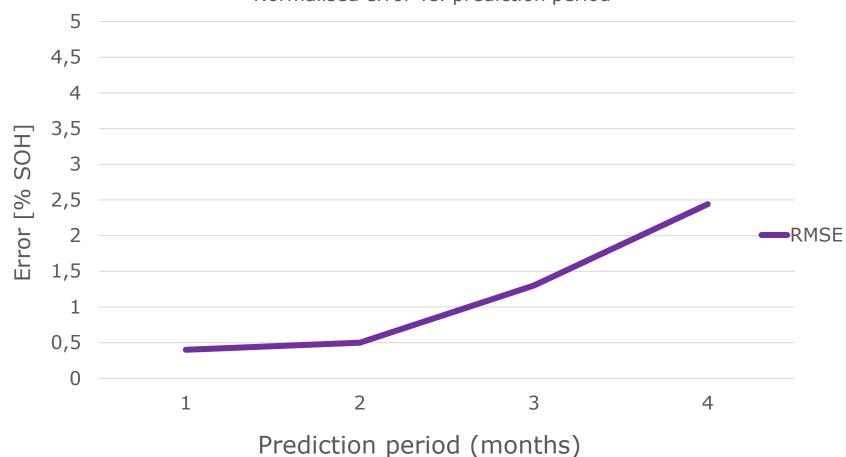
Standard: 8-12 months cell cycling in the lab

AI based method:

Use the recorded measurement data during testing to train a model that learns the correlation between fast aging cells and slow aging cells to predict the EOL behaviour of the slow aging cells.

AI Accelerated Cell Aging Tests

Accuracy: 1-4 months reduction based on 12 months test campaign



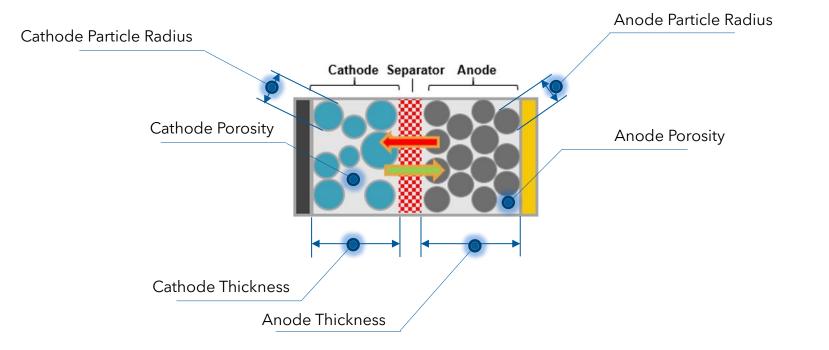
Normalised error vs. prediction period

Error rate of predicted aging values with shortened test time

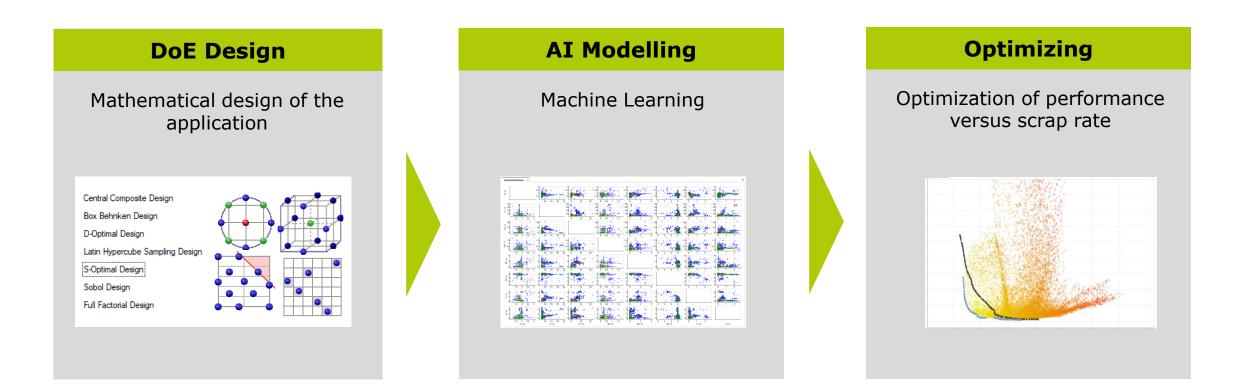
- 2 months cut (15%):
 0.5% error rate
- 4 months cut (30%):
 2.5% error rate
- Further optimization with Active DoE (AVL CAMEO[™]): 40% reduction



Battery cell factories are facing 30-50% scrap rate during production!

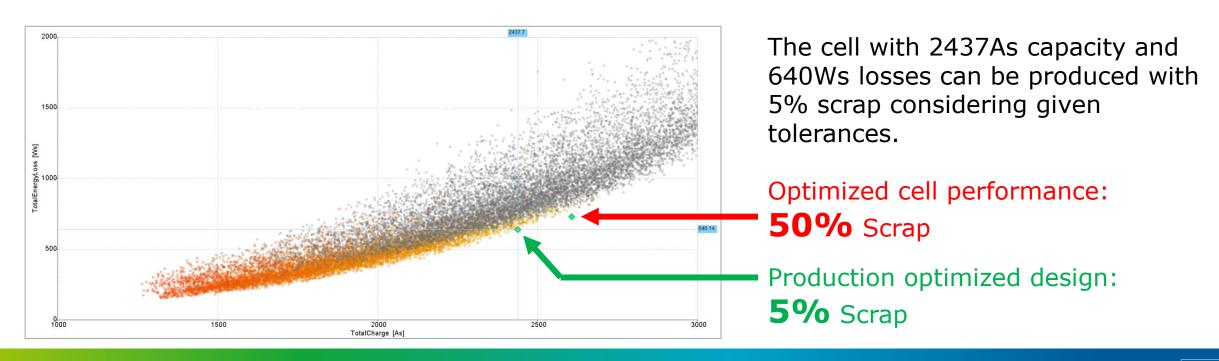


Goal: Reduction of production scrap from 50% to 5% with optimized cell performance



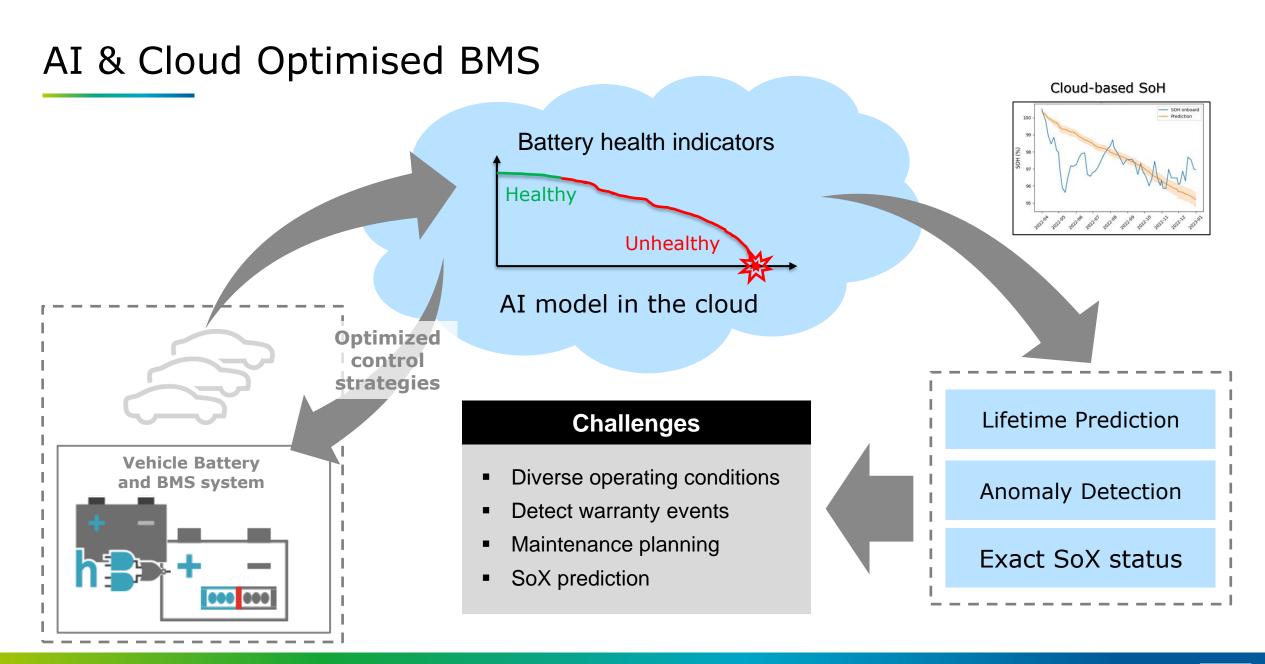
*) DoE: Design of Experiments

Parameter	Nominal	Optimized cell design	Production optimized
Capacity	2300 As	2606 As	2437 As
Losses	750 Ws	731 Ws	640 Ws
Scrap	_	50%	5%

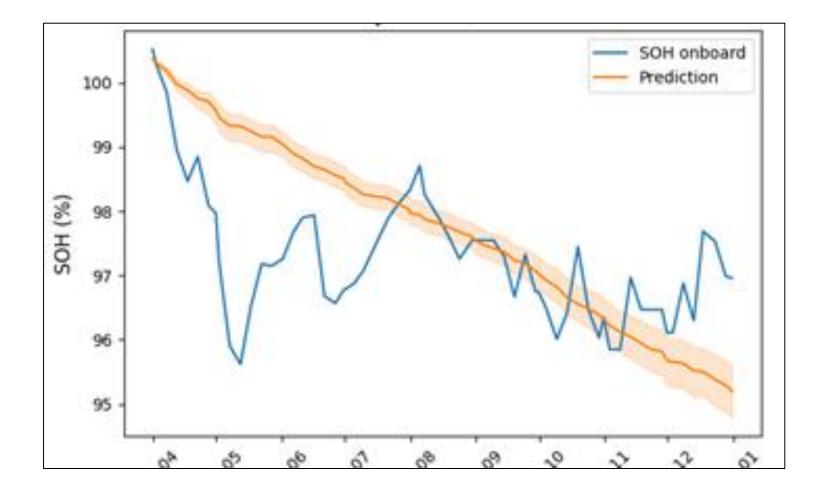




BMS Optimisation



AI & Cloud Optimised BMS



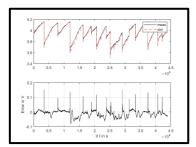
- Onboard BMS are limited in predicting SOH & SOC
- AI based cloud BMS systems provide robust trend predictions for SOH & SOH



SOH Prediction and Analysis

SOH Prediction and Analysis

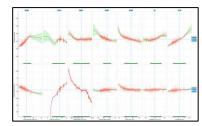
SoH Estimation On Board (RC modelling for single vehicle)





Fleet Data Analytics and RUL Prediction in The Cloud

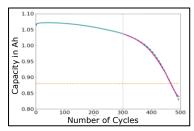
Range and SoH (Meta modelling for complete fleet)



Influencing factors on range & SoH for complete fleet

Neural Network model training for range and SoH depending on driving and ambient conditions based on the complete fleet.

Estimation of battery health based on RC parameter identification for dynamic driving cycles for each vehicle. Lifetime Prediction (Machine Learning incl. Federated Learning for model training)



Remaining Useful Life for each vehicle

Machine learning approach to predict the future behavior of the SoH based on the historic battery data. A Federated Learning approach is used to train the corresponding model over several fleets.

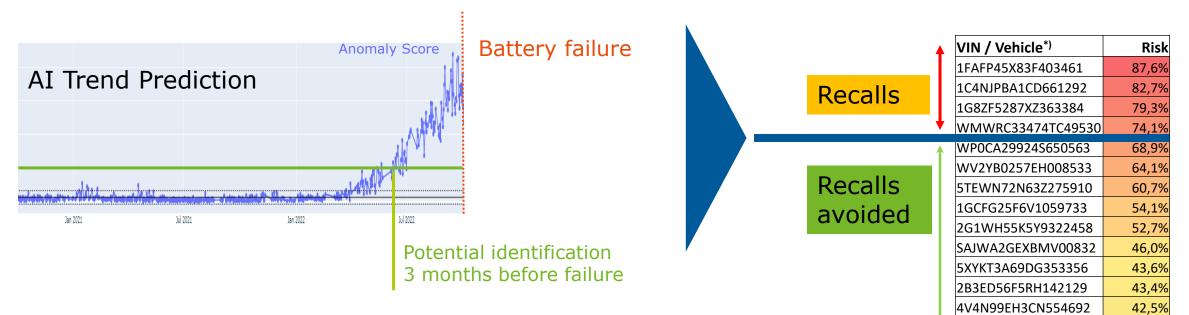
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Reduction of Product Re-Calls



Reduction of Product Re-Calls



Benefits:

- 92% less product recalls
- Hundreds of million \$ saved in repair cost
- Safeguard brand reputation

Joint publication with Jaguar Land Rover at the 10th International Symposium on Development Methodology, Nov. 2023

*) Listed VINs are not real ones

1G4HP54KX24151104

1FMCU14T6JU400773

JHMSZ542XDC028494

1GCHK23244F199207

JH4DA9340LS003571

1FAFP58S11A177991

JM3TB2MA5A0235007

JH4DC2380RS000036

WBACB4324RFL14401

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36,2%

30,8%

28,1%

26,5%

23,5%

19,2%

16,2%

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Contact



Public____

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Thank you



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