

A FRAMEWORK FOR ASSESSING THE SECOND-LIFE POTENTIAL OF LITHIUM-ION BATTERIES USING TOMOGRAPHIC AND ELECTROCHEMICAL PARAMETERS

Jannis Pietruschka

Chair of Reliability Engineering and Risk Analytics, Faculty of Mechanical and Safety Engineering, University of Wuppertal, Germany. E-mail: pietruschka@uni-wuppertal.de

Leon Golimbek

Chair of Reliability Engineering and Risk Analytics, Faculty of Mechanical and Safety Engineering, University of Wuppertal, Germany. E-mail: leon.golimbek-hk@uni-wuppertal.de

Olaf Günnewig

diondo GmbH, Germany. E-mail: olaf.guennewig@diondo.com

Stefan Bracke

Chair of Reliability Engineering and Risk Analytics, Faculty of Mechanical and Safety Engineering, University of Wuppertal, Germany. E-mail: bracke@uni-wuppertal.de

Abstract: Driven by increasing environmental awareness and the demand for emission-free energy sources, electromobility has become a central focus of sustainable transport development. The widespread adoption of light electric vehicles (LEVs) is expected to contribute significantly to achieving global climate goals. Lithium-ion batteries (LIBs) serve as their primary energy source but typically reach the end of their first life cycle after a capacity loss of 20–30%. A second-life application in stationary energy storage systems with lower functional demands is only feasible if the degradation state of each battery is accurately assessed and quantified. Such evaluation enables reliable conclusions about remaining performance capability and safety-related aspects. Electrochemical impedance spectroscopy (EIS) provides quantifiable indicators of degradation. However, future aging behavior is difficult to predict due to limited usage data. A complementary, non-destructive approach is the visual inspection of internal structures using computed tomography (CT). Tomographic analyses reveal and quantify additional degradation symptoms that can enhance predictive aging models. This paper introduces a novel methodological framework that correlates electrochemically measurable indicators with visually observable anomalies to forecast the reliability of LIBs in second-life applications. The framework, developed within an ongoing research project, outlines all implementation phases and associated methods. Initially, reference measurements of newly produced LIBs using EIS and CT are conducted to enable automated detection of visual error appearances through artificial intelligence (AI)-based anomaly detection. Subsequently, defined aging cycles are performed under continuous monitoring of electrochemical and structural parameters. By combining the acquired data, the relationship between degradation mechanisms and visual manifestations is established. Finally, the proposed methods are evaluated with respect to their diagnostic efficiency and economic viability, providing a foundation for reliable and sustainable second-life utilization of lithium-ion batteries.

Keywords: battery cells, computer tomography, functional- and safety related failures, degradation, Second-Life.

1. Introduction

Lithium-ion batteries are widely used as energy storage systems in numerous electronic applications due to their high energy density, low self-discharge rate, high

open-circuit voltage, and long cycle life (Taecheon et al. 2019). Depending on the manufacturer, vehicle architecture, and battery design, traction batteries consist of a large number of individual cells.

A traction battery is generally considered to have reached its end of life (EOL) when its usable capacity has decreased by approximately 20-30 % relative to its nominal value, as such degradation leads to a significant reduction in vehicle range and performance. However, for applications with lower performance requirements, such as stationary energy storage systems, these batteries may still be suitable for further use. The deployment of batteries in second-life applications therefore enables an extension of their overall service life and contributes to environmental sustainability (Zhu et al. 2021).

Prior to reuse or repurposing, the condition of LIBs must be assessed using suitable diagnostic methods. Commonly applied test procedures focus on directly measurable indicators such as capacity and internal resistance or impedance. However, a reliable assessment of the battery state of health (SOH) additionally requires an understanding of the underlying degradation processes. Battery degradation arises from a combination of electrochemical reactions and physical structural changes within the cell (Zhu et al. 2021). These mechanisms primarily result in capacity fade but may also trigger functionally or safety-critical effects, such as increased internal resistance or, in extreme cases, thermal runaway. A major challenge in second-life assessment is that detailed operational data from the first-life usage phase are often unavailable, making it difficult to reconstruct the degradation history of individual cells.

Computed tomography offers a non-destructive approach for investigating internal battery structures by reconstructing a high-resolution three-dimensional model from a large number of X-ray projection images. This technique enables the analysis of degradation mechanisms that appear as geometric or density-related changes within the cell, without requiring disassembly or prior knowledge of the operational history. As such, CT has the potential to provide valuable insights into the current aging state of lithium-ion batteries beyond purely electrochemical measurements.

To validate the potential of CT as a non-destructive diagnostic tool for battery second-life assessment, this work aims to establish a comparative framework that links battery lifetime data with CT-based evaluation results. In this context, three key challenges are addressed:

(i) Definition of suitable CT measurement procedures for the detection of functionally and safety-critical patterns. This includes identifying an appropriate balance between scan duration and measurement accuracy, particularly with regard to production-related anomalies that may be obscured by increased noise in faster scans. At the same time, the CT process must remain economically and ecologically viable for practical application.

(ii) Differentiation between benign anomalies and degradation-related features. While Ioannou et al. (2024) demonstrated visible differences between a new cell and a cell aged to approximately 30 % SOH, these observations were based on different cells of the same type, limiting direct comparability (Ioannou et al. 2024). An initial electrochemical assessment as an data documentation is therefore essential to enable reliable interpretation of visual features observed in CT scans.

(iii) Development of an automated evaluation approach capable of detecting, classifying, and distinguishing critical features in CT data from harmless anomalies, as well as correlating them with potential production-related influences.

2. Measurement Systems and algorithms

The following section presents the state of the art and research relevant to the framework for the methods to be used. For further information please have a look into the given references.

2.1. Computer Tomography

Computed tomography is well suited for the detection of functionally and safety-critical defects in lithium-ion battery cells. This applies both to final inspection during cell manufacturing prior to first use and to the assessment of cells already in service with regard to second-life applications. CT has been successfully applied for several decades in industries such as aerospace, automotive engineering, plant and apparatus engineering, and electrical engineering, particularly for the detection and analysis of functional and safety-relevant defects (Pfeifer 2002; Schmitt and Dietrich 2023). The technique enables near-complete geometric characterization of components, including both external and internal contours, largely independent

of component geometry, subject to material-related limitations. In addition, internal defects can be detected with spatial resolutions down to approximately 1 μm and quantitatively evaluated with dimensional accuracies on the order of 5 μm , depending on the CT system configuration and the applied inspection procedure.

The automated manufacturing of lithium-ion battery cells is a highly complex process that requires continuous monitoring and control. Even minor deviations from the intended cell design may significantly affect cell lifetime and, in extreme cases, lead to internal short circuits associated with the risk of thermal runaway during aging or subsequent field operation. Alongside established inline sensor technologies - such as coating thickness measurements of cathode and anode layers, optical surface inspection for the detection of foreign particles, contaminants, or scratches, and various electrical test methods - industrial CT is increasingly employed as a non-destructive testing technique for battery cells and modules to identify internal defects that are not accessible by surface-based inspection methods.

2.2. Electrochemical impedance spectroscopy

Electrochemical impedance spectroscopy is used to determine the frequency-dependent alternating current resistance (impedance) of a battery. By recording the impedances across various alternating voltages applied to the battery, an impedance spectrum is obtained that allows conclusions to be drawn about the physical and electrochemical ageing effects as well as the state of ageing of the battery cells comparing them with each other. In particular, contributions from ohmic resistance, charge-transfer processes, and mass-transport phenomena can be identified and quantified. The high-frequency real-axis intercept of the impedance spectrum is commonly associated with the purely ohmic resistance of the battery, which is influenced by cell design, electrode materials, and electrolyte properties (Barsoukov and Macdonald 2005). Due to its ability to resolve these processes, EIS is widely used to assess degradation mechanisms and the state of health of aged batteries, as well as to compare used cells with reference measurements

of new cells. However, these method focus on electrical cell function and cell health, but not on the visual internal functional or safety-critical faults that can cause unexpected defects.

2.3. Autoencoder

Autoencoders are neural network architectures designed for unsupervised representation learning. As illustrated in Fig. 1, the architecture comprises two main components: an encoder that maps the input data into a compact latent representation and a decoder that reconstructs the original input from this representation. The network is trained by minimizing a reconstruction loss between the input and the reconstructed output, typically using the mean squared error or related similarity measures.

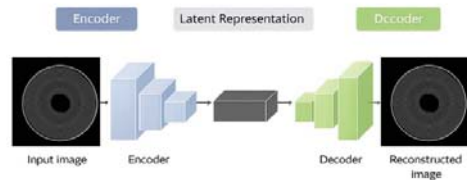


Fig. 1. Conceptual illustration of a convolutional autoencoder.

In image-based applications, convolutional autoencoders (CAEs) are commonly employed. Instead of fully connected layers, CAEs use convolutional layers to exploit spatial locality and translation invariance, which are key properties of image data (Yamashita et al. 2018). The encoder part of a CAE progressively extracts hierarchical feature representations while reducing spatial resolution, whereas the decoder mirrors this structure using upsampling or transposed convolutions to reconstruct the input image (Dumoulin and Visin 2016).

Autoencoders are frequently applied to anomaly detection tasks in an unsupervised or semi-supervised setting. The underlying assumption is that the model learns an efficient representation of typical, non-defective data, while anomalous structures cannot be reconstructed with the same accuracy. As a result, reconstruction errors can be used as indicators of potential anomalies (Sarker 2021; Hicks et al. 2022).

For a given image x , the reconstruction error can be expressed as the absolute or squared difference between the input and its reconstruction \hat{x} eg. Eq.: $e(x) = |x - \hat{x}|$.

Regions with elevated reconstruction errors are interpreted as deviations from the learned normal data distribution. This reconstruction-based anomaly detection principle has been successfully applied in medical imaging as well as in industrial inspection scenarios, including X-ray and CT-based defect detection (Fuchs et al. 2021; Yang and Guo 2024).

A common extension of the standard autoencoder is the denoising autoencoder (DAE). During training, noise is deliberately added to the input data, and the model is trained to reconstruct the original, noise-free input. This encourages the network to learn more robust and generalized representations rather than memorizing fine-grained noise patterns (Pascal Vincent et al. 2008). In the context of CT data, denoising autoencoders can reduce sensitivity to imaging artifacts and intensity fluctuations, which are inherent to high-resolution tomographic (Shorten and Khoshgoftaar 2019).

3. Measurement Results

In this chapter, exemplary results obtained using the proposed framework are presented and analysed. The selected settings and parameters serve as a baseline for subsequent investigations.

3.1. Experimental setup

To investigate degradation-related mechanisms, a comprehensive experimental aging study was conducted on a total of 80 cylindrical lithium-ion battery cells. Three different 18650-cell types were examined in varying quantities, namely Samsung 30Q, Samsung E35, and LG M26. The primary objective of the aging experiment was to induce representative first-life degradation under controlled and reproducible conditions. For this purpose, the cells were subjected to accelerated aging using a standardized constant-current constant-voltage (CCCV) charge-discharge protocol with a cycling current of 2 A-cycling was performed using a SkyRC MC300 battery analyzer, while voltage and current profiles were continuously recorded.

Independent of the aging procedure, diagnostic measurements were conducted at predefined intervals to characterize the evolving electrochemical and structural state of the cells. These diagnostics included regular capacity and DC internal resistance measurements, as well as electrochemical impedance spectroscopy performed after every 50 charge-discharge cycles. In addition, temperature data were recorded to ensure consistent operating conditions and to support the interpretation of degradation effects. Beyond electrochemical diagnostics, selected reference cells and cells exhibiting anomalous behavior were subjected to CT-scans, and geometric measurements of the outer cell diameter were carried out to capture mechanically induced degradation phenomena. The aging tests will be continued for at least 1000 cycles to represent the end of first-life operation. The resulting dataset forms the basis for a subsequent second-life assessment, in which the measured electrochemical, electrical, and structural indicators are correlated with the remaining usable capacity and performance of the cells.

3.2 Data analysis

Recent advances in CT technology, particularly the combination of photon-counting X-ray detectors with MetalJet X-ray sources, enable the development of high-speed CT systems capable of 100% inline inspection of battery cells at production-scale cycle times. The deployment of such systems has the potential to substantially enhance quality control efficiency and, consequently, to reduce the time to market for battery cells. The features of interest within battery cells typically exhibit characteristic dimensions on the order of 50 μm or larger. Their reliable detection requires both high spatial resolution and sufficient X-ray penetration through materials with high attenuation coefficients, such as copper, nickel, manganese, and cobalt. To meet these requirements, CT systems employ high-performance X-ray sources with very small focal spot sizes in combination with high-efficiency flat-panel X-ray detectors, ensuring adequate image quality under the constraints of high-throughput operation.

For the CT examinations of the battery cells described here, a μ -CT system based on a granite manipulator with transmission X-ray source (manufacturer: XRAY WorX, model: 240

TCHE Plus, energy range: 50 – 240 keV, focus size: 0.9 μm) and flat-panel X-ray detector (manufacturer: Varex, model: 4343DXI, pixel matrix: 3k x 3k, pixel size: 139 μm) is used (cf. Fig. 2).



Fig. 2. Used $\mu\text{-CT}$ system with transmission X-ray source and flat-panel detector (Source: diondo GmbH).

To perform the CT examination, the battery cell is fixed in a suitable holder on the manipulator of the CT system to ensure a stable position during the measurement. After alignment of the sample in the X-ray beam, up to 3,000 X-ray images (so-called "projections") of the cell are taken at a full rotation of 360°, which are then calculated into volume using the mathematical method of 3D cone beam reconstruction. Based on the 3D data generated in this way, a detailed analysis of the various defects and other characteristics in the battery cell is carried out.

An example axial CT scan of sample number 30 is shown in Figure 3. Even prior to the start of the operational aging simulation, distinct visual anomalies can be identified in this cell. First, one side of the cathode coating (upper region of the image) exhibits an unusual appearance, as it ends prematurely, although both cathode coating layers (thick grey layers) would normally end at the same axial position. Second, the distance between anode and cathode is significantly reduced at the location indicated by the red arrows, which may lead to a critical reduction in the separation between the two current collectors and consequently increase the risk of an internal short circuit.

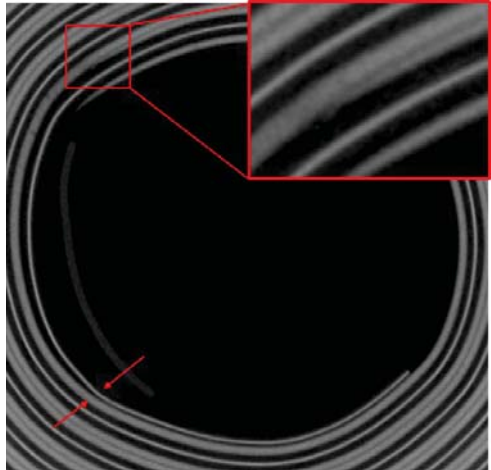


Fig. 3. CT-Scan Battery cell number 30 in initial state (after production).

In contrast, cell 30 initially shows no unusual behavior in the EIS measurement presented in Figure 4. However, cell 30 was classified as deficient after 132 charge-discharge cycles due to an unusual temperature increase and relative slower charging speed. The degradation progress inferred from the elevated temperature is also reflected in the post-test EIS measurement. As illustrated in Figure 4, the impedance spectrum of cell 30 is shifted more along the real axis compared to the intact reference cell 79, while a higher shift is observed along the y-axis. This behavior indicates a significant increase in polarization effects, higher inner resistance and is consistent with advanced electrochemical degradation of the cell.

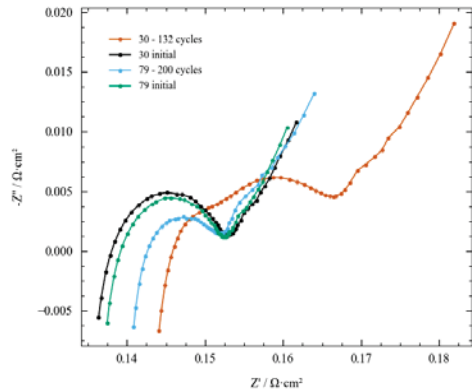


Fig. 4. EIS evaluation: initial versus degraded state (identical cell type)

The CT images confirm the indications of degradation progression observed in the EIS measurements (see Figure 5). The premature end of the cathode coating exhibits a slight waviness, which suggests the presence of internal mechanical stresses within the electrode stack over the used time. Furthermore, the region highlighted by the red arrows indicates a collapsing inner core, where the cathode coating is locally disrupted and the electrodes exhibit pronounced bulging toward the cell interior. Such structural deformations are consistent with advanced degradation processes and support the electrochemical findings derived from the impedance analysis.

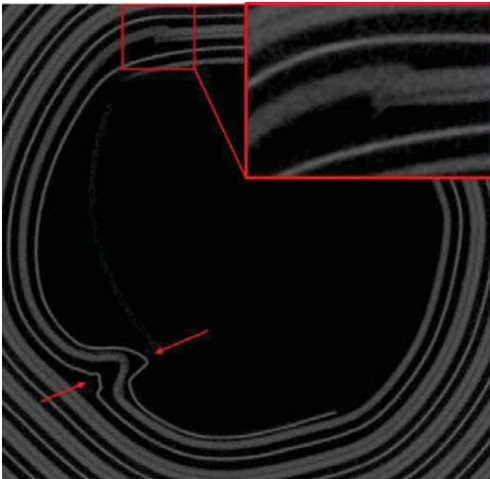


Fig. 5. CT-Scan Battery cell number 30 in defect state (after 132 charging and discharging cycles)

3.3 Anomaly-Detection model development

This section describes the current development state of the anomaly detection models used for the analysis of CT data. The focus lies on dataset preparation, model design, and the training strategy rather than on performance evaluation.

The CT dataset consists of two-dimensional slices acquired from cylindrical lithium-ion battery cells of type 18650. A subset of the slices has been manually annotated on a pixel level to mark visible defect structures. These annotations are not used during training but serve as a reference for qualitative inspection and later evaluation.

As shown in Fig. 6 To enable localized anomaly detection and to reduce computational complexity, the CT slices are subdivided into

fixed-size image patches. Patch-based processing allows the models to focus on local structural characteristics and supports spatial aggregation of anomaly scores at the slice level (Ullah et al., 2023). Patches containing insufficient structural information are excluded during preprocessing.

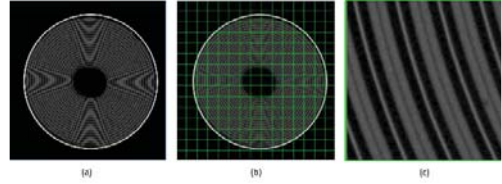


Fig. 6. Pre-Processing steps for AI-analysis. (a) Full CT-Slice, (b) Slice with 128x128 Grid, (c) Example Patch

The anomaly detection models are based on reconstruction-based convolutional autoencoders as described in Section 2.3. Two architectural variants are currently under investigation: a standard convolutional autoencoder and a denoising convolutional autoencoder. Both models follow a symmetric encoder decoder design with convolutional layers and nonlinear activation functions.

Two training configurations are considered. In a one-class setting, only visually normal patches are used for training, reflecting a purely unsupervised anomaly detection scenario. In a mixed setting, the training data may include a small proportion of anomalous samples, which reflects realistic industrial data distributions where defect-free data dominate but cannot be guaranteed exclusively (Sarker, 2021; Hicks et al., 2022).

Model training and hyperparameter optimization are conducted using a validation-based search strategy with Optuna. The search space includes parameters such as learning rate, latent dimensionality, and regularization strength. Early stopping is applied to prevent overfitting, and fixed random seeds are used to ensure reproducibility. During inference, reconstruction errors are computed on a patch level and subsequently aggregated to generate slice-level anomaly maps. Thresholds for anomaly indication are derived from validation data using percentile-based statistics.

3.4 Framework for assessing the second-life potential of lithium-ion-batteries

To qualify the proposed measurement method for evaluating the second-life potential of lithium-ion batteries, the framework illustrated in Figure 7 is introduced. The methodological approaches described in Chapter 3 are integrated within this framework and their interdependencies are systematically illustrated. The primary objective is to combine electrochemical and imaging-based methods in order to assign visually observable features in CT data of used batteries to well-defined degradation patterns, thereby enabling a data-driven lifetime prognosis for subsequent applications.

New battery cells prior to their first life are used as the reference baseline. The initial cell state is characterized by comprehensive EIS measurements and complementary CT scans. In this context, suitable CT acquisition and analysis parameters must first be verified to ensure reproducible and meaningful results. During aging, relevant performance parameters of the batteries - such as capacity and impedance derived from EIS measurements - are continuously monitored. After aging, the visually observable anomalies in the CT data can then be correlated with the electrochemical degradation behavior of the cells.

Due to the inherent geometric symmetry of cylindrical battery cells, the evaluation of tomographic slice images using artificial intelligence-based approaches, such as anomaly detection with autoencoders, is feasible for both axial and frontal views, provided that degradation-related features are visually detectable

Initial results from the ongoing project indicate that it may be advantageous to train the anomaly detection models separately for different cell types. Manufacturing-related variations between cells can otherwise lead to false anomaly indications and significantly impair the performance of the autoencoder. Nevertheless, a key advantage of the autoencoder approach lies in its unsupervised learning paradigm, which substantially reduces the training effort by eliminating the need for extensive manual defect annotation. For the validation of the model development described in Section 3.3, however, annotated data remain necessary.

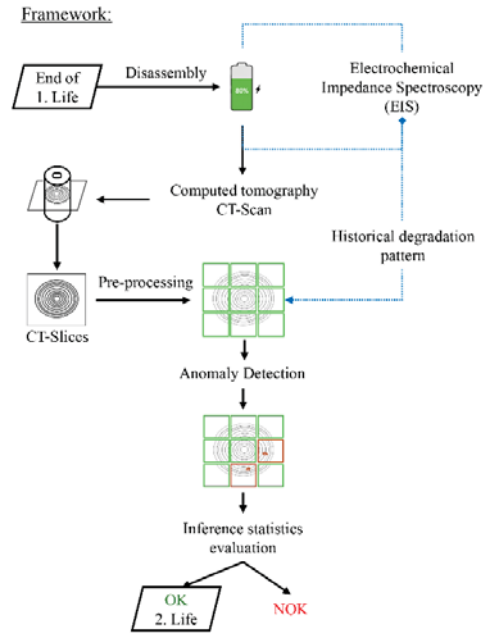


Fig. 7. Framework for the qualification of the new measurement method for evaluating the second-life potential of lithium-ion batteries

Once relevant anomalies have been detected by the autoencoder, their criticality must be assessed in a subsequent step. To this end, methods from inferential statistics, such as hypothesis testing, can be employed to evaluate anomalies not only based on individual CT slices but with respect to the entire cell volume. Definable criteria, e.g. as the cumulative number of anomalous pixels across the full cell or axis-specific trend analyses, can further support a robust classification of cells and enable a more reliable distinction between harmless anomalies and degradation-relevant features.

4. Summary and Outlook

This paper addresses the key challenges associated with the automated application of computed tomography (CT) systems for the assessment of the second-life potential of lithium-ion batteries and demonstrates how these challenges can be systematically addressed within the proposed framework. By combining methods from machine learning and inferential statistics, electrochemical interactions within the battery cell are linked to CT-based visual assessments in a consistent and verifiable manner. The presented

approach has the potential to be applied both during first-life evaluation, for quality and condition assessment, and during second-life qualification of used cells.

The initial results presented in Sections 3.2 provide first indicative evidence of the feasibility and relevance of the proposed approach as the dependency between the visual appearance and EIS-measurement. The example shown in Section 3 illustrates how early production-related anomalies can be visually distinguished, while the EIS measurement does not show any unusual behaviour. In the future, further validation is required to assess the behavior of CT scans acquired at production-relevant throughput rates.

Acknowledgement

The authors thank Hans-Werner Müller (elorec GmbH) for providing data and the German Federal Environmental Foundation (Deutsche Bundesstiftung Umwelt - DBU) for funding the presented research activities.

sponsored by



Deutsche
Bundesstiftung Umwelt

www.dbu.de

References

- Barsoukov, Evgenij, and J. Ross Macdonald. 2005. *Impedance spectroscopy: Theory, experiment, and applications*, 2nd edn. Hoboken N.J.
- Dumoulin, Vincent, and Francesco Visin. 2016. A guide to convolution arithmetic for deep learning.
- Fuchs, Patrick, Thorben Kröger, and Christoph S. Garbe. 2021. Defect detection in CT scans of cast aluminum parts: A machine vision perspective. *Neurocomputing* 453:85–96.
- Hicks, Steven A., Inga Strümke, Vajira Thambawita, Malek Hammou, Michael A. Riegler, Pål Halvorsen, and Sravanthi Parasa. 2022. On evaluation metrics for medical applications of artificial intelligence. *Scientific reports* 12 (1): 5979.
- Ioannou, Georgios, Olaf Günnewig, Martin Münker, and Stefan Bracke (eds.). 2024. *Reliability, safety and security of components and systems & prognostics system health management*.
- Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. 2008. Extracting and Composing Robust Features with Denoising Autoencoders. *ICML '08* 1096–1103.
- Pfeifer, Tilo. 2002. *Production Metrology*.
- Sarker, Iqbal H. 2021. Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN computer science* 2 (3): 160.
- Schmitt, Robert, and Edgar Dietrich. 2023. *Handbook of measurement technology in industrial production: Planning, obtaining, analysing and distributing valid measurement results*.
- Shorten, Connor, and Taghi M. Khoshgoftaar. 2019. A survey on Image Data Augmentation for Deep Learning. *Journal of Big Data* 6 (1).
- Taehoon, Kim, Song Wentao, Son Dae-Yong, Ono Luis K, and Qi Yabing. 2019. Lithium-ion batteries: outlook on present, future, and hybridized technologies. *Journal of Materials Chemistry A* 7 (7): 2942–2964.
- Yamashita, Rikiya, Mizuho Nishio, Richard Kinh Gian Do, and Kaori Togashi. 2018. Convolutional neural networks: an overview and application in radiology. *Insights into imaging* 9 (4): 611–629.
- Yang, Qiyang, and Rongzuo Guo. 2024. An Unsupervised Method for Industrial Image Anomaly Detection with Vision Transformer-Based Autoencoder. *Sensors (Basel, Switzerland)* 24 (8).
- Zhu, Juner, Ian Mathews, Dongsheng Ren, Wei Li, Daniel Cogswell, Bobin Xing, Tobias Sedlatschek, Sai Nithin R. Kantareddy, Mengchao Yi, Tao Gao, Yong Xia, Qing Zhou, Tomasz Wierzbicki, and Martin Z. Bazant. 2021. End-of-life or second-life options for retired electric vehicle batteries. *Cell Reports Physical Science* 2 (8): 100537.