Frequency-Based Parameterization of Semi-Empirical Models for State-of-Health Estimation in Lithium-Ion Batteries in Electric Vehicles

Background

- Electric vehicles (EVs) are one of the most important technologies today for achieving a sustainable future.
- However, EV battery performance remains poorly understood. An accurate, next-generation model combining physics-informed modeling techniques and data-driven approaches is urgently needed for advanced battery management systems.


[1] Plug-in America, 2014.

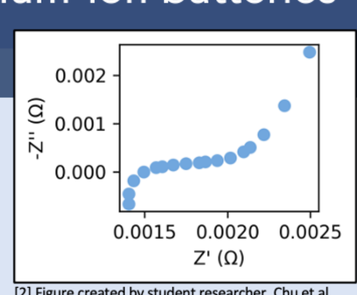
Battery EVs can have over 70% lower lifecycle carbon emissions than gas-powered vehicles.[3]

However, 62% of individuals who choose not to purchase a used EV cite concerns over battery lifespan.[4]

[5] Graphic created by student researcher using PowerPoint, 2026.

Model Pipeline

1. Lithium-Ion Batteries Aging Campaign
Electrochemical impedance spectroscopy (EIS) data, which measures responses from small electrical signals, from 22 lithium-ion batteries is analyzed.

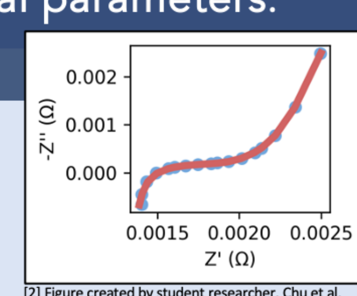


[2] Figure created by student researcher. Chu et al.

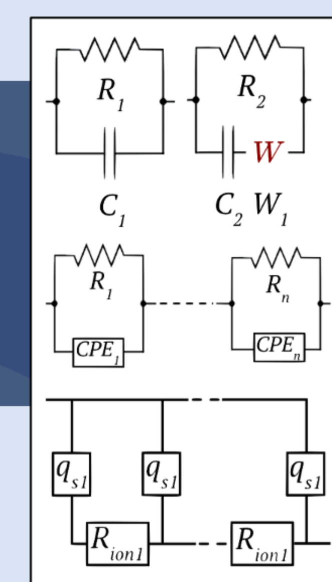
2. ECM Fitting and Selection
Equivalent circuit models (ECMs) are used to extract key electrochemical parameters.

$R_0\ L_0\ R_1\ \tau_1\ \alpha_1\ R_2\ \tau_2\ \alpha_2\ W_0$

Extracted Parameters (2 ZARC ECM)



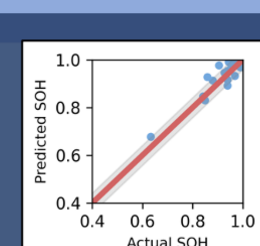
[2] Figure created by student researcher. Chu et al.


[2] Figure created by student researcher. Chu et al.

3. Machine Learning Regression Models
Extracted parameters are inputted into four regression models.


[2] Figure created by student researcher. Chu et al.

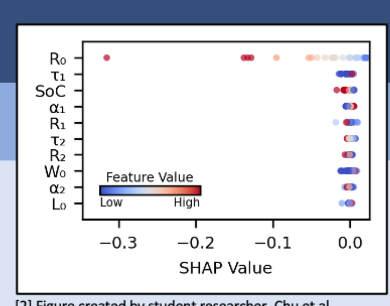
4. SoH Estimation
State-of-health (SoH) is estimated with robust error analysis.



[2] Figure created by student researcher. Chu et al.

2.36%
SoH Avg. RMSE (Random Forest)

5. Feature Multicollinearity Analysis
SHAP analysis is performed to quantify the contribution of ECM-derived parameters on SoH.



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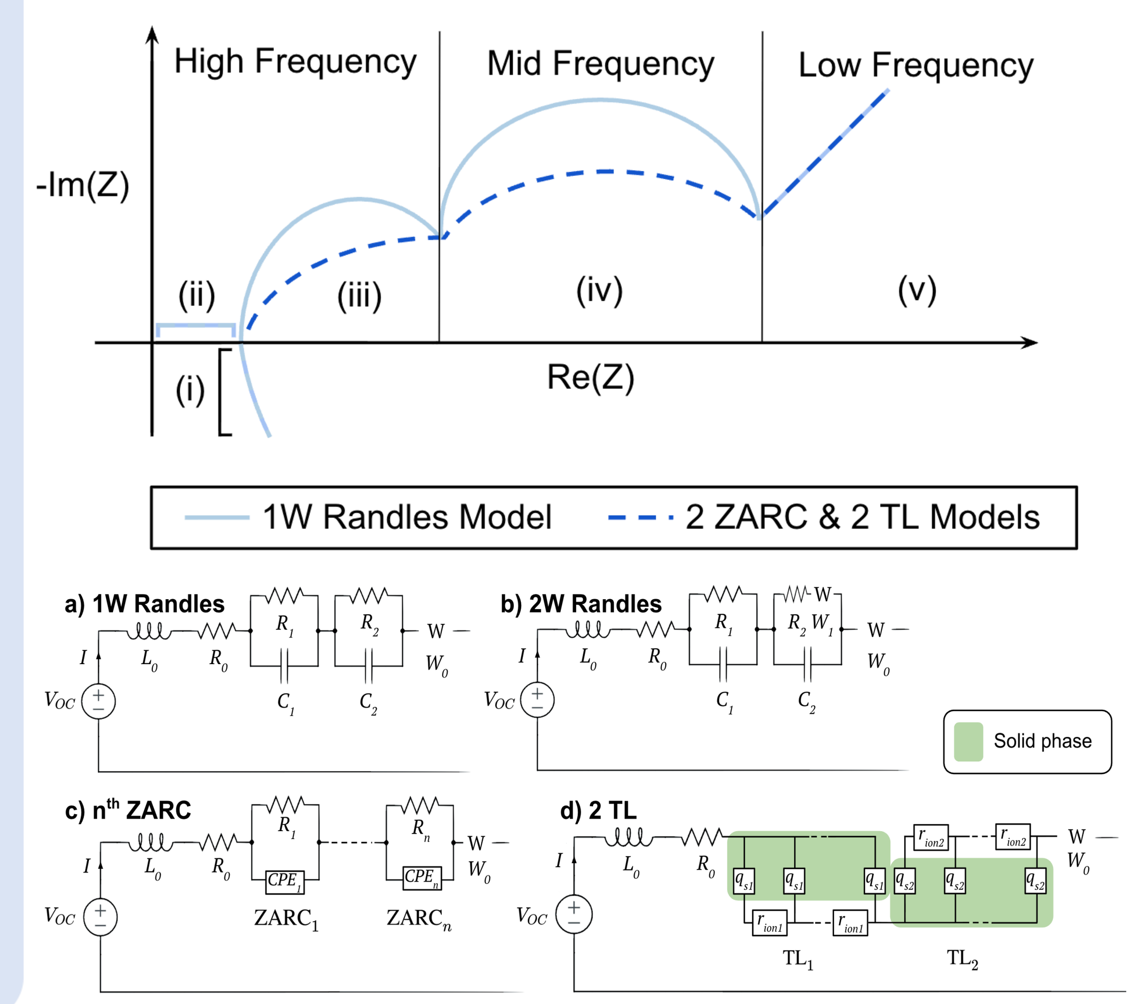
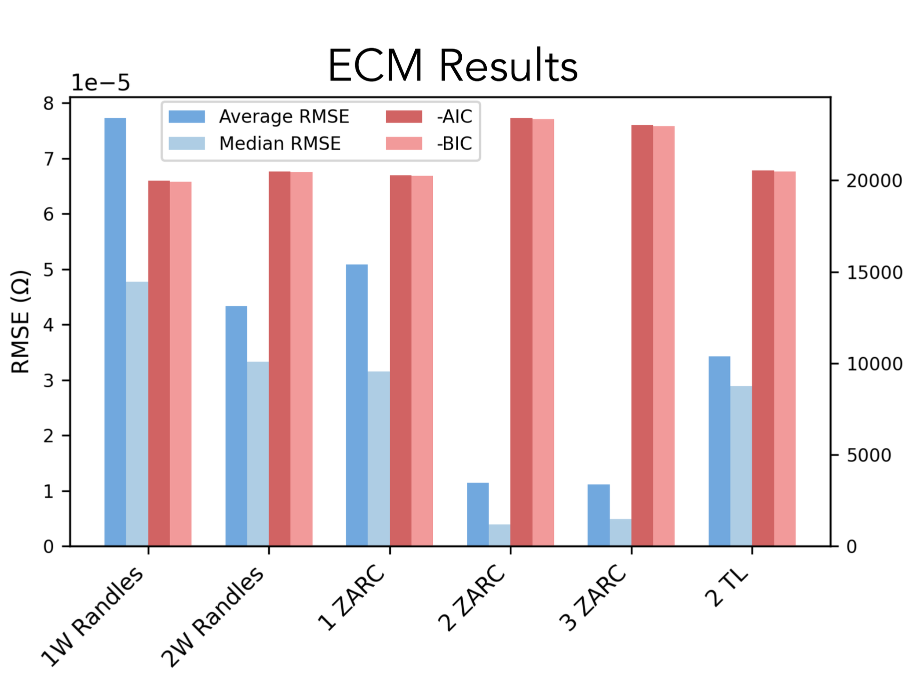
Equivalent Circuit Models

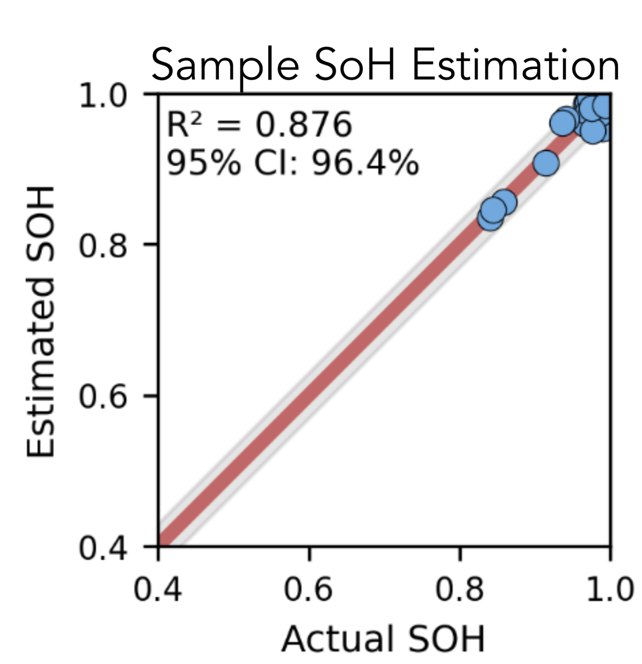


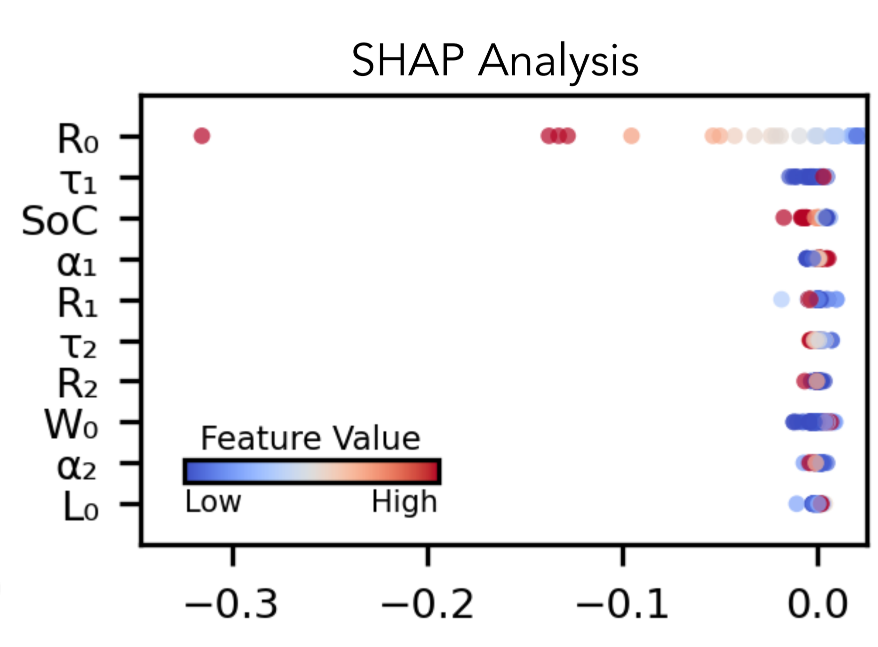
[2] Figure created by student researcher. Chu et al.

Results

This work achieves an average RMSE of 2.36% for SoH estimation via the 2 ZARC-Random Forest model. The 2 ZARC circuit was the most accurate and efficient ECM, demonstrating that the two ZARC elements successfully captured non-ideal behaviors in both RC components. The random forest model under Architecture 1 (all parameters and SoC as input features) had the lowest average RMSE. In Architecture 2 (only R_0 as input feature), the random forest model performed slightly worse. The random forest model performed relatively similarly across all SoCs, as demonstrated by Architecture 3.







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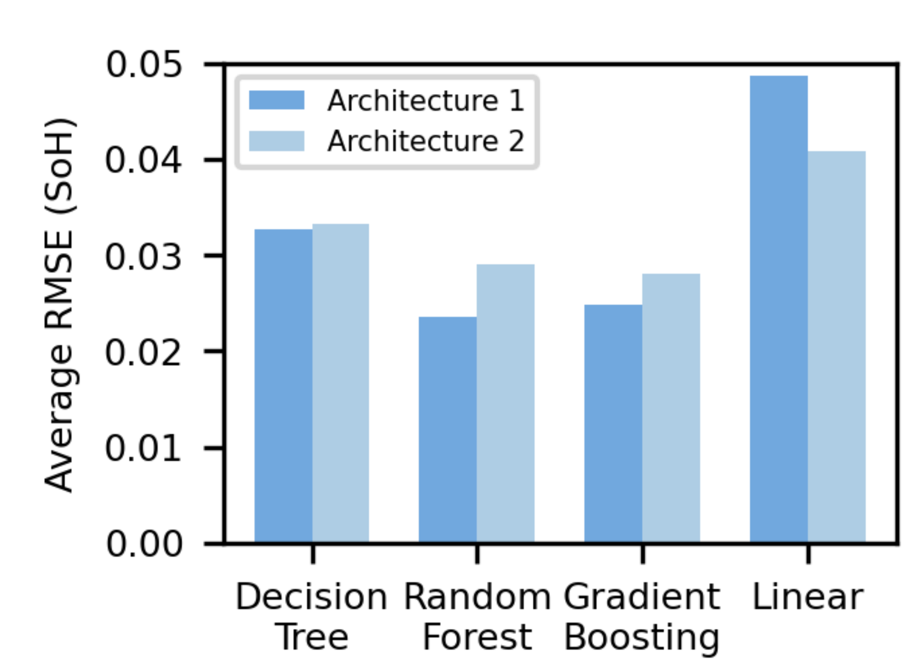
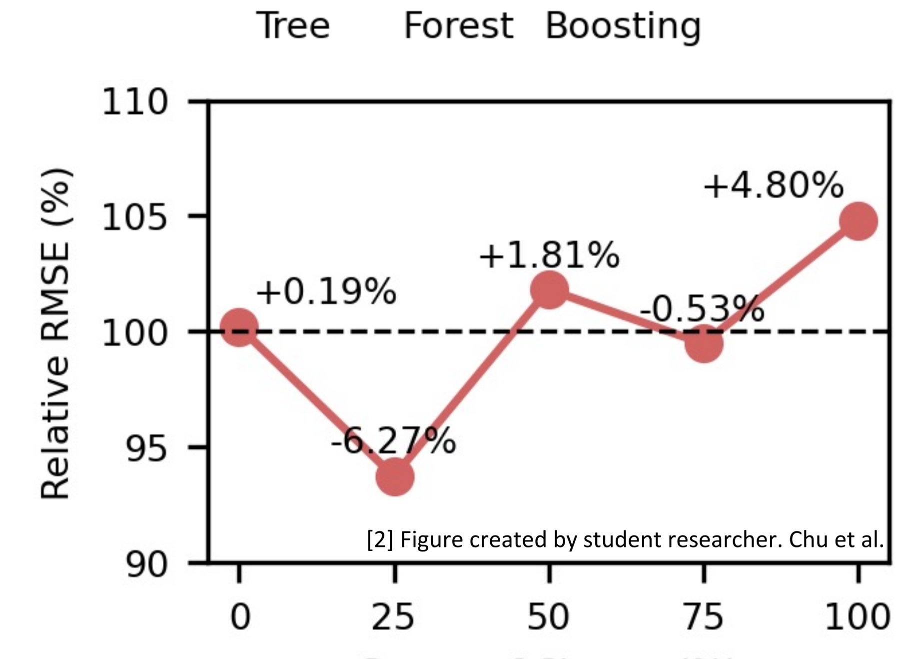
Machine Learning Models





[2] Figure created by student researcher. Chu et al.

Conclusion and Impact

This work offers contributions for a scalable and interpretable framework for SoH estimation:

1. This research provides interpretable supervised regressors to allow for feature attribution through SHAP analysis, enabling feature-level insights often absent in prior studies. These results can be used to inform battery design and manufacturing as well as for repairs to current EV infrastructure.
2. This work's error margin of 2.36% is comparable with state-of-the-art models, many of which currently lack robust datasets and interpretable feature attribution results.

Safety

Infrastructure

Affordability

Sustainability

[5] Graphic created by student researcher using PowerPoint, 2026.

This work will not only improve the safety of EVs, but also extend battery lifespans by identifying key electrochemical features, thereby reducing maintenance costs and increasing adoptability.

[1] Plug In America. (2014). https://pluginamerica.org/wp-content/uploads/2024/08/Untitled-design-15.jpg
[2] Figure created by student researcher. Chu, C. J., Thatipamula, S., & Onori, S. (2025). Frequency-based parameterization of semi-empirical models for State-of-health estimation in lithium-ion batteries. *Journal of The Electrochemical Society*, *172*(10), 100540.
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[5] Graphic created by student researcher using PowerPoint (2026).
[6] Wang, Y., Tian, J., Sun, Z., Wang, L., Xu, R., Li, M., & Chen, Z. (2020). A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems. *Renewable and Sustainable Energy Reviews*, *131*, 110015.
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