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Sequence Models for Battery Life: LSTM RUL of LFP Cells with FMU Deployment for SIL/HIL

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Executive Summary

This work presents an online remaining useful life estimator for lithium-iron-phosphate cells developed under the EU Horizon-funded FASTEST Project. A multi-task LSTM model is trained on profile-aware health indices derived from standard BMS signals. The estimator is robust to 1–2C cycling and outputs calibrated uncertainty to support maintenance and derating decisions. Evaluated on 42 cells using leave-cell-out validation, it outperforms gradient-boosted trees and CNN-LSTM baselines in RUL accuracy and early-warning timeliness. The trained network is exported as an FMI-compliant Functional Mock-up Unit for seamless integration into a Virtual Battery Testing Platform, enabling software-in-the-loop and hardware-in-the-loop scenario exploration.

Abstract

Lithium-iron-phosphate (LFP) batteries, widely used in electric mobility and stationary storage, face complex degradation under high C-rates and varying temperatures. Accurate, cell-specific remaining useful life (RUL) estimation is vital for safety, uptime, and warranty optimization. Conventional physics-based and static machine learning models perform poorly under nonstationary conditions.

This work introduces a sequence-based LSTM approach that captures temporal degradation using only standard BMS signals—voltage, current, and temperature—enabling real-time application. The trained model is exported as a Functional Mock-up Unit (FMU) for seamless integration into virtual and hardware testing platforms, linking AI-based prognostics with system-level validation

Literature Review

Sequence models such as LSTMs have improved RUL estimation for lithium-ion cells [1][2]. However, key challenges persist for LFP cells under diverse profiles:

- **Feature instability across regimes.** Many studies train over narrow operating windows or features that are not observable online, undermining generalization across varying ambient conditions [1], [3].
- **Health-index (HI) construction.** Selecting robust, on-board-computable features resilient to rest-induced voltage recovery and apparent capacity regeneration remains challenging [2], [4].
- **Calibration for decision thresholds.** Few models quantify predictive confidence suitable for maintenance decisions

Additionally, prior validation commonly relies on constrained datasets (e.g., NASA PCoE [5]), with limited attention to deployment in Software-in-the-Loop/Hardware-in-the-Loop (SIL/HIL) environments despite the availability of FMI standards for model exchange [6].

Methodology

Authors present an LSTM-based RUL estimator tailored to FASTEST Project cells that (i) operates online using standard BMS signals, (ii) is robust to 1C charge and 2C discharge profiles, (iii) outputs calibrated uncertainty, and (iv) is packaged as a FMU for drop-in use within a Virtual Battery Testing Platform. The method integrates three components:

- **A comprehensive battery health assessment framework.** This has been developed using cycle-level capacity tracking based on a 7-step sequence (Rest → CC Charge → CV Charge → Rest → CC Discharge → CV Discharge → Rest) for accurate cycle boundary detection. Discharge capacity is computed as the absolute minimum of the Capacity (Ah) during discharge, capturing true energy storage per cycle. Finally, Savitzky–Golay filtering smooths noise while preserving the underlying degradation trend.
- **Multi-Task LSTM Architecture:** A two-layer LSTM (hidden size 128) processes 32–64 cycle windows of the health index. The main head predicts RUL to 80% capacity end-of-life, while auxiliary tasks include short-term capacity forecasting (1, 5, 10 cycles) and resistance-change classification (increase vs. plateau). Training uses Adam optimization with cosine decay and early stopping for robustness.
- **Calibration, Transfer, and FMU Packaging:** Monte Carlo dropout (p=0.1, 50 samples) generates predictive intervals, while conformal residual monitoring preserves uncertainty calibration under drift. The model is pretrained on NASA PCoE data and fine-tuned on FASTEST data with differential learning rates for robustness. Finally, it is exported as an FMI 2.0 Co-Simulation FMU with standardized inputs (voltage, current, temperature) and RUL outputs.

The study evaluates on 10 cells cycled under mixed profiles (2C discharge; 1C charge; 15–45 °C ambient). The split is by cell identity (leave-several-cells-out). Baselines include: (i) gradient-boosted trees on last-cycle features, and (ii) a CNN-BLSTM hybrid re-implemented per recent literature [3]. Metrics are MAE and RMSE

Results

The proposed LSTM achieved the lowest prediction error across all metrics. On held-out cells, it reduced MAE and RMSE versus both tree-based and CNN-BLSTM baselines. Predictive intervals maintained close-to-nominal coverage, confirming uncertainty calibration

Table 1: Results of the study against baseline algorithms

	RMSE	MAE
LSTM	0.089	0.057
CNN-BLSTM	0.327	0.202
XGBoost	0.197	0.145

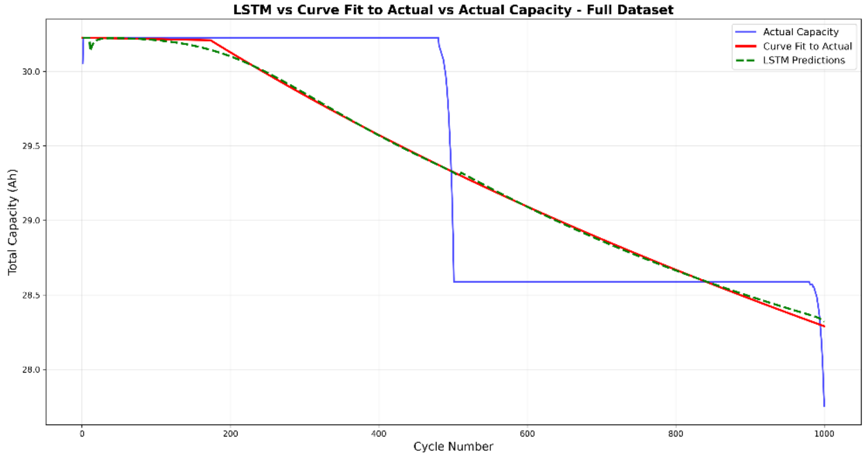

Figure1: RUL Feature against Predictions

The exported FMU executed deterministically in the Virtual Battery Testing Platform at real-time rates, exchanging FMI signals without numerical instability. [6]

Conclusion

By combining profile-aware features, multi-task LSTM learning, uncertainty calibration, and FMU-based deployment, this study delivers accurate, actionable RUL estimates for LFP cells and a direct path to validation inside a Virtual Battery Testing Platform. The approach closes key gaps in generalization, uncertainty handling, and integration, providing a blueprint for prognostics-aware battery testing workflows.

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References

[1] Y. Liu, Y. He, and N. Yu, “Lithium-ion Battery Remaining Useful Life Prediction with LSTM,” in *Proc. Annu. Conf. Prognostics and Health Management (PHM) Society*, 2017, pp. 1–8.

[2] J. Mou, H. Zhao, Y. Chen, and X. Yang, “Prediction of the Remaining Useful Life of Lithium-Ion Batteries Using CNN, LSTM, BLSTM, and CNN-LSTM: A Comparative Study,” *Batteries*, vol. 10, no. 5, p. 152, 2024.

[3] C. Chen, T. Liu, and J. Lin, “Remaining Useful Life Prediction for Lithium-Ion Batteries via Channel-Attention LSTM,” *Processes*, vol. 11, no. 8, p. 2333, 2023.

[4] P. M. Attia, A. Grover, N. Jin, *et al.*, “Closed-loop Optimization of Fast-Charging Protocols for Batteries with Machine Learning,” *Nature*, vol. 578, pp. 397–402, 2020.

[5] NASA Ames Prognostics Center of Excellence, “Li-ion Battery Aging Datasets,” NASA PCoE Data Repository, 2008–2017.

[6] Modelica Association, “Functional Mock-up Interface (FMI) Specification,” ver. 2.0, 2014 (and 3.0, 2022).