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AI Powered Battery Health Monitoring for Enhanced Electrical Vehicle Performance

Dr, Nikolaus Keuth[1], Gerhard Schagerl[1]

[1] *AVL List GmbH, Hans List Platz 1, 8020 Graz, Austria,*
nikolaus.keuth@avl.com

Executive Summary

Battery electric vehicles (BEVs) require enhanced battery monitoring for optimal performance. AVL introduces data driven methods to analyze battery health using advanced machine learning techniques on centralized data platforms. This approach supports better decision-making across the development cycle, from reducing production waste to monitoring battery health in customer fleets. Effective data analytics help identify abnormalities, predict battery life, and improve development efficiency by processing data from simulations, tests, and real-world fleets, contributing to sustainable and high-quality BEV solutions.

Keywords: AI – Artificial Intelligence for EVs, Batteries, Digital Twins

1 Introduction

The landscape of mobility has changed significantly in recent years due to the increasing demand for environmentally friendly and sustainable transportation solutions. Battery electric vehicles (BEVs) have experienced notable growth as part of this shift, representing a step toward emission-free mobility. However, these advancements present new challenges that need to be addressed.

One primary challenge in developing and using BEVs is preventing errors that could lead to problems in real-world applications. Traditional validation and error analysis methods are often insufficient because error susceptibility changes with actual vehicle usage. Effective error prevention requires advanced data analysis methods that evaluate and process data throughout the development process.

This article discusses how combining data from the development process with field data and artificial intelligence can identify potential issues and find solutions to enhance the safety and performance of BEVs. The key challenges for such a data-driven approach include:

- Data Integration: Integrating diverse data sources from various stages of the vehicle lifecycle—design, production, and field use—is complex and requires sophisticated data management systems.
- Real-Time Data Processing: Processing and analyzing data in real-time to make prompt decisions is essential for maintaining vehicle performance and safety, yet it remains a substantial technical challenge.
- Error Prediction and Prevention: Advanced predictive analytics are necessary to anticipate potential issues before they occur in the field, but these tools are still evolving and require further refinement.
- Scalability: Scaling data-driven solutions to support a growing fleet of BEVs while ensuring reliability and efficiency is a significant challenge.

- Security: Ensuring the security and privacy of the vast amounts of data generated by BEVs is critical, as any breaches could have serious consequences.

By addressing these challenges through innovative data integration and real-time analytics, the BEV industry can improve error prediction and prevention, ensuring safe and efficient vehicle operation. This supports the broader goal of achieving sustainable and eco-friendly transportation solutions.

2 Data Analytics for BEV Development

2.1 Requirements

To advance battery development through data-driven approaches and allow teams to uncover new insights using modern data analysis, the following prerequisites are essential:

- Expertise in battery systems and vehicle integration
- Adequate infrastructure and data platforms
- Proficiency in advanced data analysis techniques

For data-driven development to be effectively implemented, these capabilities must be well integrated to improve product development efficiency.

The requirements for data collection include:

- Feature Selection: Identify relevant features such as vehicle speed, engine load, fuel consumption, and ambient air temperature.
- Sampling Rate: Maintain a minimum sampling rate of 1 Hz to capture detailed data.
- Data Sources: Utilize multiple data sources, including CAN signals, telematics, and diagnostic trouble codes (DTCs).
- Data Storage: Establish a structured and traceable storage system for easy access and analysis.
- Environmental Conditions: Consider environmental factors like weather and traffic conditions in data analysis.
- Integration Test-Bed: Use early integration test-beds to detect and resolve issues before hardware components are available.

These prerequisites are crucial to the implementation of data-driven methodologies in the development of battery electric vehicles.

2.2 Battery Systems and Vehicle Integration

The development of battery systems involves contributions from various specialized fields, including mechanical engineering, thermal system design, and the programming and calibration of the Battery Management System (BMS). Each discipline requires specific data evaluations and must communicate these needs to those developing evaluation methods. Additionally, vehicle monitoring functions need to be considered during development. This process entails defining the data requirements for collection by the BMS. Typically, data aggregation involves basic statistical calculations such as identifying minimum, maximum, and average values, or generating histograms. The challenge is to balance reducing the volume of transmitted data while ensuring that all crucial damage-related measurements are captured. The objective is to gather enough data for thorough monitoring while maintaining efficient data collection (1).

2.3 Data Analytics Platform

The centralized processing of data collected from simulations, test benches, and vehicles is essential for optimizing its value. This platform provides the necessary infrastructure for large-scale data capture, storage, and analysis. Typically, these processing pipelines are hosted in scalable cloud environments, enabling efficient data preprocessing, execution of analysis routines, monitoring functions, as well as visualization and reporting for engineering teams and after-sales quality and service departments.

Vehicle development includes various environments such as simulation, component testing, system-level testing, and on-road testing. The types of tests conducted vary based on the environment and stage of the development process. Additionally, as system complexity and dependencies increase, it is important to analyze data independently from the test cycle and the individual requesting the data.

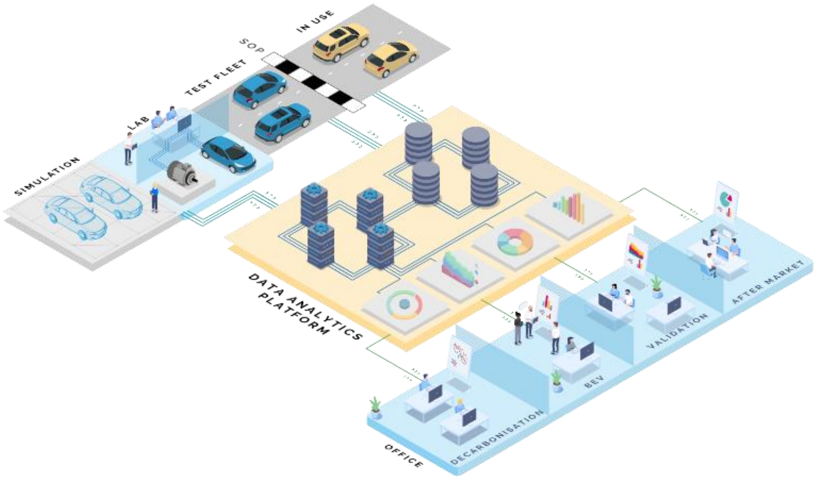

Figure 1: Demonstrates how a Data Analytics Platform can standardize test comparisons regardless of the test environment.

To achieve cross-test analytics, the platform's design enables standardized analytics to be performed irrespective of testing patterns. The core methodology follows three steps:

Events of interest within a measurement are detected based on mathematical rules. These rules can involve any form of mathematical checks on raw data channels, such as boundary overshoots, stable measurement detections, or identification of set measurement flags. Examples include start events, load shifts, and charging/discharging (driving) events.

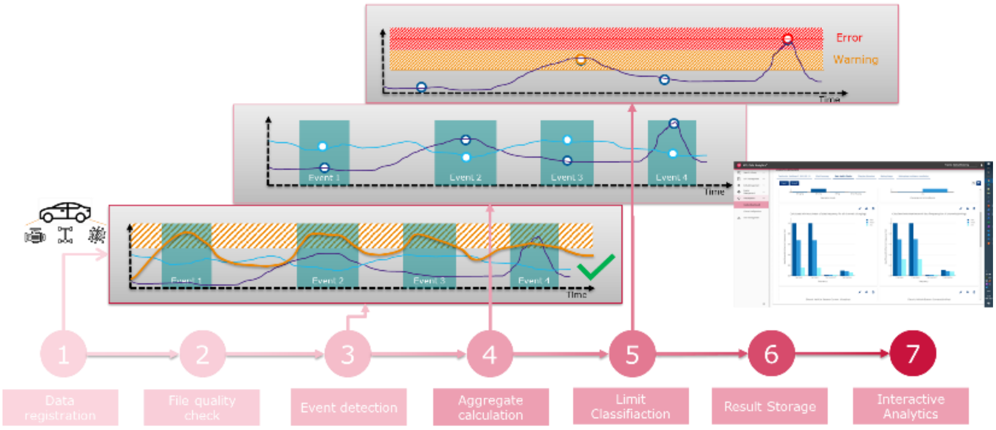

Figure 2:Illustrates the Data Analytics principle based on events and aggregates.

Aggregates are calculated within the detected events and later provided to users for system analysis or correlation between test environments. The calculated aggregates can range from simple statistical values like min, max, mean, and standard deviation of a channel to more complex computations such as histograms, FFTs, or heatmaps. In the final step, boundaries are applied to the aggregates to classify them as warnings or errors.

All this information is stored in a high-performance result store, enabling efficient querying for visualization or analytical purposes. For result analysis, a web-based solution offers visual ad hoc analytics. Various plot types, including trend, scatter, histograms, and heatmaps, help identify outliers

or points of interest, facilitating further data examination. For ongoing result monitoring, dashboards with multiple pages can be defined, providing standardized data insights. These dashboards also support regular reporting and exports.
Basic statistics and threshold-based monitoring functions can track development progress to some extent, but they fall short of maximizing the potential of the data collected. Considering the substantial amount of data and various influencing factors, employing advanced machine learning techniques is required to deeply analyze abnormal behaviors, accurately estimate the battery's State of Health (SOH), and perform predictive analysis on the remaining battery lifespan (4)(5).

2.4 Analysis Methods

The AVL Data Analytics™ platform utilizes a variety of analytics methodologies to process and interpret data. These include:

- Descriptive Analytics: What has happened?
- Diagnostic Analytics: Why has something happened?
- Predictive Analytics: What could happen in the future?
- Prescriptive Analytics: Which measures need to be taken?

The platform focuses on event-based analytics, aggregating information to identify key events and trends. This methodology allows for an in-depth analysis of system behavior and helps in identifying anomalies and patterns.

2.5 AI Methods

AVL Data Analytics™ employs advanced AI and machine learning techniques to enhance predictive capabilities and automate decision-making processes. Key methods include:

- Intelligent Anomaly Detection: Identifying outliers and unexpected events in the data streams.
- Federated Learning: Training models across multiple datasets while keeping the data decentralized to ensure privacy.
- Graph Neural Networks (GNN): Analyzing relationships and dependencies between different entities within the data to explain causalities.

These AI methods are designed to offer robust, scalable, and efficient analytics solutions, enabling timely and accurate insights for engineering decisions.

3 Application Fields

In the following sections, we will describe specific application examples and analysis methods for various stages of development or various testing environments.

3.1 Cell Aging Tests

Cell Testing is a new challenging topic in the automotive industry. Cell Testing is done for 4 main topics:

- Cell Selection to validate supplier data.
- Model parameter estimation to parametrize simulation models.
- Pack Hardware Design to understand and prevent aging.
- BMS Software Design to control the battery for performance and thermal safety.

Different to classical testing tasks cell testing is done in large scale and over long time. 4000 to 5000 cells are assessed at the same time under different temperature and charging / discharging condition.

Especially for aging test testing takes months and even years. Data is delivered daily. Data analytics methods implemented facilitate the seamless and continuous monitoring of all tested

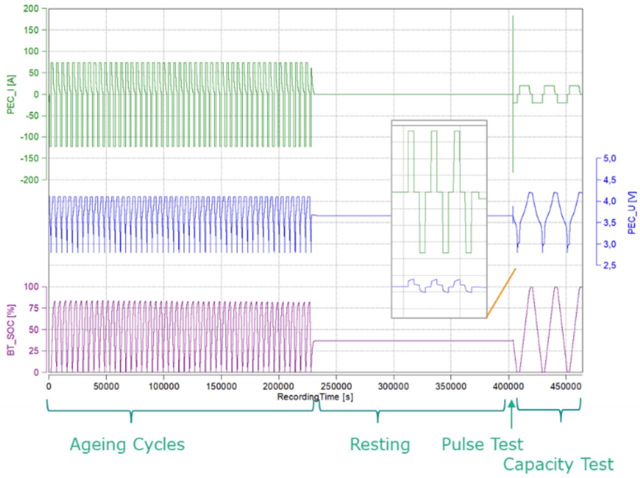

Figure 3: Automotive cell test cycles

channels simultaneously. From this data, cell characteristics are calculated based on well-defined cycle patterns, such as resting-charging-resting-discharging cycles or standardized cycles like the hybrid pulse power characterization (HPPC).

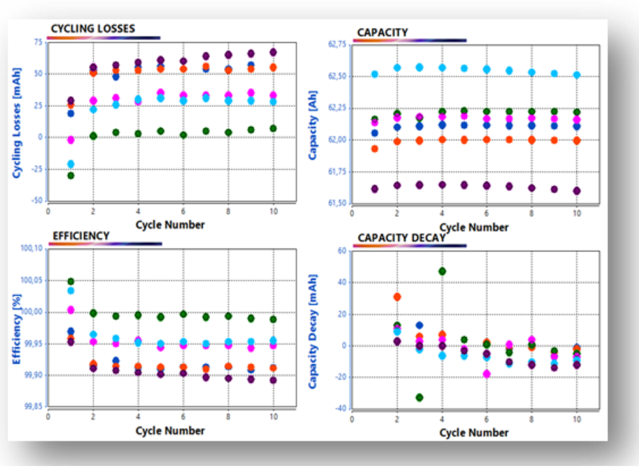

Figure 4: Characteristics calculated for a cell test

Characteristics such as internal resistance, capacity decay, differential capacity, cell heat-up, and many others are computed for these cycles.

Data analytics enables the simultaneous correlation of various measurements across multiple cells, allowing for the cross-comparison of new cells with earlier variants. Through continuous analysis during testing, it becomes feasible to terminate tests that will not yield additional insights or where a set of cells has reached their end of life. Additionally, the same analytics can be utilized in cell production for end-of-line tests to reduce rejects, lower production costs, and minimize waste.

3.2 Module and Pack Testing

After cell selection and pack design, the assembled module and packs are tested on the battery test system. The main development purpose is assessing the aging behavior and the parametrization of the BMS models.

For aging and performance testing again similar test cycles as in fig. 3 are applied. To assess batteries in a more realistic scenario a method was developed to generate artificial real world aging cycles based on data information coming from Test Fleet and customer fleet data. Data analytics supports here in the calculation of usage space analysis out of measurement result from trips conducted in the real vehicle. Based on the usage space analysis artificial cycles can be build, to assess batteries more realistic and ensure testing in all critical areas of future operation.

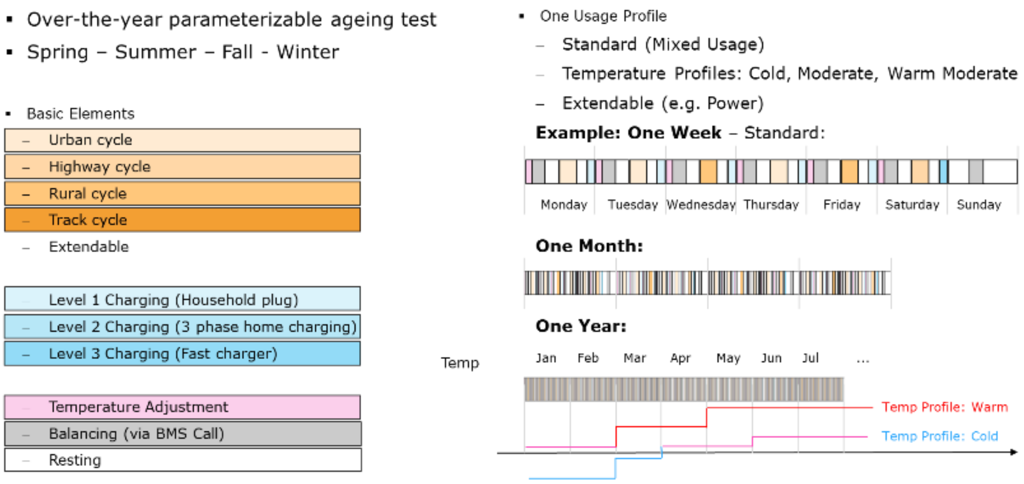

Figure 5: Artificial real-world test based on usage space analysis

The test results are processed by the data analytics to again calculate characteristics of the battery for direct correlation and analysis.

Additionally, the data is used to parametrize a semi physical battery model for usage in the BMS system as well on the testbed.

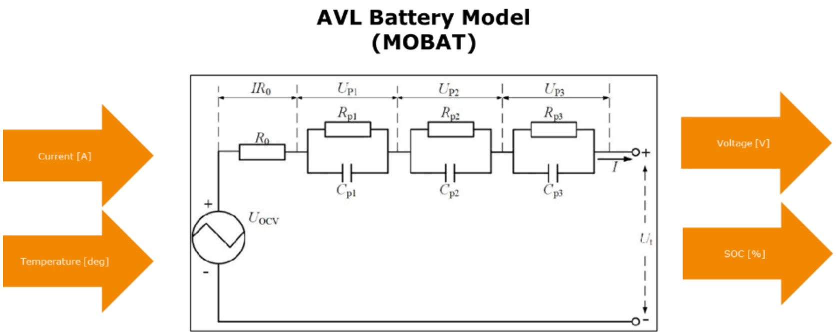

Figure 6: Model structure for a semi-physical battery model

By continuous training of the model prediction of aging can be done in the early state of testing and later for parametrization of the aging part of the model.

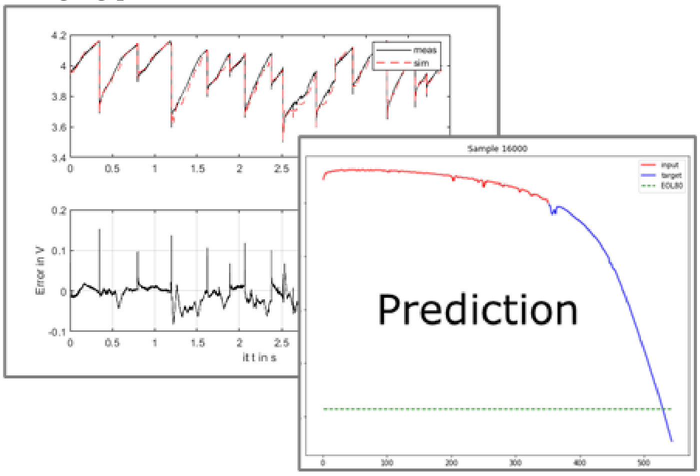

Figure 7: Prediction of aging in early testing phases

3.3 Test and Validation Fleet

In the late stages of development, the focus is primarily on function validation and integration testing. More than 2000 test cases on vehicles are still conducted to confirm the robustness of functions.

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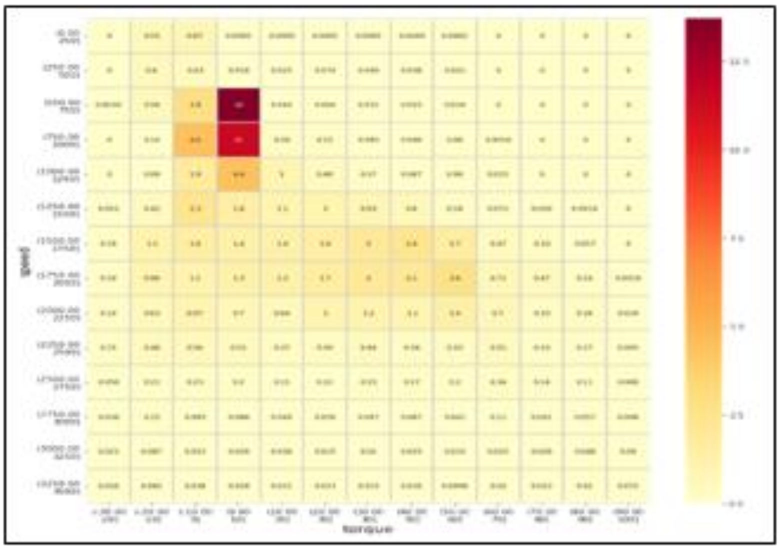

Figure 8: By comparing usage data and data from the validation fleet, a "Blind Spot Analysis" can be conducted to identify operating modes that have not yet been sufficiently tested

However, it is often difficult to figure out from the flood of test data whether all operating conditions have been adequately tested. When data from customer fleets and data from validation fleets are processed in the same analysis platform, a "Blind Spot Analysis" can be performed to find states that need more testing (see fig. 7).

The data analytics platform allows in addition to blind spot analysis, the possibility to build meta models based on characteristic values out of test fleet data, which allow to decide the main influencing factors for aging and performance of the battery. Based on these models BMS parameters can be optimized to extend lifetime and prevent thermal damage.

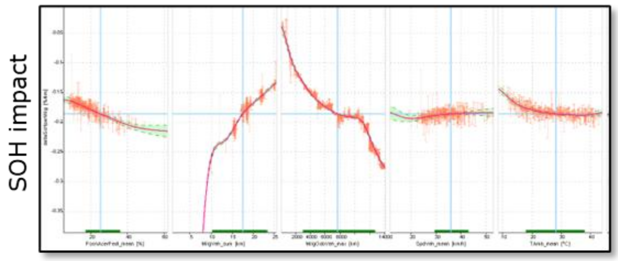

Figure 9: The response surface model describes the parameters which have the highest impact on battery aging.

One of the significant aspects of fleet testing operations for industrial vehicles is the ability to optimize test programs and enhance predictive maintenance. This involves leveraging AI-driven data analytics solutions to maximize engineering efficiency and minimize total cost of ownership (TCO). By adopting advanced machine learning algorithms, it is possible to predict and prevent failures, thereby reducing warranty costs and unplanned downtime.

Data collection during test cycles and real customer usage is paramount. This data is processed to determine the extent of damage caused by different usage scenarios. The goal is to ensure that test cycles accurately reflect real-world conditions, and any discrepancies can be addressed to improve product quality.

The integration of SiL (Software-in-the-Loop) and HiL (Hardware-in-the-Loop) methodologies further enhances the development process. Using these innovative approaches allows early detection and resolution of issues, even before all components are available in hardware. This proactive strategy ensures a smoother and more efficient development cycle.

Furthermore, predictive maintenance benefits from utilizing real-time data from telematics, workshops, and dealer services. This data helps in creating accurate risk scores for individual vehicles, facilitating targeted preventive maintenance actions. Ultimately, this approach not only boosts customer satisfaction but also significantly enhances the longevity and reliability of the vehicle fleet.

3.4 Battery Monitoring in the InUse Phase

Once the production and sale of battery electric vehicles (BEVs) have begun, there is significant interest in monitoring the battery's health status (SOH) and detecting abnormal behavior of the battery system. Assessing the current state of a battery includes information about its performance, internal resistance, and remaining capacity. Through vehicle connectivity, this data is transmitted to the cloud environment. Data-driven models based on machine learning (ML) algorithms are executed in the data analysis platform, which can be used for the entire vehicle fleet. By employing trained neural networks (NN), it is possible to predict the remaining lifespan of individual batteries. Training these models typically requires a large amount of data. To improve analysis quality, data from the development phase, such as cell and pack tests, can also be used for training. It is essential for the results from the development process to be processed in the same data platform as the data from the customer fleet. This not only enables comparisons between test benches, pre-series vehicles, and customer vehicles but also modern machine learning techniques such as "Transfer Learning" (TL) [6].

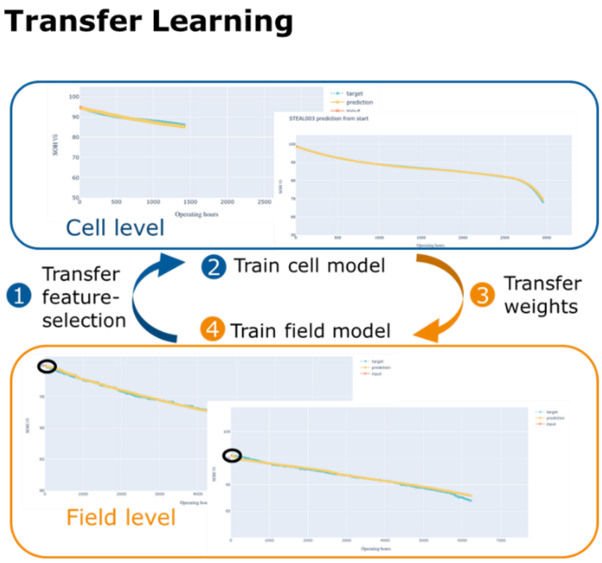

Figure 11: Principle of transfer learning

Transferring knowledge from a test bench dataset to the customer fleet significantly reduces the required data volume in this use case. Through cloud-based monitoring and fleet-wide analysis, the behavior of an individual battery and its deviations from the typical and current behavior of all battery packs in the fleet can be quickly analyzed, and proper countermeasures can be taken, such as temperature control during the charging process. Based on the learned main influencing factors, the current State of Health (SoH) as well as a prediction of the remaining lifespan for each battery pack in the vehicle fleet are calculated, allowing for recommendations on efficient use and extension of durability to be derived.

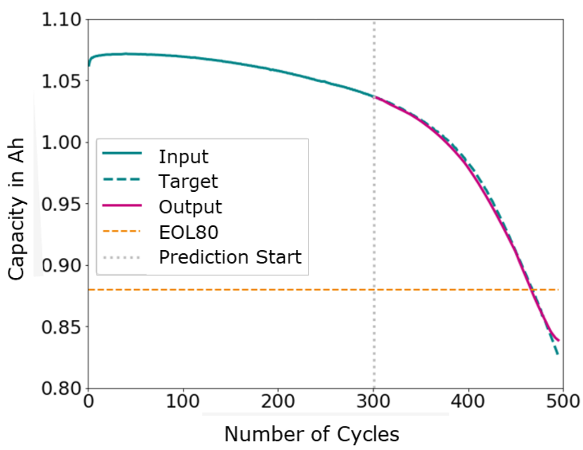

Figure 10: Prediction of SoH Model based on fleet data

4 Conclusion

Digitizing the development process and using data-driven methods are the keys to improving development efficiency. AVL supplies an analysis platform capable of processing data from the development process, whether it comes from a simulation environment, a test bench, or a test vehicle. Intelligent and scalable evaluation methods allow for the analysis of hundreds and thousands of measurements and their comparison against the corresponding requirements from the Design Validation Plan. The high degree of automation leads to a significant reduction in efforts in the field of data evaluation. Additionally, the ability to search for and reuse data results in a reduction in testing efforts, both on test benches and in test fleets.

Furthermore, the data platform allows for the integration of development data and data from the customer fleet, enabling the realization of further innovative use cases. Monitoring battery health status and predicting remaining lifespan are just the first examples among a multitude of possibilities.

By combining expertise and advanced analysis methods, integrated on a data platform, the potential for efficiency improvement in many development projects has already been proven (see fig. 10).

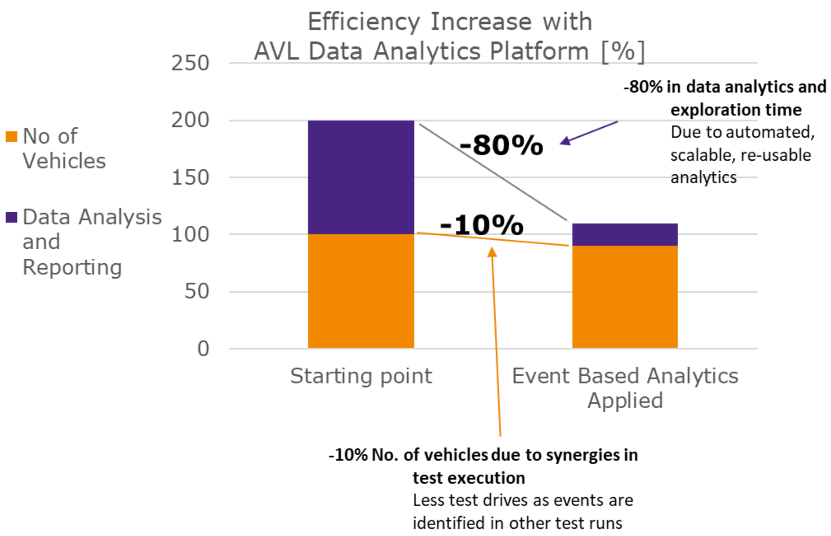

Figure 12: Saving potential by usage of the data analytics methods

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Presenter Biography

Dr. Nikolaus Keuth studied mechanical engineering with an emphasis on automotive engineering, as well as automation and control theory, at the Technical University in Vienna. He earned a PhD in automation and control, specialising in data-driven modelling, from the same university in 2004. Dr. Keuth joined AVL List GmbH in 2005 and has taken on several roles since then. Initially serving as a project manager, he later became a product manager and eventually managed the department for data analysis and modelling products. Currently, Dr. Keuth is the head of product and solution management for data analytics products focused on battery and cell development in the automotive industry.