International Journal of Applied Power Engineering (IJAPE)
Vol. 14, No. 3, September 2025, pp. 569∼578
ISSN: 2252-8792, DOI: 10.11591/ijape.v14.i3.pp569-578

AI-driven solutions for Li-ion battery performance and prediction

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Article Info

Article history:

Received Jul 10, 2024
Revised Jan 11, 2025
Accepted Jan 19, 2025

Keywords:

Battery management system
Lithium-ion battery
Remaining useful life
State of charge
State of health

ABSTRACT

Batteries serve as crucial power sources for essential portable devices like electric vehicles, smartphones, and laptops. The widespread adoption of Li-ion batteries, while beneficial, has unfortunately led to a surge in adverse incidents. The sudden failure of batteries in both industrial and lightweight applications poses significant economic risks across various industries. Consequently, researchers are intensifying their focus on enhancing battery state estimation, and management systems and predicting remaining useful life (RUL). This paper is structured into three main sections. Firstly, it delves into the acquisition of battery data, encompassing both commercially available and freely accessible Li-ion battery datasets. Secondly, the exploration extends to techniques for estimating battery states through advanced battery management systems. The paper investigates battery RUL estimation, categorizing and evaluating diverse prognostic methods applied to Li-ion batteries based on crucial performance parameters. The review includes scrutiny of commercially and publicly available datasets for various battery models and conditions, considering different battery states and the role of advanced battery management system (BMS). In the final section, the paper concludes with a comparative analysis of Li-ion battery RUL prediction, incorporating exploration into various RUL prediction algorithms, and mathematical models, and introducing an AI-based cloud monitoring system.

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1. INTRODUCTION

It has turned out that the electric vehicles (EVs) as well as the clean energy technologies continue to expand at a fast pace, which has become one of the dominant ways of tackling global environmental and energy issues. The conventional energy sources such as those that produce toxic gases are gradually being substituted by environmentally friendly electric automobiles. Central to EV technology is the battery, which comprises four critical components: electric design, mechanical design, thermal design as well as battery management system (BMS) [1]. Due to the social development and manufacturing of highly efficient and instantaneous power control technologies as a result of the advancing modern technologies, batteries particularly those used within

EVs have become extremely vital in an attempt at offering ever reliable green energy storage mechanisms. Energy storage has hence emerged as one of the most promising industries due to the increasing need for energy-intensive products such as consumer electronics and advancement in the utilization of renewable energy [2], [3]. New energy sources displacing the traditional and continuous supply systems including nuclear, coal, and oil and replacing them with renewable energy systems including wind and solar energy is causing disruption of the systems especially in developing countries. This shift is putting in place conditions that require new advanced energy storage systems to respond to complex energy market structures [4], [5]. Different types of storage such as electrochemical which has a high efficiency, mechanical, chemical, and thermal storage have different capacities, and days of storage. From these, the rechargeable electrochemical systems bearing the most popularity due to conveniences such as high energy density, light weight and flexibility particularly the lithium-ion (Li-ion) batteries. Li-ion batteries are higher performing than other battery technologies including lead-acid, redox flow, sodium sulphur batteries among others that make its application in aviation industry, satellite communication, marine applications and EVs. They also drive various home appliances like refrigerators, laptops and wandering devices like mobile phones among others [6]. This report implies that Li-ion batteries have some of the unique benefits such as long cycle-life, high energy density and low maintenance hence the technology is universally applied. But they also have some disadvantages for example, they are expensive, are easily damaged when they are fully charged or cause fire risks.

In the case of the electrical vehicles, two variables namely the state of health, and the state of charge significantly affect both the safety, and output of the vehicle. Battery energy management (BEM) strategies therefore seek to enhance the state of health (SoH) and state of charge (SoC) of Li-ion batteries for increased life cycle of the battery bank together with increasing efficiency of the induction motor [7], [8]. While there are certain conventional ways of controlling speed such as using dynamo-meter and other similar technologies, the recent innovative BEM methods involve model-in-loop techniques that mimic battery performance and therefore reduces the battery's life cycle. They prevent the reduction of SoC rate and slow down the SoH decline that distorts the general battery dependability [9]. As the use of Li-ion batteries expanded widely there has been a significant focus on the number of charge discharge cycles, remaining useful life (RUL), and degradation analysis. It is very important for accurate estimation of RUL preventing battery failures and maintaining superior system performance [10]. Although there are so many benefits associated with Li-ion batteries, they experience high degradation and failure rates, this makes battery management system and accurate RUL models to be more crucial. Better estimation of RUL leads to the necessity of having better datasets, and several organizations have been developing datasets for different battery models [11], [12]. These datasets are very useful in enhancing battery health estimations, and also in minimizing the time taken in developing new datasets needed for battery research, as well as enhancing the dependability of systems used in battery management. Using these datasets, researchers will be able to increase the accuracy of RUL estimations as well as battery health assessment [13], [14]. Many approaches have been made to effective and accurate assessment of SoH and RUL in the Li-ion batteries. Through a system simulation approach involving electrochemical techniques and data analysis methods of statistics, evaluation of state estimation algorithms is provided [15]. Furthermore, support vector machines (SVM) has been used to improve the accuracy of RUL of battery through improving the accuracy of the mentioned model. The current developments in the Li-ion battery technology call for more extensive and up-to-date reviews of the methods aimed at the estimation of RUL [16], [17]. Gaps in current research: Although there are advancements being made on the study of battery health and performance degradation, there are still loopholes in measuring different methodologies available. Several studies are still missing in the current research that addresses the interaction between the battery management algorithms and the estimation of RUL [18], [19]. This gap is important for maximizing the performance of batteries as well as eliminating failures. Thus, there is a need to explore BMS and RUL estimation models to obtain the best results in battery control [20].

Research contributions and new directions: This research aims at filling these gaps by providing an assessment of both the public and commercial datasets in batteries storage. It assesses superior state estimation methods utilizing BMS and dissects different types of RUL prediction techniques. The study focuses on three key areas: another sub-field is the battery data acquisition, deep estimation of battery health utilizing progressive BMS, and methods of RUL estimation [21], [22]. This work also identifies the pros and cons of the approaches presented when analyzing datasets and comparing RUL prediction models. The contribution of this study is therefore in comparing a number RUL prediction algorithms and mathematical model [23]. The paper presents a cloud monitoring system that is intended to increase the capabilities of stream processing and upgrade battery health predictions. This study establishes that it is possible to improve the accuracy of the RUL of Li-ion cells by incorporating findings from data analysis with other suitable methods [24], [25]. Future directions: In the future, the studies will continue on how to add machine learning and big data implemented into the battery control systems. The highlighted advanced technologies in papers described have the capabilities to enhance battery efficiency, its durability and energy density. Furthermore, other methods such as correlation matrices, pair plot, time series plot and box plot will also be utilized to understand certain behaviour of Li-ion battery particularly during discharge cycles. These visualization tools offer valuable insights into performance changes and degradation patterns, further advancing battery health monitoring and RUL prediction behaviour during discharge cycles. For the prediction of RUL explanation shown in Figure 1.

Figure 2 depicts a fundamental battery management system concept. This method aids in knowledge of the differences among numerous battery states and RUL, in particular within the context of real-global business and commercial conditions. The number one recognition of this overview is to provide a comparative look at battery RUL estimation procedures, incorporating battery management, and offering complete statistics on commercially and freely available online battery datasets.

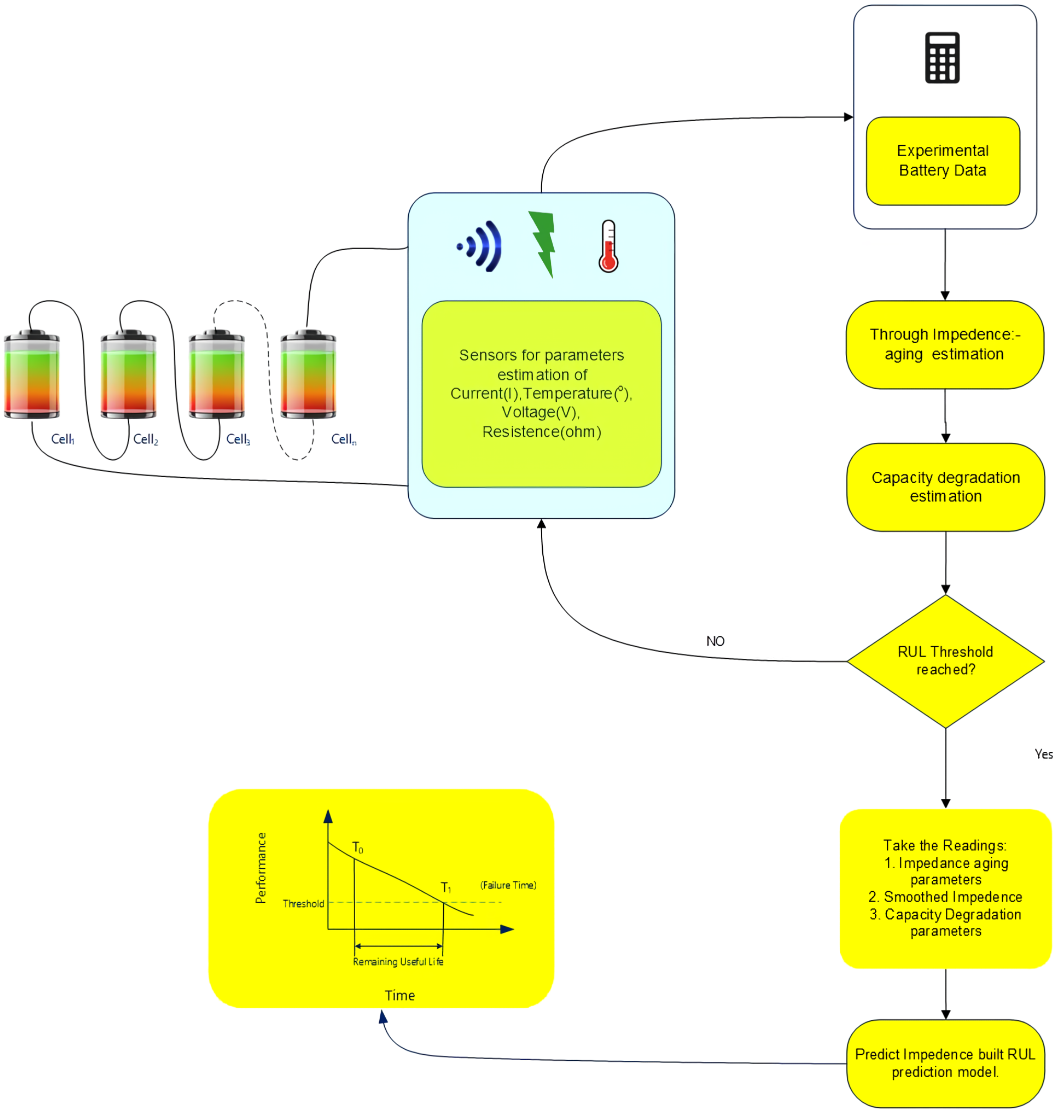


Figure 1. Predicting RUL through Li-ion battery data acquisition process

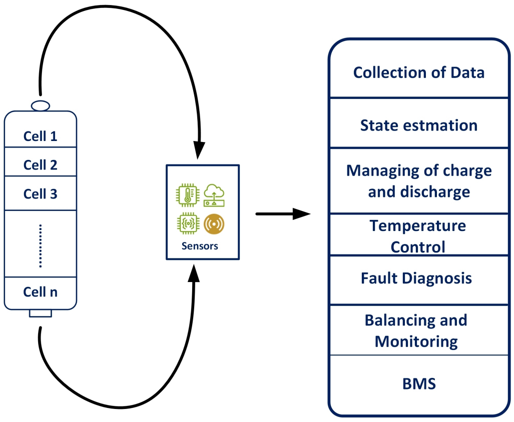


Figure 2. Visualizing battery management procedures

2. PROPOSED METHOD

The proposed framework gives an improved methodology and high level of sophistication for performance evaluation and accurate estimation of the predictive capability of lithium-ion batteries supported by state of art data acquisition, BMS, and RUL assessment techniques. It unfolds across three key pillars:

2.1. Battery data acquisition

This step is about the effective use of the lithium-ion battery data pool which includes both proprietary and open-sourced data sets. Through highly targeted choice of the best battery cells and the subsequent collection of highly accurate parameter data related to the cell state of charge, voltage, current, and temperature, the study aims to arrive at a set of very solid health indicators (HI) on which the accurate calculation of RULs will be based. Some of the main trends observed in the process of data acquisition include the following stringent requirements imposed on the functional performance of the data acquisition systems to achieve extremely high dependability and versatility with respect to the operating conditions.

2.2. Estimation of battery states

A wireless BMS on the programmable logic controllers (PLC), supervisory control and data acquisition (SCADA), and GSM modules is a modern solution that allows the monitoring of the battery's prerequisites such as voltage, current, and temperature. This dynamic monitoring approach is highly reliable and flexible which makes it possible to perform well in many different environments. Wireless technology integration offers enhanced data transfer and remote system management capabilities that enhance battery effectiveness as well as decision-making.

2.3. RUL estimation methods

RUL estimation methods: As in the previous phase, a detailed comparative evaluation of different prognostic models is made with an emphasis put on RUL prediction. The technology comprises the AI-based methods of cloudy monitoring and the latest mathematical calculations facilitating the further improvement of battery performance predictions. They also augment the estimated RUL's precision while also providing insights into the battery behavior under various scenarios, which is a paradigm shift in battery management. The proposed study is something unique in the field as it embeds modern approaches to data acquisition, advanced algorithms of prediction, and sophisticated BMS technologies into a single research for the purpose of maximizing energy storage solutions in electric vehicle and portable applications.

3. METHODOLOGY

Wireless implementation of battery management systems (BMS) is carried out with the help of PLC for data processing in real-time with the help of SCADA systems and GSM modules for industrial temperature monitoring. This integration ensures seamless data handling and monitoring, enabling operators to keep track of system parameters efficiently. It also enhances system flexibility and reduces wiring complexity, leading to easier maintenance and scalability.

3.1. Battery monitoring system (BMS)

A 2.4 GHz wireless communication module also ensures low power and low-cost signal for transmitting other important issues like voltage, current, and temperature to facilitate data acquisition from the battery system. The use of such modules enhances the reliability of wireless transmission while maintaining energy efficiency and cost-effectiveness, making it suitable for large-scale industrial applications. Additionally, it supports seamless integration with IoT platforms, enabling remote monitoring and advanced data analytics. This contributes to predictive maintenance and improved overall system performance. Furthermore, the scalability of these modules allows easy expansion of the monitoring network as system requirements grow.

3.2. Safety assessment

In order to prevent early battery failures, a new safety assessment approach is established to detect and prevent possible battery failures. It monitors constantly all internal variables, including chemicals and physical changes and external factors for instance, thermal and electrical loads. By analyzing conditions in real-time, the system is able to prevent overcharging, over-discharging, and overheating thus increasing battery life and preventing explosions.

3.3. Data acquisition and analysis

In this work, a number of high-accuracy sensing elements are used in order to measure some characteristics of the battery such as its voltage, its resistance, the current through it, the temperature and the capacitance. These measurements are taken across eight modules; each of the modules comprises twelve cells. The nominal voltage is distributed with each of the individual cells featuring 3.7 volts of power potential, that takes the total voltage of a fully charged module to 44.4 V. This way of connecting the battery allows the accurate and intricate observation of its working. Data acquisition process forms the type of cyclic behavior of the battery in the process of discharging processes. Thus, through collecting such data, the researchers can plot time series plots illustrating the dynamic of these parameters. Such plots assist in tracking battery degradation and the performance of the battery for each discharging cycle being performed on the battery. In addition, it is possible to perform a correlation analysis aimed at making conclusions on interdependence of various parameters with each other, for instance, how temperature is dependent on voltage or current. High accuracy sensors, collection of data at different stages during the discharging cycles across long term gives a clear indication of the battery performance across the cycles. It is also the information which can be valuable to make the proper decisions on the use of the batteries in the future and increase the overall reliability of the system, as shown in Figure 3.

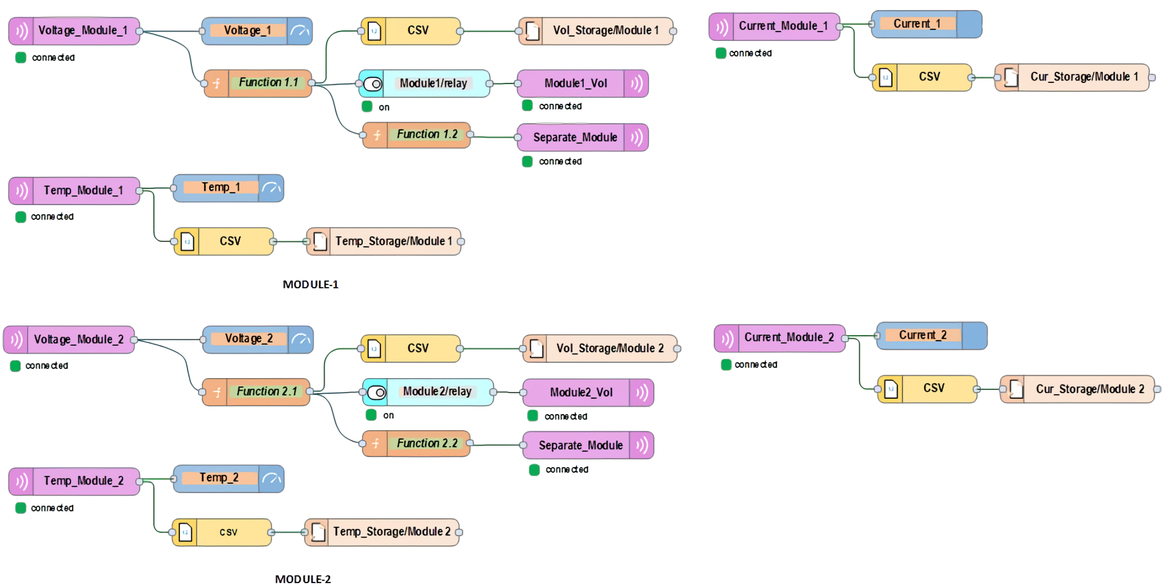


Figure 3. Visualizing battery management procedures

3.4. Statistical techniques and data-set selection

Exploratory data analysis techniques including correlation analysis and box plots are employed to determine the likelihood of a relation between battery parameters as well as their trends within charge-discharge cycles. The data collected is subject to rigorous inclusion and exclusion criteria, which means that only high quality data from commercial and public source is used. This make the outcome of the analysis reliable, repeatable, and sound having a solid groundwork for future investigations on lithium-ion battery performance and control. After the acquisition of experimental battery data, it becomes imperative to conduct assessments for impedance aging parameter estimation and capacity degradation parameter estimation. These evaluations are crucial in determining the remaining useful life (RUL) threshold or ascertaining whether it meets the specified criteria. This analytical process involves measuring impedance aging and capacity degradation to gauge the operational longevity and performance deterioration of the battery, contributing to a comprehensive understanding of its life cycle dynamics.

4. RESULTS AND DISCUSSION

Although there are distinct uses of RUL prediction methodologies for lithium-ion batteries (LIBs), most methodologies have not yet been utilized to predict the RUL of LIBs, thus pointing to areas that can be explored in the future. These unexplored areas offer potential for advancing battery life forecasting techniques. Future research can leverage emerging tools like machine learning and hybrid modeling to enhance prediction accuracy. By integrating data driven approaches with physics-based models, researchers can better capture complex degradation mechanisms under varied operating conditions. Additionally, incorporating adaptive algorithms that learn from real-time battery performance data can significantly improve long-term RUL prediction and facilitate smarter battery management systems.

4.1. Prediction of the behaviour of the battery

The following regions present huge research scopes: In the outlined suggested model, there are three forms of assessment namely: i) The complementary nature of analytical methodologies with the similar method makes it promising to enhance the prognostication accuracy of the RUL of lithium-ion cells. Thus, combining the identified basic approaches to data analysis with the other methods, Burns and Summer will believe that the dependability of the RUL results can be improved considerably in practice. This combination of methods is necessary especially as the battery characteristics demonstrate more features in the development of its behavior that affects the predictions accuracy; ii) This has made it necessary to look for other better sources of data with which the accuracy of estimating the remaining useful life (RUL) can be enhanced. As mentioned earlier, to achieve high levels of RUL prediction it is imperative to work with high quality data therefore, future research should focus primary on seeking better data sources. This will be especially helpful because it will cover data obtained under varying operational conditions as well as battery states that will improve RUL estimation; iii) Multi-state joint estimation can be used to several states such as state of charge (SoC), state of energy (SoE), state of power (SoP), state of health (SoH), state of temperature (SoT), as well as state of stress (SoS) to expose the enhanced battery management methodologies. In other words, by jointly estimating these different states, the BMS provides a more accurate representation of battery conditions hence improving its capacity to estimate RUL while at the same time improving its overall performance; and iv) Hence other research potentialities in the future of battery management may also include, AI and machine learning, and big data analysis. Thus, the combination of different approaches in the estimation enhances the level of precision and can form a basis for enhancement on the estimation of RUL with regard to BMS.

4.2. Discharging behaviour of Li-ion battery

The conducted visualizations present a comprehensive analysis of the behavior of lithium-ion (Li-ion) batteries during the discharge process. Through a series of analytical techniques, including the generation of a correlation matrix and the visualization of pair plots, the interrelationships between various parameters such as cell voltage, current, and temperature were examined. Time series plots were employed to elucidate the temporal dynamics of these variables throughout the discharge cycles, providing valuable insights into their behavior over time. Additionally, boxplots were utilized to illustrate the distribution of cell voltage, current, and temperature across different cycle numbers, enabling the identification of trends and patterns associated with cycle progression. By systematically conducting these visualizations, a holistic understanding of the behavior of Li-ion batteries during discharge was attained, facilitating informed decision-making and optimization strategies for battery performance enhancement. This approach contributes to the advancement of battery research and the development of efficient energy storage solutions. We mentioned the different techniques in Figure 4 and Figures 5(a), and 5(b) as correlation and box plot respectively.

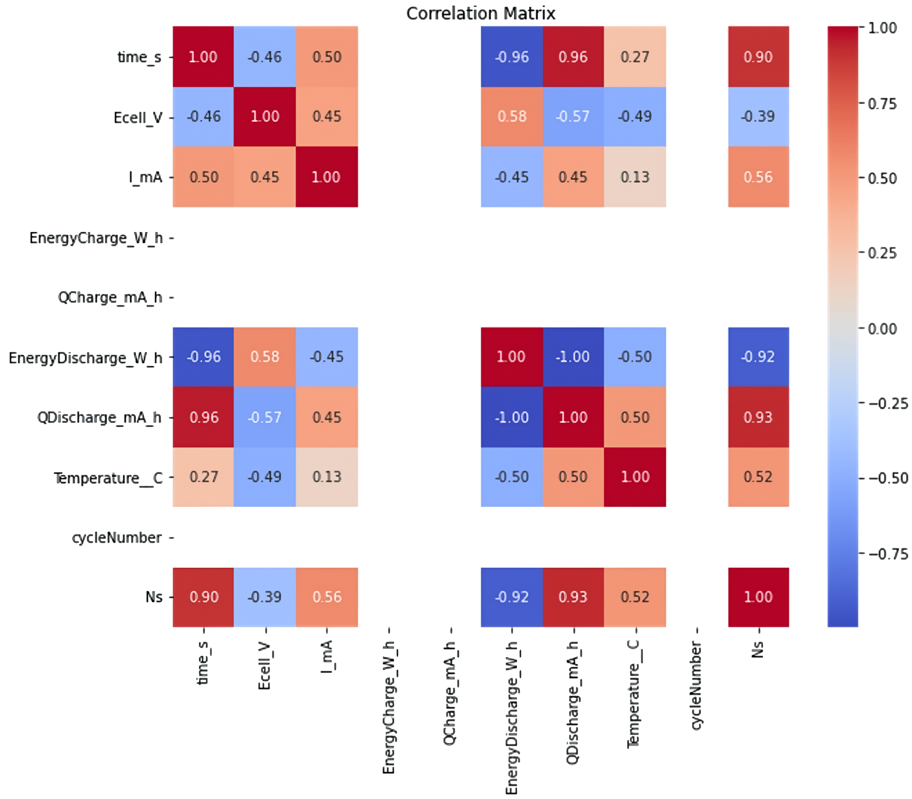
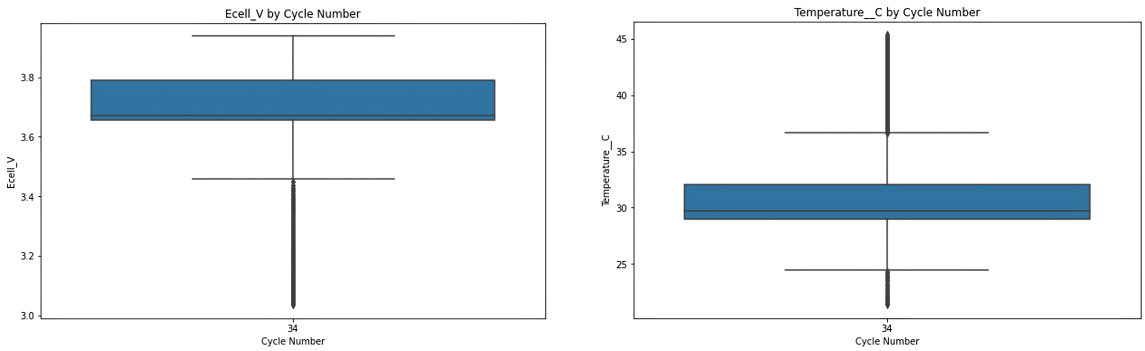


Figure 4. Correlation matrix of Li-ion battery while discharging in different cycle



(a) (b)

Figure 5. Discharging battery box plot according to the cycles: (a) voltage of the battery and (b) temperature of the battery

5. CONCLUSION

In conclusion, this paper highlights the critical importance of advancing battery state estimation, and management systems, and forecasting the remaining useful life (RUL) of lithium-ion (Li-ion) batteries. The widespread adoption of Li-ion batteries in essential portable devices such as smartphones, laptops, and EV has led to increased attention on mitigating adverse incidents and economic risks associated with battery failures. Through a structured review, the paper emphasizes three main sections: the acquisition of battery data, techniques for estimating battery states using advanced battery management systems, and battery RUL estimation methods. By scrutinizing commercially and publicly available datasets for various battery models and conditions, as well as evaluating diverse prognostic methods, the paper provides insights into the current landscape of Li-ion battery research. The comparative analysis of RUL prediction algorithms and mathematical models, alongside the introduction of an AI-based cloud monitoring system, underscores the need for innovative approaches to enhance battery performance and safety in both industrial and lightweight applications. As researchers continue to explore and develop advanced battery management techniques, this paper serves as a valuable resource for guiding future research directions and addressing the challenges associated with Li-ion battery technology.

FUNDING INFORMATION

The authors declare that this research did not receive any specific grant from public, commercial, or not-for-profit funding agencies.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Sthitprajna Mishra	✓	✓	✓	✓	✓	✓		✓	✓	✓				✓
Chinmoy Kumar Panigrahi						✓	✓		✓	✓		✓		
Subhra Debdas	✓		✓	✓		✓			✓			✓	✓	
Atri Bandyopadhyay			✓			✓				✓		✓		
Srikanth Velpula		✓		✓				✓	✓					✓
Amit Kumar Sahoo		✓		✓						✓			✓	✓
Pabitra Kumar Tripathy			✓		✓			✓	✓					✓

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject Administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding Acquisition
Fo	: **Fo**rmal Analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no known financial, personal, or professional conflicts of interest that could have influenced the work reported in this paper. All contributions to the research and manuscript preparation were conducted impartially and independently. This declaration ensures transparency and upholds the integrity of the research process.

DATA AVAILABILITY

The data presented in this study are hypothetical and were generated solely for the purpose ofconceptual analysis and methodological illustration. As such, no real-world datasets were used or made available.

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