Physics-Informed Neural Networks for Battery Surface Temperature Estimation using On-board Multiplexed EIS and Cyclic Aging Data

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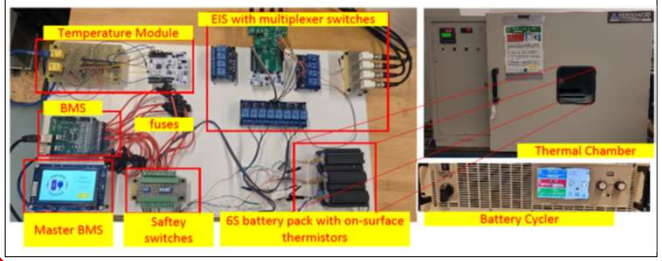
Abstract

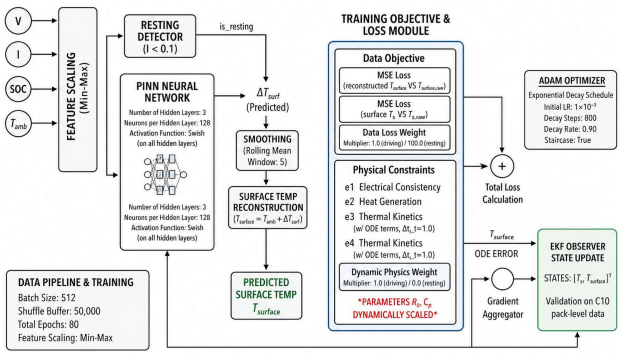
Accurate battery thermal state estimation is challenging due to varying ambient conditions and lifecycle degradation. This paper proposes an adaptive Physics-Informed Neural Network (PINN) that embeds lumped-parameter thermal kinetics into its loss formulation for robust surface temperature prediction. Trained exclusively on low-temperature data (0°C and 10°C), the model successfully extrapolates to an unseen 30°C environment, achieving maximum instantaneous errors below 1.1°C across HWFET, UDDS, and US06 drive cycles. To address long-term degradation, accelerated aging tests over 900 cycles were conducted, revealing a steady thermal drift of 1°C per 100 elapsed cycles. An on-board multiplexed electrochemical impedance spectroscopy (EIS) system isolated this drift to high frequency (1 kHz to 10 kHz) Ohmic resistance shifts at the electrode interfaces. Consequently, an Extended Kalman Filter (EKF) is integrated to continuously recalibrate internal thermal states based on real-time EIS tracking, mitigating the compounding physics loss. This combined PINN-EKF framework provides a highly generalizable, degradation-aware thermal management solution bridging empirical data and physical laws.

Key Highlights & Motivation

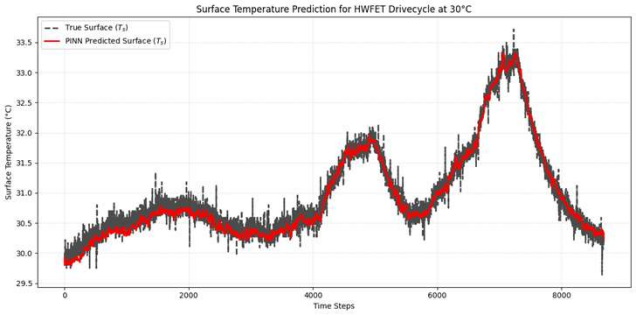
- **Zero-Shot Boundary Extrapolation:** Trained strictly on cold profiles ($0°C$, $10°C$), the network accurately extrapolates to warm conditions ($30°C$) without unconstrained divergence.
- **Thermodynamic Loss Embeddings:** Integrates coupled ordinary differential equations (ODEs) and an Arrhenius-based heat generation model directly into the neural network objective function.
- **Longitudinal Aging Diagnosis:** Empirical 900-cycle accelerated degradation testing quantified a continuous thermal drift of $1°C$per 100 elapsed cycles under invariant load and ambient parameters.
- **High-Frequency Impedance Tracking:** In-situ multiplexed EIS localized the lifecycle drift to the 1 kHzto 10 kHzband, linking the drift directly to growing interface Ohmic resistance (R_{ohmic}).
- **Closed-Loop Adaptation:** An Extended Kalman Filter (EKF) dynamically recalibrates core states and resistance parameters, maintaining total estimation error within $\pm 1.5°C$across 900 cycles.

Experimental Setup

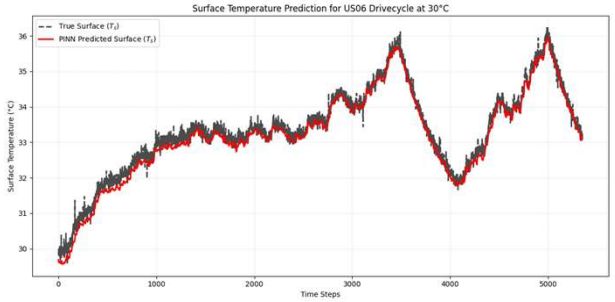




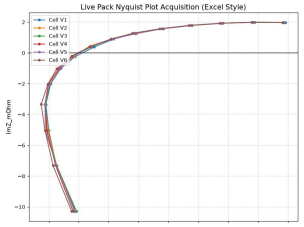
Physics Informed Neural Network (PINN) Architecture



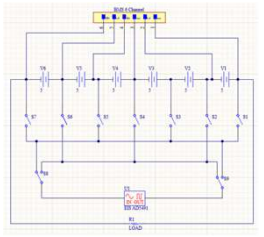
Surface temperature estimation for HWFET drive cycle at 30°C



Surface temperature estimation for US06 drive cycle at 30°C



EIS Plot



Multiplex Configuration

Parameter	Value
Number of Inputs	3
Batch Size	512
Hidden Layer Neurons	128
Epochs	80
Learning Rate	0.001
Optimizer	Adam

Table 1: Hyperparameters

Conclusions

- **Generalization:** The thermodynamic physics constraint successfully bounds predictions under zero-shot conditions ($30°C$ extrapolation), holding maximum transient errors under $1.1°C$.
- **Aging Drift Identification:** Identified an empirical $1°C$rise per 100 cycles over 900 cycles, pinpointing interfacial R_{ohmic}increase (1 kHz to 10 kHz) as the primary degradation source.
- **Closed-Loop Reliability:** The hybrid PINN-EKF framework bounds lifecycle estimation error to within $\pm 1.5°C$, providing an adaptive and computationally lean solution for next-generation Battery Management Systems.

References

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