# DIFFBATT

# A Diffusion Model for Battery Degradation Prediction and Synthesis

**Hamidreza Eivazi**[1,3,*], **André Hebenbrock**[1,3], **Raphael Ginster**[2,3], **Steffen Blömeke**[2,3], **Stefan Wittek**[1], **Christoph Herrmann**[2,3], **Thomas S. Spengler**[2,3], **Thomas Turek**[1,3], **Andreas Rausch**[1,3]

[1]Clausthal University of Technology, [2]Technische Universität Braunschweig, [3]Battery LabFactory Braunschweig (BLB)

*he76@tu-clausthal.de

NEURAL INFORMATION PROCESSING SYSTEMS

TU Clausthal

Technische Universität Braunschweig

circularLIB

## Introduction

**Lithium-ion Batteries.** Li-ion batteries are pivotal in energy storage due to their high energy density and long cycle life. Despite their advantages, challenges such as safety risks, environmental impacts, and complex degradation processes persist.

**Capacity Degradation.** Battery capacity degradation occurs through calendar and cycle aging. This degradation reduces the battery's capacity over time and is very individual depending on, e.g., usage behavior and environmental conditions. Despite extensive research, predicting the rate of capacity loss remains a challenge.

## Battery Life Prediction

**Machine Learning in Battery Life Prediction.** Machine learning (ML) is increasingly employed to predict battery degradation by estimating the state of health (SOH) and remaining useful life (RUL).

**Our Contribution.** This work introduces DiffBatt, a diffusion model specifically tailored for battery degradation. DiffBatt functions as a probabilistic model to capture the inherent uncertainties in aging processes and a generative model to simulate battery degradation over time. We believe DiffBatt offers a promising pathway toward developing a foundational model for battery degradation.

## Methodology

**Architecture.**
DiffBatt is based on U-Net architecture and employs

- Diffusion Processes
- Classifier-Free Guidance
- Early Cycle Data
- Transformer Encoder

to generate high-quality SOH curves. Our model can be utilized for RUL prediction, SOH estimation, and SOH synthesis.

**Conditioning.**
Battery information, e.g., the capacity matrix or a diffusion timestep, is embedded and fed into intermediate layers of the network.

**Inference.**
DiffBatt maps Gaussian noise into a new SOH curve through the reverse diffusion process.

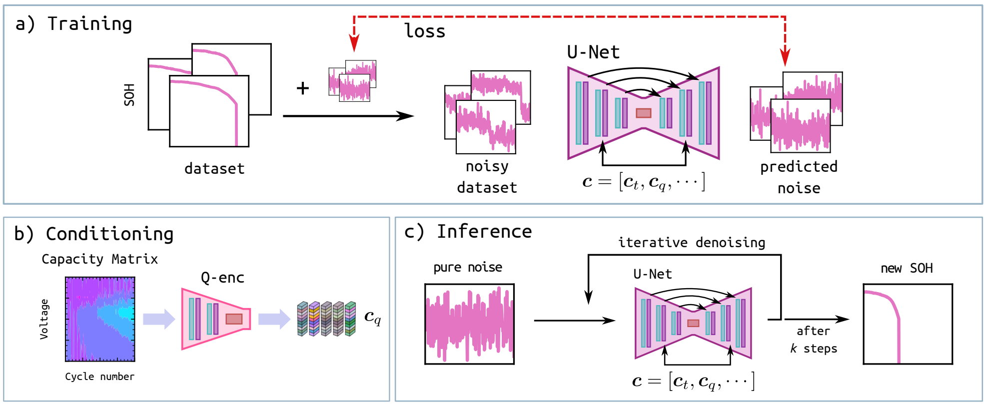



Figure 1: Schematic view of the model architecture. Adapted and modified from the work by [1], with permission from the authors.

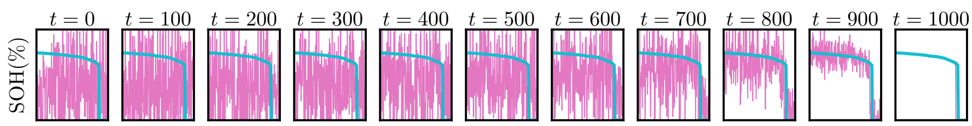


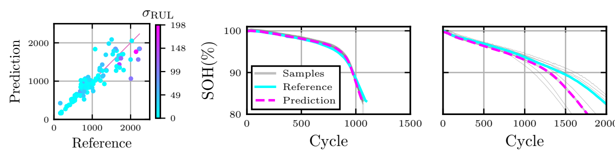

Figure 2: Denoising steps for one test sample of the `MATR` dataset.

## RUL and SOH Prediction

We conduct a comprehensive evaluation based on several open datasets.

Table 1: Results obtained from DiffBatt for RUL prediction against benchmark results reported in [2]. For models sensitive to initialization, values in the table correspond to the mean error and the standard deviation, $\text{mean}_{\text{std}}$, across ten seeds. Values that are underlined represent the best results from the benchmarks in BatteryML, while values that are **bold** indicate the overall best results.

| **Models** | MATR1 | MATR2 | HUST | SNL | CLO | CRUH | CRUSH | MIX | Mean |
|---|---|---|---|---|---|---|---|---|---|
| "Discharge" model | 329 | **149** | **322** | 267 | 143 | 76 | >1000 | >1000 | 411 |
| "Full" model | 167 | >1000 | 335 | 433 | **138** | 93 | >1000 | 331 | 437 |
| PCR | 90 | 187 | 435 | 200 | 197 | 68 | 560 | 376 | 264 |
| PLSR | 104 | 181 | 431 | 242 | 176 | **60** | 535 | 383 | 264 |
| XGBoost | 334 | 799 | 395 | 547 | 215 | 119 | 330 | 205 | 368 |
| Random forest | $168_{9}$ | $233_{7}$ | $368_{7}$ | $532_{25}$ | $192_{2}$ | $81_{1}$ | $416_{5}$ | $\mathbf{197}_{0}$ | 273 |
| MLP | $149_{3}$ | $275_{27}$ | $459_{9}$ | $370_{81}$ | $146_{5}$ | $103_{4}$ | $565_{9}$ | $451_{42}$ | 263 |
| CNN | $102_{94}$ | $228_{104}$ | $465_{75}$ | $924_{267}$ | >1000 | $174_{92}$ | $545_{11}$ | $272_{101}$ | 464 |
| LSTM | $119_{11}$ | $219_{33}$ | $443_{29}$ | $539_{40}$ | $222_{12}$ | $105_{10}$ | $519_{39}$ | $268_{9}$ | 304 |
| Transformer | $135_{13}$ | $364_{25}$ | $391_{11}$ | $424_{23}$ | $187_{14}$ | $81_{8}$ | $550_{21}$ | $271_{16}$ | 300 |
| DiffBatt (ours) | $\mathbf{88}_{4}$ | $235_{16}$ | $368_{23}$ | $\mathbf{125}_{11}$ | $140_{14}$ | $119_{6}$ | $\mathbf{294}_{18}$ | $202_{6}$ | **196** |




(a) RUL prediction (b) SOH prediction

Figure 3: Results obtained from DiffBatt for RUL prediction and SOH estimation on the `MIX` test datasets. (a) Predicted RUL against the reference, colored by the standard deviation $\sigma_{\text{RUL}}$. (b) Generated samples and selected predictions, compared against the reference SOH for test samples with the lowest (left) and highest (right) uncertainty in the predictions.

**Key Takeaways.** DiffBatt exhibits a mean RMSE of 196 across all datasets, outperforming all other models. These results illustrate DiffBatt's efficacy in learning from and generalizing across diverse data sources.

## References

[1] F. Fürrutter et al. Quantum circuit synthesis with diffusion models. *Nat. Mach. Intell.*, 6(5), 2024.

[2] H. Zhang et al. BatteryML: An open-source platform for machine learning on battery degradation. In *ICLR*, 2024.

## Code and Data

https://github.com/HamidrezaEiv/DiffBatt

GitHub Paper

**Acknowledgement.** This research was conducted within the Research Training Group CircularLIB, supported by the Ministry of Science and Culture of Lower Saxony with funds from the program zukunft.niedersachsen of the Volkswagen Foundation (MWK | ZN3678).