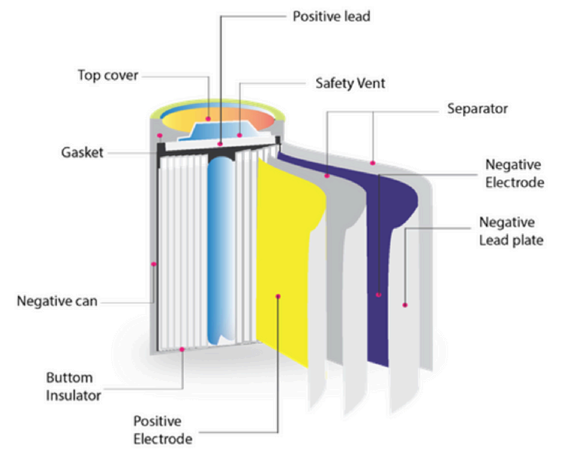
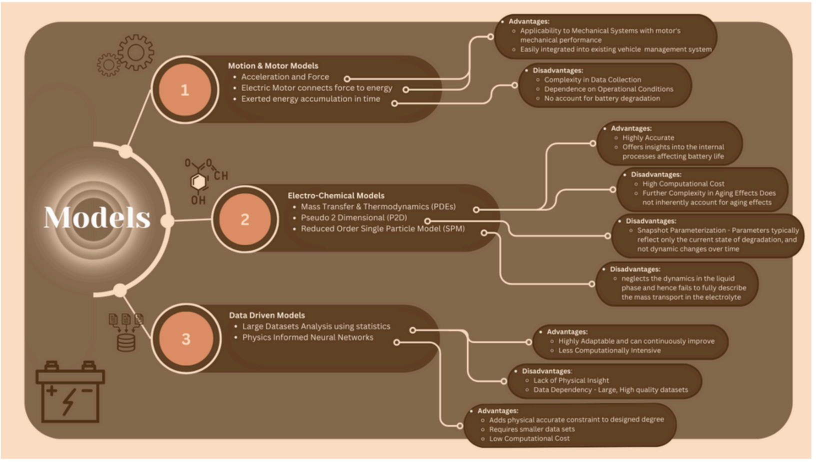
# ENHANCING BATTERY PERFORMANCE VIA P.I.N.N PREDICTOR

Lapid H. Bar-David, Dr. Anna Clarke
Faculty of Mechanical Engineering, Technion – Israel Institute of Technology

## Introduction

Efficient battery management is essential for autonomous electric vehicles (EVs). This research presents a novel approach using Physics-Informed Neural Networks (PINNs) to predict battery State of Health (SoH) and State of Charge (SoC) in real time. By integrating physical laws into machine learning models, we aim to optimize battery lifespan and energy efficiency without relying on massive datasets.

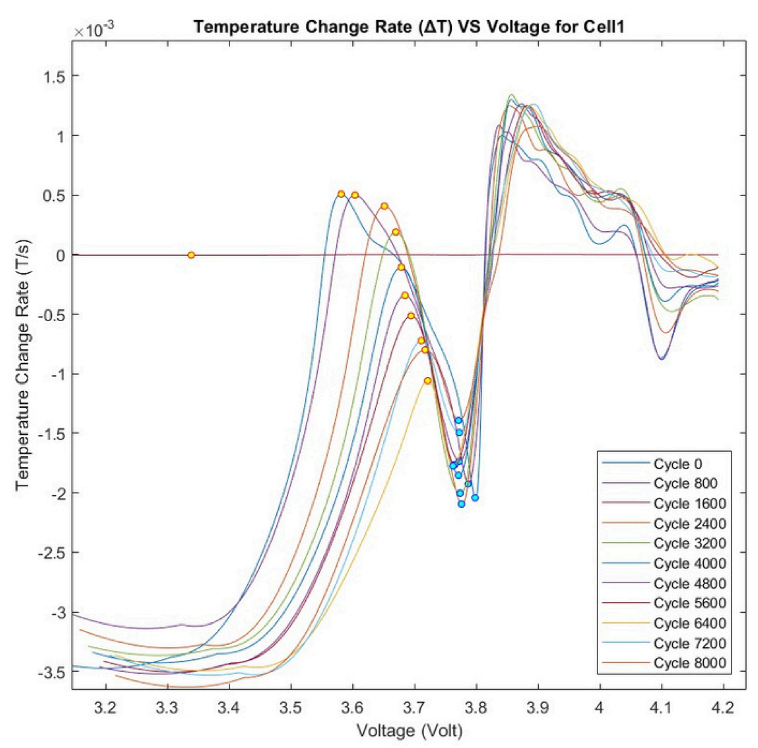


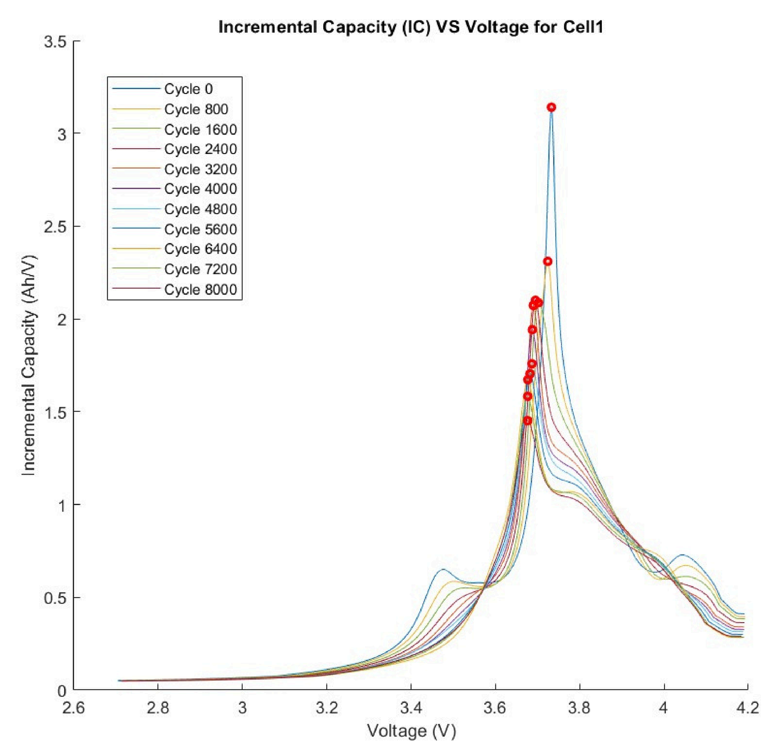




Traditional data-driven models, while powerful, often require large and specific datasets, making them hard to generalize across different battery types and operational environments. Conversely, physics-based models, though accurate, are computationally intensive and unsuitable for real-time applications in embedded systems.
This research addresses this gap by developing a Physics-Informed Neural Network (PINN)—a hybrid model that embeds physical laws into the training process of a neural network. By fusing real-world battery data with constraints derived from electrochemical principles, this method improves predictive accuracy, ensures physical plausibility, and maintains computational efficiency.
Ultimately, the work demonstrates a scalable, real-time solution for battery state estimation—essential for next-generation autonomous electric vehicles operating in dynamic, data-scarce environments.

## Methods

We trained a PINN using key features from lithium-ion battery charge/discharge cycles—specifically the Peak Incremental Capacity (P-IC) and thermal characteristics. The model includes physical constraints reflecting battery degradation, embedded directly into the loss function. Data were sourced from Oxford and NASA battery datasets, smoothed and processed using Gaussian and averaging filters. Hyperparameters were fine-tuned through extensive sensitivity analysis.




1. Voltage $[V]$
2. Charge $[Ah]$
3. Temperature $[°C]$
4. Time $[s]$

From which 4 key features were extracted for in depth analysis:

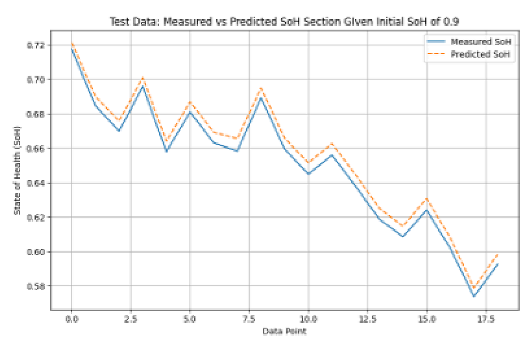
1. P-IC - Peak of Incremental Charge of a charging cycle $[Ah/V]$
2. Left-Peak - Typical first peak of the DT-Voltage curve of a discharge cycle
3. Middle-Valley - Typical latter minimum point of the DT-Voltage curve of a discharge cycle
4. Voltage-Difference - Between that of the Left-Peak and that of the Middle-Valley

where the DT curve is the rate of change in temperature of a discharge cycle, presented over the changing voltage $[°C/s]$.

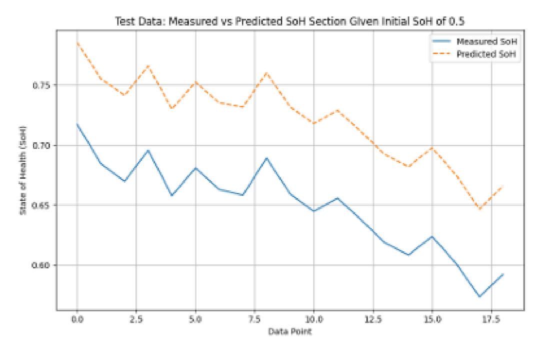
This research primarily relies on the data and models provided by kindly by Jinhua et al. Whereas the database used for comparison of the PINNs is taken from the open source Oxford and NASA websites consisting of numerous Lithium-ion Battery cells data on both charge and discharge cycles, for which the key parameters were documented in time.

## Results

The PINN achieved a normalized MAPE as low as 0.0007 on test data, outperforming conventional neural networks. Visual comparisons of predicted vs. real SoH show strong agreement. Incorporating physical constraints improved convergence, even with limited training data. SoH predictions remained robust under varied initial conditions and trajectories.




(a) Predicted SoH versus real SoH of a battery starting from mid-life SoH given initial SoH of 0.9.




(b) Predicted SoH versus real SoH of a battery starting from mid-life SoH given initial SoH of 0.5.

Figure 6: Predicted SoH vs. Real SoH of a battery starting from mid-life SoH given different initial SoH fed to the network.

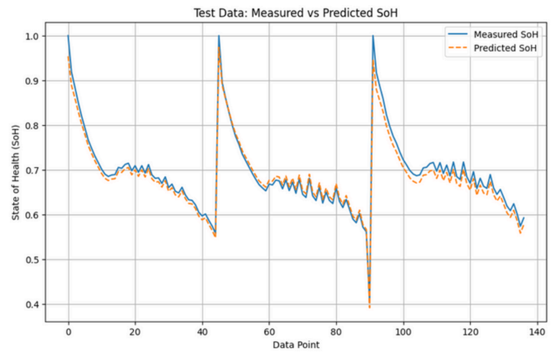



Figure 10: Predicted SoH VS Real SoH of the Test Batch

## Conclusions

Physics-informed learning significantly improves the reliability and adaptability of battery state estimation. This method enhances battery longevity and energy efficiency in EVs while enabling deployment in resource-constrained real-time systems. Challenges remain in model generalization and onboard integration, but the approach shows strong potential for scalable real-world application.

## Acknowledgments

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