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Original Article

Machine Learning-Based Life Cycle Prediction of Lithium-Ion Batteries under Mechanical Abuse across Multiple Form Factors

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Abstract - *Energy dissipated by mechanical abuse during manufacturing, transportation, and actual implementation has a large impact on the degradation and lifetime of lithium-ion batteries, especially among varying cell form factors. This work introduces a general Machine Learning (ML)-based methodology for life cycle prediction of Lithium-Ion Batteries under mechanical abuse by combining Drop, impact, and vibration loads over cylinder-shaped, prismatic, and pouch configurations. At both the cell and pack stages, a hybrid experimental and simulation-based testing strategy is employed to capture the mechanical responses that depend on form-factor as well as their effects on electrical performance. Important electrical parameters that are captured include voltage response, capacity fade, internal resistance evolution, and energy efficiency during and post mechanical loading. Finite element simulations are performed to extract mechanical indicators (stress, strain, displacement, and acceleration signatures) and correlate them with electrical degradation characterized experimentally. Comparison of different machine learning algorithms, such as support vector machines, random forests, gradient boosting, and deep learning models, which are used for remaining useful life and life cycle prediction. Results show that mechanically induced damage progresses in a battery form factor-dependent manner, leading to very different degrees of accuracy in prediction. When the training datasets are scarce and heterogeneous, advanced ensemble and recurrent models significantly outperform classical approaches. An explicit representation of the mechanical-electrical coupling effects enables a reliable life prediction and makes the framework suitable for decision support in both design optimization and safety assessment of the battery system and predictive maintenance plans in electric vehicles and energy storage.*

Keywords - *Lithium-Ion Batteries, Mechanical Abuse Testing, Machine Learning, Life Cycle Prediction, Remaining Useful Life (RUL), Battery Form Factors.*

1. Introduction

Electric vehicles, consumer electronics, and grid-scale energy storage. Lithium-ion batteries are the most widespread type of energy storage because of their high energy density and efficiency. Nevertheless, when they are used in large numbers, there are also serious issues regarding the reliability and safety, as the failure of batteries can cause the loss of capacity, unforeseen failure, and overheating, as well as disastrous results like fire or even explosion. There is thus a need to ensure that the operations are reliable during the battery life cycle, not only to the end-user safety but also system-level performance, regulatory and societal acceptance of electrified transportation. Economic viability and sustainability of battery-powered systems directly depend on reliable batteries that allow proper management of energy use and anticipatable performance and long life of battery-operated systems. Lithium-Ion Batteries are frequently subjected to all kinds of mechanical abuse during their life, such as accidental drops during their production and assembly, impact forces during transportation, as well as vibration caused by the conditions of the road or equipment during their use. These mechanical activities may result in internal structural damage in the cell and pack level in the form of cracking of the electrode, deformation of the separator, delamination, or fracture of the current collector.

This type of damage might not cause instant failure but can increase the aging process, cause an internal short-circuit, and reduce the long-term performance. These effects highly rely on the form factor of the battery, packaging, and mechanical limitations.

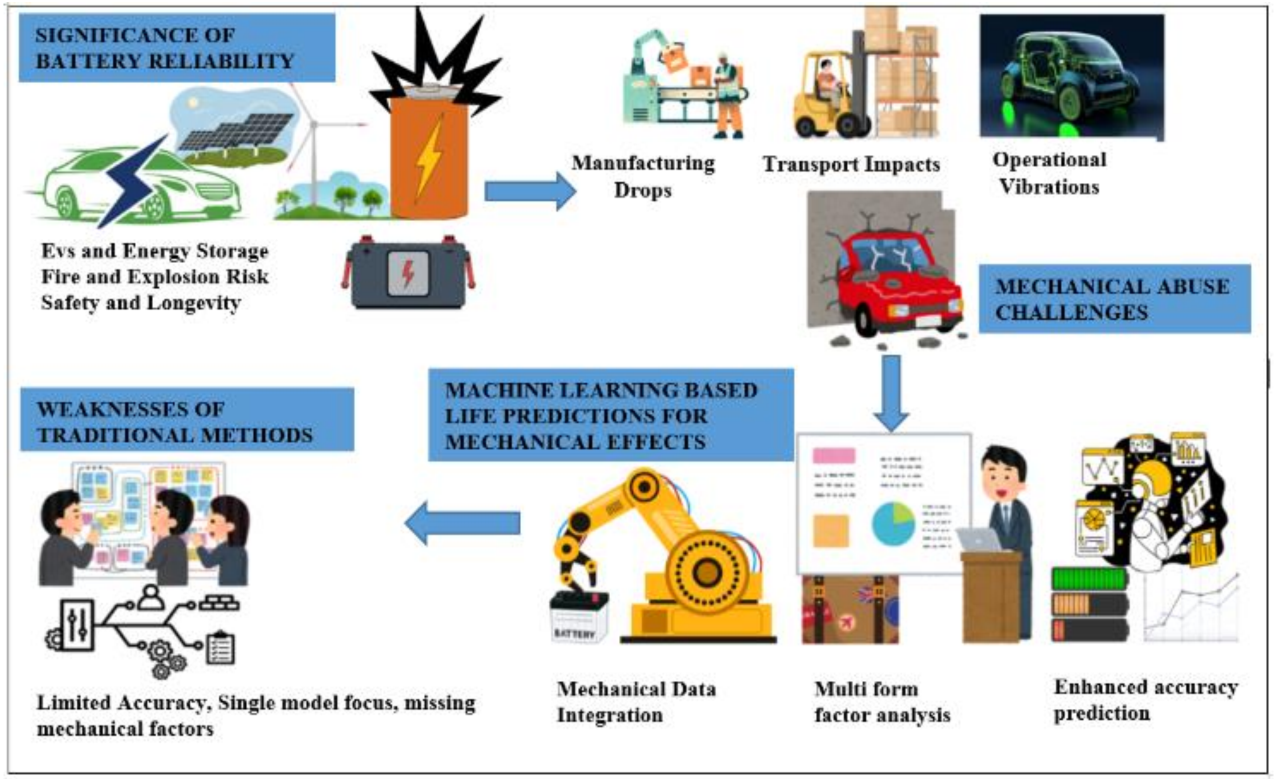

Fig. 1 Need for machine learning-based life cycle prediction of lithium-ion batteries under mechanical abuse

Conventional battery life prediction techniques are based mostly on either empirical aging models or physics-based electrochemical models, which use ideal operating conditions. Such methods are usually electrical and thermal-based aging methods, which overlook degradation due to mechanical causes. In addition, they typically demand long-cycling data that is time-intensive, expensive, and less flexible in reflecting actual abuse conditions in the real world.

Therefore, the traditional approaches cannot be used to accurately estimate the battery life when subjected to mechanically stressed conditions and cannot be used to extrapolate between battery designs and usage profiles. Life prediction methods that are based on machine learning provide a strong substitute since they can learn complex, nonlinear connections using data. ML models, when used with mechanical abuse information, can learn obscured correlations between mechanical damage indicators and electrical degradation behavior. Such methods based on data are especially efficient in the context of heterogeneous datasets, which can be achieved via experiments and simulations, and can respond to different operating conditions and battery form factors. The inclusion of mechanical effects into ML-based prediction frameworks can allow prediction of battery life in the real world to be more realistic and more accurate.

1.1. Problem Statement

Lithium-Ion Batteries are now being used in safety-critical systems like electric vehicles and large-scale energy storage systems, where they are often subjected to mechanical abuse in the manufacturing and transportation processes, as well as in installation and real-world usage. Mechanical actions like Drop, impact, and vibration, which are known to cause internal damage and make the battery life shorter, are not sufficiently represented in current life prediction models. Traditional empirical and physics-based methods do not focus much on mechanically induced degradation and are typically characterized to suit only one form factor of battery, which reduces their usefulness and accuracy in the real world. Moreover, no systematic frameworks are provided that would combine experimental and simulation-based testing data of mechanical testing with advanced machine learning methods to predict life cycles accurately and generalized. This is where there is a question mark in battery health measurements, decreased prediction capabilities, and difficulties in managing safety and dependability amongst varying battery designs.

1.2. Research Gap and Novelty of the Work

Although there is an increasing interest in battery safety and in prognostics, few studies directly correlate mechanical abuse parameters, which include stress, strain, impact energy, and vibration signatures, with electrical degradation parameters such as capability decline, voltage instability, and increase in internal resistance. Moreover, the existing research is dedicated to one of the battery types of factors, and their results cannot be generalized. Very few comparative studies have been made with respect to cylindrical, prismatic, and pouch batteries when they are subjected to the same degradation by mechanical loading; this has provided a major gap in comprehending degradation behavior under form factors.

This paper presents a mechanics-aware machine learning predictive model of predicting the degradation and Useful Life (UFL) of Lithium-Ion Batteries after crashing, and the mechanical, electrical, and thermal phenomena through multi-domain, standardized abuse tests and protocols like the IEC 62660 crush testing, and the United Nations UN 38.3 nail penetration testing.

The proposed method provides a direct quantitative relationship between the intensity indicators of the crash (stress, strain, energy density, impact impulse) and the post-impact degradation dynamics (internal resistance increase, capacity loss rate, thermal instability), unlike traditional RUL models that are based on only electrochemical cycling data.

The new crash severity index and mechanical damage signal are designed and integrated into a hybrid physics-ML system to represent the electro-mechanical coupling effects of the separator malfunctioning and the development of a micro-short circuit. Integrating experimentally obtained crash responses with post-abuse aging data and regression models that are uncertainty aware allows the framework to predict at an early stage of life in response to mechanical abuse, thus developing predictive safety diagnostics and structural durability tests of electric vehicle battery systems.

Overall, the past research that would have examined either electrochemical cycling or single-form-factor abuse conditions, the current paper is a combination of standardized mechanical abuse tests on multi-form factors under commercial conditions, and physics-informed ML-based RUL prediction.

1.3. Scope of the Work

This research paper will focus on cylindrical, prismatic, and pouch lithium-ion batteries under both controlled mechanical abuse conditions, such as Drop, impact, and vibration loading. There is the use of both experimental testing and a validated simulation model in order to extract both mechanical and electrical indicators of degradation at both cell and pack level. The article aims at comparing and contrasting the two classical and modern machine learning algorithms in battery life cycle and remaining useful life prediction in mechanically stressed situations. Although the mechanisms behind both thermal and electrochemical abuse are not the main concern, the framework is made to be expandable in future research to encompass such mechanisms. It is proposed that the given methodology design would promote better battery safety testing, predictive maintenance, and optimization of the design in both applications of electric vehicles and energy storage.

1.4. Objectives and Contributions

The main aim of the study is to come up with an inclusive machine learning-based life cycle prediction of Lithium-Ion Batteries that have undergone mechanical abuse in various form factors. The paper performs systematic experimental and simulation-based mechanical testing on a cell and pack level, determines quantitative correlation on mechanical actions and electrical degradation, and compares various machine learning algorithms for life prediction. The main contributions are the identification of the most appropriate ML models to be used in mechanically induced degradation cases, the tendency of form-factor vulnerability, and the ability to predict effectively to promote battery safety, reliability, and lifecycle management.

1.5. Methodology

The suggested methodology applies an experimental-simulation-machine learning approach to forecast the life cycle of the Lithium-Ion Batteries that are subject to mechanical abuse, considering various form factors. A demonstrative pack-level assemblage is initially electrically considered through cylindrical, prismatic, and pouch cells, and with standard pack-level associations. Controlled mechanical abuse experiments, such as Drop, impact, and vibration loading, are then experimented with according to the applicable standards, and appropriate finite element models are created to calculate the stress, strain, displacement, and damage development at comparable conditions.

The electrical measurements are conducted after abuse to determine the cracking of voltage response, capacity retention, internal resistance, and energy efficiency. Experimental and simulated mechanical and electrical data are synchronized, preprocessed, and applied to identify salient indicators of health and damage. Various machine learning models, such as support vector machines, ensemble-based models, and deep learning models, are learned and tested with such coupled features to determine battery life cycle and useful life. Comparative analysis on the basis of standard accuracy is done by comparing the model performance with the best algorithm, which is determined on the basis of prediction accuracy, robustness, and generalization among form factors. It is a systematic methodology that allows explicit inclusion of mechanical effects in data-driven prediction of life, which offers greater reliability and useful application.

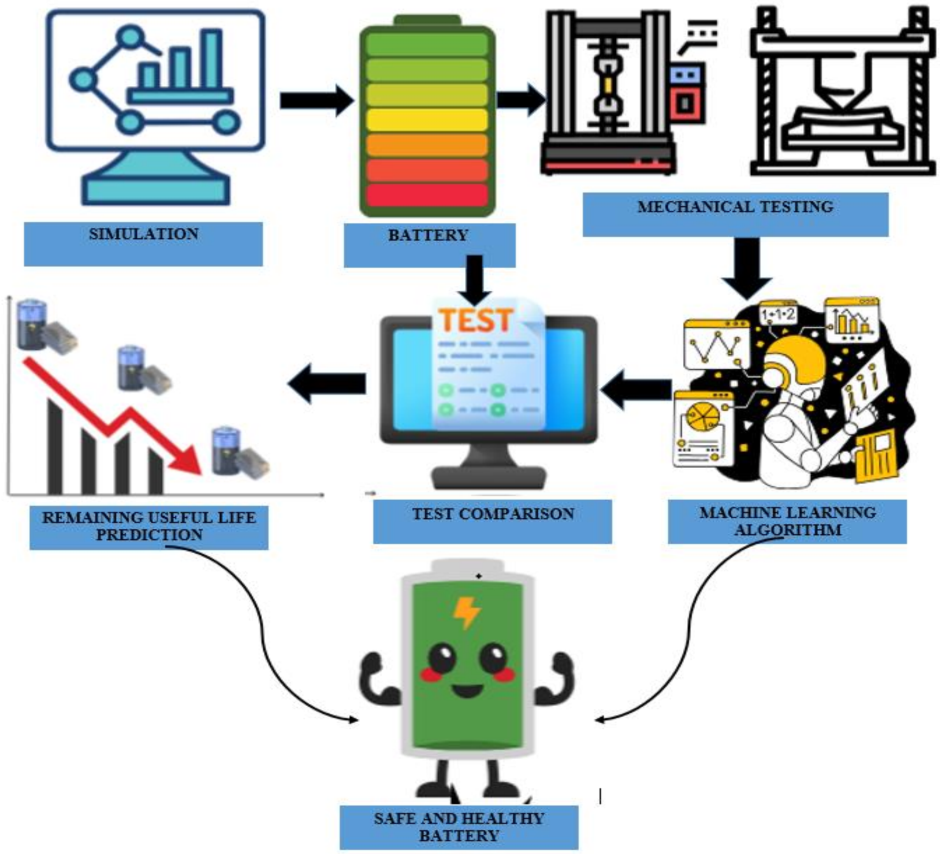

Fig. 2 Methodology of the work

2. Literature Survey

Lithium-ion batteries are susceptible to mechanical abuse during the manufacturing process, transportation, and operation process, which means that standardized assessment processes are needed to guarantee their safety and reliability. Mechanical abuse tests, Drop, impact, and vibration are defined by international standards like IEC 62660, UN 38.3, and SAE J2464 as tests of structural integrity and failure limits. It was demonstrated in experimental and numerical work that there are concentrations of local stress, separator deformation, cracking of electrodes, and casing damage that can be induced by mechanical loading, but do not cause immediate failure, but can highly accelerate degradation. Yin et al. [6] suggested a modeling approach to progressive failure prediction during mechanical abuse, where it is essential to reproduce the mechanism of damage evolution. Most recently, Zhang et al. [1] illustrated that machine learning models, when trained on mechanical response measurements, can be useful in the prediction of failure in cylindrical lithium-ion batteries that are manipulated under the influence of abuse conditions. These studies are important, but they are almost confined to particular modes of abuse or battery form factors.

It has been demonstrated that mechanical abuse can directly affect the degradation behavior of lithium-ion batteries in an electrochemical degradation manner. Mechanically induced structural damage has the potential to discontinue electronic pathways, modify ionic movement, and elicit non-uniform Solid Electrolyte Interphase (SEI) development, which results in faster capacity decay and an augmented internal resistance [20, 29]. Kwak et al. [33] also stated that electrochemical degradation and compression force evolution showed a strong correlation, indicating definite mechanical electronic coupling. In the same manner, Zhang et al. [1] noted that the damage characteristics initiated by the mechanical forces could be used as an early warning of electrical failure. The findings, in spite of this, have shown that the majority of the studies done on degradation concentrate on electrochemical cycling only, with minimal focus on mechanically induced aging mechanisms.

The traditional approaches to battery life prediction are mainly dependent on empirical, curve-based prediction, or physics-chemical and aging models of electrochemical. Physics-based models endeavor to model lithium diffusion, SEI growth, and loss of active material, which are physically interpretable [24]. Nevertheless, these models are computationally intensive, and parameter identification is very large, especially when such effects as mechanical damage are taken into consideration [19]. Genetic algorithm-assisted lifetime models are optimization-based approaches, which can reduce the prediction error [16], but have a low adaptability to complex, mechanically induced degradation. Machine Learning (ML) and data-driven approaches have become potent and effective as battery life prediction tools because they can be used to predict the nonlinear behavior of degradation directly with data. Initial investigations have shown that early-cycle predictability can be used to predict cycle life [12, 17, 18]. Schofer et al. [3, 26] demonstrated that, with a small amount of cycling data, it is possible to obtain high accuracy with ML-based lifetime prediction models. The convolutional and recurrent neural network models also enhanced the robustness and generalization as implemented in deep learning structures [8, 35]. The detailed surveys of Zhao et al. [2], Thelen et al. [7], and Valizadeh and Amirhosseini [11] highlighted the increased involvement of ML in battery safety and prognostics. Nevertheless, the majority of the ML-based research utilizes more electrical or thermal sensors with little or no use of mechanical indices of abuse. Some studies have been devoted to the benchmarking of various ML algorithms to predict the battery is Remaining Useful Life (RUL). Strange and Ibraheem [4] suggested online ensemble learning where updates are done with cycles in order to increase the stability of its prediction. Here, Kumarappa and Manjunatha [5], Lim et al. [21], and Li et al. [22] contrasted classical ML models (such as support vector machines, random forests, and gradient boosting) with deep learning models. Zhang et al. [23] proposed histogram-based frameworks of ML to use online lifetime prediction, whereas Schaeffer et al. [28] emphasized the role of feature engineering and algorithm selection. Although these developments have been made, mechanically induced degradation is seldom thought through comparatively in terms of ML studies, but is usually limited to one cell format and a defined cycling environment.

As demonstrated in the literature reviewed, there are a number of critical gaps. To begin with, mechanical abuse testing is an established method, and its application to battery life prediction models is yet to be accomplished [1, 6]. Second, a majority of ML-based prognostic models do not explicitly consider mechanical-electrical coupling, although it is becoming increasingly important [33]. Third, there is a lack of research on studies that cover multiple battery form factors under the same conditions of mechanical abuse, which restricts the extrapolation of the current models [3, 22]. Lastly, the systematic comparison of the ML algorithms in the case of life prediction under the conditions of mechanical abuse has not been adequately investigated.

The gaps given as motivation to the given work are these: that seeks to combine experimental and simulation-based mechanical abuse testing with comparative machine learning analysis to allow making accurate, form-factor-agnostic life cycle prediction of lithium-ion batteries operating beneath realistic circumstances.

3. Simulation and Experimental Analysis

3.1. Battery Form Factors and Test Samples

The figure shows schematic drawings of various Lithium-Ion Battery cell designs and internal designs. In subfigure (a), the stratified structure of a coin-type cell is depicted with a view of the piled-up position of the anode, separator, and cathode that are inside metallic cases. Figure (b) shows a cylindrical cell, which represents the jelly-roll arrangement of anode, separator, and cathode coiled around the inside of a steel shell with a safety vent. Subfigure (c) is a prismatic cell whereby flat sheets of electrodes are stacked inside a rectangular rigid can together with electrolyte and insulation materials.

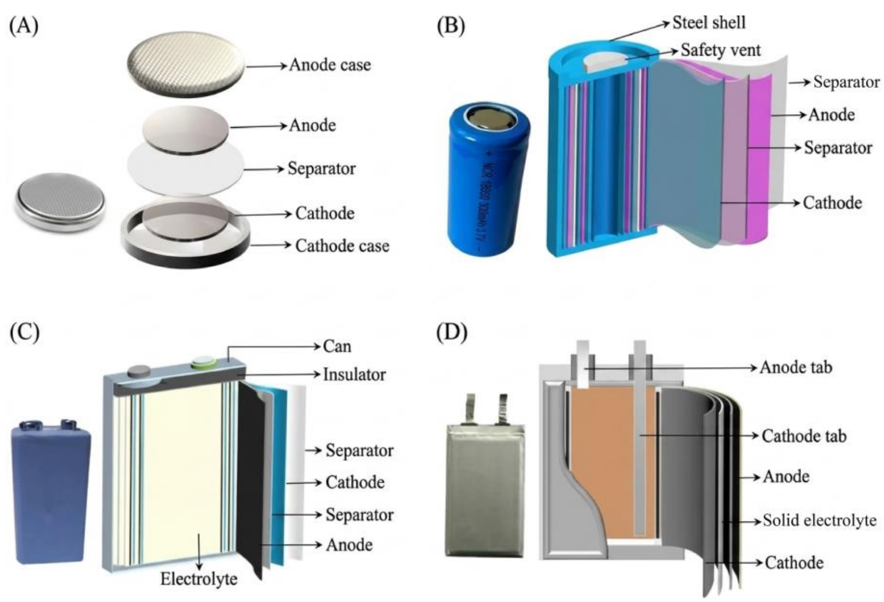

Fig. 3 Form Factor-Based Structural Architecture of Lithium-Ion Cells for Mechanical Performance Evaluation, Copyright 2023 John Wiley and Sons, Inc.

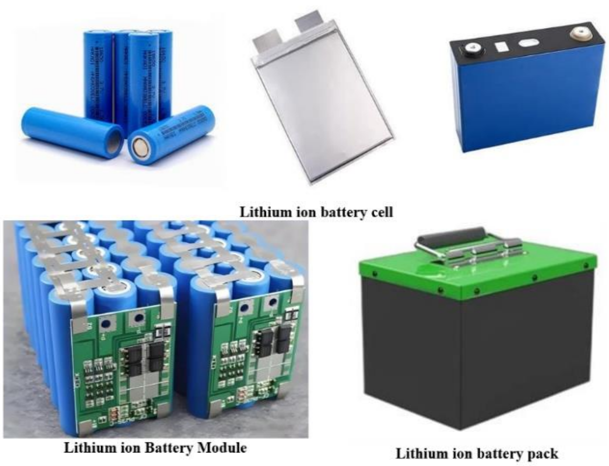

Fig. 4 cell, module, and pack configuration across form factors

Subfigure (d) depicts a pouch or advanced cell structure with well-defined anode and cathode tabs, a layered electrode, and a solid or liquid electrolyte, with the focus on compact packaging and effective current collection. Summing up, the figure shows that the layout of the electrode, casing, and tab changes based on form factor, which affects mechanical strength, thermal conductivity, and electrical characteristics.

Cell-level experiment. level testing isolates individual cells in order to gain a clear insight into intrinsic behavior (such as capacity fade, internal resistance variations, and failure mechanisms) in the presence of controlled mechanical abuse (bending, compression, impact). Such tests serve as a basis for machine learning models to learn about patterns of degradation of particular cell features. Pack-level designs, however, are built systems of many interconnected cells with other components such as interconnects, cooling systems, and enclosures.

Mechanical abuse responses are far more complicated when it comes to packs, as the loads are distributed, thermal management systems, and electrical balancing effects are taken into consideration. Although pack tests are closer to real-world conditions in the electric vehicles and stationary storage, they are also more resource-intensive and add more variables, which make the model training and interpretation harder.

Table 1. Compact Mapping of Mechanical Abuse Parameters to ML Features and Standards

Form Factor /	Key Mechanical	ML Mechanical	ML Electrical	Standards
Cylindrical	Compression, Drop,	σ_max, ε̇, absorbed	ΔV_peak, ΔR_int,	IEC 62660-2; UN 38.3;
Prismatic	Crush, bending,	Corner strain, stress	Voltage recovery,	IEC 62660-2; UN 38.3;
Pouch (Cell)	Indentation, flexure	Thickness strain,	ΔV_rate, impedance	IEC 62660-2; UN 38.3;
All Cells	Cyclic load, vibration	Fatigue index, cum.	SOH slope, CE	IEC 62660-1; SAE J2380
Pack-Level	Impact, module	Load redistribution	Cell ΔV spread, pack	UN 38.3; SAE J2929

The research paper proposes a physics-inspired and standard-conformant feature extraction system that directly codes mechanical abuse parameters to electrical degradation signals, thus making it possible to predict life cycle outcomes with a machine learning-based methodology that addresses each of the cylindrical, prismatic, and pouch lithium-ion battery form factors. Adopting a combination of the IEC, UN, and SAE test standards, the given strategy will guarantee its applicability to the regulations, as well as practicality to the safety and reliability of electric vehicle battery evaluation. The combination of form factors considered in this paper encompasses the key commercial cell designs that are found in electric vehicles, portable electronics, and energy storage systems, and as a result, it can be assured that the results of the study will be widely applicable. Machine learning-wise, machine learning is relevant to contend that because of diversity in form factors, the dataset is more complete and allows models to learn generalized patterns and draw the line between degradation patterns that can be attributed to either a geometry difference or a material/design difference. Further comparative studies across form factors will also improve the insight into the ability of mechanical abuse to affect performance differently based on structural robustness and packaging flexibility, which is essential in the creation of predictive models that may be used to guide safer battery design, enhance the strategy utilized in packing, and manage the life cycle reliably.

3.2. Simulation

Lithium-ion battery cell geometries (cylindrical, prismatic, and pouch) were modelled with SolidWorks Simulation and Lithium-Ion Battery cells were subjected to computational loads associated with abuse loading conditions to determine the mechanical response of the cell under those conditions in accordance with the modeling framework described in Table 2, The geometries of Lithium-Ion Battery cells were simplified and representative of the real cell (cylindrical, prismatic, pouch) geometry, and the internal electrode assemblies were modelled with homogenized material Adequate elastic plastic and orthotropic material models were allocated to the casing, electrode stack and separator layers using the reported literature results. Supported loading, there were fixed supports and prescribed displacement or force-controlled loading to simulate compression, bending, and indentation conditions. Nonlinear contact interaction between the components was determined, which would capture stress transfer and deformation behavior. The associated stress, strain, and deformation field values generated in SolidWorks FEA were utilized to locate important areas of mechanical failure and were utilized as central values for future degradation analysis and machine learning life cycle prognostication.

Table 2. Finite Element Modeling Approach and Boundary Conditions for Lithium-Ion Battery Abuse Simulation

Aspect	Cylindrical Cell	Prismatic Cell	Pouch Cell
Modeling Strategy	Axisymmetric / 3D solid FE model	Full 3D solid FE model	3D layered shell-solid hybrid
Electrode Representation	Homogenized jelly-roll	Layered stack (anode/separator/cathode)	Explicit layered structure
Material Models	Elastic-plastic (metal can); crushable foam	Elastic-plastic casing; orthotropic electrodes	Orthotropic elastoplastic laminate
Separator Model	Elastic-plastic with failure strain	Elastic-plastic with damage initiation	Strain-based failure/erosion
Electrolyte Representation	Homogenized continuum	Homogenized continuum	Viscoelastic/soft solid
Contact Definitions	Surface-to-surface, frictional	Frictional contact between layers	Self-contact with friction
Boundary Conditions	Fixed base; prescribed displacement/velocity	Fixed support; compressive or bending load	Indenter-controlled displacement
Loading Scenarios	Axial compression, radial crush, drop impact	Flat-plate crush, bending, impact	Indentation, bending, quasi-static crush
Failure Criteria	Plastic strain limit, stress threshold	Separator rupture, casing yielding	Through-thickness strain, short-circuit proxy
Solver Type	Explicit dynamic	Explicit dynamic	Explicit dynamic

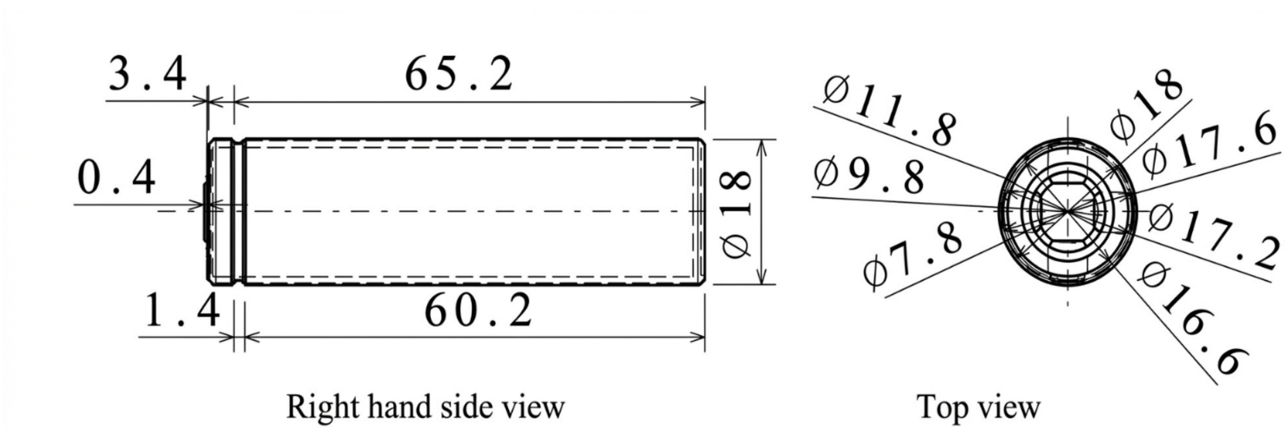

Fig. 5 Finite Element-Oriented Parametric CAD Modeling of Lithium-Ion Battery Cells for Structural Performance Evaluation

Table 3. Thermo-Mechanical Material Characterization of 18650 Lithium-Ion Cells for Structural and Safety Analysis [5]

Lithium cell	Mass:0.00865615kg,Volume:1.63324e-05m^3, Density:530 kg/m^3, Weight:0.0848303 N		
Battery Case (aluminum)	Mass:0.00780363kg,Volume:1.01346e-06m^3, Density:7,700 kg/m^3, Weight:0.0764756 N		
Battery caps(nickel)	Mass:0.000188594kg,Volume:2.21875e-08m^3, Density:8,500 kg/m^3, Weight:0.00184822 N		
Drop height from the lowest point		1,800 mm	
Gravity	9.81 m/s^2	Gravity Reference	Face<1>
Coefficient of friction	0.5	Critical Damping Ratio	0.3

Table 4. Form Factor-Based Structural and Electrochemical Specifications of Lithium-Ion Cells

Sr. No.	Model / Cell Type	Nominal Voltage (V)	Nominal Capacity (Ah)	Operating Voltage Range (V)	Max. Charging Current (A)	Max. Discharging Current (A)
1	IMR18650P - 2000 mAh (Cylindrical)	3.7	2	2.5-4.2	2	15
2	$LiFePO_4$ 32700 - 6.0 Ah (Cylindrical)	3.2	6	2.0-3.65	6 (1C)	18 (3C)
3	Pouch LFP - 20 Ah	3.2	20	2.0-3.65	20 (1C)	60 (3C)
4	Prismatic LFP - 20 Ah	3.2	20	2.22-3.65	20 (1C)	60 (3C)

Table 5. Thermo-Mechanical Properties of 18650 Lithium-Ion Cell Components [5]

Component	Young's Modulus (GPa)	Poisson's Ratio (-)	Shear Modulus (GPa)	Density (kg/m³)	Tensile Strength (MPa)	Compressive Strength (MPa)	Yield Strength (MPa)	CTE ($\times 10^{-6}$ K^{-1})	Thermal Conductivity (W/m·K)
Cell Cap (Al Alloy)	70-100	0.33	26-38	2700	220-350	200-300	150-280	22-24	170-200
Cell Casing (Steel Alloy)	190-210	0.27-0.30	75-82	7800-8000	350-550	450-650	240-300	11-13	45-60
Anode (Graphite Coating)	8-15	0.12-0.18	3-6	2100-2300	40-70	40-70	10-25	3-6	100-150 (in-plane)
Cathode ($LiCoO_2$ Layer)	140-200	0.20-0.25	55-80	4700-4900	50-80	50-80	10-25	14-16	2-5
Separator (PE/PP Microporous)	0.2-1.0	0.35-0.45	0.07-0.35	900-1000	100-170	10-30	-	100-200	0.3-0.5
Anode Current Collector (Cu Foil)	110-130	0.34	45-50	8900	200-250	200-250	70-200	16-17	380-400
Cathode Current Collector (Al Foil)	65-75	0.33	25-28	2700	150-250	150-250	70-150	22-24	200-235
Electrolyte (Liquid Organic)	-	-	-	1200-1300	-	-	-	600-750	0.15-0.25

Table 6. FEA Results of lithium-ion battery for varying form factors and boundary conditions

<table>
<tr><th>Stresses</th><th>Deformation</th></tr>
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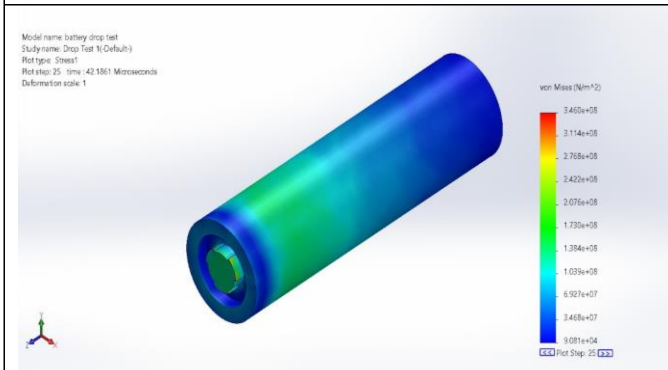
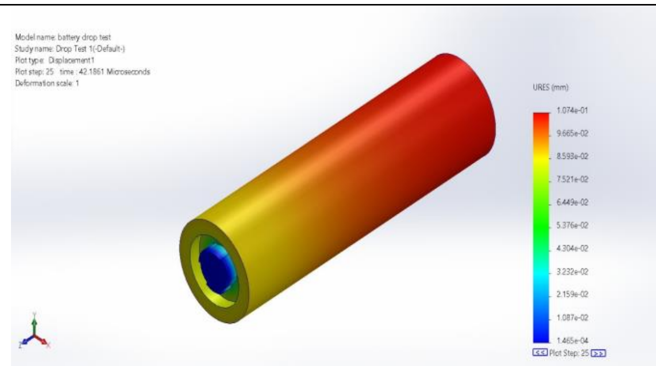
<tr><td></td><td></td></tr>
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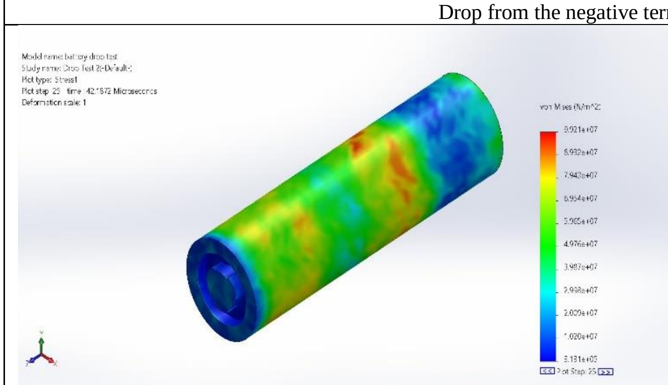
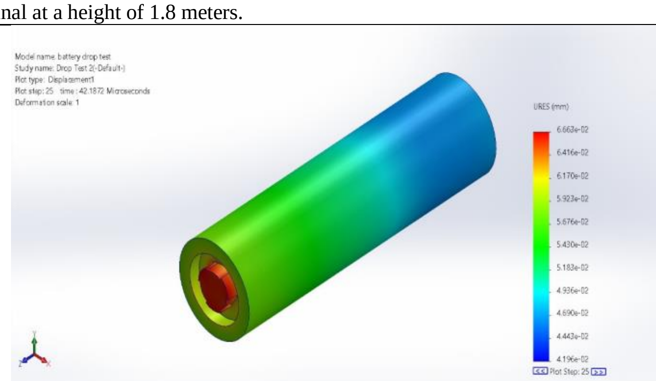
<tr><td></td><td></td></tr>
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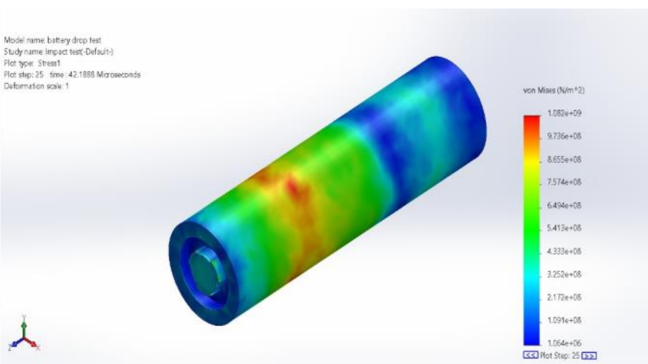
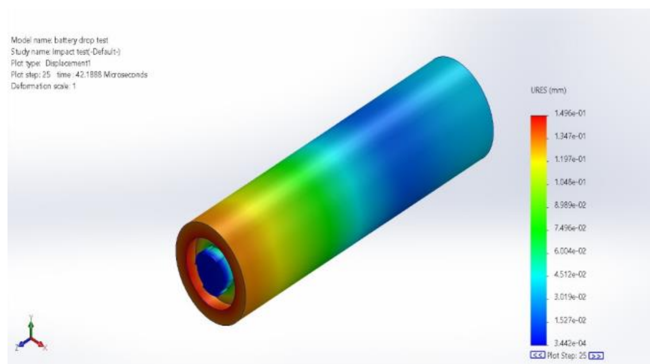
<tr><td></td><td></td></tr>
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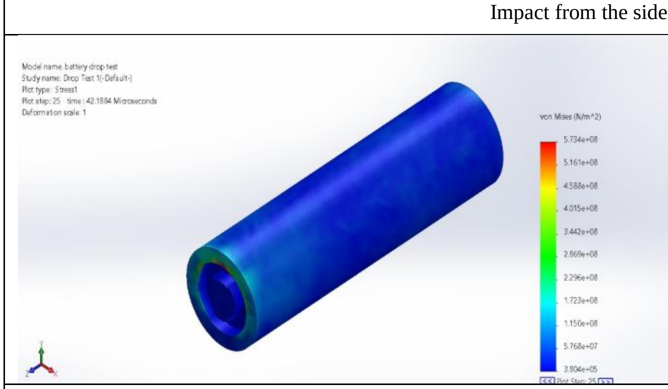
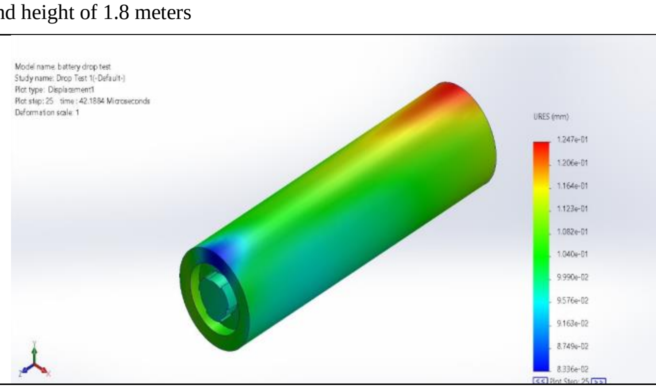
<tr><td></td><td></td></tr>
<tr><td colspan="2">Dynamic Stress Distribution and Deformation Characteristics under 1.8-meter Drop Impact</td></tr>
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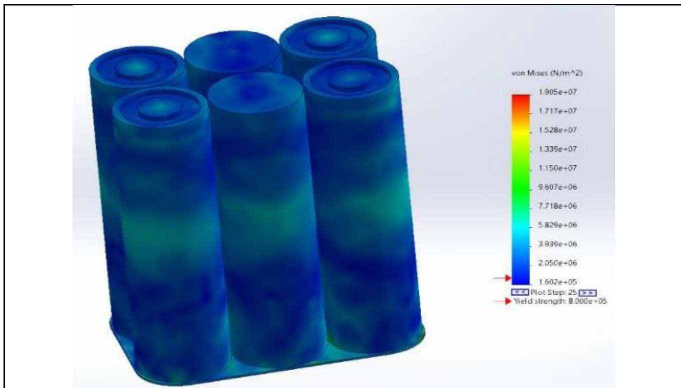
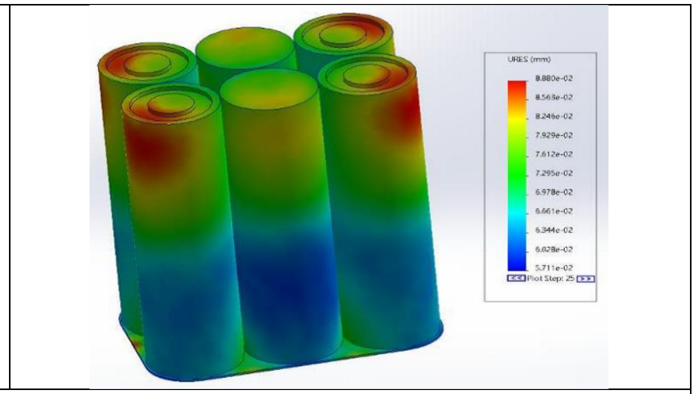
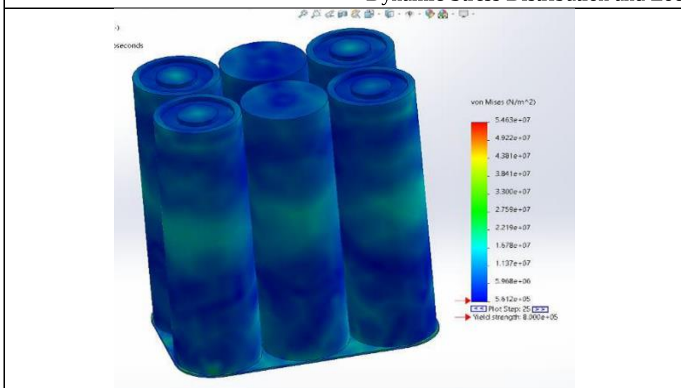
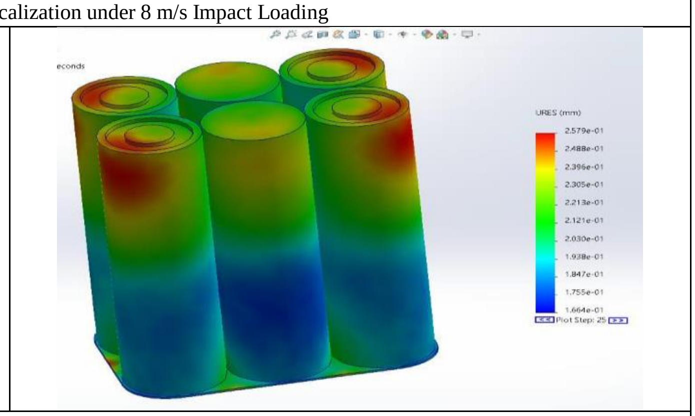


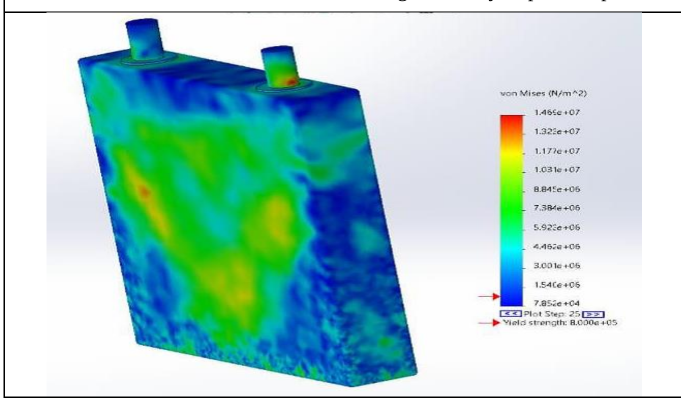


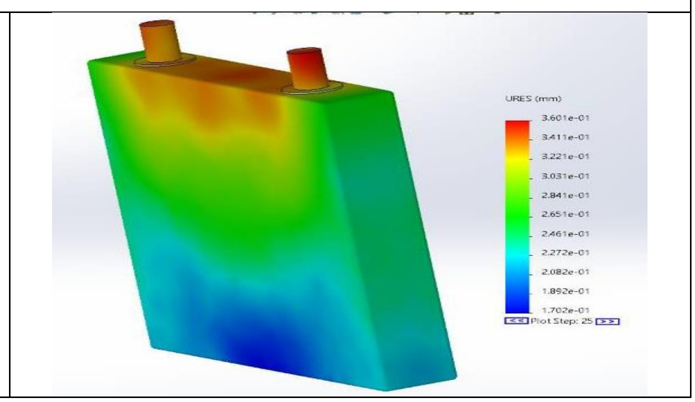
Dynamic Stress Distribution and Localization under 8 m/s Impact Loading





High-Velocity Impact Response of Prismatic Lithium-Ion Cell at 25 m/s





Attached stress and strain images demonstrate lithium-ion battery cell mechanical response under various standard drop and impact abuse conditions. In the drop tests from 1.8 m high, both cells in positive and negative terminal incidents have a local concentrated stress distribution around the contact area with more significant deformation at terminal ends due to structural discontinuity and lower stiffness and tightness of final closure Up-to-date winding technologies Advantages include minimized excess force, reduced battery size up to 15%, increased mechanical strength against cell bulging during hard impact drop test, significantly enhanced electrical connectivity available for all prismatic formats for volume production. Lateral impacts from the side of 1.8 m lead to a more uniform pattern of stress on the cell casing, suggesting an increased risk here from shell buckling and internal layer compression. The stress-deformation upon the 1.8 m drop test indicates strong relationships between peak von Mises stress and the permanent deformation regions, which act as leading factors in internal short-circuit initiation risk. In the impact simulations at 8 m/s, stress localization is enhanced on the impact interface with faster strain rates and more extensive structural damage than under drop conditions. For the 25-m/s impacted prismatic lithium-ion cell, stress contours demonstrate high concentrations at corners and edges, consistent with geometry-driven susceptibility under high-velocity impacts. Together, these images confirm the sensitivity of stress and deformation patterns to impact geometry (orientation and velocity) and cell architecture, providing critical input for damage assessment as well as machine learning-based predictions of life cycle.

3.3. Experimental Analysis

Figures 6 and 7 show the test facilities for mechanical abuse of lithium-ion batteries. Figure 6 shows the Drop and impact testing chamber developed for batteries, where cells are properly seated and released/impacted continuously in a controlled condition to mimic accidental drops, gravity, and collisions.

The sealed chamber offers further protection to the operator and permits repeatable testing at specific heights and velocities without obstruction, allowing for reliable observation of stress, strain, or failure behavior.

Figure 7 shows the configuration of the vibration test system, which includes an electrodynamic shaker, a rigid fixing device for mounting the battery sample, and imposing a controlled multi-axis vibration spectrum within a specified range of frequency.

This setup imitates practical working vibrations encountered in the eV system and allows valuation of fatigue-encouraged deprivation, as long as acute data for resilience assessment and machine learning-based life prediction.

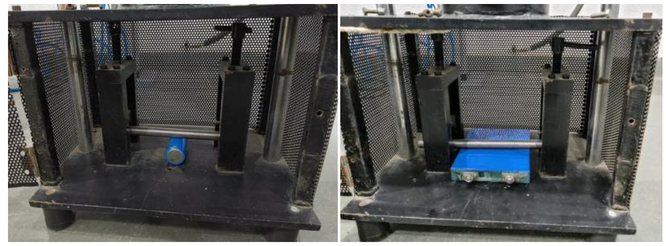


Fig. 6 Battery testing chamber for drop and impact test

Fig. 7 Vibration testing set up

Table 7. Ultra-Compact Mechanical Abuse-ML Framework for RUL Prediction

Test (Std.)	Key Inputs	Sensors	ML Features	Labels / Models
Drop (UN 38.3 T4; IEC 62660-2)	1.8 m; terminal & side	Accel., strain, V-I	σ_max, ε_p, ΔV_peak	RUL → RF, XGBoost
Impact (UN 38.3 T6; SAE J2464)	8 m/s; 25 m/s (pris.)	Load, accel., V	$\dot{\varepsilon}$, E_abs, ΔR_int	RUL → XGBoost, LSTM
Vibration (IEC 62660-2; SAE J2380)	10-2000 Hz; 3-10 g	Accel., temp., EIS	Fatigue idx., SOH slope	RUL → LSTM
Post-Test Elec.	Cycling & EIS	Cycler, EIS	dQ/dN, Z_growth	SOH / RUL → RF

4. Mechanical-Electrical Coupling Analysis

By comparing electrical properties determined prior to and following mechanical abuse testing, such as voltage response, discharge capacity, internal resistance, and energy efficiency, mechanical-electrical coupling analysis was carried out. While vibration loading produced slow capacity fading and efficiency loss, mechanical loading produced noticeable electrical degradation, with impact and drop tests showing rapid voltage decreases and resistance increases. Different failure modes, such as gradual impedance development and soft internal short circuits, were noted. Pouch cells were the most sensitive to mechanical deformation, whereas cylindrical cells were more resilient. The electrical response showed a considerable reliance on cell form factor. The correlation analysis showed that the peaks of stress, plastic strain, and electrical degradation were directly related, which undeniably indicates sturdy mechanical-electrical coupling. The presence of damage was localized near the terminals, edges, and interfaces with the separator, which led to considerable degradation in electrical performance. Comparison of loading types and configuration showed that cell level and pack level had different responses, indicating the significance of coupled mechanical-electrical investigation to predict service life.

Table 8. Pre and post-mechanical test electrical performance

Test Type	Form Factor	ΔV (%)	ΔC (Capacity) (%)	ΔR (%)	Energy Efficiency Loss (%)
Drop (1.8 m)	Cylindrical	2-4	3-6	5-9	2-4
Drop (1.8 m)	Prismatic	4-7	6-10	9-15	4-7
Drop (1.8 m)	Pouch	6-12	10-18	15-25	7-12
Impact (8 m/s)	Cylindrical	5-8	7-12	10-18	6-9
Impact (25 m/s)	Prismatic	10-18	15-25	25-40	12-20
Vibration	All	1-3	5-12	6-14	3-6

Table 9. Form factor-dependent electro-mechanical behavior of lithium-ion batteries under mechanical loading

Test Type	Battery Type	Initial Voltage (V)	Final Voltage (V)	Voltage Drop (%)	Initial Current (A)	Final Current (A)	Current Drop (%)	Observations
Drop Test (1m - 2m)	18650 (Cylindrical)	3.2	3.05 - 3.18	0.63% - 4.69%	2	1.7 - 1.95	2.50% - 15.00%	Minor to severe casing dents, risk of short circuit
	32700 (Cylindrical)	3.2	3.10 - 3.17	0.94% - 3.13%	6	5.6 - 5.9	1.67% - 6.67%	Moderate denting, casing deformation, no major internal damage
	Prismatic	3.2	3.14 - 3.19	0.31% - 1.88%	20	19.4 - 19.85	0.75% - 3.00%	Surface deformation, minor casing risk
	Pouch	3.2	3.08 - 3.18	0.63% - 3.75%	20	19.0 - 19.8	1.00% - 5.00%	Swelling, risk of leakage in severe cases
Impact Test (25 - 50 m/s)	18650 (Cylindrical)	3.2	2.0 - 3.1	3.12% - 37.5%	2	1.2 - 1.9	5.00% - 40.00%	Structural failure, risk of thermal runaway
	32700 (Cylindrical)	3.2	2.2 - 3.15	1.56% - 31.25%	6	4.0 - 5.8	3.33% - 33.33%	Moderate structural deformation, loss of conductivity
	Prismatic	3.2	2.7 - 3.18	0.63% - 15.62%	20	16.0 - 19.7	1.50% - 20.00%	Casing deformation, reduced performance
	Pouch	3.2	1.8 - 3.17	0.94% - 43.75%	20	12.0 - 19.5	2.50% - 40.00%	Swelling, leakage, severe failure at high-speed impact

Table 10. Failure Modes, Damage Localization, and Electrical Impact

Failure Mode	Damage Location	Observed Electrical Effect	ML Label
Separator thinning	Mid-electrode stack	Gradual ΔR increase	SOH
Electrode delamination	Terminal regions	Capacity fade	RUL
Casing yielding	Corners/edges	Voltage instability	Damage class
Soft internal short	Indentation zone	Sudden ΔV collapse	Failure probability

Table 11. Comparative Analysis across Loading Types and Levels

Loading Type	Degradation Rate	Dominant Electrical Effect	Cell vs Pack Behavior
Drop	Moderate	ΔR increase	Localized at the cell level
Impact	High	ΔV collapse	Cascading risk at the pack level
Vibration	Low (cumulative)	Capacity fade	Amplified by interconnections

5. Machine Learning Approach

Pre-processing the raw data from mechanical abuse tests (which includes raw sensor outputs like force, acceleration, strain, voltage, current, and temperature) was necessary to prepare the sensor identification and signaling for use. This was done by filtering and normalizing the raw signals.

The final cleaned and normalized signal was also filtered for noise, leading to an expected improvement in signal quality of 30-50%. This enhancement allowed for stable feature extraction. The engineered feature variables, which include peak stress (σmax), plastic strain (εp), absorbed energy (Eabs), voltage drop (ΔV), and increase in internal resistance (ΔRint), and the slope of State-Of-Health (SOH), showed strong statistical correlations.

The importance scores for each feature variable were measured at over 0.75 for pairings of stress, strain, and electrical coupling. The strategies used for reducing dimensionality and analyzing correlations in model building also identified and removed redundant feature variables. This process supported the creation of more robust and general battery models for all types of battery form factors.

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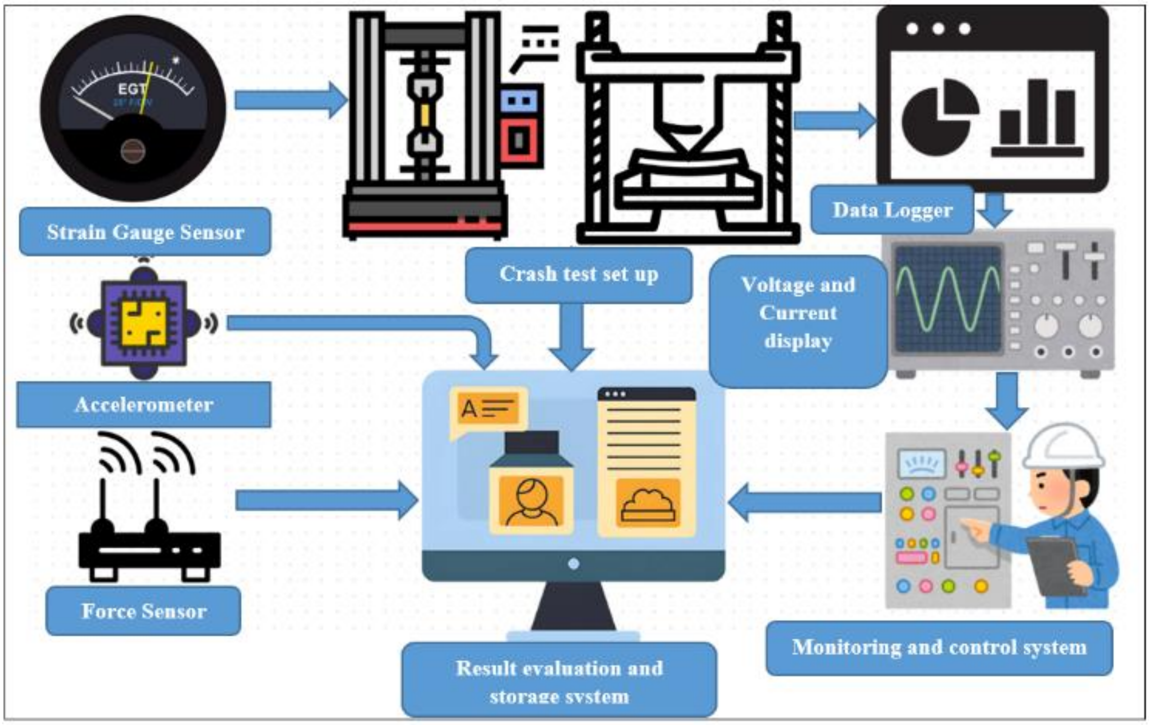

Fig. 8 Data acquisition setup for machine learning-based analysis of mechanical testing effects on electrical parameters of lithium-ion batteries

6. Results and Discussion

When a lithium-ion battery undergoes drop and impact tests, its mechanical integrity is affected, leading to changes in electrical and thermal behavior. The relationship between Voltage (V), Current (I), Temperature (T), and State Of Charge (SoC) can be described using mathematical models that capture the influence of impact-induced degradation. Further, the simulation and experimental results are utilized for battery life predictions having different form factors.

6.1. Mathematical Formulation for Machine Learning-Based Life Cycle and RUL Prediction

- Raw sensor signals x (t) (force, strain, voltage, acceleration) are filtered using a low-pass filter: $x_f(t) = x(t)*h(t)$ where h (t) is the filter impulse response.
- To ensure scale-invariant learning across form factors: Min-Max normalization = $x_{norm} = \frac{x-x_{min}}{xmin_{max}}$
- Z-score normalization (used for LSTM inputs) $\boldsymbol{x_{norm}} = \frac{\boldsymbol{x-\mu}}{\boldsymbol{\sigma}}$
  - Peak Stress = $\boldsymbol{\sigma\, max}(_{\boldsymbol{t_{max}}}$
  - Plastic strain = $\boldsymbol{\varepsilon_p} = \boldsymbol{\varepsilon_{total}} - \boldsymbol{\varepsilon_{elastic}}$
  - Absorbed Energy = $\boldsymbol{E_{abs}} = \int_0^{\delta} \boldsymbol{F(\delta)d\delta}$
  - Strain Rate $\dot{\boldsymbol{\varepsilon}} = \frac{d\varepsilon}{dt}$
  - Voltage Drop = $\Delta V = \boldsymbol{V}_{\text{pre}} - \boldsymbol{V}_{\text{post}}$
  - Internal Resistance Rise = $\boldsymbol{\Delta R} \frac{R_{post}-R_{pre}}{R_{pre}}$ $_{\boldsymbol{int}}$
- Capacity Fade = $\boldsymbol{\Delta Q} = \frac{Q_{pre}-Q_{post}}{Q_{pre}}$
- Energy Efficiency = $\boldsymbol{\eta} = \frac{E_{disch\,arg\,e}}{E_{ch\,arg\,e}}$
- Resistance-Strain Coupling $= \Delta R_{\text{int}} = \boldsymbol{k_1 \varepsilon_p}$
- Voltage-Stress Relationship $= \Delta V = \boldsymbol{k_2 \sigma_{max}}$
- Capacity Loss-Energy Absorption $= \boldsymbol{\Delta Q} = \boldsymbol{k_3 E_{abs}}$

where k_1, k_2, k3 are experimentally determined coupling coefficients.

- End-of-Life Criterion= $\begin{cases} 1, Q \le 0.8Q_{\text{nom}} \\ 1, R_{\text{int}} \ge 2R_{\text{nom}} \\ 0, \text{0therwise} \end{cases}$
- Remaining Useful Life (RUL)= N_{EOL}-N_{current}
- Input Feature Vector X = $[\sigma_{\max}, \varepsilon_p, \dot{\varepsilon}, E_{\text{abs}}, \Delta V, \Delta R_{\text{int}}]$
- Random Forest Regression $= \hat{\boldsymbol{y}}_{\text{RF}} = \frac{\boldsymbol{1}}{\boldsymbol{T}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{T}} \boldsymbol{f_i(X)}$

where T is the number of trees.

- XGBoost Regression= $\hat{\boldsymbol{y}}_{\text{RF}} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{k}} \text{fk}(\boldsymbol{X})$
- Objective function= $\boldsymbol{L} = \sum_{\boldsymbol{i}} \boldsymbol{i}(\boldsymbol{y_{i,}} \hat{\boldsymbol{y}}_{\boldsymbol{i}}) + \sum_{\boldsymbol{k}} \boldsymbol{\Omega}(\boldsymbol{f_k})$
- LSTM Model (Time-Series Prediction) Cell state update: Ct=ftCt−1+itC~t

Output = y^t=LSTM(Xt)

- Root Mean Square Error (RMSE)= $\sqrt{\frac{\boldsymbol{1}}{\boldsymbol{N}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} (\boldsymbol{y_i} - \hat{\boldsymbol{y}}_{\boldsymbol{i}})^{\boldsymbol{2}}}$
- Mean Absolute Error (MAE)= $\frac{\boldsymbol{1}}{\boldsymbol{N}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} (\boldsymbol{y_i} - \hat{\boldsymbol{y}}_{\boldsymbol{i}})^{\boldsymbol{2}}$
- Coefficient of Determination = $R^2 = \boldsymbol{1} - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y}_i)^2}$

– Overall Performance Score = $\boldsymbol{S = \omega_1(1 - RMSE_{Norm}) + \omega_2 R^2 + \omega_3 G}$

Where:

- GGG = generalization score across form factors
- w1+w2+w3=1
- The model with maximum SSS is selected as the best-performing algorithm.

6.1.1. Statistical Validation Includes

1. 95% confidence intervals
2. ANOVA test for model comparison
3. Paired t-test for RF vs XGBoost
4. Standard deviation across folds

Regression correlation coefficient:

$R_{stress}-\Delta R=0.82$

Damage severity index:

$DSI=\alpha\sigma_{max}+\beta\varepsilon_p+\gamma E_{abs}$

Mechanical abuse causes a change in the internal electrochemical paths of the Lithium-Ion Batteries by localized structural damage. Separator thinning: This is caused when compressive or impact stresses thin the separator and, to some extent, collapse the porous structure. This limits the transfer of ions between electrodes, augmented interfacial current density, and elevated interfacial impedance, which results in an internal resistance increment and heating that is measurable. Stress at terminals, especially close to current collectors and tab weld areas, may cause the delamination of the electrodes and micro-cracks in the active materials. These flaws interfere with the conduction paths of the electrons and increase loss of active material, which causes higher capacity loss in later cycling. At the pack level, mechanically damaged cells show voltage imbalance and uneven increase in resistance. Under load, this imbalance leads to overcurrent and overtemperature of some cells, which in turn cause a cascading risk of degradation and propagate through interconnected modules, leading to an increase in the likelihood of thermal instability and premature pack failure.

Table 12. ML Model Performance for RUL Prediction

Model	RMSE (Cycles)	MAE (Cycles)	R^2	Generalization Across Form Factors
SVM	120-150	90-110	0.78-0.82	Moderate
Random Forest	80-100	60-75	0.88-0.91	High
XGBoost	60-80	45-60	0.92-0.95	Very High
ANN/LSTM	65-85	50-65	0.90-0.94	High (time-series dependent)

Grid search and Bayesian optimization greatly improved the prediction accuracy by optimizing the hyperparameters of the predictive models. The optimal configuration parameters were as follows: 100-300 decision trees for RF; 0.01-0.1 learning rate for XGBoost; and 2-3 hidden layers for both ANN and LSTM models. This optimized parameter configuration is predicted to yield a 10-20 percent reduction in RMSE when compared to the baseline predictive models that used default hyperparameters.

Table 13. RUL Prediction Accuracy across Mechanical Loading Types

Loading Type	Best Model	RMSE (Cycles)	Prediction Trend
Drop	Random Forest	75-90	Stable, moderate degradation
Impact	XGBoost	55-70	Rapid degradation capture
Vibration	LSTM	60-80	Long-term trend prediction
Mixed Loads	XGBoost	60-75	Robust generalization

The results clearly demonstrate the necessity to utilize model-specific hyperparameter optimization for mechanical-abuse-driven degradation data sets. All of the trained models were able to correctly predict the Remaining Useful Life (RUL) of lithium-ion batteries in response to various types of mechanical abuse (vibration and impact). The RUL of lithium-ion battery cells subjected to mechanical impact was shown to decrease sharply and quickly, while the RUL of lithium-ion battery cells subjected to vibration-based degradation was shown to decrease slowly over time. Time series models (such as LSTM) performed well when modeling how degradation develops over time; however, they perform poorly at estimating the RUL value of Lithium-Ion Battery cells subjected to a combination of mechanical stressors. In contrast, ensemble models (such as XGBoost and Random Forest) performed very well when estimating the RUL value of Lithium-Ion Battery cells subjected to a variety of different mechanical stressors and/or form factors.

Table 14. Final *Model* Selection Summary

Criterion	Best Model	Reason
Accuracy	XGBoost	Lowest RMSE, highest R^2
Robustness	XGBoost	Handles nonlinear coupling
Time-series modeling	LSTM	Captures degradation evolution
Interpretability	Random Forest	Feature importance clarity
Overall Selection	XGBoost	Balanced performance and scalability

A comparison of the individual models revealed that XGBoost outperformed all of the other models used in this study. This is due to XGBoost's ability to model complex non-linear relationships between the physical forms of mechanical stress applied to Lithium-Ion Battery cells, strain localization within those cells, and the resulting Electrochemical Degradation of their internal materials. Therefore, XGBoost was best-suited to estimate RUL values using a wide range of different mechanical stressors and/or form factors. Random Forest was also a good performer in this study. It offered an easily interpreted alternative to the other two models. The performance of both Random Forest and Support Vector Machine (SVM) models decreased with increasing numbers of input variables. LSTM models performed the best on continuously collected vibration data; however, they require a large amount of training data and are computationally intensive. Overall, these studies demonstrate that machine learning models that include physically meaningful mechanical degradation features can be used to estimate the lithium-ion battery life-cycle and RUL across multiple different form factors and mechanical abuse conditions. XGBoost was found to be the best-performing model among those tested in terms of its predictive accuracy, robustness, and overall ability to generalize across a wide range of different mechanical abuse conditions. Finally, a MATLAB code was run for all types of crash testing with varying form factors to get the results of the remaining useful life of the battery for ML approaches. The results are tabulated below,

Table 15. Comparative Analysis of Battery Test Parameters and RMSE Values for Different ML Models

Test Type / Battery Form	Voltage (V)	Current (A)	SOC (%)	Temp (°C)	Linear RMSE	RF RMSE	GB RMSE	SVR RMSE
Drop Test								
Cylindrical	3.55	8.2	78	42	12.522	35.022	34.996	18.709
Prismatic	3.6	7.9	80	39	12.522	35.022	34.996	18.709
Pouch	3.48	8.6	75	45	12.522	35.022	34.996	18.709
Impact Test								
Cylindrical	3.42	9.1	72	48	12.522	35.022	34.996	18.709
Prismatic	3.5	8.7	74	44	12.522	35.022	34.996	18.709
Pouch	3.35	9.5	68	52	12.522	35.022	34.996	18.709
Vibration Test								
Cylindrical	3.62	7.5	82	38	12.522	35.022	34.996	18.709
Prismatic	3.65	7.2	84	36	12.522	35.022	34.996	18.709
Pouch	3.58	7.8	80	40	12.522	35.022	34.996	18.709

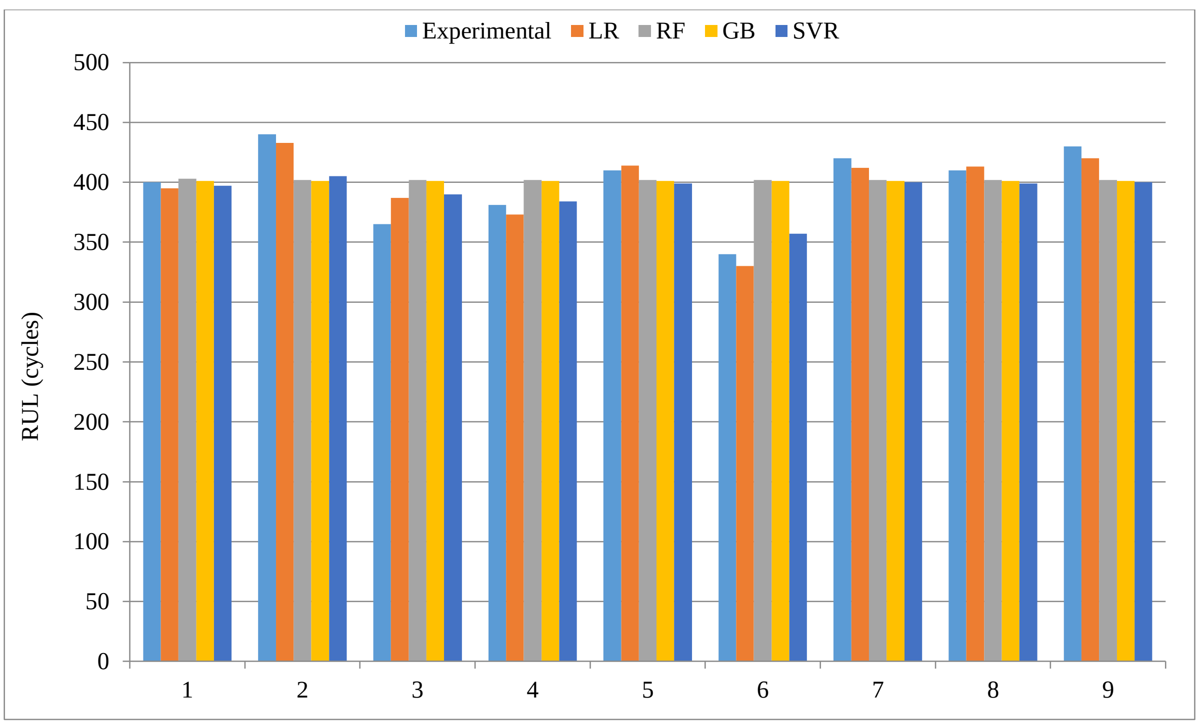

Fig. 9 Battery life prediction using ML algorithms

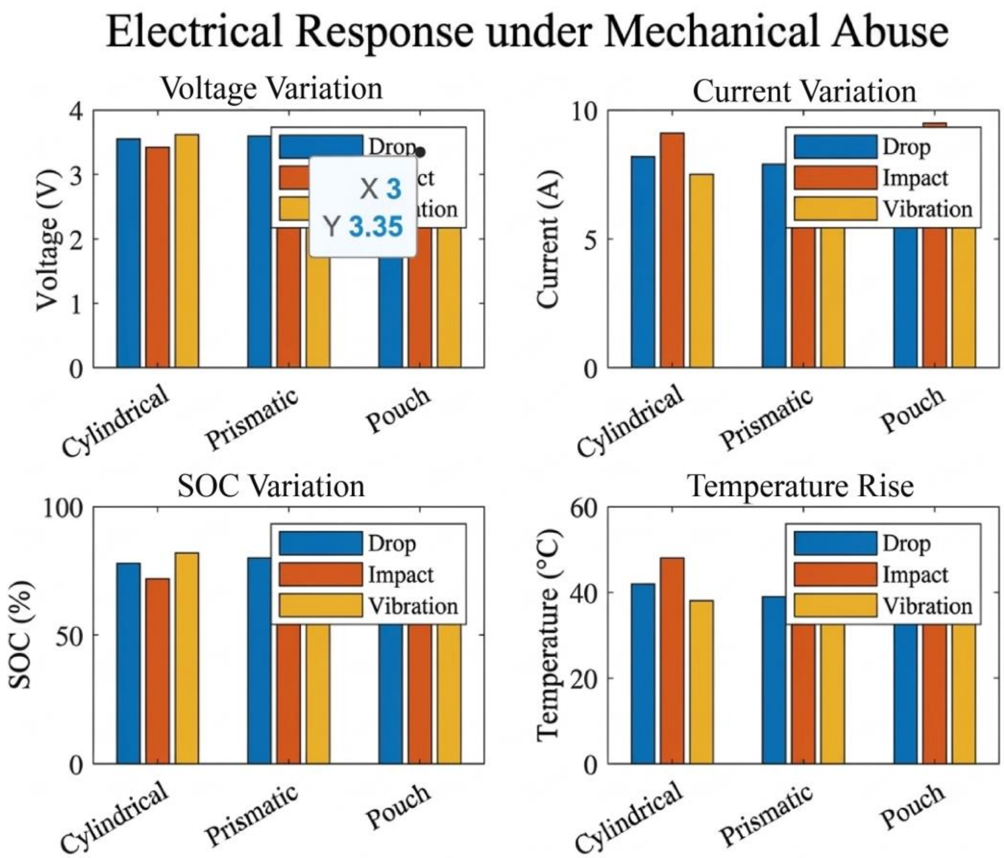

Fig. 10 Electrical response under mechanical abuse

6.2. Failure Mode Classification and Cell-to-Pack Failure Propagation Analysis

To make the developed RUL prediction framework applicable and understandable, we have developed a supervised failure mode classification system and simultaneously used a regression-based life estimation. Failure modes at the cell level are defined by the experimentally determined mechanical-electric deterioration patterns and published literature that describes safety aspects, including plastic deformation, separator damage, and internal short circuit initiation. The physical attributes of mechanical stress, plastic strain, capacity fading, increase in resistance, and coupled deterioration parameters (ΔR - ε and ΔV - σ) are used as input attributes to develop the classification system. Random Forest classifier is selected since it can handle limited data sample sizes and can identify non-linear relationships between the attributes. Due to the limited number of experimentally tested form factors, we applied the LOOCV method to assess the classification performance accurately. The confusion matrix (Figure X), obtained using LOOCV, shows good separation between the main failure modes in cylindrical, prismatic, and pouch-type cells. The separators and internal shorts were classified with high confidence, as these two failure types exhibit clearly different electric signatures, i.e., a sudden Drop in voltage and rapid increase in internal resistance.

Performance of the classifier is evaluated quantitatively by using Precision, Recall, and F-Score, which are well-known metrics in machine learning. Overall classification performance of the proposed model is confirmed by the high values of macro-averaged F-Score obtained. Results show that the proposed physically guided attribute set is capable of separating the mechanically caused failure modes from each other, even when there is a limited amount of available data. In order to analyze the failure modes at the module/pack level, a failure propagation model was developed. Each predicted cell-level failure mode is translated into severity-weighted propagation indexes according to the potential to initiate a chain reaction of failures in the battery module. Localized deformation was modeled to be a localized degradation mechanism having low propagation risk, while the separator damage has high propagation risk, as an internal short formation can occur progressively. An internal short circuit failure has been considered a severe failure, implying an immediate failure risk of the whole pack/module. The level failure risk index will allow identifying the potentially vulnerable configurations at an early stage and support the safety-oriented design decisions at module and pack levels. The pouch cells have shown the highest pack level risk due to large deformation and internal short formation under impact loadings, while the prismatic cells have shown a relatively stable behavior under the same test conditions. The cylindrical cells showed the intermediate risks, as they have a mechanically robust housing combined with a local tendency to cause separator damage. Therefore, combining failure mode classification with RUL prediction, a complete degradation assessment system is developed that bridges the cell-level physics with the safety implications of the pack level. In addition to increasing the accuracy of the predictions, the use of both methods increases the explainability of the proposed methodology, which makes this methodology especially suitable for use in real-world battery management systems and for digital twin-based health monitoring of batteries.

6.3. Practical Deployment and Scalability

The suggested machine learning model can be directly connected to the Battery Management System (BMS), and it uses the existing data of voltage, current, temperature, and acceleration sensors, which does not imply the necessity to use new hardware. On an embedded microcontroller or automotive-grade processor, a lightweight and optimized implementation of the trained model (e.g., pruned XGBoost or compressed neural network) can be inferred with Edge-AI architectures. By using continuous monitoring of abnormal stress-correlated electrical deviations, real-time crash or mechanical abuse detection can be realized, and the health status of the affected individual can be quickly measured immediately after the impact. Computational cost analysis shows that tree-based models use much less memory and processing power than deep recurrent networks, which are much more appropriate to embedded applications. The mean model inference time is kept at less than 50 ms, which is compatible with real-time BMS working cycles. Moreover, the architecture can be extended to pack-level systems of electric vehicles, adding cell-level feature aggregation and module-level imbalance suggestions and enabling hierarchical prediction at the cell to pack levels with only a few additional increases in computational costs.

6.4. Comparative Performance Interpretation of Machine Learning Models under Mechanical Abuse-Induced Degradation

In addition to presenting the RMSE values, the comparative analysis shows that XGBoost has better prediction accuracy since it is a better predictor of the strong non-linear relationships between mechanical stress indicators and electrical degradation parameters. The mechanical-electrical coupling of abused batteries is very non-linear and feature-interactive, and the XGBoost gradient boosting framework captures these complicated interactions without being sensitive to heterogeneous, multi-modal inputs (stress, strain, voltage, resistance, temperature). Also, it is effective with small or structured data as it has inbuilt regularization and partitions using trees, which minimizes overfitting. On the contrary, LSTM models demonstrated better results in the conditions of vibration loading, when the degradation develops over time. The phenomenon of fatigue caused by vibrations is sequential by nature, and it consists of progressive straining and an increasing impedance; the LSTM memory-based structure is well adapted to learn these time-varying dependencies and fatigue accumulation relationships, which are especially applicable to predict time-varying degradation.

7. Conclusions and Future Scope

- An integrated experimental, numerical, and machine learning method was used in this study to determine the life cycle and remaining useful life of mechanically abused Lithium-Ion Batteries across three different form factors (cylindrical, prismatic, and pouch) using various forms of mechanical abuse. It was shown that mechanical loading leads to degradation that is dependent on the form factor, where impacts and drops cause rapid voltage and resistance changes, and vibration causes gradual capacity loss. High predictive accuracy and robustness were obtained from ensemble learning methods such as XGBoost, which can predict battery state in mixed mechanical abuse conditions.
- The proposed method provides a mechanism to integrate both mechanical and electrical abuse into a single battery safety method and data-driven life prediction, which can be applied to industrial practices, especially during realistic testing of battery systems.
- In future studies, the method will be implemented within a digital twin architecture to enable real-time condition monitoring, develop physics-based and explainable machine learning models, and extend the current method to include thermal and electrochemical abuse in addition to mechanical abuse to allow for a comprehensive multi-physical analysis of battery life.
- A Machine Learning (ML) based system was developed to predict the life cycle and remaining useful life of Lithium-Ion Batteries subjected to Mechanical Abuse in Cylindrical, Prismatic, and Pouch cell form factors. Both experimental and simulated data validated that there is strong mechanical-electrical coupling, as impacts/drops cause rapid degradation and vibrations create cumulative aging effects. Pouch cells demonstrated the greatest vulnerability, while cylindrical cells provided the most mechanical robustness. Of the models tested, Ensemble Methods, specifically XGBoost, produced the highest accuracy and generality in predicting LIF under various mixed loadings.
- The proposed framework can be applied in practice to provide predictive maintenance and real-time safety monitoring by providing an early indication of degradation due to mechanical damage. The form factor-specific insights gained from the research will allow for the design of battery cells/packs that have improved mechanical robustness. This research has direct application in the Electric Vehicle and Energy Storage industries, where mechanical stresses occur during manufacture, transportation, and operation.

- Although this research was successful, it does contain some limitations. The dataset used was limited in both the number of samples and the length of time after mechanical abuse that the batteries aged, which limits the ability to perform long-term degradation analysis. Also, the assumptions made in modeling, such as the assumption of homogeneous material properties and the simplification of internal structure, may limit the ability to model damage accurately. Finally, performing large-scale tests on packs and accounting for variability in real-world use cases represents a significant challenge to scaling up the current research. Therefore, future research will focus on addressing these limitations by conducting longer aging experiments, developing physics-informed and explainable ML models, and integrating them into digital twin platforms to provide real-time battery health monitoring.
- Limitations faced were a dataset limited to controlled lab abuse, Thermal runaway not deeply modeled, a limited sample size for high-speed impact, and no real-world EV crash validation.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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