Failure Threshold-Aware Battery SoC Estimation using Machine Learning

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***Abstract*—It is critical to correctly estimate the state of charge (SoC) of batteries. Its purpose is to ensure a longer cell lifespan and safe battery use. In this paper, a dataset containing the SoC, temperature, and discharge capacity of a battery was used to evaluate machine learning candidates for efficient estimation and classification. Furthermore, the machine learning model differentiates between good (functional battery within a threshold of 80%) and bad (needing replacement) batteries.**

***Index Terms*—Battery Management, Machine Learning, RUL, SoC**

I. Introduction

The state of charge (SoC) for the battery pack in a battery electric vehicle (BEV), hybrid vehicle (HV), or plug-in hybrid electric vehicle (PHEV) is analogous to a fuel gauge, requiring accurate estimation to ensure safe operation and increased cell lifespan [1]. Because of their characteristics, lithium-ion batteries have become ubiquitous. Accurate estimation of the SoC of Li-ion batteries will aid in optimal usage and save replacement costs. However, SoC estimation remains difficult because its measurement is usually inaccurate, except in the laboratory or when using a battery management system [2]. Two estimation methods have dominated research; the data driven, and the model driven approaches. Due to the complexities and difficulties associated with the model-driven approach, the data-driven approach has received research attention. To that end, deep and machine learning approaches have shown great promise for SoC estimation [1], [3].

The following contributions were made in this research:

1) We evaluated machine learning candidates for SoC estimation.
2) We employed a public battery dataset for the assessment of the effectiveness of the proposed machine learning technique for SoC estimation.
3) We carried out machine learning classification of Good and Bad batteries based on the available data.

II. Background Information

A. Battery State of Charge (SoC) Estimation Overview

A battery's level of charge in relation to its capacity is known as its "SoC". SoC is measured in percentage point units (0% = empty; 100% = full). The inverse of SoC, the depth of discharge (DoD), is another way to express the same measurement (100% = empty; 0% = full) [1]. A battery's current condition is typically discussed in SoC, whereas DoD typically addresses a battery's lifespan after repeated use [1]. An assessment of a battery's potential energy can be made using the SoC parameter, which can be seen as a thermodynamic quantity [4].

For instance, in all variants and manufacturing years of the Mitsubishi Outlander PHEV, the driver is shown a SoC that is 0% of the vehicle's actual 20-20% charge level (assuming zero level as the lowest level of charge permitted by car producer). Another example is the BMW i3 REX (Range Extender variant), where roughly 6% of SOC is set aside for PHEV-like activities. Tesla has stated that their SoC should be less than 95%, however some experts have suggested between 30% and 80%. These numbers serve as the SoC estimation threshold, as stated in [5].

SoC is typically hard to measure directly. However, it can be estimated in two different approaches using direct measurement variables: offline and online. The battery needs to be charged and drained in offline methods like Coulomb counting at a constant rate. This method estimates battery SoC, but they are time-consuming, expensive, and interfere with actual battery performance. To address this, researchers are looking for some online approaches [2].

III. System Methodology

A. ML-based Battery SoC Estimation and Classification System Model

The following ML models were evaluated for their estimation accuracy and classification cost: Tree algorithms, KNN, Naive Bayes, SVM, and Discriminant models. Threshold accuracy was set at 99.3% for estimation accuracy, while classification error allowable was set at 1. Control or threshold performance was set using MATLAB optimizable ensemble learner application.

B. Dataset Description

The dataset was provided by [6]. Battery storage life tests were performed on a total of 144 Li-ion cells at four different temperatures (-40°C, -5°C, 25°C, and 50°C) using three different SoC values (0% SOC, 50% SoC, and 100% SoC). In all, twelve (12) cells were stored at -40°C, -5°C, 25°C, and 50°C. Four of the 12 cells stored at each temperature were at 50% SoC, four were at 100% SoC, and four were at 0% SoC. Every

TABLE I
PERFORMANCE EVALUATION OF MACHINE LEARNING MODELS

Model	Accuracy (%) Without PCA	Accuracy (%) With PCA	MCE Without PCA	MCE With PCA	Training Time (s) Without PCA	Training Time (s) With PCA
Fine Tree (Without Optimization)	99.3	96.7	1	5	**3.13**	**1.16**
Optimized Tree	99.3	96.7	1	5	18.30	23.09
Optimized KNN	99.3	**98.7**	1	**2**	27.49	36.71
Optimized Naive Bayes	99.3	97.4	1	4	44.68	54.15
Optimized SVM	99.3	91.4	1	13	76.46	108.44
Ensemble Decision Trees	99.3	**98.7**	1	**2**	72.52	110.04
Discriminant Models	Failed	Failed	Failed	Failed	Failed	Failed

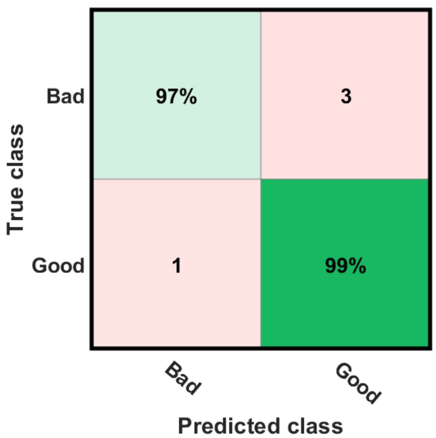

Fig. 1. Sample Confusion Matrix showing the binary classification of the Battery into Good or Bad based on the temperature, discharge capacity, charge/discharge time, and SoC estimation

three weeks, 48 cells received capacity testing and impedance measurement; every three months, 48 cells undertook capacity testing and impedance measurement; and every six months, 48 cells experienced capacity testing [4] [6].

C. Data Preprocessing and Experimental Environment

The dataset was divided into three categories: validation (10%), training (70%) and testing (20%). The simulation was executed in MATLAB R2019b machine learner application on a system configuration of Intel(R) Core(TM) i5-8500 CPU @ 3.00GHz, 24GB RAM. The effect of principal component analysis (PCA) feature extraction on the model accuracy was evaluated.

IV. PERFORMANCE EVALUATION

The results in Table I gave the following insights.

1) PCA as a feature extraction method had a significant effect on the model's estimation accuracy, training time, and classification performance. However, future work may include examining the impact of other feature extraction approaches.
2) While optimization helped to improve the performance of most machine learning models evaluated, it was, however, not significant to the performance of TREE algorithms.
3) Ensemble and/or Hybrid machine learning models are promising approaches for SoC estimation. However, they increased training and testing time as well as computation complexity.
4) PCA worsened the training time of all models evaluated except the TREE algorithms. Fine Tree had a significant reduction in training time from **3.1309s to 1.1605s**

V. CONCLUSION

This work evaluated machine learning candidates for SoC estimation of Li-ion batteries. Future works will address the possibility of integrating the machine learning model in a digital twin-based scenario. It will also be exciting research to evaluate deep learning candidates.

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REFERENCES

[1] M. A. Hannan, D. N. T. How, M. S. H. Lipu, M. Mansor, P. J. Ker, Z. Y. Dong, K. S. M. Sahari, S. K. Tiong, K. M. Muttaqi, T. M. I. Mahlia, and F. Blaabjerg, "Deep Learning Approach Towards Accurate State of Charge Estimation for Lithium-Ion Batteries using Self-Supervised Transformer Model," *Sci Rep*, vol. 11, no. 19541, pp. 106–111, 2021. [Online]. Available: https://doi.org/10.1038/s41598-021-98915-8

[2] S. M. Rezvanizaniani, Z. Liu, Y. Chen, and J. Lee, "Review and Recent Advances in Battery Health Monitoring and Prognostics Technologies for Electric Vehicle (EV) Safety and Mobility," *Journal of Power Sources*, vol. 256, pp. 110–124, 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775314001098

[3] X. Li, H. Jiang, S. Guo, J. Xu, M. Li, X. Liu, and X. Zhang, "SOC Estimation of Lithium-Ion Battery for Electric Vehicle Based on Deep Multilayer Perceptron," *Computational Intelligence and Neuroscience*, vol. 2022, no. 3920317, p. 12, 2022.

[4] S. Saxena, C. Hendricks, and M. Pecht, "Cycle life testing and modeling of graphite/licoo2 cells under different state of charge ranges," *Journal of Power Sources*, vol. 327, pp. 394–400, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775316309247

[5] "Why is the State of Charge (SoC) in EVs Is Important," Sept. 4, 2020. [Online]. Available: https://auto.keemut.com/why-is-the-state-of-charge-soc-in-evs-is-important/

[6] S. Saxena, C. Hendricks, and M. Pecht, "Storage Data and Test Description," in *Center for Advanced Life Cycle Engineering (CALCE) Battery Data*, M. Pecht, Ed. A.James Clark School of Engineering, University of Maryland, 2016. [Online]. Available: https://calce.umd.edu/battery-data#Storage