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Remaining Useful Life (RUL) Estimation for Lithium-Ion Battery Using Extreme Learning Machine

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Abstract
Study proposes a new method for predicting the remaining useful life (RUL) of lithium-ion batteries using the Extreme Learning Machine (ELM) algorithm by employing advanced feature extraction techniques to identify critical parameters influencing battery degradation. The model captures intricate patterns in battery health, enabling precise RUL prediction by analyzing voltage, current, temperature, and capacity data. A correlation investigation executed in this paper emphasizes the importance of designated variables, for example, discharge capacity dwindle and inner resistance, in identifying lifecycle of the battery. The ELM is an advanced machine learning algorithm, which has high speed for problem-solving capability, and is used to design a vigorous prognostic approach. Experiment-based results analysis validates that the suggested method accomplishes higher correctness and computational speed compared to conventional approaches. The algorithm's enactment is authenticated via several performance matrices (i.e., AE, MAPE and R^2), validating model's reliable enactment in concrete actual circumstances. Presented study delivers an appreciated algorithm for BLI health diagnosis, augmenting the consistency and reliability of BLI in EVs, RES, and further uses. The outcomes emphasize the impending of AI/ML methods in evolving analytical maintenance for ESS.
Keywords - *Artificial Intelligence, Feature extraction, Remaining-Useful-Life (RUL), Lithium-Ion Battery (BLI), Online Monitoring, Health Indicator,*

ED	Energy density
ESS	Energy storage system
AE	Absolute Energy
MAPE	Mean absolute percentage error
BLI	Lithium-ion battery
RUL	Remaining useful life
ELM	Extreme Learning Machine
AI	Artificial Intelligence
ML	Machine Learning
EV	Electric Vehicles
SDR	Self-discharge rate
PM	Predictive maintenance
FNN	Feedforward neural network
CA	Correlation analysis
HI	health indicators
HMS	Health monitoring systems
RE	Renewable energy
HL	Hidden layer
LSS	Least-squares solution
BP	Backpropagation

EMS Energy management systems
MPGI Moore-Penrose generalized inverse

1. INTRODUCTION

BLIs have developed as the support of contemporary ESS due to their great ED, low SDR, and long cycle life [1]. Their extensive usage by several electronics, EVs, aerospace applications, and large-scale grid ESS. Although these leads, the enactment and security of BLI, deteriorate gradually, hovering trepidations about their consistency and durability [2]. A few strategic encounters in this area is to precisely evaluation the RUL of BLI—a parameter that envisages how long the BLI can endure to operate excellently before demanding renewal. Appropriate and particular BLI's RUL assessment not only confirms the harmless process of BLI-powered arrangements but also enables PM, price reserves, and finest reserve managing. Elderly in BLIs consequences in capability dwindle and augmented inner resistance because of embryonic chemical-physical progressions. These deprivation instruments are frequently multifarious and pretentious by a diversity of influences for example rate of charge discharge, temperature, ecological circumstances, and practice outlines. Subsequently, modest practical or instruction-based methodologies are inadequate to apprehend the particulars of BLIs deterioration. The upward attentiveness in data-driven procedures has enabled the engagement of ML methods for BLI's RUL calculation, amid which the ELM outlooks out owing to its debauched-learning swiftness, negligible anthropological involvement, and robust simplification competencies. ELM, a single-layer FNN, is known for its capability to acquire nonlinear dealings from data with great proficiency, creation it predominantly appropriate for instantaneous BLIs health monitoring applications.

In this study, a novel method is proposed to BLI's RUL assessment by incorporating variable finding, variable CA, and the usage of non-electrical HI with an ELM algorithm. Dissimilar conformist methods that depend on deeply on electrical signals such as voltage, current, and inner resistance, this investigation presents a innovative standpoint through combining non-electrical signals—factors that are repeatedly unnoticed nevertheless can deliver evocative acumens into the BLI's degradation procedure.

Through accumulative number of industrialized coincidences, transportation catastrophes, and unfluctuating disastrous actions in air-company crosswise numerous countries, in several circumstances the foundation was sketched back to unnoticed BLI failures or thermal runaway incidents [3-5]. These instances highlight the critical essential for vigorous and pre-emptive BLI's HMS. In aeronautics, for occurrence, BLI are utilized in acute methods fluctuating from alternative illumination to avionics. A catastrophe to identify primary cryptograms of deprivation can prime to severe circumstances. Comparable jeopardies happen for EVs and ER storage systems, where undiagnosed BLI catastrophes or breakdown can consequence in organization collapses, monetary fatalities, and ecological dangers.

The projected approach is alienated into numerous significant phases. Primarily, collected data from BLI's testing or actual arrangements is composed, comprising electrical and non-electrical indicators. Thereafter, pre-processing procedure is implemented to remove the nonlinearity and spikes. Consequently, significant variables are mined, and CA is accomplished to comprehend the interdependencies midst these variables. The useful HIs are recognized commencing the greatest dominant variables, helping as a participation to the ELM algorithm, which is accomplished to envisage the BLI's RUL.

The ELM discriminate itself commencing outmoded NN through arbitrarily allocating involvement of weights and biases in HL, shadowed through systematically calculating the yield weights at output utilizing a LSS. This not only hurries the training procedure nonetheless also moderates the jeopardy of indigenous minima, a conjoint concern in BP-based algorithms. The debauched-learning swiftness of ELM marks it predominantly alluring for solicitations where instantaneous handling is indispensable, such as in-aircraft BLI's 24/7-hour care or vigorous EMS.

Numerous significant influences are completed in presented study: 1) Outline of the usage of non-electrical signals in BLI's RUL calculation, which supplements a innovative measurement to HM. 2) Highlight the prominence of data-driven variable extraction and assortment thereafter CA in enlightening approache enactment. 3) Exploiting the processing competence of ELM for rapid and precise BLI's RUL assessment, creation the algorithm appropriate for entrenched arrangements and instantaneous solicitations. 4) Listing down a perilous cavity in BLI's protection and PM, presented study has undeviating insinuations for the consistency and efficacy of approaches that hinge on on BLIs.

In deduction, the emergent requirement on BLIs transversely miscellaneous solicitations demands for cannier and nonviolent HMS. Through coincidences and method catastrophes pleasant supplementary predominant because of insufficient BLI's HM, there is a strong requirement for inventive methodologies that drive outside outmoded rehearses. Through applying progressive signal handing out, variables production, and the control of ELM, proposed approach intentions to provide a vigorous, accessible, and real-world resolution for BLI's RUL assessment. The amalgamation of non-electrical HIs arrangements this work separately and unfastens novel boulevards for investigation in BLI's monitoring, with the impending to augment protection, moderate interruption, and encompass the functioning life cycle of precarious structures wide-reaching.

The presented paper is organized as follow: Section-1 represents the introduction and section-2 Brief Information about Globally Available Energy Storage (ES) Database. Methodologies is mentioned in section-3, which includes data collection, Extreme Learning Machine (ELM) Model Formulation, Performance Analysis. Section-4 shows the results and discussion. And finally, section-4 represents the conclusion.

2. Brief Information about Globally Available Energy Storage (ES) Database

In this section we covers various measurements of the installation in the global ES database, which include the following information: 1) per year ES installation, 2) cumulative sum of ES installation, 3) by application, rated power of ES installation, 4) by application, rated capacity of ES installation. The broad category of selected technologies includes electrochemical battery and chemical storage, electro-mechanical energy storage (i.e., compressed air energy storage, flywheel, and pumped hydro storage) and thermal energy storage (Heat thermal storage, Latent heat: Sensible heat)

Table 1. Energy Storage Installations (Electro-chemical battery & chemical storage, Electro-mechanical energy storage, and thermal energy storage)

Data Source	Total available		with Operational status	
	Total Rated Power (kW)	Units Count	Total Rated Power (kW)	Units Count
Demonstration Projects	14583	16	3790	5
EIA-860 (2021)	26846300	625	3944300	280
EU Data	6520400	61	3193800	47
GESDB	180880121	1635	163193235	1310
Total	**214261404**	**2337**	**170335125**	**1642**

Table 2. Technology-1 (Electro-chemical battery and chemical storage: electro-chemical capacitor, flow battery, hydrogen storage, lead-acid battery, lithium-ion battery, Nickel-based battery, Sodium based battery, Zinc based Battery)

Data Source	Total available		with Operational status	
	Total Rated Power (kW)	Units Count	Total Rated Power (kW)	Units Count
Demonstration Projects	14533	14	3740	4
EIA-860 (2021)	26622300	619	3881300	276
EU Data	96150	25	47950	19
GESDB	4117008	1007	1801837	742
Total	**30849991**	**1665**	**5734827**	**1041**

Table 3. Technology-2 (Electro-mechanical energy storage: compressed air energy storage, flywheel, and pumped hydro storage)

Data Source	Total available		with Operational status	
	Total Rated Power (kW)	Units Count	Total Rated Power (kW)	Units Count
Demonstration Projects	-	-	-	-
EIA-860 (2021)	224000	7	63000	4
EU Data	6409850	34	3133850	27
GESDB	173841154	414	159200644	367

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Total	**180475004**	**455**	**162397494**	**398**

Table 4. Technology-3 (Thermal energy storage: Heat thermal storage, Latent heat: ice and liquid air energy storage, Sensible heat: Child water, concrete blocks, rocks, sand-like particles, molten salt)

Data Source	Total available		with Operational status	
	Total Rated Power (kW)	Units Count	Total Rated Power (kW)	Units Count
Demonstration Projects	-	-	-	-
EIA-860 (2021)	-	-	-	-
EU Data	12000	1	12000	1
GESDB	2921959	214	2190754	201
Total	**2933959**	**215**	**2202754**	**202**

As per the literature, technology-1 (Electro-chemical battery and chemical storage) is a key contributor to managing moderate demand. The technology-1 includes the following type of battery storage: 1) electro-chemical capacitor, 2) Flow battery (i.e., Hydrogen-bromine flow battery, Iron-chromium flow battery, Vanadium redox flow battery, Zinc-bromine flow battery, Zinc-iron flow battery, Zinc-nickel oxide flow battery), 3) hydrogen storage, 4) Lead-acid battery (i.e., Advanced lead-acid battery, Hybrid lead-acid battery/electro-chemical capacitor, lead-carbon battery, Valve regulated lead-acid battery), 5) Lithium-ion battery (i.e., Lithium polymer battery, Lithium-ion titanate battery, Lithium-iron phosphate battery, Lithium-manganese oxide battery, Lithium-nickel-cobalt-aluminum battery, Lithium-nickel-manganese-cobalt battery), 6) Nickel-based battery (i.e., Nickel-cadmium battery, Nickel-iron battery, Nickel-metal hydride battery), and 7) Sodium based battery (i.e., Sodium-ion battery, Sodium-nickel-chloride battery, Sodium-sulfur battery)

3. METHODOLOGY

3.1 Data Collection

Data Collection is an important step in the development of an AI/machine learning model for RUL prediction and estimation of LIB using ELM. Precise, relevant and widespread data is mandatory for proper learning and endorsing the acceptable performance of the dynamic RUL estimation model. For this study, real-time experimental data is collected from NASA [6], which includes comprehensive information of recorded impedance, Ah value, current, voltage, temperature, and resistance for both charging and discharging conditions of the battery for four categories of batteries. Both charging and discharging procedures are performed at constant current (CC) mode at 1.5 A and 2 A, respectively.
The tedious process of charging & discharging set-ups is clogged when the batteries touch end-of-life (EOL) criteria (i.e., 30% rated capacity of the battery. The collected data is used for feature extraction and AI/machine learning model development using ELM. The recorded qualities during charging condition have been represented in Figure 1, 2 and 3.

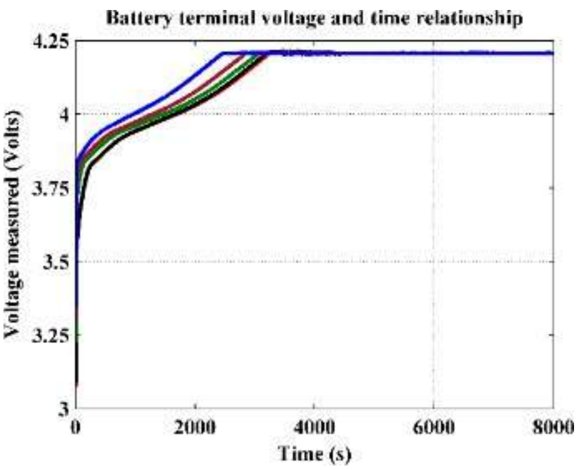

Figure 1: Terminal voltage versus time representation during charging condition

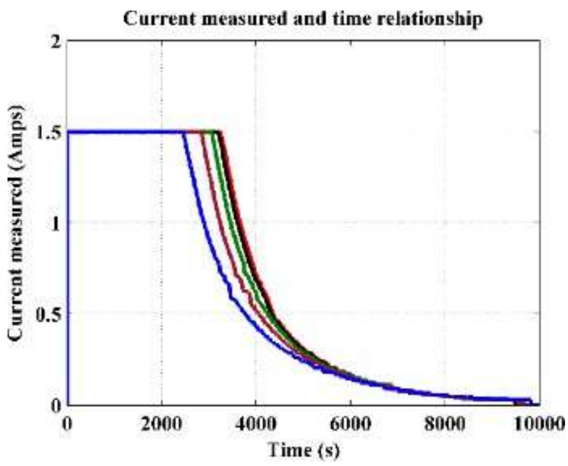

Figure 2: Current measured versus time representation during charging condition

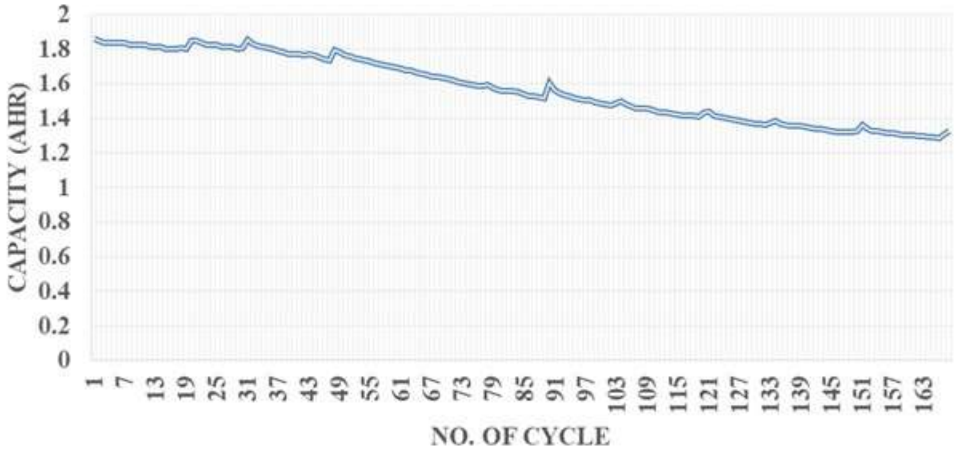

Fig. 3. Battery capacity (Ah)

3.2 Extreme Learning Machine (ELM) Model Formulation [7]

The ELM provides a fast and efficient learning algorithm used for training single-layer feedforward neural networks (SLFNs). Unlike traditional neural networks that require iterative tuning of weights through backpropagation, ELM randomly assigns input weights and biases to determine the output weights analytically. This inimitable methodology meaningfully diminishes training time although preserving virtuous oversimplification enactment.

ELM enlargement succession instigates by choosing the numeral of HN and adjusting input weights and biases indiscriminately. Once the HL output milieu is premeditated by means of an activation function, the output weights are calculated by means of the MPGI. The methodology empowers more rapidly training and circumvents communal concerns approximating indigenous minima.

ELMs have extended attractiveness in modern years, in meadows for instance classification, regression, and variables extraction and selection, particularly for enormous datasets where swiftness is essential. Investigators have also anticipated discrepancies like kernel-based ELM and connected consecutive ELM to improve tractability and enactment.

Generally, the uncomplicatedness, swiftness, and efficiency of ELM create them a dominant unconventional to outmoded learning methods. By means of the continuing enlargement, ELMs are expected to show a progressively significant protagonist in actual ML solicitations.

The precise demonstration and step-wise-step implementation for the ELM algorithm is as follow:

Let us have training dataset with its target value as an output:

$$[(I_i, O_i) \mid I_i \in R^n, O_i \in R^m, i = 1, 2, ..., N] \quad (1)$$

Where, Ii=input (battery parameters such as capacity, voltage, current, etc.), Oi=output (RUL), N=number of total training samples, n=no. of input variables, m=no. of output variables

The output of the ELM:

$$f(I) = \sum_{j=1}^{L} \beta_j \bullet h_j(I) = H(I)\beta \quad (2)$$

Where, $h_j(I) = g(w_j \bullet I + b_j)$ =activation function, w_j =weight vector for input neurons (j), b_j =bias of j neurons, β_j=weight of output neuron, $H \in R^{N \times L}$ =output at hidden layer, $\beta \in R^{L \times m}$ =output weight, and

$$\beta = H^{\tau} O, \quad (3)$$

H^{τ} =moore-penrose pseudoinverse of H matrix, $O \in R^{N \times m}$ target output

3.3 Feature Extraction

Online health assessment of a battery is a challenging task due to its dynamic condition. Generally, the capacity of a battery depends on internal resistance and capacitance, which is too hard to measure an exact and precise value during dynamic conditions such as the running condition of EVs and operation. So, here is a health indicator, which is derived from the measured voltage during charging and discharging conditions with respect to time.

$$TI_{(i)}\Big|_{DVI} = \left| T_{(i)DV\max} - T_{(i)DV\min} \right| \quad (4)$$

where, $T_{(i)DV\max}$ = time at high voltage magnitude, $T_{(i)DV\min}$ = time at low voltage magnitude and i= cycle number

Now, a vector of these calculated TI for 168 cycle of discharging condition has been formulated as:

$$TI_{Raw} = [TI_{(1)}, TI_{(2)}, TI_{(3)}, \ldots\ldots, TI_{(i)}]^T \qquad (5)$$

This vector (Eq. 5) is used as a input feature for RUL estimation of the battery.

3.4 Performance Analysis

In this paper, the performance analysis is executed by using Absolute error (AE), root mean squared $(0 \le \%RMSE \le 0.5)$, degree of fitness $(0 < R^2 \le 1)$ and MAPE, which are computed as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n}(Ah - \overline{Ah})^2 / n} \qquad (6)$$

$$R^2 = 1 - \left(\sum_{i=1}^{n}(Ah - \overline{Ah})^2 \Big/ \sum_{i=1}^{n}(Ah - \overline{Ah})^2 \right) \qquad (7)$$

$$AE_{RUL} = |A_{RUL} - P_{RUL}| \qquad (8)$$

$$MAPE_{RUL} = \left((1/n) \sum_{i=1}^{n} |A_{RUL} - P_{RUL}| / |A_{RUL}| \right) * 100 \qquad (9)$$

where, $\overline{Ah}$ =estimated capacity after transformation (predicted)

4 RESULTS AND DISCUSSION

After extraction of features, correlation analysis is performed, which provide the validation of the usability of the extracted features for online health monitoring and RUL estimation of the battery.

An indirect feature using time w.r.t the voltage measurement is used for this study to evaluate the feature matrix TI_{Raw} (as shown in Eq. 4 and 5). The extracted feature matrix is correlated with respect to the actual battery capacity as shown in Figures 4 and 5, respectively. The correlation indicates that both figures are looking similar and not too different. The curves shown in Fig. 4 follow the same pattern as the curves are available in Fig. 5.

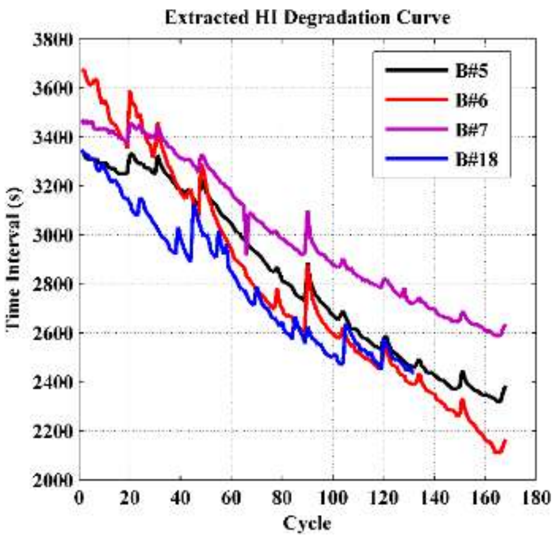

Figure 4: Extracted HI degradation Curve

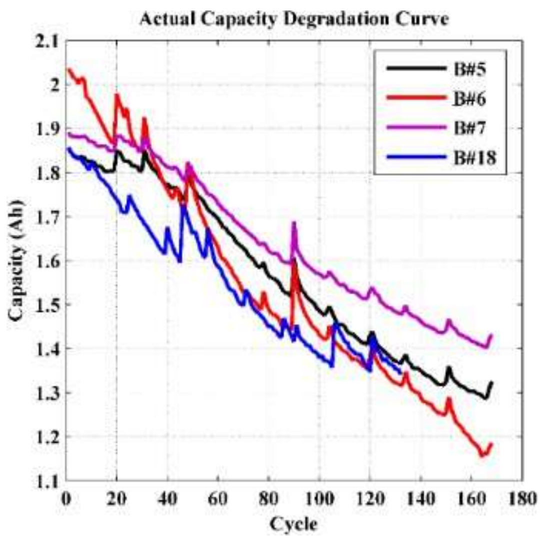

Figure 5: Actual Battery Capacity Curve

The correlation analysis of both figures is tabulated in Table 5 by using Pearson Correlation, which indicates a high acceptability limit of the extracted feature for RUL estimation of the battery.

Table 5. Correlation Analysis Representation

Time	Pearson Correlation
Before Transformation	0.9944

After Transformation	0.9985

After the correlation analysis (CA), the performance demonstration of the extracted feature for capacity evaluation is performed, as shown in Table 6. The performance for evaluation of capacity is analyzed for the different values of lambda (used in Box-Cox transformation), and R^2 and MAPE are computed for NASA battery-5. Demonstrated result shows the high value of R^2, which allow us to use extracted feature for RUL estimation.

Table 6. Feature's Performance Analysis

Battery used	Lambda	MAPE	R2
B#5	1.125	0.099	0.998

Based on the performance analysis of the extracted feature, ELM model is developed to estimate the RUL using new feature matrix instead of actual capacity (Ah) of the battery and validation results are tabulated in Table 7 for various cycles.

Table 3. ELM based RUL estimation

Cycle number	Measured RUL	ANN-based RUL [1]	ELM-based RUL	AE_{ANN}	AE_{ELM}	Proposed approach Acceptability
20	115	114	113	1	2	Less
42	105	100	104	5	1	More
122	85	84	84	1	1	Same
198	65	60	63	5	2	More
274	45	40	42	5	3	More

5 CONCLUSIONS

This study presents an efficient approach for estimating the RUL of lithium-ion batteries using the ELM model. By employing non-electrical data for feature extraction, a robust health indicator was developed, offering a unique perspective beyond conventional electrical signals. The extracted features were found to have a strong correlation with the actual capacity of the battery, validating their effectiveness for predictive maintenance. Additionally, a brief overview of the Globally Available Energy Storage (ES) Database provides context to the broader landscape of energy storage research and its growing importance. The proposed ELM model was evaluated using the NASA battery dataset and demonstrated superior performance as compared to existing models from the literature.

Going forward, future work may focus on integrating multi-source data, including temperature, mechanical stress, and environmental conditions, to enhance prediction accuracy. Furthermore, adaptive or hybrid models combining ELM with other ML techniques could be explored to improve robustness in real-world applications. Expanding the model's applicability to different battery chemistries and configurations will also be valuable. The results from this study provide a foundation for further development of intelligent, data-driven battery health management systems.

Acknowledgments

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