

Data-Driven Optimization of Recyclable Battery Cells for Electrified Systems Using Machine Learning Regression Models

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Abstract—This work presents a data-driven framework for optimizing and evaluating recyclable battery cells for electrified systems using machine learning (ML) techniques. A custom battery tester circuit is designed to measure critical parameters that are voltage, current, capacity, internal resistance, and temperature. This work explores the prediction of the remaining useful life (RUL) of battery cells. Several regression algorithms are evaluated for RUL, where the Random Forest model achieved the best performance with the lowest Mean Absolute Error (MAE) and strong generalization across test sets, showing effectiveness in forecasting battery lifespan. The measured parameters of the recyclable battery are used to train multiple supervised ML models to estimate the battery's State of Charge (SoC) and State of Health (SoH). This study compares several regression algorithms for the dataset of the recyclable battery cells. Results showed that Random Forest and Gradient Boosting achieved the lowest MAE, confirming their robustness and accuracy for SoC estimation under variable thermal conditions. A hybrid numerical approach is used to estimate the SoH, which combines capacity fade and resistance growth and provides an effective unsupervised degradation analysis. This ML study helps in forecasting the performance of the recyclable battery cells that are configured for the battery packages in the electrified system applications.

I. INTRODUCTION

Battery systems are fundamental components in modern systems, powering a wide range of devices, such as, electrified systems, electric mobility (e-mobility) systems, portable devices, and other utilities. Traditional batteries show significant environmental challenges, including resource consumption, recycling, and toxic waste generation, whereas using recyclable battery cells shows limitations with respect to the performance. The target and goal of using recyclable batteries are to solve these challenges by enabling the

extraction and re-use of valuable materials, which conserves natural resources and minimizes waste, contributing to a greener and more sustainable tomorrow in the real-world [1-2]. The integration of AI into the lifecycle of recyclable batteries represents a promising advancement, which can optimize various stages, from the design and manufacturing of batteries with improved recyclability to predictive maintenance and health management during operation. Furthermore, AI-driven models facilitate the identification and sorting of battery waste, improving recycling efficiency and ensuring higher recovery rates of critical materials. ML algorithms also play a pivotal role in forecasting degradation patterns and enabling second-life applications of batteries, thereby maximizing their lifespan before recycling [2-3].

Deploying AI and ML techniques makes battery systems smarter as the use of resources, cut costs, and help speed up the shift to more sustainable battery technologies [3]. In this paper, many benefits of recyclable batteries are explored, the obstacles that still prevent them from becoming widely adopted, and how AI-driven solutions are changing the way of the battery design, use, and recycling of battery cells. Ultimately, the goal is to highlight how these techniques can build a more resilient and environmentally friendly energy future. In this work, a data-driven approach is proposed to optimize and evaluate the use of recyclable battery cells. The ML and AI tools are utilized to evaluate and estimate the performance of the recyclable battery cells that are configured to provide power to e-mobility systems [4-5]. A battery tester circuit is designed and developed to measure parameters of the battery cells, which performs controlled discharge and estimates the voltage, current, internal resistance, temperature, capacity accumulated, and the SoC. Regression models are designed and developed to predict



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SoC and SoH from those measured parameters, where the predicted SoC by the regression model is compared with the estimated SoC of the battery tester circuit [6]. Different data sets and types are used for the ML models to validate the performances and estimation of the recyclable battery cells, as described in Section V & VI.

This paper is structured as follows. Section I explains the benefits of deploying AI and ML techniques for recyclable battery cells. Section II illustrates the literature search of the AI and ML tools for the battery systems. Section III describes the methodology of the battery tester circuit development and the models of the AI and ML tools. Section IV illustrates experimental results of the battery tester circuit and ML & AI models for the battery cells. Section V explains the system analysis and discussion of the developed ML and AI models. Finally, the conclusion is drawn in Section VI.

II. LITERATURE SURVEY

The ML techniques have emerged as a transformative tool in battery research, particularly for analyzing chemical, material properties, and its performance. Various ML software tools are extensively utilized in both academia and industry to advance the understanding and development of battery cells. This survey examines prominent ML models and tools, their primary functions, and their advantages and disadvantages with respect to the usage of the battery cells.

TensorFlow, created by Google, is an open-source ML framework that supports flexible and scalable construction and training of models across a range of application areas such as computer vision and natural language processing. Its architecture uses dataflow graphs and tensor-based computation, making it suitable for large-scale ML tasks in both research and production. Despite these advantages, the framework requires a steep learning curve and higher computational demands [7]. PyTorch, developed by Facebook's AI Research lab, is an open-source ML framework that adopts a dynamic and Pythonic programming style. In contrast to TensorFlow's broader, more established ecosystem for model deployment, PyTorch's design and community support have led to its widespread adoption in academic research, although its deployment capabilities are still evolving relative to TensorFlow's mature tooling [8]. Tran, *et al.*, demonstrated the use of scikit-learn to develop regression-based models for predicting the thermal and electrical performance of lithium-ion batteries, highlighting its simplicity, computational efficiency, and suitability for prototyping and small-to-medium-scale battery systems. However, the study also implies that scikit-learn is mainly limited to traditional ML algorithms and is not intended for deep learning or large-scale applications, where more specialized frameworks are required [9].

Various ML techniques and tools are developed for the fault diagnosis to ensure the safety and efficiency of battery systems. Support vector machines (SVM), artificial neural networks (ANN), and decision trees are widely used for fault diagnosis, where SVMs are particularly effective in high-dimensional spaces and robust to overfitting; although, they can be computationally intensive. On the other hand, ANN technique can capture complex relationships and is adaptable to various problems, but it requires large amounts of data and can be prone to overfitting. Decision trees technique is a

simple to understand and interpret, requiring little data preprocessing, while they may overfit and be less effective for more complex problems. Beyond these methods, other approaches such as ensemble methods (e.g., random forests, gradient boosting), clustering techniques (e.g., k-means, hierarchical clustering), and deep learning (e.g., convolutional neural networks (CNN), recurrent neural networks (RNN)) have increasingly applied to fault diagnosis due to their ability to handle complex data patterns. Each technique has its advantages and limitations, and the choice of method often depends on the specific characteristics of the battery system and the available data [10]. Implementation of short-term memory (LSTM) technique is used in e-mobility systems to diagnose faults by focusing on electromechanical conversion chains. The technique uses data like voltage, current, and speed from a simulated models for the fault diagnosis, which helps the system to identify fault conditions and refine the fault diagnosis before it happens in real-world scenarios. The LSTM has many advantages like high accuracy, and, it works well for sequence prediction tasks which is good for analyzing time-series data from vehicle sensor. Although, LSTM is so complex specially in real-time systems, where the computational resources are low, it needs to be trained with large data set, and it can be easily distributed with any noisy or inaccurate input which leads to poor fault detection [11]. Deep learning architectures like CNN and LSTM are used to analyze time-series data and handle large amount of real-time data of battery system. Those approaches help in prediction of failures by some complex patterns, which increase diagnostic accuracy and they could handle noise, incomplete, or inconsistent data; however, implementing those models need computational resources which could be expensive and take a lot of energy [12]. Zhang, *et al.*, used SVM, neural network (NN), and deep learning approaches like CNN and RNN techniques to identify faults from the powertrain raw data. The developed models could be trained with time to be suitable for adaptation with new types of faults which also could help in predicting faults. However, it was too complex to be implemented, where it depended on the data and was difficult to understand how the fault is determined [13]. An advanced method was developed to determine the faults of lithium-ion battery systems of e-mobility, which combined discrete wavelet transform (DWT) and general regression neural networks (GRNN). The main aim of the DWT was to remove noise while processing voltage data, the GRNN used some features like variance, covariance, and voltage differences between battery cells to handle the nonlinear data and high fault tolerance. This method increased accuracy and speed of the process, which was very beneficial in safety of e-mobility; however, it had disadvantages like high complexity, very sensitive in tuning of parameters [14].

Accurate estimation of SoC and SoH is critical for the reliable operation and longevity of battery systems. SoC estimation involves predicting the remaining charge in a battery, and a variety of techniques are employed for this purpose. Traditional methods such as Kalman filters and particle filters are widely used. Kalman filters are efficient for real-time applications and provide good estimation accuracy, although they assume system linearity and may require extensive tuning. Particle filters handle nonlinearities better

than Kalman filters and are adaptable to various models, but they are computationally expensive and require more processing power [15]. In addition to these methods, various AI and ML techniques are increasingly being applied to enhance SoC estimation, artificial neural networks (ANNs) could model complex nonlinear relationships in battery behavior; although they require large datasets for accurate predictions. SVMs techniques were also used to classify battery states with high accuracy in high-dimensional spaces, however they could be computationally intensive. More recently, deep learning approaches such as RNN and LSTM networks have shown promise for handling time-series data, making them particularly useful for dynamic battery environments. These AI techniques provided more flexibility and adaptability compared to traditional methods, especially when dealing with large and complex datasets [16]. Li *et al.*, introduced a novel hybrid Kalman filter that enhanced the accuracy of SoC estimation by incorporating temperature compensation and adaptive noise covariance. This hybrid method dynamically adjusted to environmental changes, where it showed reliable SoC predictions, especially in varying operational conditions, thereby addressing a key limitation of conventional techniques [17]. In contrast, Pisani, *et al.*, evaluated simpler ML methods, such as decision trees and random forests, to predict SoC based on historical data and battery characteristics. They highlighted that ANN and deep learning were often favored for their predictive capabilities, simpler models could achieve competitive accuracy with significantly lower computational demands. This made them particularly suitable for resource-constrained environments where efficiency was crucial [18]. Chung, *et al.*, focused on LSTM networks, emphasizing their ability to capture temporal dependencies in battery behavior, which were not only outperform traditional methods but also surpass other ML approaches, particularly in long-term predictions. They illustrated a diverse landscape of techniques for improving SoC estimation, from advanced filtering methods to ML and deep learning strategies, each with its strengths and applications [19]. SoH estimation assesses the overall health and remaining lifespan of a battery. Techniques like equivalent circuit models (ECM), data-driven models, and hybrid models are used. ECMs provides a good balance between accuracy and complexity and are widely used in the industry, although they require parameter identification and may not capture all degradation mechanisms [20]. Data-driven models leverage large amounts of data and can capture complex degradation patterns, but they require extensive data collection and can be computationally intensive [21]. Chen, *et al.*, presented a robust approach for estimating the SoH of lithium-ion batteries through an ECM approach. The authors developed a method to identify model parameters, which allowed the ECM to effectively reflect the battery's health status. Their findings demonstrated that the ECM could reliably estimate remaining capacity and overall battery health across multiple charge-discharge cycles, striking an effective balance between model complexity and accuracy [20]. In contrast, Su delved into various ML techniques for SoH estimation. He gathered the dataset from battery testing to develop predictive models that could capture complex degradation patterns. The models excelled at capturing nonlinear degradation behaviors

compared to traditional methods [22]. Huang, *et al.*, discussed the integration of ECM and data-driven approaches, showcasing the benefits of hybrid models in enhancing estimation accuracy and robustness. They analyzed different hybrid techniques and highlighted that the battery health did not only improve estimation but also extended lifespan predictions for batteries [23].

The choice of ML software tools for chemical and material analysis in batteries depends on the specific requirements of the research or industry project. TensorFlow and PyTorch are preferred for deep learning applications due to their flexibility and scalability, while Scikit-learn is ideal for simpler and more traditional ML tasks. The choice of techniques for fault diagnosis, SoC, and SoH estimations depends on the specific application and the available data. This work focuses on the ML models and AI tools to reuse the recyclable battery cells. The following sections describe the proposed battery tester circuit that is designed and developed to gather the parameters of the recyclable battery cells. These collected datasets are used to forecast the behavior of the recyclable battery cells through ML and AI tools.

III. SYSTEM DESIGN OF BATTERY TESTER CIRCUIT AND ML MODELS

This study purpose-built battery-tester circuit with a supervised ML pipeline to estimate the SoC and SoH. The methodological approach is mainly three parts. In the first approach, firmware (FW) and hardware (HW) are brought in, along with electrical and thermal parameters of controlled discharge and the external verification process through a commercial tester. In the second scheme, the measurement datasets are pre-processed for learning and modeling, the learning process feature definition, pre-processing, training, and validation are schematized. In the third approach, model selection findings and a two-stage evaluation approach are presented, with an ablation quantifying the temperature input feature contribution. This work adds two contributions that are equipment and analytics scheme. On the instrumentation side, the battery tester circuit performs SoC estimation, cross-validates it against open-circuit voltage and internal resistance, and stores a detailed, time-synchronized feature set that minimizes characterization time without loss of precision. On the analytics side, comparative benchmarking for SoC prediction with different regressors with and without temperature is conducted followed by testing on an unseen dataset to assess generalization. Hardware and analytics work together to form an end-to-end process from embedded measurement to deployable models.

A battery tester circuit is used to measure the parameters (voltage, internal resistance, temperature, and SoC) of the battery cells to train these parameters and build the ML models. The used battery tester circuit is based on the previous battery tester circuit with upgrades, which was developed and had limitations [24]. The upgrades include improving the HW and FW to eliminate the limitations of the previous battery tester circuit. The previous battery tester measured the voltage and current over time, where a constant discharge current was achieved through a resistor of the battery cell under test. Initially, the battery voltage started from $V_{\max}$ as it was fully charged, after which the discharge process continued, the voltage continued to drop until it

reached the minimum voltage (cutoff voltage that is 2.7 V), and the SoC was estimated based on CC (column counting) method from the constant discharging current [15]. This approach takes a long time for characterizing the battery cells and the CC SoC estimation process relies on obtaining the full current profile during the battery cell's discharge, where the SoC process was happening till the cutoff voltage was achieved. The proposed battery tester circuit is programmed to estimate the SoC from the current discharge regardless of voltage value set by SW or HW, which saves both time and battery charge. The SoC value depends on the open-circuit voltage (V_{OC}) and internal resistance [25], so the updated battery tester circuit estimates the SoC using the CC topology from the discharge current, the FW validates and verifies the estimated SoC with the internal resistance and the V_{OC} through a lookup table (array), as shown in the flowchart (Fig. 1). The schematic of the upgraded battery tester circuit is illustrated in Fig. 2, which comprises an Arduino Nano microcontroller (MCU), amplifier, LCD, temperature sensor, and a load resistor. The Arduino Nano MCU is chosen for its simplicity, small size, and extensive library support, and the amplifier (LM358) is used to drive the switch (transistor Q_1) at a constant current. The load resistor (R_1 , 100 Ω , 10 W) is used to ensure safe power dissipation during testing, whereas three 100 Ω resistors are connected in parallel to limit the current, which guarantees the constant amount of current discharge, even if the applied input voltage varies. The LCD provides easy monitoring of the battery tester readings, which communicates with the MCU through I²C topology.

The proposed battery tester circuit is upgraded from the previous battery tester circuit with respect to the HW & FW systems, which are displaying, monitoring temperature, current selection control, enhanced alerts and test flow, and improving capacity estimation. Multi-pages display with instant switching of the measured parameters that are voltage, capacity, internal resistance, temperature, and SoC. Display state loops through four screens using UP/DOWN buttons to avoid "hanging" and improves user experience. Nine distinct current levels (0–620 mA), controlled on-the-fly via UP/DOWN buttons, PWM increment/decrement, and immediate display update. More flexible discharge testing and capacity adaptation for different battery sizes. Dual-tone audio feedback for start/stop, clear visual "Test Complete", and final readings are deployed, with additional confirmation step before starting. Capacity is calculated with time broken down into hours/minutes/seconds, uses unsigned long math for overflow protection.

Different data sets are collected from recyclable battery cells, each containing measurements collected from good and bad recyclable battery cells. The datasets cover the entire cycle, from a fully charged state to an empty state, with capturing variations in the SoC across different operating conditions. Five input parameters of the battery cells are considered as potential predictors of estimating SoC and SoH, which are voltage, current, capacity, internal resistance, and temperature.

Two experiments are conducted to test the effective of temperature on prediction accuracy, where the collected datasets are with and without temperature data.

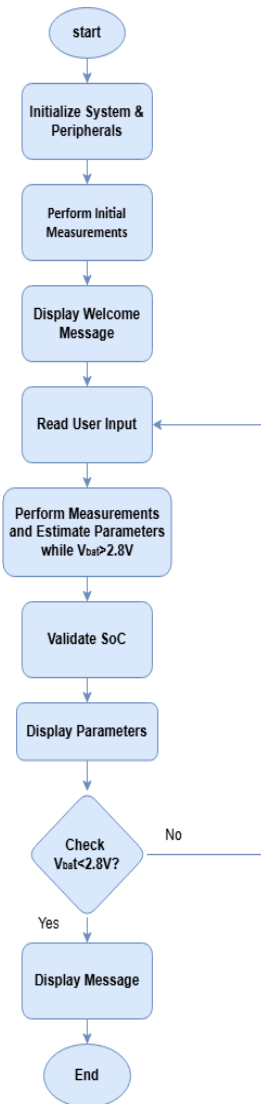


Fig. 1. Flowchart of upgraded battery tester

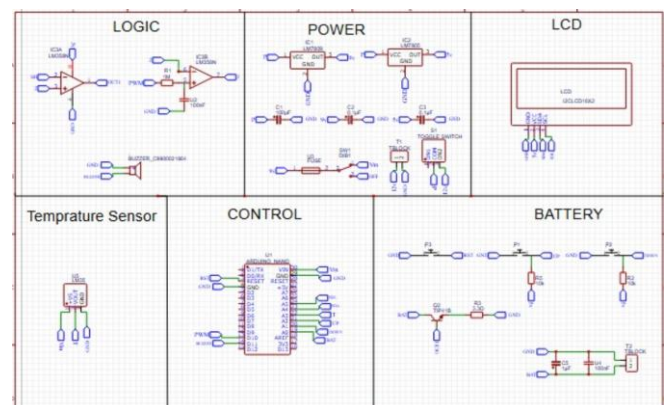


Fig. 2. Schematic of upgraded battery tester

The SoC and SoH of the recyclable battery cells are estimated using a combination of numerical and ML methods. SoC is

estimated with a supervised regression model trained on time-series data collected from the battery operating under various test conditions. The model employed a feature vector of voltage, current, capacity, internal resistance, and in some cases, temperature to judge the influence of thermal effect on prediction accuracy. The data-driven enabled accurate mapping from electrical parameters to corresponding SoC values. For SoH estimation, a quantitative, unsupervised approach is applied, as there are no cycle-wise health labels in the dataset. Two measures of degradation—capacity fade and growth of internal resistance—are extracted to define the prevailing aging mechanisms. Both measurements are normalized and combined into a unified SoH measure to quantify both electrochemical and resistive degradation effects. Finally, a smoothing filter is applied to the estimated resulting SoH trend to denoise and emphasize the long-term degradation trend of the cell.

A different set of ML regression models is used to find the most effective model that is used for the SoC estimation. The proposed regression models are Random Forest Regressor, Gradient Boosting Regressor, AdaBoost Regressor, Linear Regression, Ridge Regression, Lasso Regression, Support Vector Regressor (SVR), K-Neighbors Regressor, and Decision Tree Regressor. These models are evaluated based on the MAE (mean absolute error) value, where the best model shows the MAE of the specific recyclable battery cell either good or bad ones. Two verification processes are used to evaluate the model as follows. In the first verification step, datasets are divided into 80% training data and 20% test data, to make sure that each model is trained on the most of the data while keeping some for testing. In the second verification step, the chosen model (lowest MAE from the first verification) is tested using a new independent dataset which is not previously used in training or testing. The main purpose of this second verification is to make sure about the predicted data twice under different battery conditions.

Data mining plays a crucial role in extracting useful insights from large datasets, particularly when it comes to analyze battery performance. In this project, the goal is to build and train a model to predict various battery parameters, such as its RUL and using real-world data collected from a battery tester. This section covers the process, the datasets used, the models applied, and the anticipated future steps. The developed model is trained on an openly available dataset from Kaggle before using the collected data from battery tester circuit to validate the performance. This dataset includes information about the RUL of various battery cells, which is a key metric in battery health prediction, where the Kaggle data [26] helps in experimenting using different ML models and refine the approach before working with the more specific dataset from the battery tester. The RUL refers to the time or number of cycles a battery is expected to continue functioning effectively before it can no longer meet performance requirements. Estimating RUL is critical in applications, where battery reliability is important, such as electrified systems and renewable energy storage. By predicting the RUL, battery usage can be optimized and avoid unexpected failures, ultimately reducing costs and improving safety. Tracking the RUL during battery testing affirms forecasting the nearing the end of battery's useful life, allowing for proactive management. It also serves as a vital

metric to compare the degradation rate of different battery cells and train models for predictive maintenance [27]. To estimate the RUL of the battery cells, several performance-related features from the dataset are used. The input parameters include: Cycle_Index, Discharge Time (s), Decrement 3.6–3.4V (s), Max. Voltage Dischar. (V), Min. Voltage Charg. (V), Time at 4.15V (s), Time constant current (s), Charging time (s), and the corresponding RUL value as the target variable. Each of these parameters reflects a different aspect of the battery's charge–discharge behavior. For example, six different machine learning models are trained to predict RUL from these input parameters: Random Forest, Decision Tree, SVM, K-Nearest Neighbors (KNN), Gradient Boosting, and AdaBoost. The Random Forest model is an ensemble of multiple decision trees that combines their predictions for better accuracy and generalization. It reduces overfitting and handles complex relationships between features effectively. This model gives the best results for RUL prediction. The Decision Tree model is a simple tree-based model that splits data based on feature thresholds to make predictions. It is easy to interpret and fast to train but can overfit on small datasets if not pruned properly. The SVM uses hyperplanes to separate data points and find the optimal decision boundary. SVM is powerful for classification; although, SVM can be slower and less accurate on larger or noisy regression datasets like the recyclable battery cells. The KNN predicts values based on the closest training samples in feature space. It is intuitive and non-parametric but it becomes computationally expensive with larger datasets. The Gradient Boosting builds models sequentially, where each new model corrects the errors of the previous one. It provides strong predictive power but requires careful tuning to avoid overfitting. The AdaBoost model is another boosting method that focuses on misclassified samples by assigning them higher weights. While it can improve weak learners, it is sensitive to noisy data and outliers, which affected its RUL prediction accuracy [28].

The ML models are used for estimating SoC from the collected data of the battery tester circuit to validate the estimated SoC (based on CC) from the battery tester circuit. The collected data are good and bad recyclable battery cells, whereas the ML models forecast the performance of these battery cells. The proposed ML models are Linear Regression, Ridge Regression, Lasso Regression, Decision Tree, Random Forest, Gradient Boosting, AdaBoost, SVR, and KNN. Linear Regression model assumes a linear relationship between the input features (x) and the target (y). It fits a line (or hyperplane) that minimizes the sum of squared residuals, which is defined as [29]:

$$\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n \quad (1)$$

$$\hat{\theta} = (X^T X)^{-1} X^T y \quad (2)$$

where, θ represents the model parameters (weights and intercept). The Ridge Regression adds an L_2 penalty term to the loss function to reduce overfitting by shrinking coefficients. The L_2 penalty refers to the squared magnitude of all coefficients which is defined as [28]:

$$\min(\theta) ||y - X\theta||_2^2 + \lambda ||\theta||_2^2 \quad (3)$$

where, λ controls the strength of regularization. The lasso regression adds an L_1 penalty, which can shrink some coefficients to zero, performing feature selection, which is defined as [28]:

$$\min(\theta) ||y - X\theta||_1 + \lambda ||\theta||_1 \quad (4)$$

The decision tree model splits the dataset recursively into subsets that minimize prediction error such as mean squared error (MSE). The MSE is defined as [30]:

$$MSE_{Split} = \sum_{i \in left} (y_i - \hat{y}_{left})^2 + \sum_{i \in right} (y_i - \hat{y}_{right})^2 \quad (5)$$

where, y_i is the actual target value, $\hat{y}_{left}$ and $\hat{y}_{right}$ are the mean target values of the left and right child nodes, respectively. The random forest averages the predictions from multiple decision trees trained on different data subsets to improve robustness and reduce variance, which is defined as [30]:

$$\hat{y} = (1/N) \sum_{i=1}^N T_i(x) \quad (6)$$

where, N is the total number of trees in the forest. The gradient boosting builds trees sequentially, whereas each new tree corrects the errors of the previous model using gradient descent on the loss function, which is defined as [31]:

$$F_m(x) = F_{m-1}(x) + \eta h_m(x) \quad (7)$$

where, m is the iteration index, η is the learning rate controlling step size, and $h_m(x)$ is the weak learner (typically a small regression tree) trained to fit the residuals of the previous model. The AdaBoost model combines multiple weak learners by reweighting samples so that the next model focuses more on previously misclassified instances, which is defined as [32]:

$$F(x) = \sum_{m=1}^M \alpha_m h_m(x) \quad (8)$$

$$\alpha_m = \log((1 - e_m)/e_m) \quad (9)$$

where, α_m is the model weight proportional to its accuracy. The SVR model fits a function within an ε -insensitive tube and minimizes error outside it, balancing model flatness and tolerance for deviations, which is defined as [33]:

$$\min_{\{w, b\}} (1/2) \cdot ||w||^2 + C \sum_{i=1}^m (\xi_i + \xi_i^*) \quad (10)$$

subject to:

$$y_i - (w^T x_i + b) \leq \varepsilon + \xi_i$$

$$\begin{aligned} (w^T x_i + b) - y_i &\leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* &\geq 0 \end{aligned} \quad (11)$$

where, w is the weight vector, b is the bias term, ξ_i and ξ_i^* are slack variables for errors outside the ε margin, and C is a regularization constant controlling the trade-off between flatness and tolerance to error. The KNN model predicts the target value by averaging the outputs of the k nearest training samples based on a distance metric like Euclidean distance, which is defined as [34]:

$$\hat{y}(x) = (1/k) \sum_{i \in left} y_i \quad (12)$$

The ML equations are used for estimating the SoC with and without temperature data, where the feature vector is initialized for time step as [29]:

$$X(t) = [V(t), I(t), cap(t), R_{int}(t), T(t)] \quad (13)$$

where, V is the terminal voltage, I is current (A), R_{int} is internal resistance (m Ω), C is accumulated capacity (mAh or Ah), and T is temperature ($^{\circ}\text{C}$) — optional feature. The trained regressor $f(x)$ estimates SoC as [29]:

$$f(x_t) = SoC(t) \quad (14)$$

The model $f(x)$ is learned from data (not a fixed physics formula). Given the battery's instantaneous, directly measurable signals (x), it outputs an estimate SoC. The SoH is estimated through a purely numerical, unsupervised approach. Since the measured data lacked cycle-wise SoH labels, a physics-based numerical estimation is implemented. Two degradation indicators are considered, which are capacity fade and resistance growth. The SoH decreases as the available charge capacity diminishes relative to the rated nominal capacity. The SoH decreases as the internal resistance increases due to aging mechanisms and loss of active material. The instantaneous SoH is therefore defined as the normalized combination of these two independent degradation factors. The SoH based on capacity scheme is defined as [29]:

$$SoH_{cap}(t) = \frac{Q(t)}{Q_{rated}} \quad (15)$$

where, $Q(t)$ is the measured accumulated capacity at time t and Q_{rated} is the nominal rated capacity of a new cell. The SoH based on resistance scheme is defined as [29]:

$$SoH_{res}(t) = \frac{R(0)}{R(t)} \quad (16)$$

where, $R(0)$ is the internal resistance measured at the beginning of life (first data point) and $R(t)$ is the instantaneous internal resistance. To improve robustness

against noise or temporary fluctuations, both indicators are fused equally [29]:

$$SoH_{num}(t) = \frac{1}{2}(SoH_{cap}(t) + SoH_{res}(t)) \quad (17)$$

The resulting series is smoothed with a 5-point moving average filter to obtain a continuous health trend.

IV. EXPERIMENTAL DATA AND ANALYSIS

The battery tester circuit of one battery holder is built, where the LCD displays the measured parameters that are voltage, internal resistance, SoC, temperature, and battery capacity, as shown in Fig. 3. These measured parameters data are saved in log files using the UART protocol, which are used for the ML. The user navigates through the menus of the battery tester through tactile switches, as described in Section III. The measurements of the battery tester circuit are verified and validated using known battery cells and an external battery tester, where the measured parameters are compared with the parameters of name plate of the battery cells. A Liitokala battery tester is used to validate the FW of the proposed battery tester circuit, where the battery capacity and internal resistance are compared. Recyclable battery cells (with and without name plates) are used to measure their parameters (capacity and internal resistance) and compared with the Liitokala battery tester. The maximum error percentage of the capacity and internal resistance are 0.65 and 5.2 %, respectively, which affirm the accurate measurements of the battery circuit.

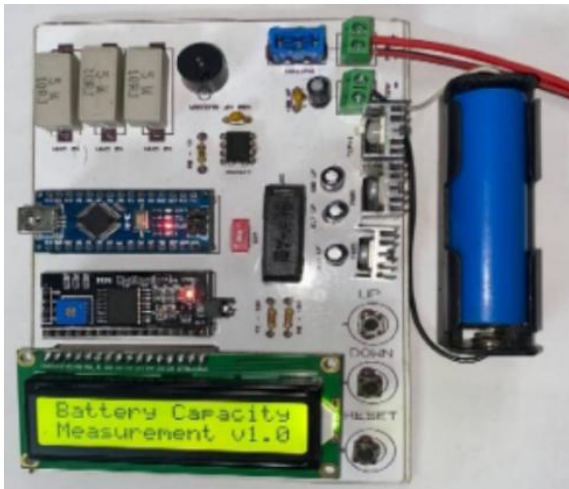


Fig. 3. Proposed battery tester circuit

The Kaggle dataset [26] is used for the ML of the RUL, where each model is evaluated with respect to the MAE that measures the average difference between predicted and actual RUL values — lower MAE means better accuracy. The time period of the train and test dataset is reported for each model, as listed in Table I. The random forest and decision tree show the lowest MAE and less time value, respectively. Overall, the Random Forest model achieves the lowest MAE with a good balance between accuracy and computation time, making it the most suitable candidate for future model refinement for the real battery tester data of the recyclable battery cells. Fig. 4 illustrates the scatter plot, histogram

error, and residual plot, where scatter with regression line plot compares the actual values (on the x-axis) with the predicted values (on the y-axis) from the Random Forest model. The closer the points are to the diagonal line, the more accurate the predictions, as illustrated in Fig. 4(a). A perfect model would have all points lying on this line. The histogram of errors plot shows the distribution of prediction errors (difference between predicted and actual values). A well-performing model typically has a narrow, centered distribution with most errors close to zero. The residual plot displays the residuals (errors) against the predicted values, as shown in Fig. 4(c). Ideally, the residuals should be randomly scattered around the horizontal line at zero, indicating no clear pattern and unbiased predictions. Patterns/trends could indicate issues with the model, where these results reflect the initial experiments using the Kaggle dataset, and further tuning is done for the real dataset from the battery tester.

Table I. Mae And Time Of Ml Models For Rul

Model	MAE	Time (sec)
Random Forest	2.674390	0.044941
Decision Tree	2.883344	0.002311
SVM	17.03846	0.929667
KNN	3.636907	0.011726
Gradient Boosting	5.728628	0.004883
AdaBoost	11.35746	0.012682

The collected dataset of recyclable battery cells from the battery tester is used for the proposed ML. The results are given per feature setting and dataset (with/without temperature data), which are chosen model, most significant hyperparameters, test MAE (initial verification), independent-set MAE (follow-up verification), and Δ MAE to quantify the contribution of temperature. This presentation gives an open, reproducible platform for selecting the functional SoC estimators. For the initial verification, the data are split into 80% of the data for training and 20% for testing for the verification. Tables II and III represent the MSE, MAE, and R_2 score of the good battery cells with and without temperature data, respectively. The lowest MSE and MAE are achieved of the good battery cells of using Gradient Boost and Random Forest model with and without temperature data, respectively. Same performance and pattern are observed of the ML models of the bad battery cells, as listed Tables IV and V. The analysis and data show that the ML model of the dataset including the temperature shows higher R_2 score and lower MSE and MAE than the ML model of the dataset without temperature data. The MSE and MAE values of the bad recyclable battery cells are higher than the good recyclable battery cells, because of the low life time of the bad battery and fast degrading over time. These results illustrate the importance of the temperature data, especially for the bad recyclable battery cell, as the

temperature increases while discharging of the bad recyclable battery cells.

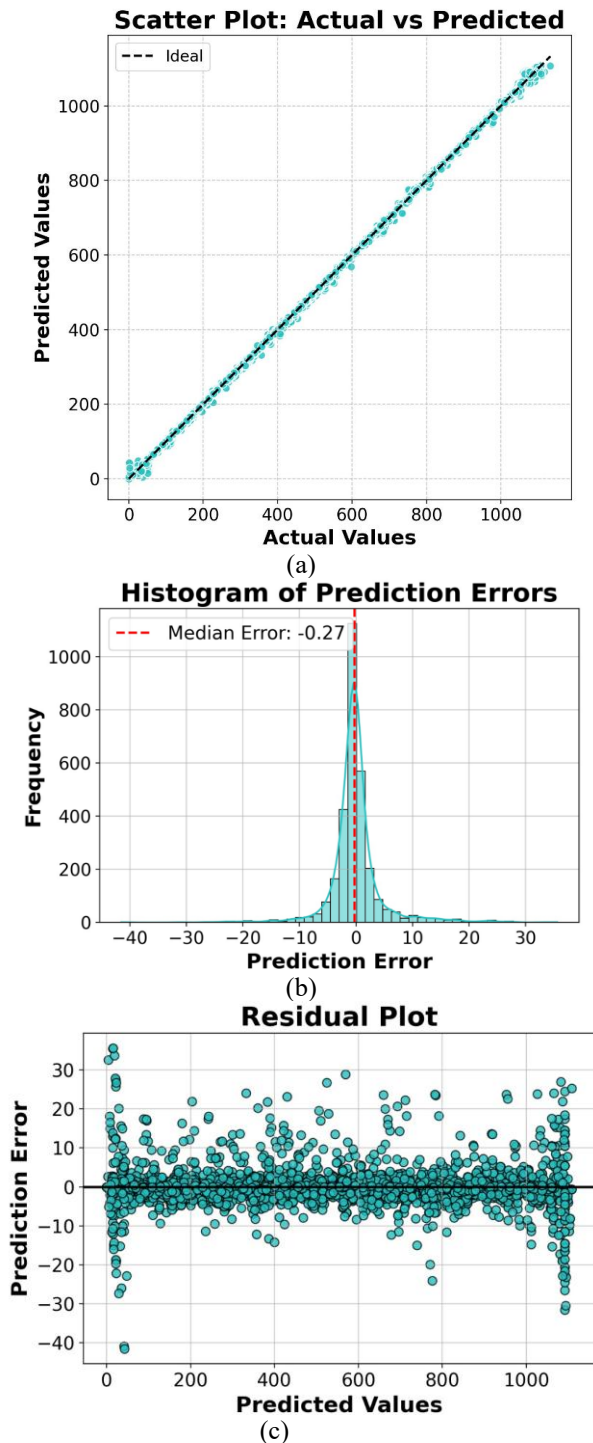


Fig. 4. RUL results of (a) scatter plot, (b) histogram error, and (c) residual plot

The developed ML models are validated using an independent dataset containing operational measurements from different battery cells, where voltage, current, internal resistance, temperature, and capacity readings are collected over a 2-minute discharge period. This external dataset is not used during model training, ensuring that the validation process truly evaluates the generalization capability of the proposed approach. The second stage of validation compares

the SoC estimated by the ML models with the measured SoC obtained directly from the battery tester, which serves as the ground-truth benchmark. This evaluation reflects the generalization ability of the trained models when tested on unseen operational data. The MAE of the SoC of the good battery cells with and without temperature are 0.3032 and 0.3598; although, the MAE of the bad battery cells are 3.5564 and 3.614, respectively. The performance comparison demonstrates that the SoC estimation from the ML-based approach is well aligned with the measured SoC for healthy batteries, while the estimation accuracy decreases for degraded bad battery cells due to their nonlinear behavior while discharging.

Table II. Performance of ML Models of Good Battery Cells With Temperature

Model	MSE	MAE	R ² Score
Random Forest	0.135260	0.286751	0.999807
Gradient Boosting	0.130932	0.282711	0.999814
AdaBoost	10.772254	2.860413	0.984659
Linear Regression	26.831218	3.952419	0.961788
Ridge Regression	26.828516	3.952860	0.961792
Lasso Regression	27.171612	4.151354	0.961303
Support Vector Regressor	0.681579	0.467522	0.999024
K-Neighbors Regressor	0.176062	0.316200	0.999749
Decision Tree	0.135626	0.287002	0.999807

Table III. Performance of ML Models of Good Battery Cells Without Temperature

Model	MSE	MAE	R ² Score
Random Forest	0.128990	0.279590	0.999816
Gradient Boosting	0.130807	0.282408	0.999814
AdaBoost	10.772254	2.860413	0.984659
Linear Regression	26.850925	3.947539	0.961760
Ridge Regression	26.848138	3.947998	0.961764
Lasso Regression	27.171612	4.151354	0.961303
Support Vector Regressor	0.169031	0.318137	0.999759
K-Neighbors Regressor	0.153348	0.298671	0.999782
Decision Tree	0.128952	0.279512	0.999816

Table IV. Performance of ML Models of Bad Battery Cells With Temperature

Model	MSE	MAE	R ₂ Score
Random Forest	0.480580	0.537255	0.999118
Gradient Boosting	0.464488	0.536658	0.999148
AdaBoost	1.907825	1.117717	0.996499
Linear Regression	88.97285	7.200109	0.836711
Ridge Regression	88.96625	7.201977	0.836723
Lasso Regression	91.54232	7.540931	0.831995
Support Vector Regressor	3.737671	1.121381	0.993140
K-Neighbors Regressor	0.765967	0.631741	0.998594
Decision Tree	0.483797	0.538982	0.999112

Table V. Performance of ML Models of Bad Battery Cells Without Temperature

Model	MSE	MAE	R ₂ Score
Random Forest	0.448353	0.526973	0.999177
Gradient Boosting	0.449926	0.530315	0.999174
AdaBoost	1.907525	1.117717	0.996499
Linear Regression	110.286862	8.172627	0.797594
Ridge Regression	110.284860	8.175130	0.797597
Lasso Regression	111.078613	8.448170	0.796141
Support Vector Regressor	1.435098	0.668823	0.997366
K-Neighbors Regressor	0.569687	0.571926	0.998954
Decision Tree	0.448867	0.526996	0.999176

The SoH of the battery cells is estimated numerically using both capacity and internal resistance indicators extracted from the diagnostic dataset. The initial internal resistance value at the beginning of operation is used as the reference resistance $R(0)$. The first SoH indicator reflects the reduction in effective capacity and is calculated as the ratio between the measured capacity and the rated capacity of the cell, the second indicator accounts for degradation-induced resistance growth and is computed as the ratio of the reference resistance to the current resistance.

A backend system is implemented using FastAPI, a high-performance web framework designed for building and serving machine learning applications. The system exposes an endpoint (predict) that receives sensor and diagnostic data

from battery cells, including voltage, current, resistance, temperature, and capacity. Upon receiving the input, the API dynamically loads the appropriate ML model (.joblib file) depending on the selected mode—either for full-to-empty or full-to-low discharge evaluation. The model then predicts the SoC using a trained regression algorithm. In addition to SoC estimation, the backend computes and displays the SoH based on two key parameters: the ratio of the measured to rated capacity and the ratio between reference internal resistance and the current measured resistance. These two indicators are averaged to form a combined SoH value, which is further bounded between 0 and 1 to ensure valid health representation. The entire prediction pipeline is encapsulated within a RESTful interface, allowing seamless integration with the frontend visualization system and external monitoring devices. The modular structure enables model updates and the inclusion of temperature-dependent behavior through a toggle (use_temp), providing flexible adaptability for different operational conditions. Fig. 5 illustrates the GUI (graphic user interface) of the backend code that displays the SoC and SoH value, where the battery cell is selected, either good or bad battery cell.

Fig. 5. GUI of the battery cell parameters

V. DISCUSSION AND FUTURE WORKS

This section illustrates the static analysis of the developed ML models for the recyclable battery cells. The future works of the ML & AI tools are suggested for the battery systems regarding the battery tester circuit and ML tools in this section as well. Fig. 6 presents a statistical summary of the prediction errors obtained from the selected RUL regression model. The model demonstrates strong predictive performance, evidenced by a near-zero mean error (-0.04) and median error (-0.28), indicating negligible systematic bias in the predictions. The dispersion of errors is relatively low, with a standard deviation and root mean squared error (RMSE) of approximately 5.06, confirming stable estimation accuracy across samples. The MAE of 2.65 further highlights the model's robustness in capturing the underlying degradation trends. Although, the error range spans from -41.67 to 33.88 , these extreme values correspond to rare outliers and do not significantly affect overall performance,

as reflected by the coefficient of determination ($R^2 \approx 1.00$). Collectively, these statistical metrics confirm the high accuracy, consistency, and generalization capability of the proposed RUL model for battery lifespan prediction.

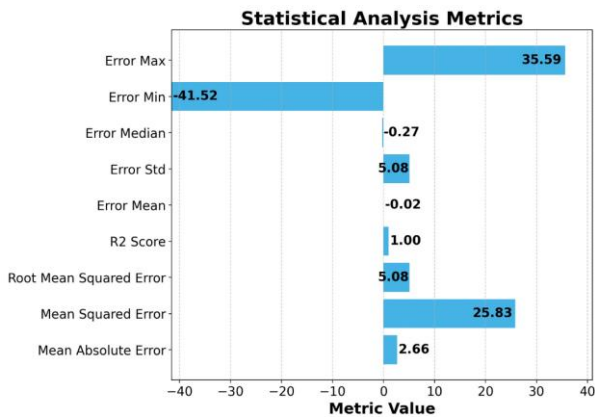


Fig. 6. Error analysis of RUL

The Decision Tree model for SoC estimation on good battery cells without temperature input demonstrates excellent predictive performance. The actual versus predicted scatter plot shows predictions tightly clustered along the ideal diagonal line, indicating strong alignment between predicted and actual SoC values across the entire discharge range from approximately 10% to 100%, as shown in Fig. 7(a). This near-perfect linearity is further confirmed by the residual plot, which displays residuals randomly distributed around zero with minimal systematic bias, as illustrated in Fig. 7(b).

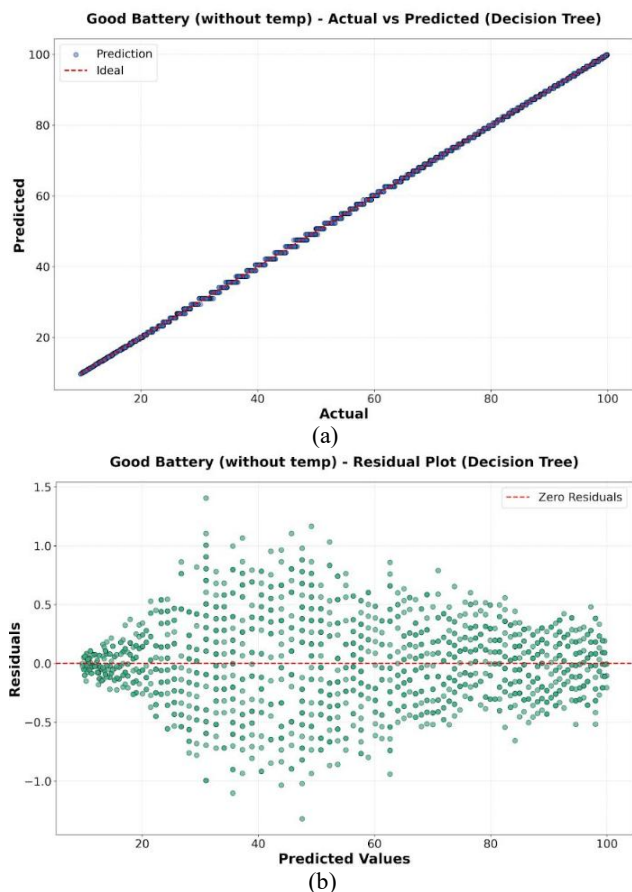


Fig. 7. Error analysis of SoC for good recyclable battery cells without temperature data

The Gradient Boosting model for the SoC estimation on good battery cells with temperature as an input feature exhibits exceptional predictive accuracy. As shown in Fig. 8(a), the actual versus predicted scatter plot reveals predictions that align almost perfectly with the ideal diagonal line across the entire SoC range from approximately 10% to 100%, demonstrating the model's capability to capture the complex nonlinear relationships between input features and charge state. Fig. 8(b) illustrates the residual plot that confirms the high performance, with residuals uniformly distributed around zero and predominantly confined within ± 0.5 across all predicted values.

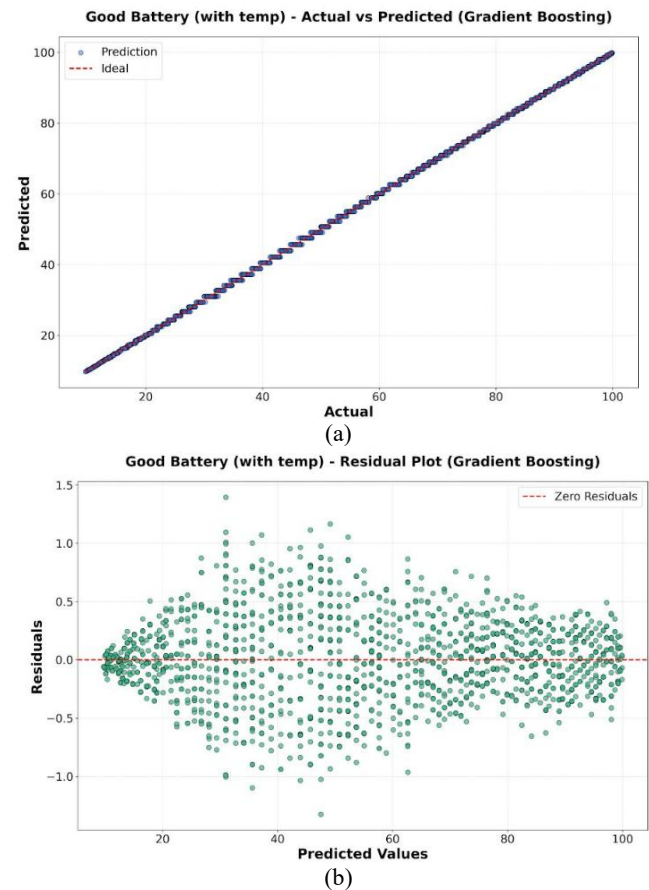


Fig. 8. Error analysis of SoC for good recyclable battery cells with temperature data

The Random Forest model for SoC estimation on bad recyclable battery cells without temperature input demonstrates strong predictive performance despite the degraded condition of the cells. The actual versus predicted scatter plot (Fig. 9(a)) shows predictions closely following the ideal diagonal line across the SoC range from approximately 20% to 100%, indicating the model's ability to accurately track charge state even in degraded batteries. The residual plot (Fig. 9(b)) reveals a wider error distribution compared to good battery cells, with residuals ranging from approximately -2.0 to +2.2, and a noticeable increase in residual magnitude at higher SoC values (above 80%). This pattern suggests that degraded batteries exhibit more complex and nonlinear behavior, particularly near full charge, where internal resistance variations and capacity fade effects become more pronounced. Despite these challenges, the residuals remain randomly scattered without systematic bias.

The Gradient Boosting model for SoC estimation on bad recyclable battery cells with temperature as an input feature demonstrates robust predictive capability despite the degraded state of the cells. The actual versus predicted scatter plot (Fig. 10(a)) exhibits excellent alignment with the ideal diagonal line across the entire SoC range from approximately 20% to 100%, indicating that the model successfully captures the charge-discharge behavior of degraded batteries. The residual plot (Fig. 10(b)) reveals a relatively wide error distribution, with residuals spanning from approximately -2.0 to +2.5, which is notably larger than that observed for good battery cells.

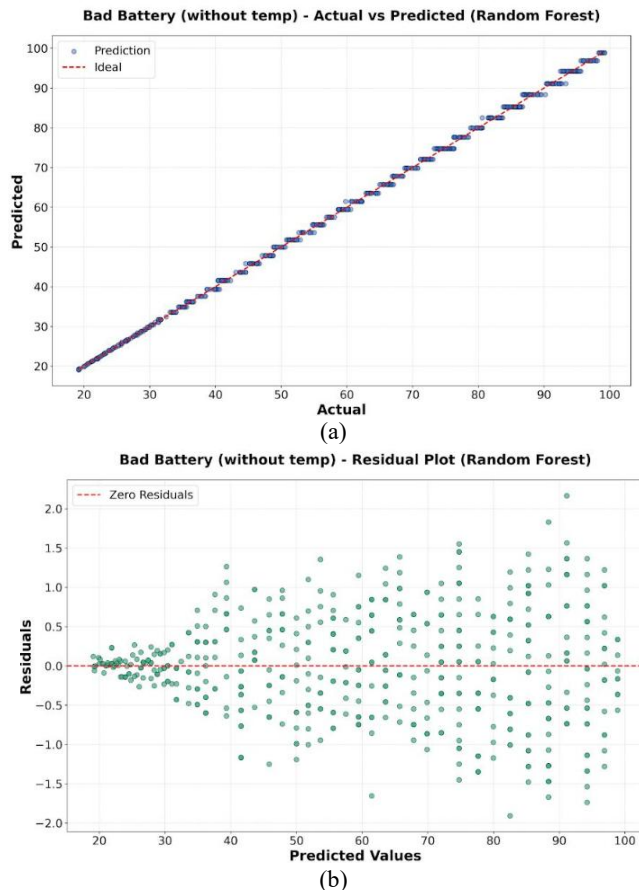


Fig. 9. Error analysis of SoC for bad recyclable battery cells without temperature data

This work focused on the development of the ML models and AI tools for the recyclable battery cell. The literature search showed various ML and AI development with respect to the battery systems, such as the manufactured material (chemistry) of the battery, safety, and SoC & SoH estimation. TensorFlow, PyTorch, and Scikit-learn tools are used to analyze and enhance the battery performance with respect to the chemistry of the batteries [7-9]. Fault diagnosis schemes are developed for safety and improve the battery/powertrain of e-mobility [10-14]. Different techniques are developed for SoC and SoH estimation, some of these schemes are used in the proposed ML models of this work; although, other ML and AI tools show limitations of the processing requirements and the complexity [15-23]. This work presented the design and development of various ML models to estimate the SoC and SoH with respect to the processing time, complexity, and accuracy, which were deployed for the measured parameters

of the recyclable battery cells. These ML models can be used to characterize and forecast the performance of the recyclable battery cells that can be used in electrified systems.

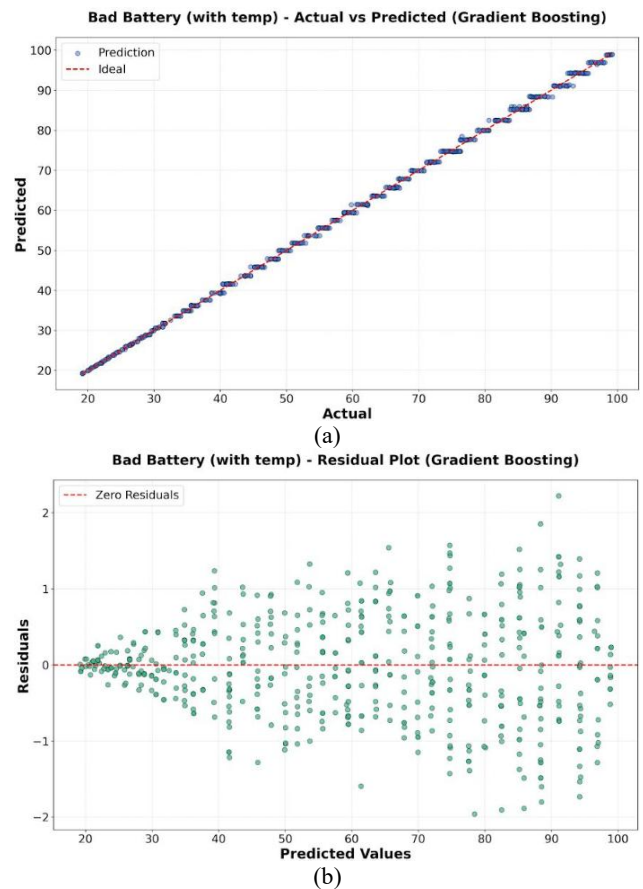


Fig. 10. Error analysis of SoC for bad recyclable battery cells with temperature data

A smart battery tester system with integration of IoT (internet of things) can be developed, it will allow automatic evaluation, data logging, remote access, cloud based analytic, and real-time tracking of battery performance. Also, another future focus would be on implementing more advanced ML like LSTM networks to capture more time-dependent behaviors under different conditions which will help in storing historic data so it will forecast in detecting faults before even it happens and make the system efficient. Moreover, it will expand the dataset to include more temperature ranges, charge-discharge cycles, and different cell chemistries will also help improve model results.

VI. CONCLUSION

This research paper presented the study of using ML for estimation and analysis of recyclable/recoverable battery cells. The customized battery tester circuit was designed and developed to measure the parameters of good and bad recyclable battery cells. Supervised ML models were conducted for the collected parameters of the bad and good battery cells. The validation process of the ML models was conducted for the dataset with and without temperature, where the ML models demonstrated the impact of temperature conditions on estimation accuracy. Random Forests model was the best with the lowest MAE for the RUL of the battery systems, as shown in Figure 4. The Random

Forest and Gradient Boosting Model were the best for the SoC prediction with and without temperature, respectively. The analysis and results showed that capacity loss and internal resistance growth parameters were the main two factors in the SoH estimation, where it provided a strong unsupervised battery degradation trend analysis. This entire integration of ML into the constructed test hardware was an excellent and scalable model for smart battery characterization that is deemed hugely valuable for electrified and sustainable recycling applications.

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