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Capacity Prediction Lithium-Ion Batteries

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ABSTRACT: The program addresses that Lithium-ion batteries have emerged as the preferred power source for a wide array of applications, including smartphones, laptops, tablets, photovoltaic systems, and electric vehicles, owing to their exceptional properties such as high cell voltage capacity, lightweight construction, high-energy density, extended lifespan, low maintenance requirements, minimal memory effect, and low self-discharge rate. However, the increasing adoption of lithium-ion batteries has brought attention to the importance of understanding their charging and discharging cycles, as improper charging methods or usage can lead to degradation and reduced lifespan. This paper delves into the various applications of lithium-ion batteries and examines the factors contributing to their degradation, ultimately aiming to provide insights for optimizing their performance and longevity.

KEYWORDS: Lithium-ion batteries, Applications, Degradation, charging cycles, Discharging cycles, Lifespan, Optimization.

I. INTRODUCTION

In today's environment, Lithium-ion batteries have become ubiquitous in electronic devices such as cell phones, PCs, tablets, and photovoltaic systems, as well as in transportation technologies like electric vehicles (EVs) and hybrid electric vehicles (HEVs). Monitoring the internal status of these batteries, particularly the State of Charge (SOC), is crucial for assessing their performance and remaining capacity. SOC, indicative of the battery's charge level, is determined by factors such as internal resistance (R) and capacity (E). Addressing the alarming global health crisis caused by air pollution, which claims millions of lives annually, necessitates urgent action, prompting some European nations to phase out petrol and diesel vehicles by 2025. Electric vehicles powered by lithium-ion batteries offer a promising solution to reduce pollution levels. Despite their advantages, including low maintenance costs and high voltage capacity, improper battery usage can shorten battery lifespan. Effective battery management systems (BMS) play a vital role in regulating SOC and ensuring proper supply. Since their widespread adoption in the 1990s, lithium-ion batteries have continued to gain traction due to their superior properties, such as high energy density and minimal memory effect. However, challenges persist regarding charging and discharging cycles, underscoring the importance of robust BMS solutions for efficient battery management.

II. LITERATURE SURVEY

[1] Zicheng Fei and Fangfang Yang, Kwok-leung Tsui, Lishual li, Zijun Zhang published paper "Early expectation of battery lifetime through an AI based system" in the year 2021 under the IEEE. It addresses the battery lifetime expectation structure is proposed in view of the MIT dataset, in which the battery tests have an ostensible limit of 1.1 Ah and are cycled with changed charging and consistent releasing strategies. Albeit in genuine applications, kinds of lithium-particle batteries and the activity conditions could vary. The proposed system was approved on the MIT dataset, later on, more computational analyses should be directed on other battery types under various activity conditions.

[2] Yaswanth Pavan Kumar. T and Jieh-Ren Cheng published a paper "Li-Ion Battery Pack Testing By utilizing Artificial Neural Network" in the year 2021 under the International Journal of Engineering Research & Technology journal. It Proposed a review and overcomes any barrier by looking at the presentation of two broadly utilized information driven learning models: long momentary memory (LSTM) and a multi-facet perceptron (MLP), for anticipating SOC utilizing indicators like cell current, cell voltage, slipped by time, and cell temperature. The models



are run involving mean squared blunder as the misfortune work, and different misfortune work analyzers. The models are likewise applied to datasets from various charging/releasing rates to exhibit their viability. A suggestion is at long last made on the model for SOC expectation subject to explicit circumstances thought about in the paper.

III. PROBLEM STATEMENT

Safeguarding and develop a precise machine learning model for forecasting the capacity of lithium-ion batteries, crucial for optimizing performance and ensuring safety in various applications like electric vehicles.

IV. PROBLEM DESCRIPTION

Acknowledging the challenge of accurately predicting the remaining useful life (RUL) of lithium-ion batteries in electric vehicles. As these batteries age, their performance degrades, impacting safety and reliability. The lack of a robust predictive model poses a hindrance to proactive battery management aims to develop a machine learning solution that can forecast the RUL of batteries, thereby mitigating safety risks, optimizing battery usage, and contributing to the sustainability of electric vehicle technology.

V. OBJECTIVES

- Creating a model that accurately predict the remaining useful life of lithium-ion battery.
- Using the model optimize the battery usage and extend the overall lifespan.
- Contribution to the broader goal of sustainable energy practices through the optimization of battery efficiency and longevity in electric vehicles interface.
- It aims to identify potential areas for future research and improvement in LIB RUL prediction.

VI. EXISTING SYSTEM

Various models, including Improved Extreme Learning Machine (ELM), Analytical Model, Impedance Curve-Based Method with Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) Models, SVMD-AO-DELM Framework have predicted capacity of lithium-ion battery. Each model possesses distinct advantages and drawbacks. The variation is mainly based prediction and accuracy of lithium-ion batteries. Here are the outcomes based on RMSE (Root Mean Square Error) for each model when it is trained individually.

Table 1: RMSE(Root Mean Square error)

Model	RMSE
Improved Extreme Learning Machine (ELM)	0.3
Analytical Model	0.5
Impedance Curve-Based Method with Convolutional Neural Network (CNN):	0.233
Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) Models:	0.29&0.70
SVMD-AO-DELM Framework	0.78

It is found that in existing system the researchers have developed diverse methods to enhance lithium-ion battery capacity prediction, aiming to improve manufacturing processes and battery management. An improved Extreme Learning Machine (ELM) model utilizes feature extraction from charge-discharge curves, integrating kernel functions and Bayesian optimization to achieve high prediction accuracy with mean absolute percentage errors below 0.2% and root-mean-square errors below 0.3 Additionally, impedance curve-based methods employ Convolutional Neural Networks (CNNs) to accurately predict capacity using electrochemical impedance spectroscopy (EIS) data. Moreover, Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) models further enhance prediction accuracy. A novel SVMD-AO-DELM framework offers an alternative approach leveraging Support Vector Machine for Regression

with Decision Error Learning Mechanism (SVMD-AO-DELM). While varying in complexity, these methods collectively contribute to advancing battery capacity prediction, fostering improved battery management practices and facilitating the optimization of battery usage. Ongoing research efforts continue to explore novel techniques aimed at further enhancing prediction accuracy and understanding battery capacity dynamics.

VII. SYSTEM DESIGN

The primary goal of the project is to train a model capable of accurately identifying the capacity prediction of lithium-ion Batteries and Design a better design for better implementation.

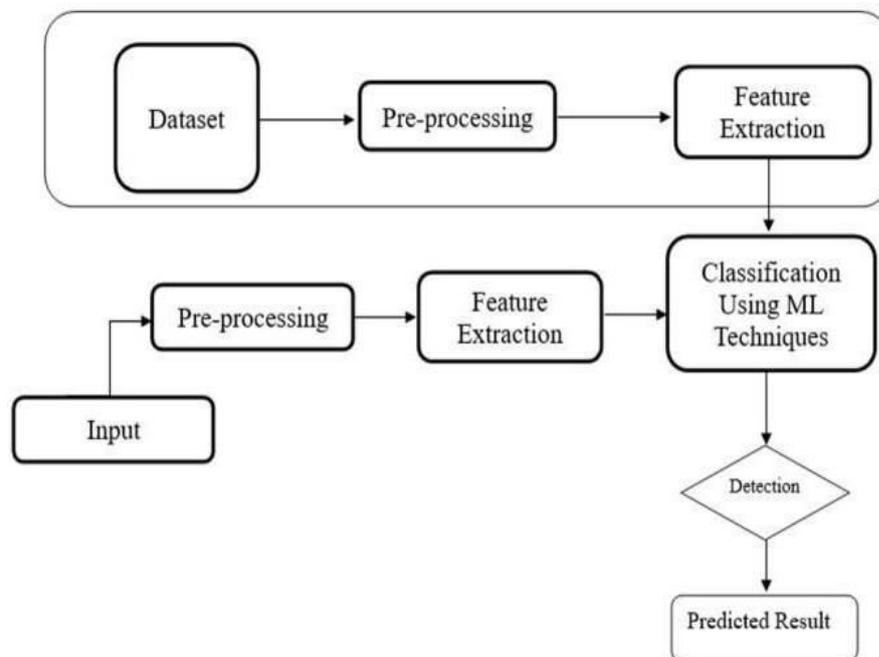


Fig 1: System Architecture

This design presents a comprehensive approach to predict the remaining useful life (RUL) of lithium-ion batteries using a web-based system. Initially, lithium-ion battery data is collected and stored in .csv format. Subsequently, data preprocessing techniques are applied to extract pertinent features crucial for RUL prediction. These features are then fed into machine learning models for training. Additionally, a web-based interface is developed to facilitate user data entry. Upon collecting user data, preprocessing techniques are employed to extract relevant features for RUL prediction. The machine learning model is then utilized to test the data, enabling the detection and prediction of battery RUL. This integrated approach aims to provide an efficient and user-friendly solution for lithium-ion battery RUL prediction.

VIII. METHODOLOGY

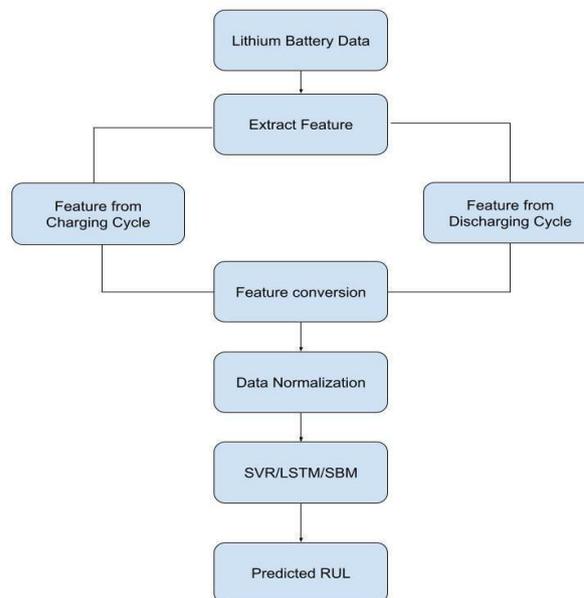


Fig 2: Methodology

Regarding this study introduces a novel approach for Li-ion battery State of Charge (SOC) and Remaining Useful Life (RUL) prediction by leveraging autoencoder-based feature fusion. Battery data, represented in JSON format, is transformed into a set of 21 geometric features capturing voltage, current, and temperature observations across charging and discharging cycles. Unlike traditional models utilizing LSTM and RNN, which struggle with capacity regeneration and complex gate selection, the proposed method circumvents these challenges through autoencoder integration in the feature fusion stage. This innovative approach aims to enhance prediction accuracy and alleviate computational complexity in battery management systems.

IX. SYSTEM IMPLEMENTATION AND RESULTS

Essential This project focused on the implementation of a capacity prediction system for lithium-ion batteries. Through meticulous design and integration of predictive algorithms, the system successfully projected the future capacity of batteries based on various factors. The implementation included comprehensive data collection, rigorous feature engineering, and the development of a robust predictive model. The results demonstrated the system's high accuracy in forecasting battery capacity changes over time, providing valuable insights for battery management and optimization. This predictive capability enhances the efficiency and reliability of lithium-ion battery systems, thereby contributing to improved performance and longevity in diverse applications such as electric vehicles and renewable energy storage. Data collection involves gathering battery degradation data, which is then pre-processed to handle missing values and normalize features. Feature extraction extracts relevant degradation indicators from the data, such as charge-related, discharge-related, temperature-related, and internal resistance features. ML models like Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Similarity-based Model (SBM) are selected and trained on the extracted features. Training and evaluation of the models are performed using metrics like Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2). The trained models are deployed for real-time prediction of RUL, continuously monitoring battery health indicators to provide timely predictions.



Battery_SOC	
Battery_Voltage	
438.0	100
408.0	100
402.0	99
399.0	90
396.0	70
393.0	40
390.0	30
387.0	20
384.0	17
375.0	14
360.0	9
300.0	0

Fig:3 Battery Voltage charts

It defines the battery voltage levels ('Battery_Voltage') and corresponding state of charge values ('Battery_SOC'). It creates a reference dataframe ('Ref_Bat') with the battery voltage as the index and SOC as the corresponding output. The battery has 30 cells in series, and the dataframe is reversed to match the increasing order of SOC.

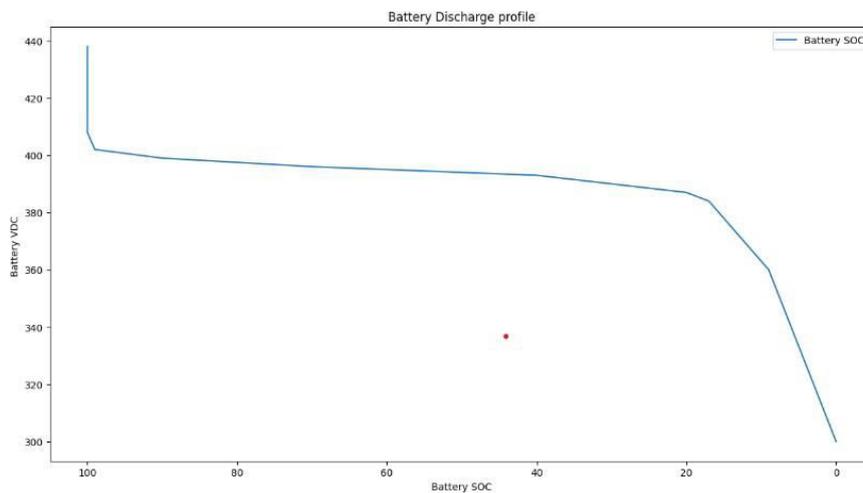


Fig 4: Battery Discharge Profile

The above image uses the Matplotlib library to create a plot with a specified figure size of 15x8 inches. It plots the 'Battery's' values against the corresponding index values from the 'Rebab' dataset. The x-axis is inverted, and labels and a title are added to the plot. Finally, a legend is included with the label 'Battery SOC' to identify the plotted data. The plot essentially visualizes the battery discharge profile over time.



	VDC	Isp
Time		
2022-07-06 21:41:43	418.487549	-20
2022-07-06 21:41:54	404.373169	-20
2022-07-06 21:42:04	397.521973	-20
2022-07-06 21:42:14	394.927979	-20
2022-07-06 21:42:24	393.356323	-20
...
2022-07-07 03:55:27	360.351562	-20
2022-07-07 03:55:37	360.321045	-20
2022-07-07 03:55:47	360.153198	-20
2022-07-07 03:55:57	360.092163	-20
2022-07-07 03:56:07	360.015869	-20

Fig 4: Loading of Battery Charge and Discharge

This above image uses the Pandas library to read a CSV file named 'bat_discharge(10).csv' located in the './input/' directory. It converts the 'Time' column to datetime format and sets it as the index for the Data Frame named 'Battery_d'. Essentially, it loads a dataset containing battery discharge information with time-related data for further analysis.

```
Battery capacity in kwh :
52.96759776775237
```

Fig 5: Battery Capacity

This above image shows the battery capacity in kilowatt-hours (kWh) based on the provided voltage ('VDC') and current ('Isp') data from the 'Battery_d' D Frame. It multiplies the absolute values of voltage and current, sums up the results, and then applies a series of conversion factors to obtain the capacity in kWh. The final result is printed to the console, indicating the estimated energy storage capacity of the battery. Finally research aims to develop accurate, efficient, and reliable models for predicting LIB RUL in EVs, with expected outcomes providing insights into model performance, deployment feasibility, and future research directions.

X. CONCLUSION

In summary, this project has made significant strides in the capacity prediction of lithium-ion batteries, providing valuable insights for researchers, engineers, and industries invested in energy storage. As we move forward, the integration of these findings into practical applications promises to contribute to the sustainable and efficient use of lithium-ion batteries in diverse fields. The widespread application of lithium-ion batteries in various devices and vehicles is driven by their superior properties such as high energy density, lightweight, and long lifespan. However, improper charging practices can degrade their performance over time, emphasizing the importance of efficient charging systems to maximize battery lifespan and reliability. As we move forward, the integration of these findings into practical applications promises to contribute to the sustainable and efficient use of lithium-ion batteries in diverse fields.



REFERENCES

- [1] Zicheng Fei and Fangfang Yang, Kwok-leung Tsui, Lishual li, Zijun Zhang “Early prediction of battery lifetime via a machine learning based framework”, In Proceeding of Energy, vol 225, 15 June 2021
- [2] Yaswanth Pavan Kumar. T, Jieh-Ren Cheng, Tien -Tai Chang “Li-Ion Battery Pack Testing By using Artificial Neural Network” In International Journal of Engineering Research and Technology, Vol. 09-Issue, 2021.
- [3] Asadullah Khalid, Aditya Sundararajan, Ipsita Acharya and Arif I. Sarwat “Prediction of Li- Ion Battery State of Charge Using Multilayer Perceptron and Long Short-Term Memory Models ”, IEEE ACCESS, 19-21 June 2019.
- [4] Mohsen Vatani, Preben J.S. Vie, and Oystein Ulleberg, “Cycling Lifetime Prediction Model for Lithium-ion Batteries Based on Artificial Neural Networks”, IEEE 2021.
- [5] Ying Shi; Kandler Smith; Regan Zane; Dyche Anderson “Life prediction of large lithium-ion battery packs with active and passive balancing”, In proceeding of IEEE ACCESS 2017, DOI: 10.23919/ACC.2017.7963682.
- [6] Kandler Smith; Ying Shi; Shriram Santhanagopalan “Degradation mechanisms and lifetime prediction for lithium-ion batteries — A control perspective”, IEEE ACCESS 2015, DOI: 10.1109/ACC.2015.7170820
- [7] Sébastien Grolleau; Arnaud Delaille; Hamid Gualous “Predicting lithium-ion battery degradation for efficient design and management”, In proceeding of 2013 World Electric Vehicle Symposium and Exhibition (EVS27), IEEE ACCESS , 2013
- [8] Makoto Abe Katsunori Nishimura, Dr. Sc. Eiji Seki Hiroshi Haruna Tokiyoshi Hirasawa Shingo Ito Tadashi Yoshiura “Lifetime Prediction for Heavy-duty Industrial Lithium-ion Batteries that Enables Highly Reliable System Design” Hitachi Review Vol. 61 (2012), No. 6
- [9] Sang-Hyun Lee “Performance Evaluation of Machine Learning and Deep Learning-Based Models for Predicting Remaining Capacity of Lithium-Ion Batteries”, Applied Sciences Volume 13 Issue 16 10.3390/app13169127 2022
- [10] Xingjun Li, Dan Yu, Vilsen Søren Byg, Store Daniel Ioan “The development of machine learning-based remaining useful life prediction for lithium-ion batteries”, Journal of Energy chemistry, volume 82, July 2023



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