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Field Data optimized Lifetime Prediction of Li-Ion Batteries in Electric Vehicle Fleets

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Kurzfassung

Lithium-Ionen-Batterien (Li-Ion) bilden die Grundlage moderner Energiespeichersysteme, insbesondere auch in Elektrofahrzeugen (EV). Während Labortests eine gezielte Charakterisierung des Batterieverhaltens ermöglichen, bietet die Analyse von Felddaten eine Bewertung des Verhaltens in der Praxis. Beispielsweise können Degradationsmuster und die Betriebseffizienz unter verschiedenen Fahrbedingungen bestimmt werden. Diese Studie untersucht Methoden zur Erfassung, Verarbeitung und Interpretation von Felddaten von Li-Ionen-Batterien, die in EV-Flotten eingesetzt werden. Der Schwerpunkt liegt auf dem Vergleich von Methoden zur Vorhersage des Gesundheitszustands (State-of-Health, SOH). Diese reichen von einfachen Ladungszyklen-Zählungen bis hin zu Algorithmen des maschinellen Lernens, die die während des Betriebs beobachteten Degradationseffekte berücksichtigen. Diese Studie basiert auf der Auswertung von 44 Elektrobussen, die in mehreren Städten im Einsatz sind. Dies ermöglicht die Bewertung unterschiedlicher Operationsbedingungen. Die Ergebnisse unterstreichen die Bedeutung von Felddaten für die Verbesserung der SOH-Schätzung. Damit geht eine Erhöhung der Zuverlässigkeit, Sicherheit und Leistung von Batterien in Elektrofahrzeugflotten einher. Dies ebnet auch den Weg für intelligentere Flottenmanagementsysteme mit optimierten Routenplanungs- und Ladestrategien.

Abstract

Lithium-ion batteries (Li-ion) are the basis of modern energy storage systems, particularly in the context of electric vehicle (EV) fleets. While laboratory testing provides controlled insights into battery characteristics, field data analysis offers a critical perspective on real-world behaviour, degradation patterns, and operational efficiency under diverse driving conditions. This study explores methodologies for collecting, processing, and interpreting field data from Li-ion batteries deployed across EV fleets. Key focus area is the comparison of state-of-health (SOH) prediction methods. Reaching from simple cycle counting to machine learning algorithms that exploit the degradation effects observed during operation. This study is based on a set of 44 electric buses, operating in multiple cities. Hence different operation and charging regimes are involved. The findings underscore the importance of field data in enhancing SOH estimation and thus battery reliability, safety, and performance within EV fleets. This also paves the way for smarter fleet management systems using optimized route planning and charge strategies.

1 Introduction

Whitin this study the benefits of ageing prediction using field data analysis shall be presented. In the first section the state of the art is summarized. The used bus fleet and the generated dataset is described in the following section. Thereafter applied algorithms, ranging from basic Ah-counting based prediction methods to more advanced methods based on machine learning approaches, are presented. Finally, the benchmark results are discussed.

1.1 Ageing Prediction Methods

Lithium-ion battery ageing prediction methods span a diverse range of approaches, each tailored to capture the complex mechanisms that govern battery degradation over time. An overview of ageing degradation mechanism and their effects is given in (1).These methods are critical for optimizing battery performance, ensuring safety, and extending lifespan. The approaches can be roughly classified into the following categories:

- **Empirical Models**: These rely on extensive experimental data to establish degradation trends. By fitting mathematical functions to observed capacity fade or internal resistance growth over time, empirical models offer straightforward predictions. However, they often lack generalizability across different chemistries, operating conditions, or usage profiles.
  Common shape functions include exponential, polynomial, or Arrhenius-based models that correlate ageing with temperature, depth of discharge, and charge/discharge rates (2). Prediction frameworks often separate degradation into two categories: calendar ageing, which occurs due to chemical instability over time even when the battery is idle, and cycle ageing, which results from repeated charge-discharge cycles. Accurate models must account for both, as their relative impact varies by application. For instance, electric vehicles experience dominant cycle ageing, while battery stationary storage systems (BESS) may suffer more from calendar ageing.
- **Electrochemical Models**: These physics-based models delve into the internal workings of the battery, simulating processes such as solid electrolyte interphase

(SEI) layer growth, lithium plating, and electrolyte decomposition (3) (4). They provide high-fidelity insights into ageing mechanisms by solving coupled differential equations that represent mass transport, charge transfer, and thermodynamics. While computationally intensive, they are invaluable for understanding root causes of degradation and for designing batteries with improved longevity.

- **Machine Learning Models**: Leveraging large datasets from battery testing and real-world usage, machine learning approaches—such as neural networks, support vector machines, and random forests—can uncover complex, nonlinear relationships between input features (e.g., temperature, voltage, current) and ageing outcomes. These models excel in adaptability and scalability. However, they require careful validation and may struggle with extrapolation beyond the training data.
- **Hybrid Approaches**: To balance accuracy and computational efficiency, hybrid models integrate empirical or machine learning techniques with electrochemical insights. For example, a model might use physics-based equations to simulate SEI growth while employing data-driven corrections for temperature effects. These approaches aim to capture the strengths of each method, offering robust predictions across diverse operating conditions (5).

While it has been shown that SOH prediction can benefit from advanced methodologies as well as from detailed study of variety of ageing effects, in practise basic empirical models are applied. This is mainly due to the challenge of extrapolating the knowledge to new cell chemistries and to real world operation. Further challenges are the data acquisition and processing. These issues are addressed in (6) and (7).

Most research institutes lack a data basis that is suitable to apply advanced machine learning approaches. Instead, often operation cycles are tested in accelerate ageing tests.

Hence most ageing prediction methods are still exclusively based on physical considerations and laboratory tests. An overview of experimental ageing investigation is given in (8).

1.2 Field Data Analysis

As outlined in the previous subsection, field data analysis emerges as a promising approach to obtain valuable information about ageing mechanisms. The necessity of laboratory-based ageing tests may be diminished while maintaining a high degree of prediction accuracy.

During operation of batteries in electric vehicles or within BESS a Battery Management System (BMS) is collecting and checking sensor data. These data include current and voltage on cell level as well as temperature of selected cells. Also, SOH estimation is performed. This includes multiple parameters that describe the performance of the battery. Furthermore, mandatory key parameters have to be stored respectively updated during battery operation in order to keep track of supply chains, resource efficiency and performance values. This is dictated by the European Union regulation Battery Passport (9), which introduces a summary of regulations to improve second life applications and recycling.

Due to computational and memory constraints only undemanding algorithms may be used on the BMS. Thus, sensor data is often also streamed to a cloud server to allow a central monitoring as well as more complex SOH estimation algorithms. Furthermore, this allows comparison between different batteries of the same type, to evaluate variations introduced by different usage conditions.

In (10) the general data management, -transfer and analysis approach as well as the opportunities and challenges are described. They distinguish between different layers that provide information to operators and manufacturers.

Despite the great potential described e.g. in (11), there is very few public available research on field data analysis. This is due restrictions carried out by operating companies and manufacturers, that gather the data. One exception is (12), where the lifetime prediction from field data is discussed. The work focuses on the combination of laboratory experiments with field data analysis. Nevertheless, they emphasize the lack of availability of large publicly accessible datasets, including validation data under real-world operating conditions.

2 Benchmark Data

A fleet of electric buses was monitored from mid-2022. The relevant signals and their time resolutions are listed in Table 1. Beside battery signals also vehicle distance and speed are used for identifying data gaps.

Signal	Unit	Time resolution
Current	A	100 ms
Voltage	V	100 ms
Temperature	°C	100 ms
state of charge (SOC)	%	On value-change
mileage	km	1 s
speed	km/h	100 ms

Table 1: Measured signals and time resolution.

In addition to analysing the data during normal operation dedicated capacity checkup tests were performed. These are further described in Section 2.2. A coarse description of the operation data is given in the next subsection. A detailed analysis, including an energy consumption estimation can be found in (13).

2.1 Operation Data

The buses typically operate 18h a day and use opportunity charging. This means that they are fast charged at designated stations. However, this intermediate charging is only partially sufficient to provide the necessary energy.

Therefore, they are also fully charged overnight in the depot. A short section of the current and voltage data is shown in Figure 1. The total time sequence is divided into different sections and classified into categories describing the operation state. For each section key parameter like charge throughput or current rate histograms are calculated. These values can be used to find suitable training data for machine learning algorithms or to determine the operation profile. This step also includes the detection of data gaps and anomalies, which is of importance for accurate SOH estimation. Flawed data could otherwise compromise the subsequent predictions.

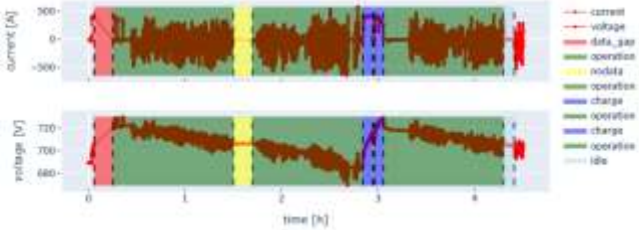

***Figure 1**: voltage and current signal during typical operation. Segments are grouped into different categories to simplify subsequent analysis*

2.2 Reference Tests

In order to validate estimations reference capacity tests are carried out on specified buses from time to time. This is very effortful, since buses have to be taken out of normal operation and the test is not fully automated. Furthermore, the procedure is very time consuming. One checkup test, which is described below lasts at least 24h. The test consists of the following steps:

- bus is driven until BMS-SOC reaches nearly zero percent
- if possible, the battery is further discharged (e.g. using heating)
- idle phase of at least 30 minutes is applied for battery relaxation
- charging with small current rate below $\frac{1}{10}C$ until BMS-SOC reaches 100%
- eventually further charging with constant voltage (CV) or pulsed charging

In Figure 2 a selection of these checkup measurements are compared with the open circuit voltage (OCV) curve. Reduced capacity leads to a compression of the charge curves. Hence cutoff voltage is reached earlier during charging.

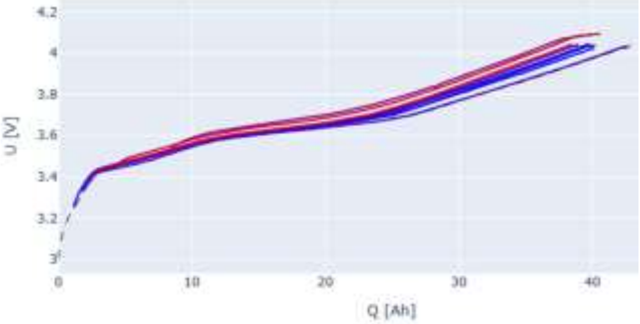

***Figure 2:** Measurement data of capacity checkup tests at different SOH. During ageing the distance to OCV curve (dashed line) is increasing.*

3 Estimation Algorithms

As outlined in the introduction section there are various elaborate ageing prediction models which are able to predict specific ageing processes. However, for application in field data analysis, empirical models are more suitable. Within this section, three methods with increasing complexity are presented. The first approach is based on public available data sheet parameter of the cell, the second one is based on laboratory ageing investigations. The third one also uses field data to enhance ageing prediction. In all methods the capacity is used as SOH indicator. This means other degradation modes like SEI growth or loss of active material are not considered for simplicity and clarity.

3.1 Baseline Estimation

A coarse SOH estimation can be performed using guaranteed mileage of the vehicle manufacturer. However, this value does not reveal information about the shape of the capacity fade during lifetime. This is illustrated in Figure 3. The shape of the curves can differ for different cell types as well as for different ageing modes. Thus, intermediate SOH prediction may be uncertain.
In addition, the ageing process only applies under specific conditions. These may differ significantly from the actual operating conditions.

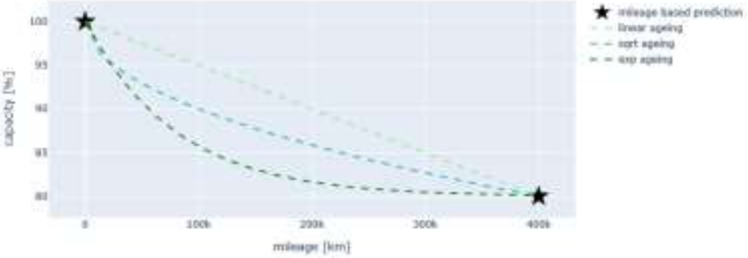

Figure 3: Illustration of various capacity curves over mileage.

3.2 Laboratory-Model based Estimation

Model based estimations not only consider charge throughput, but they also take into account the operation conditions. Typically, it is distinguished between calendric- and cyclic ageing. Calendric ageing describes the loss of capacity resulting from side reactions that take place also during idle phases. Cyclic ageing is caused by various degradation mechanism, like SEI growth or electrolyte decomposition. For calendric ageing only SOC and temperature are taken into account. For cyclic ageing typically also the current rate and the depth of discharge (DOD) is considered. Many models use the concept of weighting these input values. Hence the stress of a specific condition, like high temperature is quantified. This also applies to the model presented. It is based on the calculation of weighted full cycles w_q and weighted lifetime w_t:

$$w_q = \frac{1}{2C_{nom}} \int \alpha(SOC, I, T, DOD)\,|I|\,dt$$

$$w_t = \frac{1}{s_t} \int \beta(SOC, T)dt$$

The stressfactor functions α and β quantify the impact of the operation conditions. Accurate parametrization is a considerable challenge. Therefore, the methodology described in (14) is applied.
The two variables w_q and w_t are then used to calculate SOH. An ageing curve is used for this purpose, which describes the form of capacity loss. If no information for the cell under investigation is available, often a linear relationship is assumed:

$$c = c_0 - (c_0 - c_{EOL})\left(\frac{w_q}{l_q} + \frac{w_t}{l_t}\right)$$

l_q and l_t are the cycle life and calendar life parameter. c_0 denotes the initial capacity (typical 100%) and c_{EOL} the capacity at EOL (typical 80%).

Since chronological sequence of operation condition does not effect the SOH calculation, it is possible to use a histogram based approach. Thereby calendric and cyclic operation conditions are stored in multidimensional histograms. In Figure 4 the marginal 1-dimensional histograms for a bus of the analysed fleet are shown. It can be seen that the operation profile remains constant over the years. The temperature control keeps batteries in a comfortable region. The battery is mainly operating in the upper SOC region and the DOD is rather small.

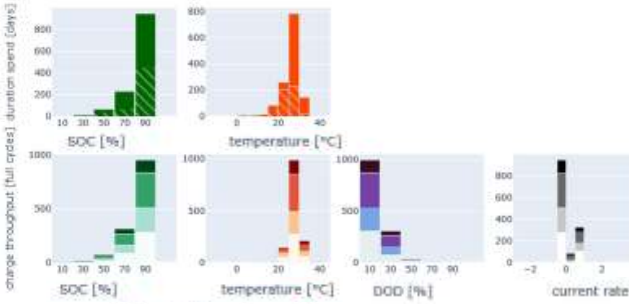

Figure 4: Histograms describing the operation of example battery.

In Figure 5 the resulting mean calendric- and cyclic stressfactors are shown. They are in the same region for almost all buses of the fleet. The calendric stress is approximately 1.0, indicating conditions similar to the reference case. The cyclic stress is even below 1, since the DOD is small. Thus, lifetime may exceed the expected value.

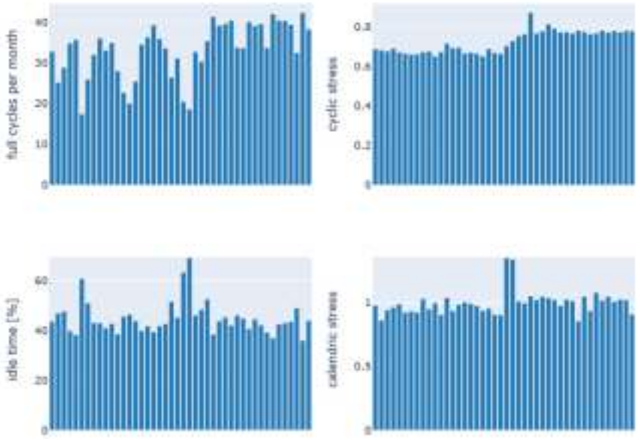

Figure 5: Monthly full cycles and idle time for all buses of the fleet as well as calendric and cyclic stress factors.

3.3 Field Data optimized Estimation

The approaches presented so far are based on laboratory tests of battery cells. However, these cannot reproduce all the effects that occur under real-world conditions. In (15), for example, it was shown that dynamic cycling can extend service life. In order to use field data to improve ageing models, several problems must be solved. To this end, the fleet model presented in (16) was developed. It enables ageing curves to be trained directly using measured voltage data. Additional time-consuming and costly reference tests are not necessary. The basic approach is shown in Figure 6.

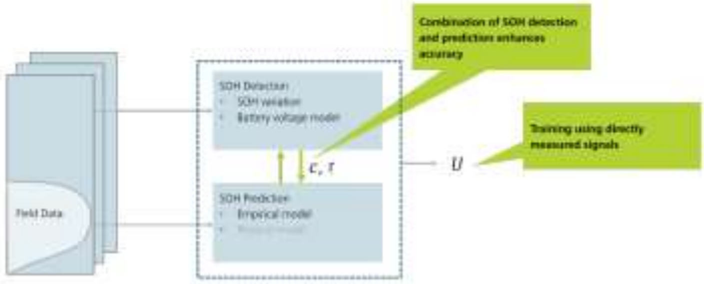

Figure 6: structure of the Fleet Model.

The fleet model combines ageing prediction with ageing detection, enabling joint learning from all fleet data. As a further advantage, in addition to the capacity loss, the increase in resistance can be determined.

4 Benchmark Results

The three presented approaches for predicting SOH were applied to the electric bus fleet. The results are evaluated using the dedicated capacity checkup tests.
The SOH estimation results of the fleet model (field data optimized estimation) are plotted in Figure 7. It appears that ageing does not proceed linearly. Instead, capacity drops sharply during the first full cycles. After that, the capacity fade rate slows down. At the end of the monitoring period the capacity of the batteries is in the range of 85%-90%. The resistance increased by only 15% at the

same time. The mean capacity prediction error is below 2% as can be seen in the boxplot.

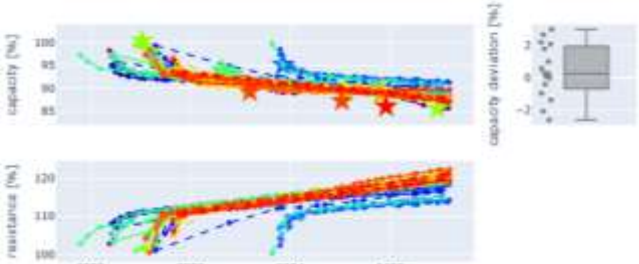

Figure 7: Capacity and resistance estimation using the field data enhanced estimation approach. Results of reference tests are plotted as star. The box plot on the right side shows the estimation error.

In Figure 8 also the results of the other methods are compared to the checkup tests. As expected, the accuracy of the baseline approach is the worst. However, even the model parameterized with laboratory data shows significant errors. Since it is not adapted to the specific cell, the capacity decrease is underestimated. This is mainly due to the nonlinear behaviour, i.e., the initial drop in capacity.

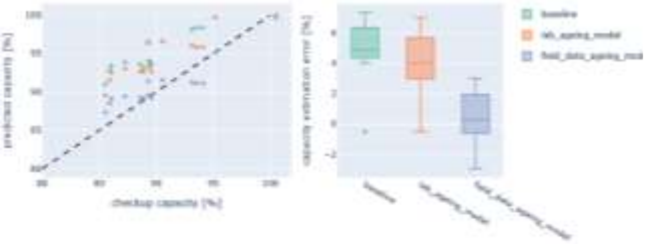

Figure 8: Benchmark of the analysed estimation methods. The left plot shows the estimated capacities compared to the checkup results. The box plot on the right shows the estimation error of each method.

5 Conclusions

The analysis of the electric bus fleet shows the importance of taking field data into account when determining ageing. Laboratory data alone cannot adequately reflect many effects under real-world conditions. Furthermore, the transfer between different cell types is questionable. These problems are solved by fitting the ageing model directly to the fleet data. Hence this benchmark study shows the importance of continuously monitoring and analysing battery data during its operation for reliable SOH prediction.

6 Literaturverzeichnis

1. *Degradation diagnostics for lithium ion cells.* **Christoph Birkl, Matthew R. Roberts, Euan McTurk, Peter G. Bruce, David A. Howey.** 2017, Journal of Power Sources, Bd. 341.
2. *Accelerated Aging Characterization of Lithium-ion Cells: Using Sensitivity Analysis to Identify the Stress Factors Relevant to Cyclic Aging.* **Lienkamp, Tanja Gewald and Adrian Candussio and Leo Wildfeuer and Dirk Lehmkuhl and Alexander Hahn and Markus.** 2020, MPDI Batteries, Bd. 6.
3. *Determination of degradation modes of lithium-ion batteries considering aging-induced changes in the half-cell open-circuit potential curve of silicon–graphite.* **Jossen, Julius Schmitt and Markus Schindler and Andreas Oberbauer and Andreas.** 2022, Journal of Power Sources, Bd. 532.
4. *Aging formula for lithium ion batteries with solid electrolyte interphase layer growth.* **Tanim, Tanvir R. und Rahn, Christopher D.** 2015, Journal of Power Sources, Bd. 294, S. 239-247.
5. *Perspective—Combining Physics and Machine Learning to Predict Battery Lifetime.* **Aykol, Muratahan und Storey, Chirranjeevi Balaji Gopal and Abraham Anapolsky and Patrick K. Herring and Bruis van Vlijmen and Marc D. Berliner and Martin Z. Bazant and Richard D. Braatz and William C. Chueh and Brian D.** 3, 2021, Journal of The Electrochemical Society, Bd. 168.
6. *Large-scale field data-based battery aging prediction driven by statistical features and machine learning.* **Qiushi Wang, Zhenpo Wang, Peng Liu, Lei Zhang, Dirk Uwe Sauer, Weihan Li.** 12, 2023, Cell Reports Physical Science, Bd. 4, S. 101720.
7. **Zhao, Nan Xu and Yu Xie and Qiao Liu and Fenglai Yue and Di.** A Data-Driven Approach to State of Health Estimation and Prediction for a Lithium-Ion Battery Pack of Electric Buses Based on Real-World Data. *MDPI: sensors.* 2022, S. 22.
8. **Marco, L.A. Román-Ramírez and J.** Design of experiments applied to lithium-ion batteries: A literature review. *Applied Energy.* 2022, S. 119305.
9. **Consortium, Battery Pass.** *Battery Passport Content Guidance.* thebatterypass.eu : thebatterypass.eu, 2023.
10. *Fleet Management Approach for Manufacturers displayed at the Use Case of Battery Electric Vehicles.* **Meisen, Friedrich von Bülow and Felix Heinrich and Tobias.** 2021, IEEE International Conference on Systems, Man, and Cybernetics.
11. *Electric Vehicle Batteries: Status and Perspectives of Data-Driven Diagnosis and Prognosis.* **Zhao, Jingyuan and Burke, Andrew F.** 8, 2022, Batteries, Bd. 10.
12. *The challenge and opportunity of battery lifetime prediction from field data.* **Howey, Valentin Sulzer.** 2021, Joule, Bd. 5.
13. *Empirical Energy Consumption Estimation and Battery Operation Analysis from Long-Term Monitoring of an Urban Electric Bus Fleet.* **Tom Klaproth, Erik Berendes,Thomas Lehmann,Richard Kratzing and Martin Ufert.** 8, 2025, World Electric Vehicle Journal, Bd. 16, S. 419.
14. *Learning the Ageing Behaviour of Lithium-Ion Batteries Using Electric Vehicle Fleet Analysis.* **Lehmann, Thomas and Berendes, Erik and Kratzing, Richard and Sethia, Gautam.** 12, 2024, Batteries, Bd. 10, S. 432.
15. *Dynamic cycling enhances battery lifetime.* **Onori, Alexis Geslin and Li Xu and Devi Ganapathi and Kevin Moy and William C. Chueh and Simona.** 2024, Nature Energy.

16. *Lithium-Ion Battery Aging Analysis of an Electric Vehicle Fleet Using a Tailored Neural Network Structure.* **Lehmann, Thomas and Weiß, Francis.** 7, 2023, Applied Sciences, Bd. 13.
17. **Zhao, Jingyuan and Burke, Andrew F.** Electric Vehicle Batteries: Status and Perspectives of Data-Driven Diagnosis and Prognosis. *Batteries.* 2022, S. 142.