Master Thesis – Mechanical Engineering

AI Model for Estimating the State of Health of Batteries

Industry Partner: Carrier Innovation Technologies GmbH

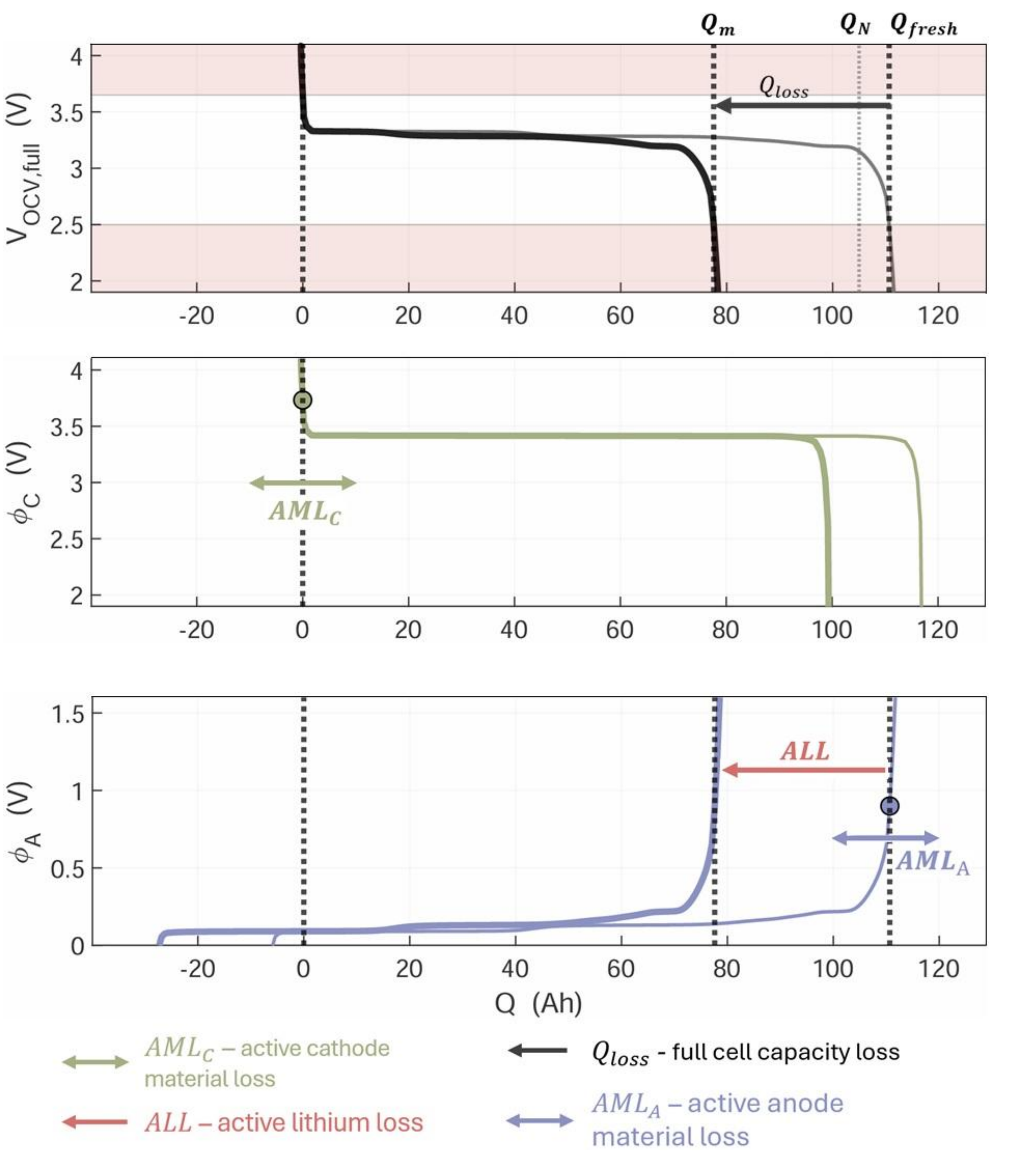

Figure 1: OCV model of a simulated $LiFePO_4$, for a fresh and aged condition. ALL requires a shift of the electrode's potentials against each other. AML_A a scaling of the electrodes' potentials.

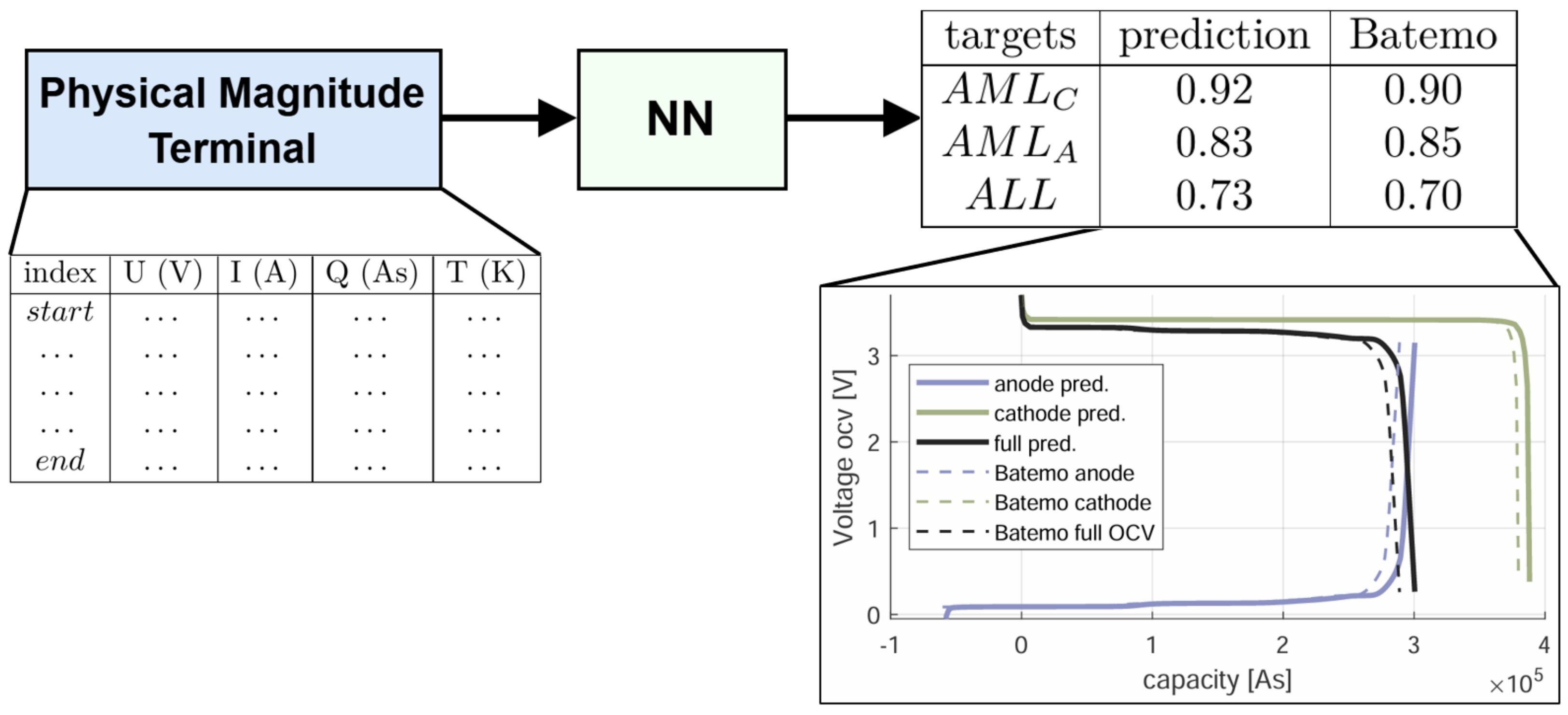

Figure 2: Data processing from operational input series till output prediction of chosen neural network (NN).

$$V_{OCV,full}^{aged}(Q) = \Phi_C(AML_C \cdot Q) - \Phi_A(AML_A \cdot Q - ALL)$$

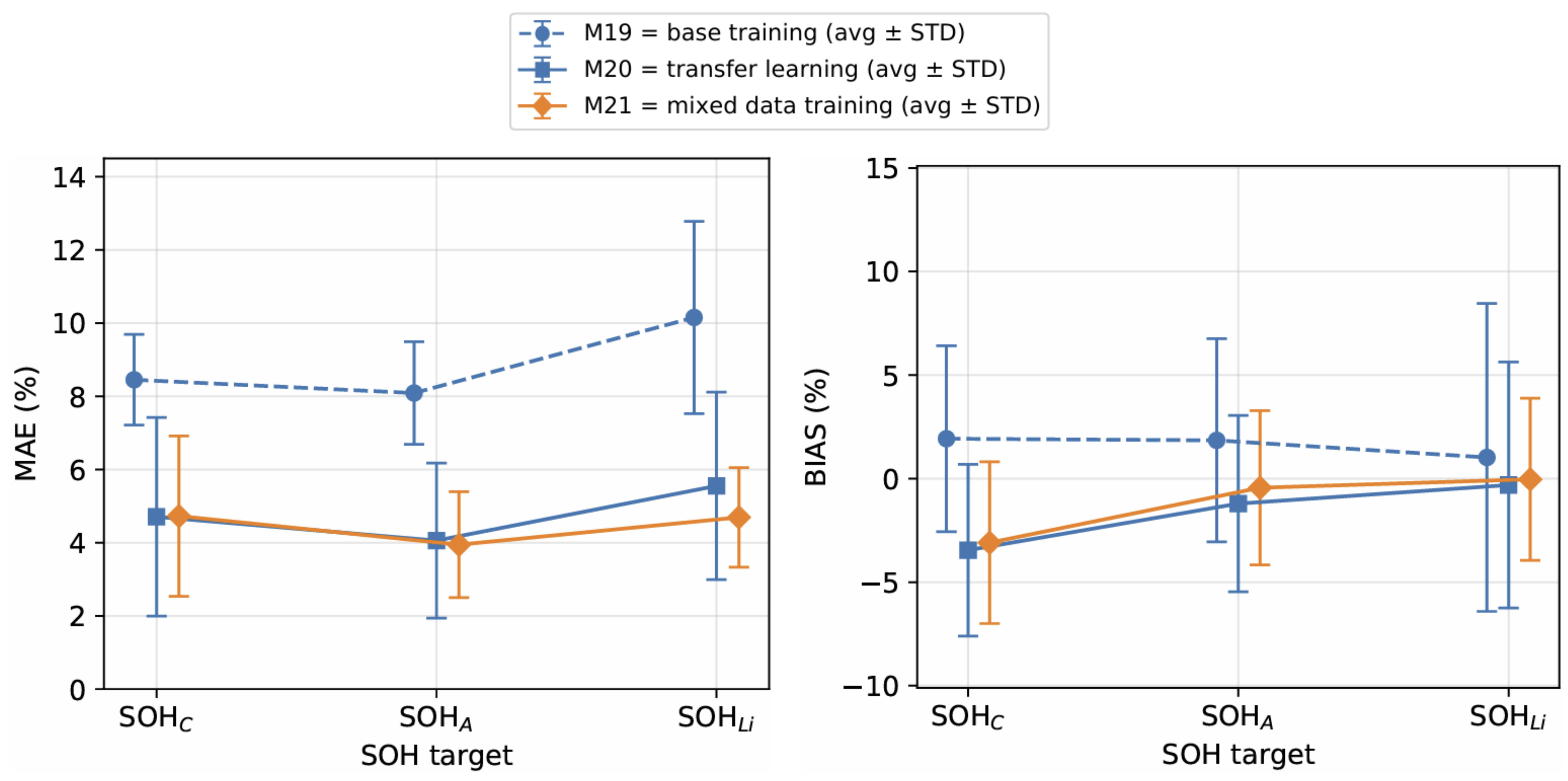

Figure 3: Mean absolute error and bias on previously unseen dynamic simulated profiles. Each point represent the mean over 230 simulations.

Problem Description

Battery health assessment has become a critical topic across multiple sectors, including industry, certification bodies, and standardization organizations. Extensive research has examined the mechanisms responsible for battery aging and different physical models are available in the literature. However, accurately estimating battery health solely from operational field data remains an open research question.

The objective of this thesis was to develop an AI-based model capable of reliably quantifying $LiFePO_4$ battery state of health using only operational data. The model should not require specialized diagnostic hardware or controlled measurement protocols.

Solution Concept

For this purpose, three capacity state of health (SOH) metrics were considered as target variables: The loss of active anode material (AML_A), the loss of active cathode material (AML_C), and the loss of active lithium inventory (ALL). These SOH targets are directly linked to the battery capacity loss Q_{loss} through the open-circuit voltage (OCV) model (Figure 1 and $V_{OCV,full}^{aged}$). Based on this relationship, an AI-framework was to predict these three SOH targets. Therefore, two neural networks (NN) architectures were selected, namely a convolutional neural network (CNN) and a temporal convolutional network (TCN). To train the NNs, synthetic battery operational data were generated using the Batemo simulation tool.

The NN estimates the SOH targets using physical battery terminal time series: voltage V, capacity Q, current I, and temperature T. From this, the full open-circuit voltage curve can be reconstructed (Figure 2), which can be used to determine the remaining battery capacity Q_m.

Results

A selected CNN model achieved an absolute prediction error of 2 % under idealized, constant operating conditions.

To test the model's performance in real-world conditions, synthetic operational profiles were simulated for the TCN architecture. In one case, the model was trained on simple data (M19) and then retrained using profiles (M20). In another case, the model was trained from the start using mixed data (M21).

The TCN model trained on mixed data (M21) achieved prediction errors lower than 5 % on a previously unseen synthetic operating profile. The results demonstrate the fundamental feasibility of the approach (Figure 3).

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