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DATA-DRIVEN MODEL TO ESTIMATE STATE-OF-HEALTH (SOH) FROM LITHIUM-ION BATTERIES

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Abstract. *The battery breakdown is a potentially catastrophic occurrence that may have severe repercussions. The ability to forecast when a Li-ion battery would die is currently restricted. The primary contribution that this study makes to the field is an investigation into the feasibility of determining whether or not thermal runaway signs may be efficiently identified in advance of the commencement of the phenomenon by making use of currently available measuring methods for heat, temperature, acoustic emission, Coulomb efficiency, or electrochemical processes. Applying these experiments to detect fault occurrences (such as short circuits) in aged cells (also known as second-life batteries) is another of the new aspects of this body of work. Another innovation that might come out of this study is the determination of the most precarious state of battery cells—that is, the state where a mechanical failure or a short circuit is most likely to occur. Probabilistic models are a viable option to consider in this scenario. Therefore, the next critical step is to determine the predicted size of these signals of interest, which are significant for commencing harmful trajectories, and then measure them. This will be done before moving on to the following crucial phase. The most significant obstacle is that cells with the same shape, chemistry, and history may (or may not) display distinct mistakes when subjected to the same stimuli (mechanical, electrical, and thermal). The purpose of the proposed thesis is to collect trustworthy data that can give physical insights into events that cause battery failures. The collected data will also be used to feed data-based models that can predict battery failures (for example, an internal short circuit). These models are used in order to cut down on the number of actual tests and, as a result, save both money and time.*
Keywords: *lithium-ion batteries; remaining useful life estimation; , machine-learning algorithms; da-ta-driven models.*

1. INTRODUCTION

The Li-Ion Battery (LIB) is an exceptionally potent tool for storing electrical energy in various electronic devices. LIBs are widely used in the modern, influential era because of their high energy storage, low cost, availability, and long service life. They have become essential components of electronic devices, such as cell phones, laptops, and electric cars, which rely on their efficient energy storage capabilities. Furthermore, the growing shift towards electric mobility promotes the use of LIBs, making energy-efficient and safe usage crucial for an environmentally friendly, resource-saving, and economic future.

LIBs are widely employed in electric and hybrid vehicles because they possess appealing features, including a high capacity to store energy, the ability to charge quickly, and minimal loss of charge over time. The automotive industry has set minimum durability standards for electric and hybrid vehicles, mandating a lifespan of at least 10 years for electric vehicles and 15 years for hybrid vehicles [1].

According to the report, the global LIB market is expected to experience significant growth over the next several years due to increasing demand for electric vehicles, portable electronic devices, and energy storage solutions. The report provides an in-depth market analysis, including market size, market share, market trends, growth drivers, challenges, and opportunities [2].

Battery aging can be categorized into two main components: calendar and cycle aging. These terms describe the changes in batteries due to different usage patterns [3]. Calendar aging refers to the effects and consequences of battery storage over time. In contrast, cycle aging is associated with the impact of battery usage during charging and discharging cycles [3].

Sometimes, batteries can experience high temperatures and other complications related to their chemical composition. These circumstances can lead to hazardous incidents. Therefore, monitoring battery aging and assessing the condition of charging and discharging processes is essential to mitigate potential risks. By regularly checking the battery's condition and monitoring its aging, we can prevent dangerous disasters from occurring [4].

Prognostics and Health Management (PHM) is a technology that employs statistical algorithms and models to evaluate and manage a system's health by analyzing a large amount of monitoring data and information [5]. PHM aims to predict potential failures in advance, make maintenance decisions based on the system's condition, and achieve condition-based maintenance, thereby improving the reliability and safety of the production process while reducing maintenance costs [6]. Estimating Remaining Useful Life (RUL) is a crucial aspect of PHM that serves as the basis for predictive maintenance plans, production plan adjustments, and parts management decisions. RUL prediction is an essential research area that enables timely maintenance decisions to prevent sudden system failures [7].

The main reasons behind spontaneous combustion events in electric cars are incorrect State of Health (SOH) estimation and inaccurate forecasting of lithium battery life. Precisely determining the SOH of LIBs is difficult due to their intricate and dynamic nature [8]. Researchers have focused on developing precise techniques to assess and predict LIB health, which presents a significant technological challenge. The SOH of LIBs changes over time and can be easily influenced by external factors. Therefore, ensuring accurate SOH estimation is crucial for preventing unexpected failures and maintaining the safe operation of electric vehicles [9].

2. MOTIVATION

Battery life estimation is crucial for optimizing the functionality and lifespan of power sources during battery operation. Accurate monitoring and appropriate maintenance strategies are essential to prevent unplanned downtime. Advanced measuring technology and emerging Artificial Intelligence (AI) techniques provide valuable insights into battery health. Figure 1 illustrates the increasing publication trend in battery RUL estimation, highlighting the growing importance of this field. However, comprehensive research covering sensors, monitoring methods, algorithms, and datasets for data-driven RUL estimation is scarce. Therefore, this study aims to address these gaps by advancing RUL estimation techniques and providing future directions. By exploring data-driven strategies, this research aims to motivate PHM researchers to enhance RUL prediction for critical batteries [10].

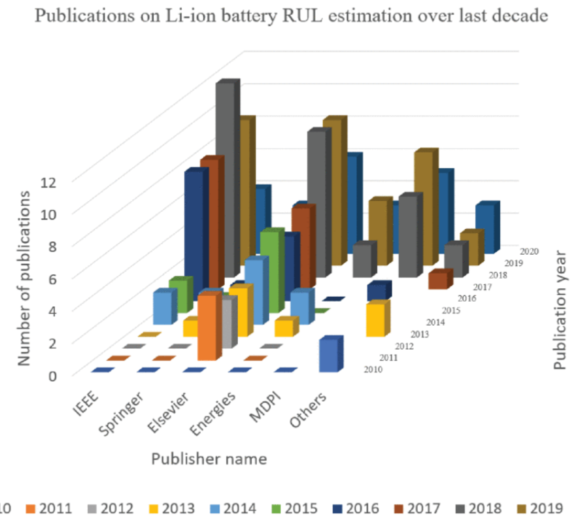

Figure 1. Publications on Li-ion battery RUL estimation over the last [10].

The estimation of SOH for batteries serves several purposes. Firstly, it ensures battery systems' safe and reliable operation, optimizing their performance and extending their lifespan. SOH provides critical information about a battery's condition, including capacity, power output, and internal resistance, enabling the prediction of maintenance needs and preventing unexpected failures.

Calculating SOH is also vital for improving battery system performance and reducing energy losses during charging and discharging. This optimization can lead to significant cost savings and positive environmental impacts. Additionally, understanding the factors influencing battery SOH helps advance battery technologies. By identifying areas for improvement, it guides the development of more innovative and efficient battery systems.

In summary, this research aims to bridge the existing research gaps in data-driven estimation RUL and contribute to advancing battery technologies. This study motivates further exploration in battery health monitoring and prognostics by addressing the importance of accurate estimation of SOH for battery system safety, performance optimization, and widespread implementation in critical applications. Researchers explore da-ta-driven strategies for RUL prediction of critical batteries.

3. OBJECTIVES

Collect and curate a high-quality dataset from battery testing that captures the aging mechanisms occurring in Nickel Manganese Cobalt (NMC) cells under real-world application conditions. Conduct a comprehensive analysis of the collected dataset to identify patterns, correlations, and critical factors influencing the SOH of NMC cells, considering factors such as temperature, State of Charge (SOC), and cycling conditions.

- Explore and compare different machine learning algorithms and techniques to design and develop accurate prediction models to estimate the SOH of NMC cells.
- Investigate the relationship between battery performance, aging mechanisms, and influential factors to gain insights into the degradation mechanisms and their impact on the SOH of NMC cells.
- Evaluate the accuracy and reliability of the developed prediction models by comparing the predicted SOH values with the actual measured SOH values obtained from NMC cell testing.
- Determine the optimal prediction model architecture for NMC cell SOH prediction based on the performance evaluation of different machine learning algorithms and techniques.
- Provide information on the feasibility and effectiveness of data-driven approaches for predicting the SOH of NMC cells, considering their potential application in practical scenarios.

By achieving these objectives, this work will contribute to developing an accurate model for estimating the SOH of NMC cells and provide valuable information on the feasibility of data-driven approaches to predict the SOH of LIBs.

4. METHODOLOGY

4.1 Battery cell

This work examines 39 single cells from Samsung for cyclic aging. These cells are specifically designed for automotive applications and are particularly relevant for low-voltage usage in vehicle electrical systems. The cells have a cylindrical shape and belong to the 21700 design. With a nominal capacity of 3 Ah, they exhibit favorable characteristics for the intended purposes. The manufacturer specifies the voltage limits for cyclic operation to be between 2.5 V and 3.63 V.

Table 1. Data of battery cell INR21700-30T.

Cell	
Battery type	NMC
Nominal capacity	3000 mAh
Nominal voltage	3.6V – 3.7V
Maximum charging voltage	4.2V
Minimum discharging voltage	2.5V
Cut-off charging current	0.01
Charging Procedure	CCCV

4.2 Aging Conditions

The first step is to collect data on LIBs commonly used in EVs. These test methods are designed and executed to ensure the accuracy and reliability of data collection. As a crucial foundation for the prediction of SOH, the gathered data may initially contain missing values, which are systematically addressed through appropriate imputation techniques to maintain the integrity of the dataset. Additionally, the data undergoes a thorough cleansing process to eliminate outliers, errors, and inconsistencies, thus ensuring the availability of high-quality data for subsequent analysis.

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The measurements conducted in this work utilized the BTS-4000-5V6A cell tester manufactured by Neware Technology Limited. This cell tester is equipped with a charging/discharge unit that enables bidirectional energy transport. Its purpose is to test and cycle individual battery cells, simulating their service life and providing insights into their performance beyond battery capacity. The Neware BTS unit comprises the tester with an integrated middle machine, an auxiliary channel cabinet featuring battery terminals or al-ligator terminals, and an internal server responsible for executing set procedures.

Each test channel of the BTS unit can operate within a current range of 0-6 A and a voltage range of 0-5 V, with a maximum power delivery of ±30 W per channel. The accuracy of current and voltage measurements is ±0.05% within the specified range. Industrial servers control the test bench, process the measured data, and transmit it to the host computer. The 2.5 to 3.6 V voltage range aligns well with the safe operating range of the cells used, making this test bench highly suitable for the tests carried out. Automation is used extensively to control the test profiles and exclusively to record raw data.

Table 2. Cycling aging test matrix.

	Temperature [°C]	Charging c-rate [C]	Discharging c-rate [C]	Number of cells
NMC	25	0.5	0.5	3
	25	1	0.5	3
	25	1	1	3
	25	1	2	3
	25	0.5	1	3
	25	2	1	3
	25	2	2	3
	25	0.5	0.5	3
	25	1	1	3
	25	2	2	3
	5	0.5	0.5	3
	5	1	1	3
	5	2	2	3

All measurements were performed in the laboratory of the C-ECOS department within the research and test facility located at the Center of Automotive Research on Integrated Safety Systems and Measurement Area (CARISSMA). The batteries were tested under three distinct current discharge rates: 0.5C, 1C, and 2C. These initial experiments were carried out at a controlled room temperature of T = 26.5 °C ± 1.5 °C, ensuring consistent environmental conditions throughout. Furthermore, a cyclic aging study was conducted for the same three current rates (0.5C, 1C, 2C). These cyclic aging experiments were carried out within a specialized temperature chamber set at a constant T = 5 °C and T = 40 °C. This chamber maintained precise temperature control to ensure the accuracy of the aging analysis.

4.3 Data Pre-Processing and Feature Engineering

The intricacies of the SOH prediction process are summarized in Figure 4.1, which provides a stepwise overview of how ML algorithms are used to predict SOH. This generic implementation flowchart serves as a comprehensive visual guide, elucidating the sequential phases within the SOH prediction pipeline. The stages encompass data pre-processing, feature engineering, algorithm selection, model training, performance assessment, and prediction.

• **Data Pre-Processing:** The journey commences with pre-processing data, a foundational stage where raw battery testing data is meticulously acquired, scrubbed, and organized. This preliminary data refinement includes cleansing data to eradicate anomalies and errors and addressing missing values. This procedural step ensures the data set is coherent and accessible to irregularities that could disrupt subsequent analysis.

• **Feature Engineering:** The subsequent phase of feature engineering involves a judicious selection of pertinent attributes from the data set that have a meaningful impact on the prediction of SOH. Moreover, domain expertise can catalyze the creation of novel attributes that enhance the model's predictive prowess. To maintain uniformity, selected features are subjected to normalization or scaling processes.

• **Model Selection:** The heart of the predictive process is the selection of an appropriate machine learning algorithm. The flow chart spotlights a variety of potential algorithms, ranging from linear regression and decision trees to support vector machines and intricate neural networks. The choice depends on factors such as the characteristics of the data set, the desired predictive precision, the interpretability, and the computational complexity.

• **Model Training:** Machine learning algorithms chosen during the previous phase undergo rigorous training on the pre-processed dataset. The dataset is typically partitioned into training, validation, and testing subsets. The model endeavors to discern and internalize patterns from the training data, optimizing its internal parameters to minimize prediction errors.

• **Model Evaluation:** The efficacy of the trained model is gauged through meticulous evaluation procedures. A suite of performance metrics, including but not limited to Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2), appraise the model's accuracy. Techniques such as cross-validation assess the model's adaptability across diverse datasets.

• **Prediction:** The culmination of these processes leads to the predictive phase, where the trained and validated model is poised for real-world application. Novel and unseen battery data can be supplied to the model, eliciting an anticipated SOH value as an outcome. This value offers valuable insights into the battery's health status and performance projection.

The exposition of this comprehensive implementation flow chart forms a foundational understanding of the intricate interplay among data pre-processing, feature engineering, algorithm selection, model training, and prediction. The ensuing sections of this thesis will delve deeper into the nuances of each stage, elaborating on the specific algorithms considered, strategies employed for feature engineering, and the granular results of performance evaluation.

4.4 Model performance metrics

In regression tasks, the goal is to predict a continuous numerical value. Various metrics are used to assess the performance of regression models. The code you provided calculates three commonly used regression metrics: MAE, MSE, and RMSE. Additionally, it calculates the R^2 score as an evaluation metric [95]. Here is a detailed explanation of these metrics:

4.4.1 Mean Absolute Error (MAE)

MAE measures the average absolute difference between the predicted and true values. It provides a measure of the average prediction error of the model [96]. MAE is calculated by taking the mean of the absolute differences between predicted and true values [97]. The Equation (1) shows how to calculate the MAE.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_{true_i} - y_{pred_i}\right| \tag{1}$$

Lower values of MAE indicate better model performance, with 0 being the best possible value.

4.4.2 Mean Squared Error (MSE)

MSE measures the average squared difference between the predicted and true values. It measures the model's average squared prediction error [96]. MSE is calculated by taking the mean of the squared differences between predicted and true values[98]. The Equation (2) for MSE is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_{true_i} - y_{pred_i}\right)^2 \tag{2}$$

MSE penalizes larger errors more than MAE, as the errors are squared. Lower values of MSE indicate better model performance, with 0 being the best possible value.

4.4.3 Root Mean Squared Error (RMSE)

RMSE is the square root of MSE and provides a measure of the average magnitude of errors [96]. It is calculated by taking the square root of MSE [97]. The Equation (3) for RMSE is:

$$RMSE = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}\left(y_{true_i} - y_{pred_i}\right)^2} \tag{3}$$

RMSE is in the same unit as the target variable, making it more interpretable than MSE. Lower RMSE values indicate better model performance, with 0 being the best possible value.

4.4.4 R^2 score

R^2 score, also known as the determination coefficient, measures the proportion of variance in the target variable explained by the model. It indicates how well the model fits the data [96]. R2 score ranges from 0 to 1, where 1 indicates a perfect fit and is the best possible value, indicating that the model does not explain the variance in the target variable [98]. The R^2 score is calculated using the Equation (4):

$$R^2 = 1 - \sum_{i=1}^{n}\frac{(y_i - \widehat{y_i})^2}{(y_i - \bar{y})^2} \tag{4}$$

where, y_i is the real value, $\bar{y}_i$ is the mean, and $\hat{y}_i$ is the predicted value. Higher R^2 scores indicate better model performance, with 1 being the best possible value.

5. RESULTS

This section presents the results obtained from implementing machine learning models designed to predict the SOH of batteries.

5.1 Battery performance degradation assessment

This method uses the maximum available battery capacity as a vital indicator to represent degradation in battery pack performance. To evaluate this health indicator, we compare it with degradation features obtained under in-orbit operating conditions. These degradation features include the following.

1. It is the same time interval between the same charge and discharge cycles.
2. The voltage drop was observed using the same voltage for charging and discharging.

Figure 2 present a visual representation of these degradation characteristics along with the degradation of the measured battery pack capacity. Figure 2 show the degradation capacity curves, which comprise 39 individual subplots. In particular, the degradation trajectories of four specific cells remain remarkably consistent, indicating a uniform degradation mechanism for batteries of the same type. Cells 1 to 21 were tested under room temperature conditions, maintaining a set temperature of T = 26.5 °C ± 1.5 °C.

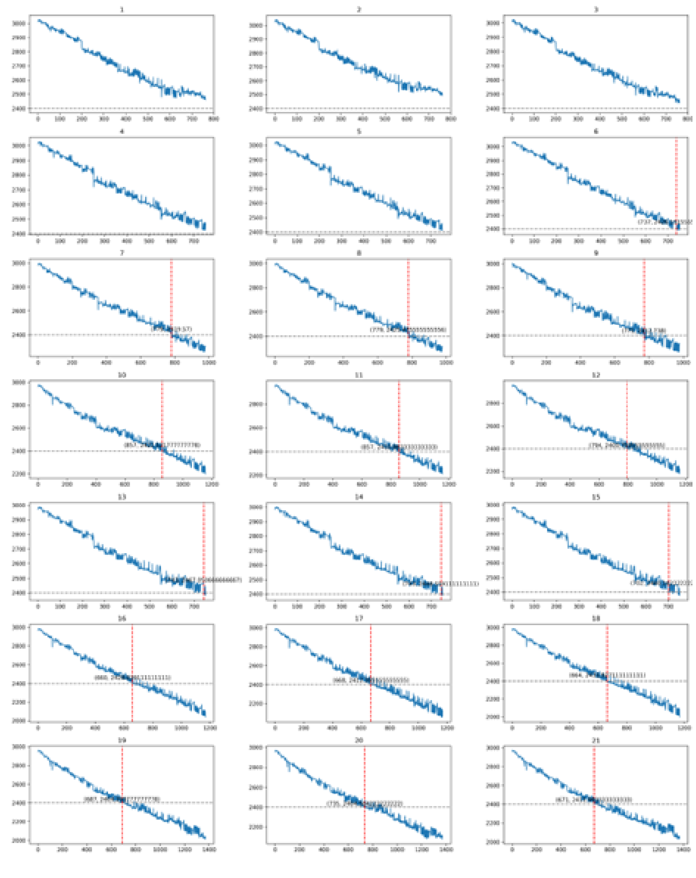

Figure 2. Degradation Capacity degradation curves of Cells 1 - 21.

5.2 Strategic Data Sampling and Visualization for Discharge Voltage

In visualizing discharge voltage over the time for each cell, a systematic approach was meticulously adopted to ensure that the resulting graphs provided a comprehensive yet manageable representation of the data. To achieve this, we strategically sampled data points at regular intervals, selecting data from every 100 cycles for graph plotting.

This sampling strategy served several crucial purposes. First, it effectively reduced the volume of data points, preventing the graphs from becoming overly cluttered and ensuring that the visual representation remained interpretable. By selecting data at intervals of every 100 cycles, we captured essential temporal changes in the discharge voltage, which are often associated with significant battery behavior shifts.

Secondly, the chosen intervals allowed us to focus on key trends and patterns in the discharge voltage over time. This level of granularity enabled us to identify critical points in the battery's performance history, such as inflection points or periods of accelerated degradation.

By adopting this approach, the resulting graphs offered a clear and insightful depiction of each cell's discharge voltage behavior throughout the cycling experiments. Not only did they facilitate a visual assessment of degradation trends, but they also supported a more in-depth analysis and comparison between cells. This methodological rigor in data visualization played an integral role in uncovering valuable insights into battery performance degradation over time.

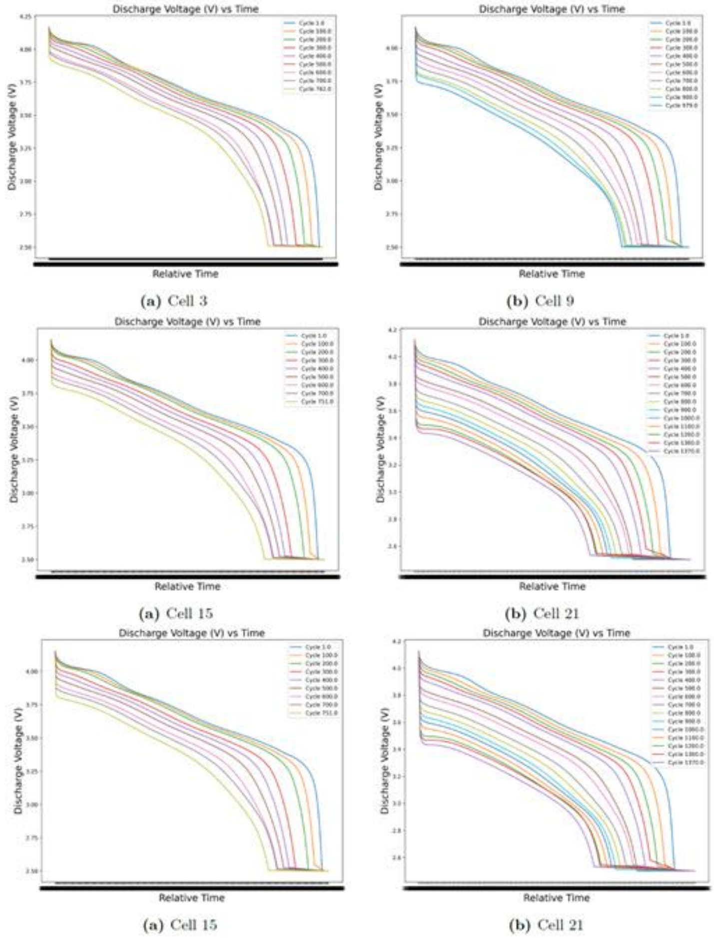

Figure 3. Discharge Voltage Variation Curves of Cells 3, 9, 15, 21, 27,36 at different cycles.

5.3 Performance of aging tracking using periodic dQ/dV analysis

Derivative of capacity to voltage (dQ/dV), a crucial parameter in battery analysis, offers valuable insights into battery performance and health for various reasons:

- **Peak Identification:** The dQ/dV curve serves as a valuable tool for pinpointing peaks associated with specific electrochemical processes within the battery. These peaks represent phase equilibria and transitions, shedding light on battery behavior and degradation mechanisms.
- **State of Health (SOH) Estimation:** Changes in the shape and position of peaks in the dQ/dV curve can be correlated with battery capacity degradation. This makes it a useful means of estimating the battery's SOH. Tracking peak evolution over time makes it possible to identify degradation mechanisms and monitor the battery's health.
- **On-line SOH Monitoring:** Incorporating dQ/dV analysis into a Battery Management System (BMS) allows real-time SOH monitoring. This enables the detection of health changes, facilitating timely actions such as adjusting charge/discharge rates or replacing the battery when necessary.
- **Applicability Across Battery Types:** The dQ/dV analysis is versatile and applicable to various LIB chemistries, cell designs, and operational conditions. It can effectively analyze aging mechanisms and estimate SOH across different battery systems.

These graphs provide a visual representation of the electrochemical behavior of the battery. Notably, you select data from every 100 cycles to plot these graphs, ensuring that the analysis captures long-term trends and behaviors within the battery.

Furthermore, your selection of specific cells for analysis is based on their operating temperatures. As shown in Figure 4 we have chosen cells 3, 9, 15, and 21, which operate at room temperature. Additionally, cell 27 operates at a temperature of 40 °C, while cell 36 operates at a temperature of 5 °C. These selections allow you to assess how temperature variations impact the battery's performance and behavior, providing critical insights into thermal effects on battery health.

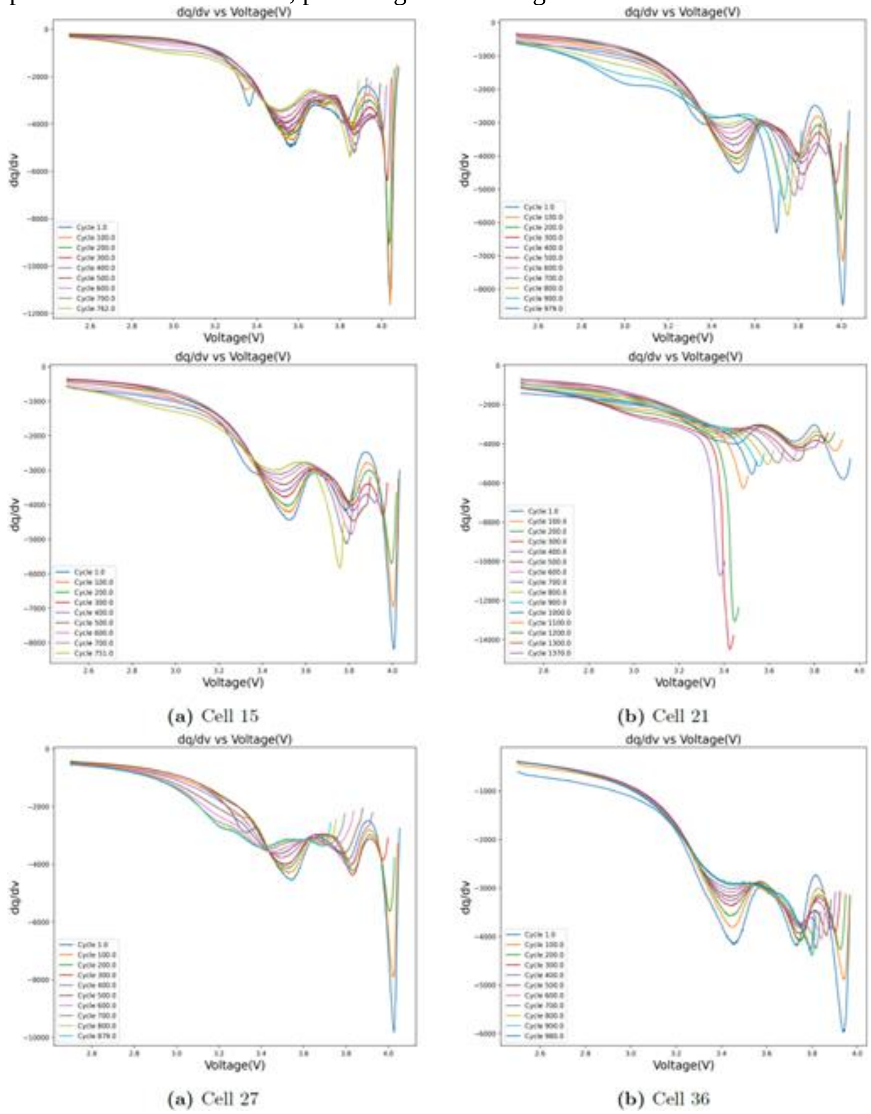

Figure 4. Capacity degradation curves of Cells 3, 9, 15, 21, 27, 36 at different cycles.

In summary, dQ/dV analysis, combined with temperature-based cell selection, graph generation, and figure selection, plays a pivotal role in understanding battery behavior, degradation mechanisms, and evaluation of SOH, making it a widely adopted technique in battery analysis and monitoring.

5.4 Model Implementation and Performance Evaluation

In this section, we delve into the implementation details and results obtained from our experiments using three distinct models for estimating the SOH of batteries: the LSTM Model, the GRU Model, and the Regression Model. The LSTM model, a type of RNN, was employed in our experiments to estimate the battery SOH. The Table 3 presents the result from the best model.

Table 3. LSTM Model Result.

Train cells	Test cell	MAE	MSE	RMSE	R^2
[2, 3]	1	0.0435	0.0024	0.0490	0.9697
[1, 3]	2	0.0375	0.0020	0.0453	0.9721
[1, 2]	3	0.0802	0.0079	0.0890	0.9071
[5, 6]	4	0.0273	0.0011	0.0341	0.9833
[4, 6]	5	0.0724	0.0070	0.0838	0.9051
[4, 5]	6	0.0462	0.0030	0.0552	0.9666
[8, 9]	7	0.0174	0.0005	0.0242	0.9920
[7, 9]	8	0.0154	0.0003	0.0189	0.9949
[7, 8]	9	0.0308	0.0014	0.0385	0.9800
[11, 12]	10	0.0243	0.0010	0.0319	0.9849
[10, 12]	11	0.0148	0.0003	0.0188	0.9942
[10, 11]	12	0.0173	0.0004	0.0223	0.9928
[14, 15]	13	0.0201	0.0006	0.0245	0.9918
[13, 15]	14	0.0156	0.0003	0.0192	0.9952
[13, 14]	15	0.0231	0.0008	0.0282	0.9894
[17, 18]	16	0.0654	0.0053	0.0731	0.9160
[16, 18]	17	0.0528	0.0078	0.0886	0.8781
[16, 17]	18	0.0233	0.0010	0.0319	0.9863
[20, 21]	19	0.0316	0.0017	0.0413	0.9764
[19, 21]	20	0.0361	0.0016	0.0411	0.9736
[19, 20]	21	0.0214	0.0007	0.0268	0.9896
[23, 24]	22	0.0130	0.0002	0.0167	0.9961
[22, 24]	23	0.0254	0.0009	0.0300	0.9870
[22, 23]	24	0.0188	0.0004	0.0215	0.9937
[26, 27]	25	0.0202	0.0005	0.0238	0.9923
[25, 27]	26	0.0301	0.0018	0.0429	0.9770
[25, 26]	27	0.0270	0.0010	0.0329	0.9834
[29, 30]	28	0.0160	0.0004	0.0204	0.9946
[28, 30]	29	0.0115	0.0002	0.0146	0.9966
[28, 29]	30	0.0383	0.0035	0.0592	0.9394
[32, 33]	31	0.0699	0.0056	0.0750	0.9328
[31, 33]	32	0.0569	0.0036	0.0607	0.9556
[31, 32]	33	0.0458	0.0026	0.0512	0.9716
[35, 36]	34	0.0162	0.0005	0.0229	0.9939
[34, 36]	35	0.0235	0.0008	0.0291	0.9905
[34, 35]	36	0.0113	0.0002	0.0153	0.9972
[38, 39]	37	0.0656	0.0091	0.0958	0.9330
[37, 39]	38	0.0244	0.0009	0.0304	0.9902
[37, 38]	39	0.1449	0.0278	0.1667	0.9744
Mean		0.0353	0.0028	0.0435	0.9728
Std		0.0259	0.0047	0.0303	0.3132

6. CONCLUSIONS

The importance of precise forecasting and assessment methods for the State of Health (SOH) of battery systems cannot be overstated in the quest for maintaining durable, functional, and cost-effective batteries. Estimating the SOH value of lithium-ion batteries presents a significant challenge due to the limited availability of long-term data, particularly for batteries subjected to hundreds of cycles with minimal aging information. This thesis has taken on this challenge by introducing a model to predict the health status of lithium-ion batteries (LIBs) using data from battery cycling tests. In particular, this research focuses on forecasting the health of battery cells that were not part of the model training data set.

In this work, we implemented various data-driven models and subjected them to rigorous evaluation. The results reveal that LSTM networks have shown exceptional capability in estimating the state of health of batteries. The model consistently achieved an accuracy rate exceeding 98% in forecasting the health of all tested batteries, underscoring its effectiveness. However, it is essential to acknowledge that achieving a reduction in the number of samples required for training the data-driven model would necessitate more stringent testing procedures. Additionally, addressing the computational complexity of the model remains a critical consideration for practical implementation.

Beyond these findings, our battery data analysis and corresponding graphs have yielded important insights. We observed distinct patterns in the data depending on the testing conditions. Specifically, we observed some noise in the data when the batteries were tested at room temperature. In contrast, cells tested in a temperature chamber exhibited significantly reduced data noise, approaching a negligible level. This observation highlights the pivotal role of temperature in the battery charging and discharging process.

In conclusion, this research contributes significantly to the field of battery maintenance by providing a robust forecasting model to estimate the SOH of LIBs. While our results are promising, it is imperative to acknowledge the limitations of this study, including the need for more extensive testing and a focus on improving computational efficiency.

7. ACKNOWLEDGEMENTS

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