TINYML FOR BATTERY CELL SOH ESTIMATION

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Developing a sophisticated Battery Management System (BMS) is a critical component of modern rechargeable energy storage systems, as it ensures the safe and efficient operation of battery cells. Core BMS functions include managing charging and discharging, estimating states of battery operation (SoX) [1], balancing cell voltages, and preventing adverse conditions such as overcharging, deep discharging, and overheating [2]. Among these, estimating the State of Health (SoH)—which reflects a battery's remaining useful life [3] and performance relative to its original condition—is particularly important for system reliability, user safety, predictive maintenance, and second-life applications [4].

SoH estimation methods are broadly categorized into model-based and data-driven approaches. Model-based methods [5] rely on electrochemical or equivalent circuit models to simulate battery behavior and estimate SoH via parameter tracking and mathematical formulations. In contrast, data-driven methods [6] use historical performance data and apply machine learning or deep learning models to learn complex, non-linear relationships between measured signals and SoH. Due to their adaptability, reduced dependence on physical modeling, and robustness under varying conditions, data-driven techniques are increasingly favored for real-time BMS integration. Accurate SoH estimation not only supports diagnostics and prognostics of battery cells but also improves the estimation of other key metrics like the State of Charge (SoC). In [7], the authors proposed an algorithm for SoC estimation that integrates SoH with voltage, current, and temperature data collected over a 60-second window. The approach uses two models: one to estimate SoH from Incremental Capacity (IC) data, and another to predict SoC using the estimated SoH and sensor data. Their findings confirm that incorporating SoH significantly enhances SoC prediction accuracy.

In [8], the authors explored the use of Tiny Machine Learning (TinyML) for real-time state-of-health (SoH) estimation of lithium-ion batteries on low-power IoT devices by developing and deploying quantized deep learning models—ANNs and CNNs—on Infineon's CY8CPROTO-062S3-4343W (Figure 1) microcontroller using the MTB-ML toolchain. These models, trained on dynamic cycling data from 18650 NMC batteries, demonstrated a balance between accuracy and resource efficiency, despite minor accuracy drops near battery degradation knee-points.[1]

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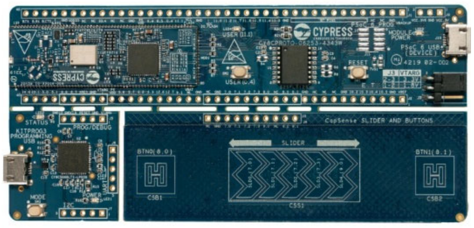

Figure 1:CY8CPROTO-062S3-4343W PSoC 62S3 target device, employed in the SENATOR Project

In [9], two data-driven methods using Electrochemical Impedance Spectroscopy (EIS) data were proposed: Method_A extracting Equivalent Circuit Model (ECM) parameters and Method_B using raw EIS data directly, with the latter—particularly via a CNN-GRU model—achieving superior performance (RMSE 1.20%, MAE 0.87%) and being optimized into lightweight TensorFlow Lite formats for TinyML conversions, enabling over 99% latency reduction and 89% compression for microcontroller-based SoH monitoring. The results of the developed deep learning models are shown in the Figures 2 and 3 for the Method_A and Method_B, respectively.

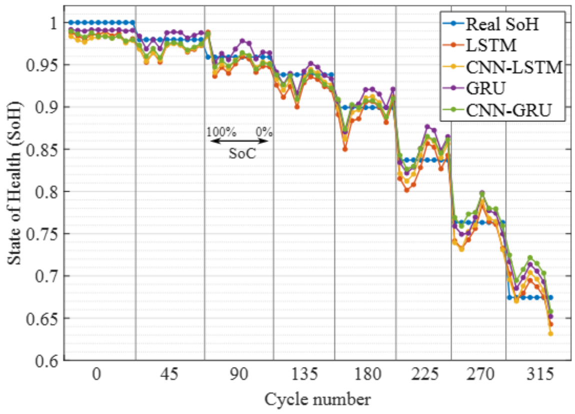

Figure 2:Performance comparison among models of Method A

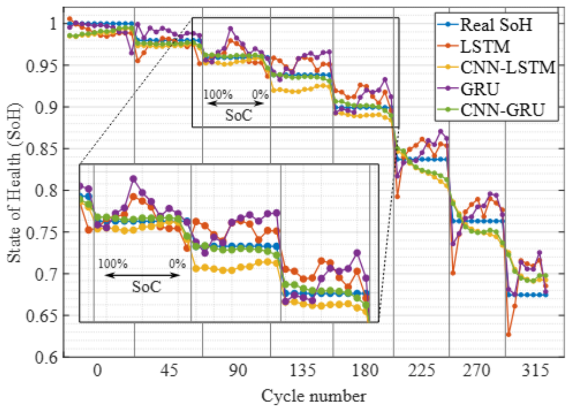

Figure 3:Performance comparison among models of Method B

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