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Experimental Investigation of Mechanical Vibration Effects on Lithium-Ion Battery State-of-Charge Estimation Using Ensemble Machine Learning Models

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ABSTRACT

Accurate state-of-charge (SoC) estimation is a critical requirement for reliable battery management systems in electric vehicles. While data-driven and machine learning approaches have demonstrated high estimation accuracy, most existing studies assume ideal operating conditions and neglect the influence of mechanical disturbances. In practical automotive environments, lithium-ion batteries are continuously exposed to mechanical vibration, which may affect electrical signals and estimation reliability.

In this study, the impact of mechanical vibration on SoC estimation accuracy is experimentally investigated using standardized vibration tests conducted in accordance with IEC 62660-2. A cylindrical 18650 lithium-ion cell is subjected to random vibration along three orthogonal axes during charge–discharge cycles. Four ensemble-based machine learning models—Random Forest, Extra Trees, Gradient Boosting, and LightGBM—are developed and evaluated under vibration-free and vibration-exposed conditions.

The experimental results demonstrate that mechanical vibration degrades the prediction performance of all investigated ensemble learning models to different extents, as reflected by higher RMSE and MAE values under vibration conditions. Among the evaluated algorithms, Extra Trees and LightGBM exhibited comparatively better robustness under vibration-induced disturbances, whereas the remaining models showed a more pronounced degradation in prediction accuracy. These findings highlight the importance of considering vibration effects when developing machine-learning-based state-of-charge estimation algorithms for practical electric vehicle battery management systems.

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1. Introduction

Lithium-ion batteries are widely used in electric vehicles due to their high energy density, long cycle life, and favorable power characteristics. To ensure safe and efficient operation, battery management systems (BMS) rely on accurate estimation of internal battery states, among which state-of-charge (SoC) plays a central role in energy management, range prediction, and operational safety [1–3].

Conventional SoC estimation methods, such as Coulomb counting and Kalman filter–based approaches, require accurate battery models and reliable parameter identification. However, parameter uncertainty, sensor noise, and environmental disturbances can significantly degrade estimation accuracy [4–6]. To overcome these limitations, data-driven and machine learning–based approaches have gained increasing attention due to their ability to model complex nonlinear relationships directly from measurement data [7–9].

Despite their promising performance, most machine learning–based SoC estimation studies are conducted under controlled laboratory conditions and neglect the influence of mechanical disturbances. In real-world automotive environments, batteries are exposed to continuous mechanical vibration induced by road roughness, vehicle dynamics, and drivetrain operation. Previous experimental studies have shown that vibration can affect battery internal structure, electrical contacts, and voltage signal stability [10–12].

Although considerable progress has been achieved in lithium-ion battery state-of-charge estimation using machine learning techniques, most published studies have evaluated their performance under controlled laboratory conditions. Existing research has mainly focused on the influence of temperature variation, battery aging, and dynamic load profiles, whereas the effect of mechanical vibration on the robustness of machine-learning-based SoC estimation has received considerably less attention. Furthermore, adaptive battery parameter estimation studies have demonstrated that uncertainty in operating conditions significantly influences estimation accuracy, emphasizing the importance of developing robust prediction algorithms capable of maintaining reliable performance under practical operating environments. Therefore, investigating the influence of mechanical vibration on ensemble learning algorithms represents an important research gap. [1,3,13]

However, the influence of mechanical vibration on data-driven SoC estimation accuracy has not been sufficiently investigated. Moreover, a systematic quantitative comparison of different ensemble learning algorithms under vibration conditions is still lacking. Based on the identified research gap, this study experimentally investigates the influence of mechanical vibration on lithium-ion battery SoC estimation using four representative ensemble learning algorithms, namely Random Forest, Extra Trees, Gradient Boosting, and LightGBM. Unlike previous studies that primarily evaluate prediction accuracy under nominal laboratory conditions, the proposed investigation focuses on the robustness of these algorithms when exposed to vibration-induced disturbances representative of electric vehicle operating environments.

The main contributions of this work are summarized as follows:

- Experimental evaluation of vibration effects on machine-learning-based SoC estimation.
- Comparative robustness assessment of four ensemble learning algorithms under identical vibration conditions.
- Analysis of vibration-induced degradation using RMSE, MAE and R^2.
- Discussion of practical implications for vibration-aware battery management systems.

2. Literature Review

Type and label section and subsection headings in the style shown in the present document.

Use numbered sections (Arabic numerals) in order to facilitate cross-references.

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2.1. SoC Estimation Techniques

The results indicate that while ensemble learning improves robustness, mechanical vibration remains a significant external disturbance affecting SoC estimation accuracy. [5]

State-of-charge estimation has been extensively studied using model-based, signal-based, and data-driven approaches. Traditional methods such as Coulomb counting and equivalent circuit models suffer from accumulated errors and parameter sensitivity. Data-driven techniques, particularly machine learning algorithms, have shown promising results by learning complex nonlinear relationships directly from measurement data. [7-9]

Ensemble learning methods, including Random Forest, Extra Trees, Gradient Boosting, and LightGBM, have gained attention due to their high accuracy and robustness. However, most existing studies evaluate these methods under static or quasi-static conditions, without considering mechanical disturbances. [16]

Mechanical vibration has been primarily investigated in the context of battery safety and degradation. Previous studies have shown that vibration can influence internal resistance, electrode integrity, and thermal behavior. These physical effects can indirectly impact electrical measurements, which are critical inputs for SoC estimation algorithms. Nevertheless, experimental studies linking vibration effects directly to SoC estimation accuracy remain limited. This work contributes to the literature by experimentally quantifying this relationship. [11]

2.2. Ensemble Learning for Battery Applications

Ensemble learning methods such as Random Forest, Extra Trees, and Gradient Boosting combine multiple decision trees to reduce variance and improve prediction accuracy. These methods have been successfully applied to SoC and state-of-health estimation under dynamic load profiles [21–23]. LightGBM, a gradient boosting framework based on decision trees, provides high computational efficiency and strong performance for large-scale regression problems [24].

Nevertheless, existing studies primarily focus on electrical and thermal operating conditions, while the robustness of ensemble models against mechanical vibration remains largely unexplored.

2.3 Mechanical Vibration Effects on Lithium-Ion Batteries

Mechanical vibration can induce microstructural damage, loosen internal connections, and increase internal resistance in lithium-ion batteries [10,25]. Experimental investigations have reported voltage fluctuations, capacity degradation, and performance instability under prolonged vibration exposure [26,27]. These disturbances may propagate into measurement signals and adversely affect data-driven SoC estimation accuracy.

2.4 Limitations of Existing SoC Estimation Studies under Realistic Operating Conditions

Most existing studies on machine learning–based SoC estimation for lithium-ion batteries are conducted under controlled laboratory conditions, where environmental and mechanical disturbances are either minimized or completely neglected. Although such conditions are useful for benchmarking algorithmic performance, they do not accurately represent real-world automotive operating environments.

In practical applications, battery packs are continuously exposed to various external disturbances, including mechanical vibration,

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temperature fluctuations, and electrical noise. These factors can significantly affect voltage and current measurements, which serve as the primary inputs for data-driven SoC estimation models. Even small perturbations in input signals can lead to noticeable degradation in prediction accuracy, particularly for models trained under idealized conditions [22,23].

Furthermore, many machine learning studies emphasize accuracy improvements through increased model complexity without adequately addressing robustness and generalization under uncertain operating conditions. This gap motivates the present study, which focuses on quantitatively evaluating the robustness of ensemble learning models under standardized mechanical vibration.

Table 1: Studies Comparison

Study	Algorithm	Vibration	Limitation
Previous SOC studies	ANN/ LSTM / EKF	No	Laboratory conditions
Adaptive ECM (SoftwareX 2023)	Adaptive estimation	No	Parameter uncertainty
Existing vibration studies	Experimental	Yes	ML comparison
This work	RF / ET / GB / LightGBM	Yes	Robustness comparison

3. Experimental Setup and Data Description

3.1 Experimental Protocol

Experiments were conducted in accordance with the IEC 62660-2 standard for reliability and abuse testing of automotive lithium-ion cells. Random vibration was applied along three orthogonal axes (X, Y, and Z) to emulate realistic mechanical operating conditions. [10]

Vibration experiments were conducted using an ASLI ES-3 electrodynamic vibration testing system with a maximum payload capacity of 100 kg and an operating frequency range of 3–3500 Hz. Based on the experimental protocol adopted in this study, sinusoidal vibration was applied within the frequency range of 10–2000 Hz, which represents the dominant vibration spectrum encountered in automotive applications. The vibration duration ranged from 60 to 300 s, while acceleration levels ranged from 0.5 g to 2.5 g according to the experimental design.

The test procedure consisted of three stages:

1. Pre-vibration cycles: Three charge–discharge cycles at a 1C rate using a constant-current–constant-voltage (CC–CV) protocol.

2. Vibration-assisted cycles: Charge–discharge cycling is performed simultaneously with random vibration applied along all three axes.

3. Post-vibration cycles: Three additional cycles identical to the pre-vibration stage to evaluate persistent vibration effects.

Table 2: Test conditions

Parameter	Value
Frequency range	10–2000 Hz
Discharge current	1 A
Ambient temperature	25 °C
Charging protocol	CC–CV

3.2 Battery Specifications and Test Conditions

A commercial cylindrical 18650 lithium-ion cell was used in the experiments. The nominal capacity of the cell was 1200 mAh. Tests were performed at an ambient temperature of 25 °C with a constant discharge current of 1 A. The vibration frequency range was 10–2000 Hz, limited to 10–200 Hz where applicable. The

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orientation of the battery cell and the applied vibration axes are illustrated in Fig. 1.

Table 3: Battery specifications

Parameter	Value
Battery type	Li-ion 18650
Nominal capacity	1200 mAh
Diameter	18.5 mm
Length	65 mm
Weight	~45 g

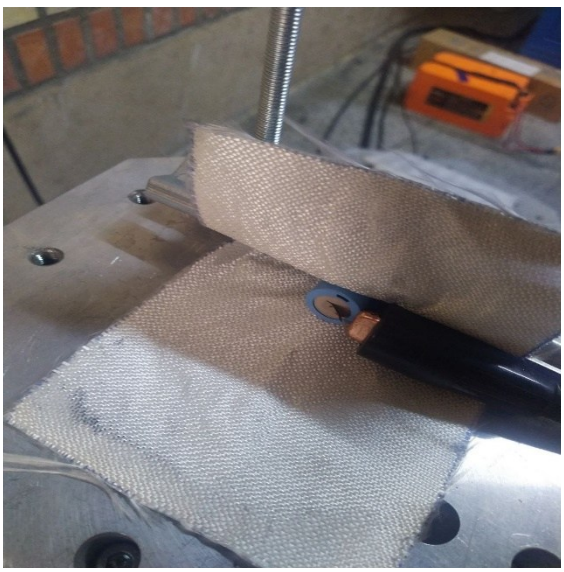

Figure 1: Orientation of the cylindrical 18650 lithium-ion battery and applied random vibration axes (X, Y, and Z) in accordance with the IEC 62660-2 standard.

3.3 Data Acquisition and Preprocessing

Battery voltage, current, temperature, and reference SoC were recorded throughout the experiments. The raw data were preprocessed to remove outliers and synchronized for machine learning model training. Feature extraction was performed using voltage, current, temperature, and their temporal characteristics.

Prior to model development, the input variables were preprocessed using the StandardScaler normalization technique to eliminate differences in feature magnitude and improve model convergence. Five input features, including voltage, current, sampling interval (dt), cycle number, and experimental step, were selected as predictors, while the battery state of charge (SoC) served as the target variable. Feature selection was based on the availability of directly measured battery signals during the experiments and their relevance to SoC estimation.

The reference SoC values used for model training and evaluation were calculated using the Coulomb Counting method. The battery current was integrated over time, considering the sampling interval and nominal battery capacity. The initial SoC was determined before each experiment under fully charged conditions, providing the ground-truth values for performance evaluation. [1]

3.4 Machine learning Strategy

Unlike conventional machine learning studies that randomly divide a single dataset into training and testing subsets, the present work adopted a cross-condition evaluation strategy. All machine learning models were trained exclusively using the measurements obtained under vibration-free conditions and subsequently evaluated using an independent dataset collected under mechanical vibration. This evaluation protocol was intentionally designed to investigate the robustness and generalization capability of the trained models when subjected to vibration-induced disturbances representative of practical electric vehicle operating environments.

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Table 4: Hyper parameters of the investigated machine learning models

Algorithms	Hyper parameters
Random Forest	n_estimators = 300, max_depth = 20
Extra Trees	n_estimators = 400, max_depth = 20
Gradient Boosting	n_estimators = 300, learning_rate = 0.05, max_depth = 5
LightGBM	n_estimators = 500, learning_rate = 0.05, num_leaves = 31, subsample = 0.8, colsample_bytree = 0.8

4. Impact of Mechanical Vibration on SoC Estimation Accuracy

4.1 Overall Effect of Vibration on Estimation Performance

SoC estimation performance was evaluated under vibration-free and vibration-exposed conditions. As summarized in Table 5, mechanical vibration resulted in a consistent increase in RMSE and MAE for all evaluated algorithms. This confirms that vibration introduces additional uncertainty into the estimation process. Fig. 2 provides a visual comparison of the SoC estimation accuracy degradation caused by mechanical vibration for all evaluated models.

A proper comparison between all ensemble learning techniques was conducted by training them with the same vibration free data set and testing them with the same vibration data set. As a result, the difference in prediction accuracy will be purely based on the stability of the learning algorithm to the vibration disturbance.

Table 5: Quantitative SoC estimation results

Model	RMSE(No Vib.)	RMSE (Vib.)	MAE (No Vib.)	MAE (Vib.)
Extra Trees	48.762557	78.985037	37.635224	70.283179
LightGBM	0.392152	67.193127	0.169025	62.993250
Random Forest	45.721344	64.652409	35.394471	60.440859
Gradient Boosting	45.376226	78.834996	35.185073	70.758670

Table 5 shows the effects of mechanical vibration on the predictive accuracy of the studied ensemble learning methods; yet, the extent of performance deterioration differs from one model to another. These variations prove the effects of vibration on the statistical properties of the obtained signals since this leads to a difference in the distribution between the training set and test set. Therefore, more generalizable algorithms suffer from smaller prediction errors, while the rest show higher performance degradation due to disturbances.

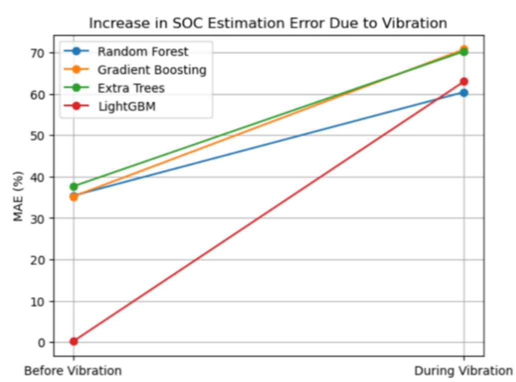

Figure 2: Error (MAE) comparison of ensemble learning models for SoC estimation under vibration-free and vibration-exposed conditions.

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4.2 Error Distribution and Signal Perturbation

Mechanical vibration introduces additional fluctuations in voltage signals, as illustrated in Figure 2, which propagate into SoC estimation errors. These perturbations affect models differently depending on their learning mechanisms.

As shown in Fig. 3 and 4, mechanical vibration introduces additional fluctuations in the voltage signal, particularly during dynamic operating phases.

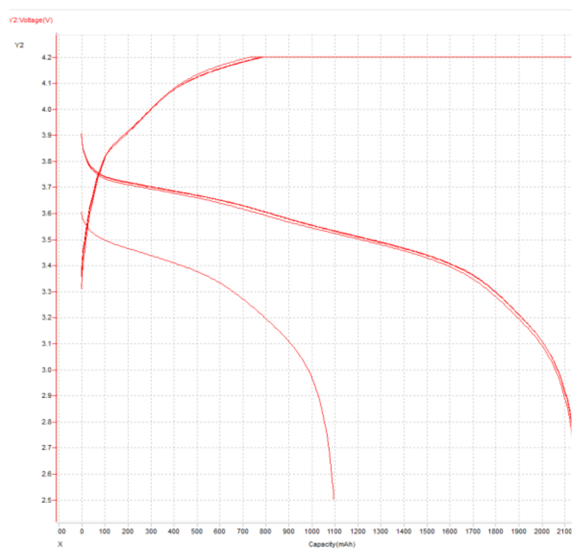

Figure 3: battery voltage profiles during charge–discharge cycles under vibration-free conditions.

As illustrated in Figure 3, the voltage signal becomes noticeably more irregular after the application of mechanical vibration. Although the overall voltage trend remains similar, local fluctuations increase because of vibration-induced disturbances, introducing additional uncertainty into the measured battery signals. Since voltage represents one of the principal input variables for SoC estimation, these perturbations directly influence the predictive performance of the machine learning models.

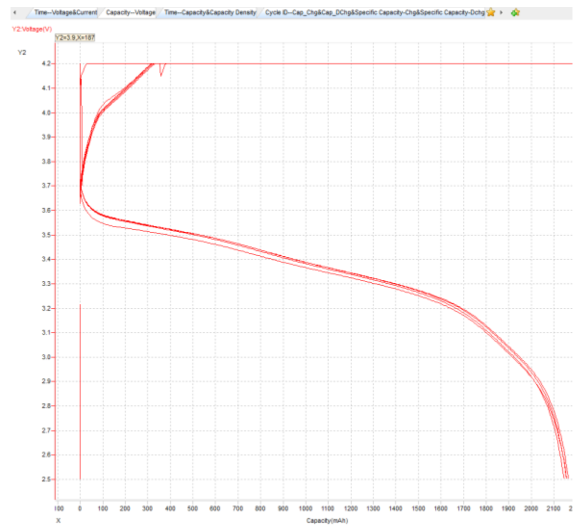

Figure 4: battery voltage profiles during charge–discharge cycles under vibration-exposed conditions.

The difference seen in the vibration-free and vibration states provides further evidence that vibration influences the timing properties of the signals being monitored from the batteries. While no frequency domain analysis is performed here, the effect of signal changes shows that vibration causes changes in the distribution of input data and thus makes prediction harder for machine learning techniques operating under nominal conditions.

4.3 Comparative Robustness of Ensemble Models

A comparative analysis revealed varying levels of robustness among the ensemble models. Extra Trees and LightGBM exhibited smaller performance degradation under vibration compared to Random Forest and Gradient Boosting. The relative sensitivity of each model to vibration-induced disturbances is further highlighted in Fig. 5.

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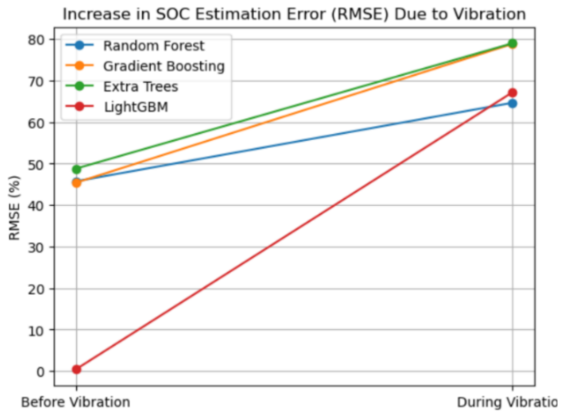

Figure 5: Percentage increase in RMSE (ΔRMSE) due to mechanical vibration for different ensemble learning models.

4.4 Model-Specific Analysis

Extra Trees and LightGBM demonstrated higher resistance to vibration-induced noise, benefiting from strong ensemble averaging and regularization mechanisms.

Random Forest showed moderate sensitivity, while Gradient Boosting exhibited the highest sensitivity due to its sequential learning structure, which amplifies noise effects.

4.5 Practical Implications for Battery Management Systems

The results indicate that SoC estimation models trained under ideal conditions may overestimate real-world performance. Robustness to mechanical vibration should therefore be considered a key criterion in algorithm selection for automotive BMS design.

4.6 Summary

The results indicate that while ensemble learning improves robustness, mechanical vibration remains a significant external disturbance affecting SoC estimation accuracy.

4. Discussion

The results show that prediction accuracy alone cannot be used to select the machine learning algorithms needed for BMS applications. As electric cars function under varying conditions of the environment and mechanics, disturbance tolerance should be taken into account alongside the traditional measures of accuracy.

Mechanical vibration affects SoC estimation accuracy through multiple mechanisms. Vibration-induced micro-movements within the battery can cause transient changes in internal resistance, leading to voltage fluctuations. Additionally, vibration can influence current measurement accuracy through sensor and wiring dynamics.

Compared to other algorithms that have been evaluated, Extra Trees had better robustness due to the inclusion of more randomness when constructing trees, which decreases the variance of the model and helps improve its generalization ability in new operational conditions. The Random Forest algorithm utilizes the power of ensemble averaging; however, it is also more susceptible to the statistical properties of the training data. Boosting algorithms iteratively minimize their errors to achieve high predictive performance in nominal conditions.

Although ensemble-based machine learning models mitigate some noise effects through averaging, they cannot fully compensate for vibration-induced disturbances. These findings highlight the importance of integrating mechanical considerations into SoC estimation frameworks, particularly for applications operating in vibration-rich environments.

Another constraint of the current research study lies in the fact that the experimental analysis of this work was carried out with the help of one commercial 18650 lithium-ion battery cell only. Even though the same battery cell was used under

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the same conditions of vibration and non-vibration to make sure that there was a fair comparison between the selected machine learning algorithms, the findings achieved from this experiment might not reflect the real performance of other battery cells as well.

The results point to vibration as a crucial parameter for consideration during the design process of machine learning algorithms for battery management systems. It may be possible to increase the robustness of such models by including datasets with vibration, feature extraction, or sensor fusion methodologies.

6. Conclusion

This study experimentally investigated the impact of mechanical vibration on lithium-ion battery SoC estimation using ensemble-based machine learning algorithms. Vibration tests conducted according to IEC 62660-2 revealed that mechanical vibration degrades estimation accuracy across all evaluated models.

Extra Trees and LightGBM demonstrated higher robustness compared to Random Forest and Gradient Boosting; however, no algorithm was immune to vibration-induced performance degradation. The results emphasize that reliable SoC estimation in real-world applications requires vibration-aware data collection, model training, and validation strategies.

Future work will focus on adaptive filtering techniques, vibration-informed feature extraction, and extending the analysis to different battery chemistries and aging conditions.

References

[1] al., Z.W.e., Impacts of vibration and cycling on electrochemical characteristics of batteries. Journal of Power Sources, 2024. 601 (2024) 234274: p. 11.

[2] al, B.S.e., Joint Estimation of SOC and SOH for Lithium-Ion Batteries Based on Dual Adaptive Central Difference H-Infinity Filter. Energies, 2024. 2024, 17, 1640. : p. 16.

[3] al., L.Z.e., Effects of Vibration on the Electrical Performance of Lithium-Ion Cells Based on Mathematical Statistics. Applied Sciences, 2017. 2017, 7, 802: p. 21.

[4] al., H.Z.e., Co-estimation of SOC and SOH for Li-ion battery based on MIEKPF-EKPF fusion algorithm. Energy Reports, 2023. 10 (2023) 4420–4428: p. 9.

[5] al., I.M.e., Comparing Machine Learning Strategies for SOH Estimation of Lithium-Ion Batteries Using a Feature-Based Approach Energies, 2023. 2023, 16, 4423.: p. 13.

[6] al., X.Z.e., Joint SOH-SOC Estimation Model for Lithium-Ion Batteries Based on GWO-BP Neural Network. Energies 2022. 2023, 16, 132: p. 17.

[7] al, S.B.K.e., Optimal estimation of SOC, SOH using machine learning models and design of control algorithm for active cell balancing in lithium ion batteries. Engineering Research Express, 2024. (2024) 045305: p. 15.

[8] Liu, Y.e.a., A Scalable Joint Estimation Algorithm for SOC and SOH of All Individual Cells within the Battery Pack and Its HIL Implementation. World Electric Vehicle Journal, 2024. World Electr. Veh. J. 2024, 15, 236.: p. 17.

[9] Zhang, L.M.a.T., Deep learning-based battery state of charge estimation: Enhancing estimation performance with unlabelled training samples. Journal of Energy Chemistry, 2023. 80 (2023) 48–57: p. 10.

[DOI: 10.22068/ase.2026.737]

[10] IEC, IEC 62660-2 in Realiability and Abuse. 2010.

[11] Wang, S., Chen, Z., & Li, J., State-of-charge estimation of lithium-ion batteries based on machine learning: A filtered approach. Journal of Energy Storage, 2023. 72, 108211.

[12] Tenawerk, Y.E., Gebremedhin, A. M., & Tesfamariam, G. T. , An ensemble learning method for state-of-charge estimation of lithium-ion batteries using machine learning. Journal of Energy Research and Applications, 2024. 6(2): p. 13.

[13] Najafi, A., Masih-Tehrani, M., Hybrid adaptive battery parameter estimation approach for equivalent circuit model toolbox, SoftwareX, Volume 24, 2023, 101534, ISSN 2352-7110,

[14] al., M.C.e., A Deep Learning Method with Ensemble Learning for Capacity Estimation of Lithium-ion Battery, in 2020 Global Reliability and Prognostics and Health Management (PHM-Shanghai). 2020, IEEE: Shanghai, China. p. 6.

[15] al., Y.E.T.e., An Ensemble Learning Method for SOC Estimation of Lithium-Ion Batteries Using Machine Learning. Journal of Electronic Research and Application, 2024. 2024, Volume 8, Issue 6: p. 9.

[16] Zhao, G., Wang, L., & Zhang, C, Artificial neural networks, gradient boosting and support vector machines for electric vehicle battery state estimation: A review. Journal of Energy Storage, 2022. 55, 105672.

[17] al, O.P.D.e., Enhanced SOC estimation of lithium ion batteries with RealTime data using machine learning algorithms. Scientific Reports, 2024. (2024) 14:16036: p. 17.70

[18] Chen, M., Xu, B., & Zhang, Y. (2025). Hybrid machine learning framework for predictive maintenance and anomaly detection in lithium-ion batteries using enhanced random forest. Scientific Reports, 2025. 15, 90810.

[19] Liu, H., Yang, Q., & Sun, F., Efficient state-of-charge estimation for electric vehicle batteries based on extra-trees and LightGBM regressors. Heliyon, 2024. 10(8), e19807.

[20] Naseri, F., Farjah, E., Ghanbari, T., Kazemi, Z., Schaltz, E., & Schanen, J-L., Online Parameter Estimation for Supercapacitor State-of-Energy and State-of-Health Determination in Vehicular Applications. I E E E Transactions on Industrial Electronics, 2020. 67(9), 7963-7972.: p. 11.

[21] Lingfeng Fan, P.W., Ze Cheng, A remaining capacity estimation approach of lithium-ion batteries based on partial charging curve and health feature fusion. Journal of Energy Storage, 2021. 43 (2021) 103115: p. 9

[22] Zhang, J., & Lee, J. (2011). A review on prognostics and health monitoring of Li-ion battery. Journal of power sources, 196(15), 6007-6014.

[23] Hu, X., Li, S., & Peng, H. (2012). A comparative study of equivalent circuit models for Li-ion batteries. Journal of Power Sources, 198, 359-367.

[24] Saneep, K., Sundareswaran, K., Nayak, P. S. R., & Puthusserry, G. V. (2025). State of charge estimation of lithium-ion batteries using PSO optimized random forest algorithm and performance analysis. Journal of Energy Storage, 114, 115879.

[25] Saneep, K., Sundareswaran, K., Nayak, P. S. R., & Puthusserry, G. V. (2025). State of charge estimation of lithium-ion batteries using PSO optimized random forest algorithm and performance analysis. Journal of Energy Storage, 114, 115879.

[26] Xiao, F., Li, C., Fan, Y., Yang, G., & Tang, X. (2021). State of charge estimation for lithium-ion battery based on Gaussian process regression with deep recurrent kernel. International Journal of Electrical Power & Energy Systems, 124, 106369.

[DOI: 10.22068/ase.2026.737]