Mechanical Strain Feature Extraction for Data-Driven SOH Estimation in 18650 Li-Ion Cells

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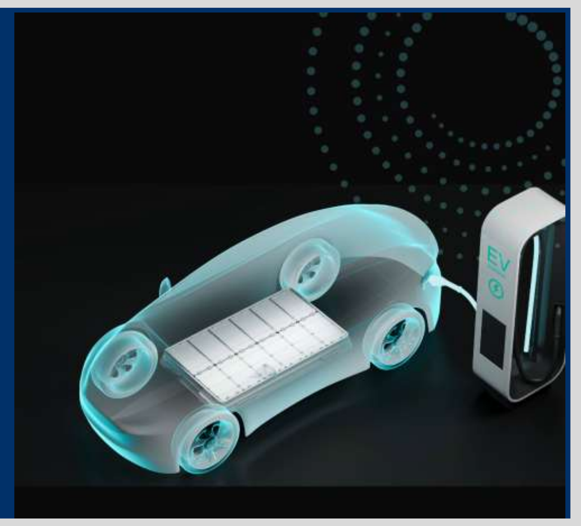
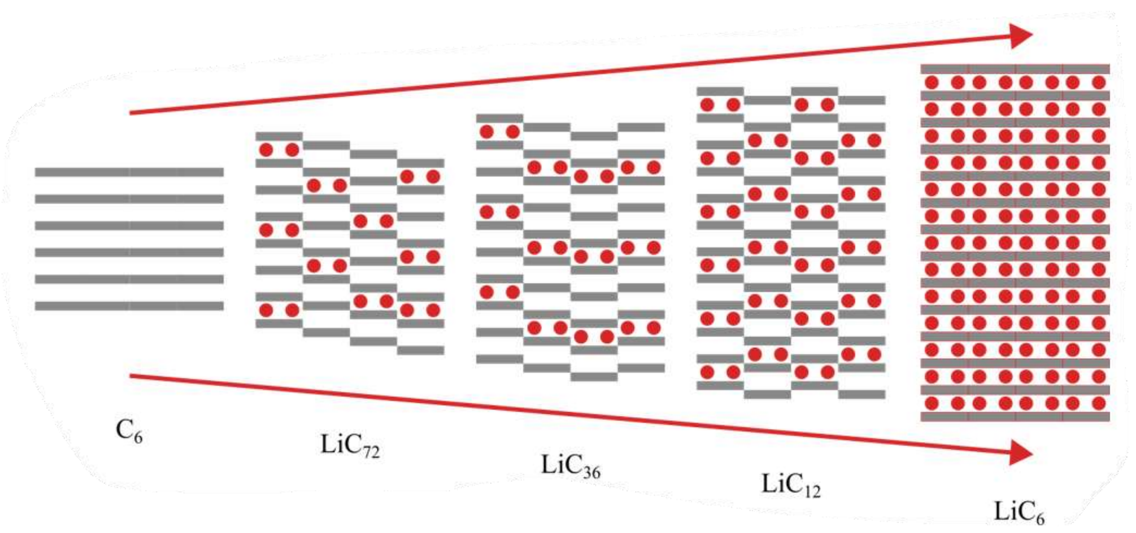


Introduction

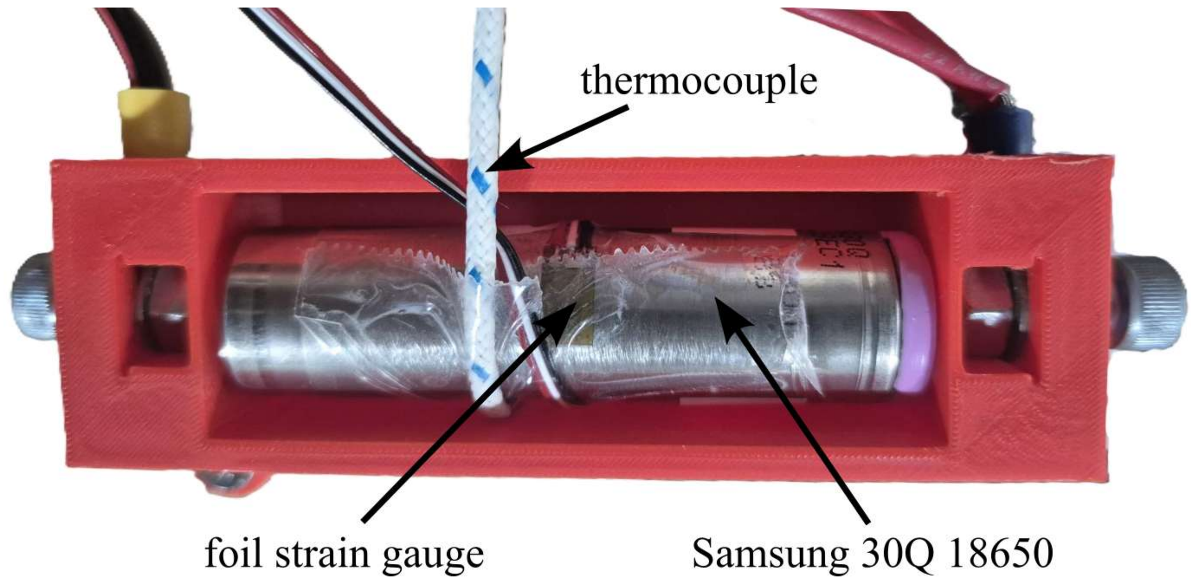
Ensuring safe operation of lithium-ion batteries requires accurate monitoring of state of health (SOH), especially under abnormal conditions such as overcharge. Traditional SOH estimation from electrical-based parameters struggles to capture internal processes occurring inside the cell. Mechanical strain sensing offers a non-invasive way to observe internal electrochemical and structural changes.



Lithium intercalation into layered graphite ($C_6 \rightarrow LiC_6$).

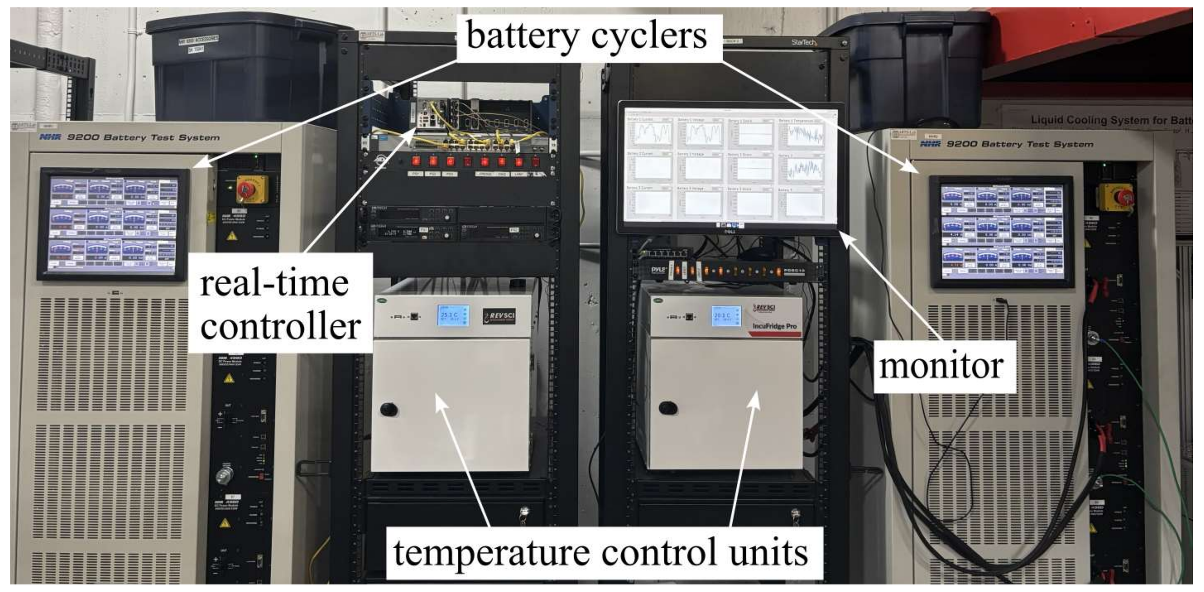
Objectives

- Evaluate whether external strain measurements can serve as reliable indicators of SOH in 18650 lithium-ion cells.
- Extract features from residual strain to quantify degradation.
- Train a Random Forest regression model to estimate SOH using strain-derived features.
- Assess feature importance to identify the most physically meaningful predictors.



Experimental setup showing the instrumented 18650 cell with strain and temperature sensing.

Method



Laboratory battery-testing setup featuring NHR test systems, central control racks with temperature units and monitoring stations for real-time data acquisition.

Cell & Cycling Protocol

- Samsung 30Q 18650 cell (3000 mAh).
- CCCV charge at 1C.
- CC discharge at 1C.
- One-hour rest between cycles.
- Cycling continued until 80% capacity.

Instrumentation

- Foil strain gauge mounted circumferentially
- Temperature, voltage, and current

Strain Decomposition

Strain for each cycle was decomposed into:

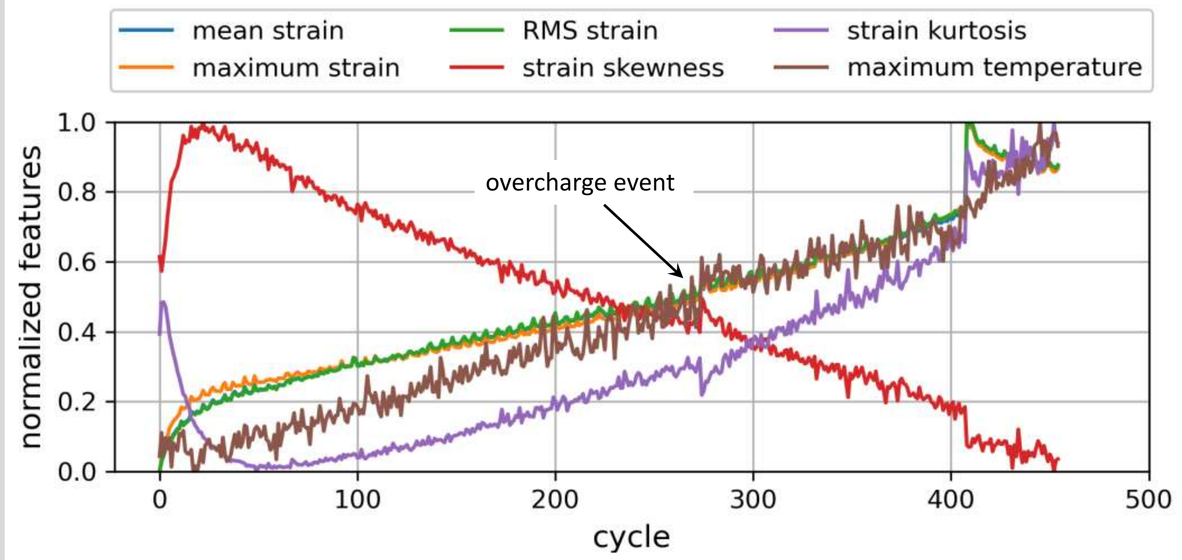
- **Offset** — irreversible deformation.
- **Slope** — reversible SOC-dependent strain.
- **Residual** — nonlinear intercalation-driven behavior.

Collected Data

Full cycling dataset including strain, temperature, voltage, current.

Features extracted were mean strain, maximum strain, RMS strain, skewness, kurtosis, crest factor, impulse factor, RMS frequency, and frequency center.

Results



Normalized strain- and temperature-based features over cycling, showing their evolution from 0–500 cycles.

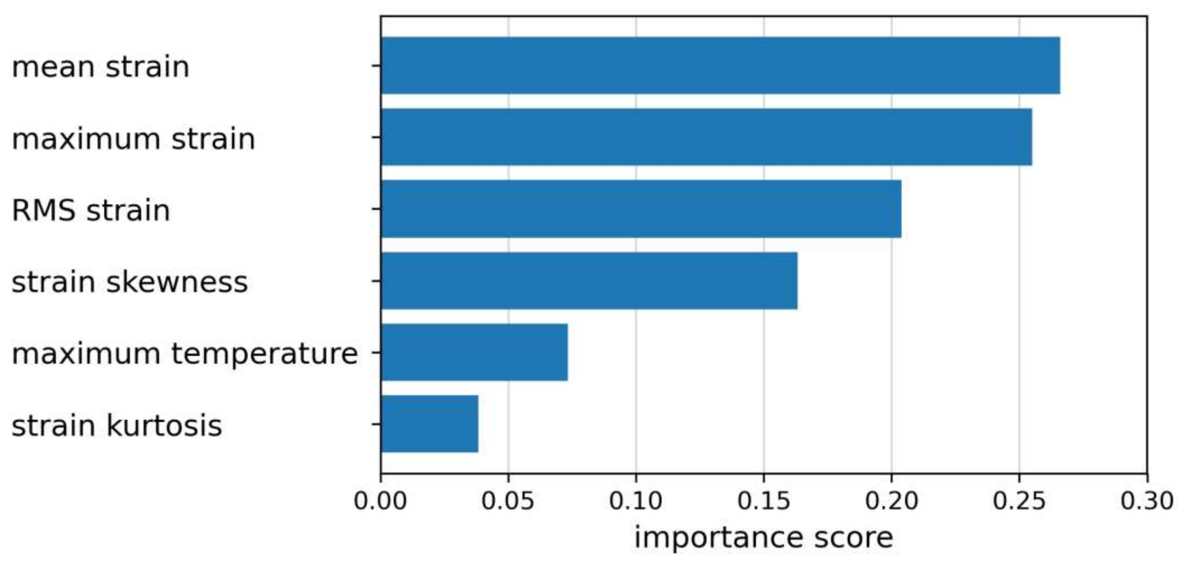
Feature Behavior

Residual-strain-derived features evolve consistently with cycling and correlate with capacity fade.

Random Forest feature importance highlights:

- Mean strain
- Maximum strain
- RMS strain

as the most influential predictors.



Feature importance ranking for SOH prediction, showing mean strain as the dominant contributor.

Model Performance

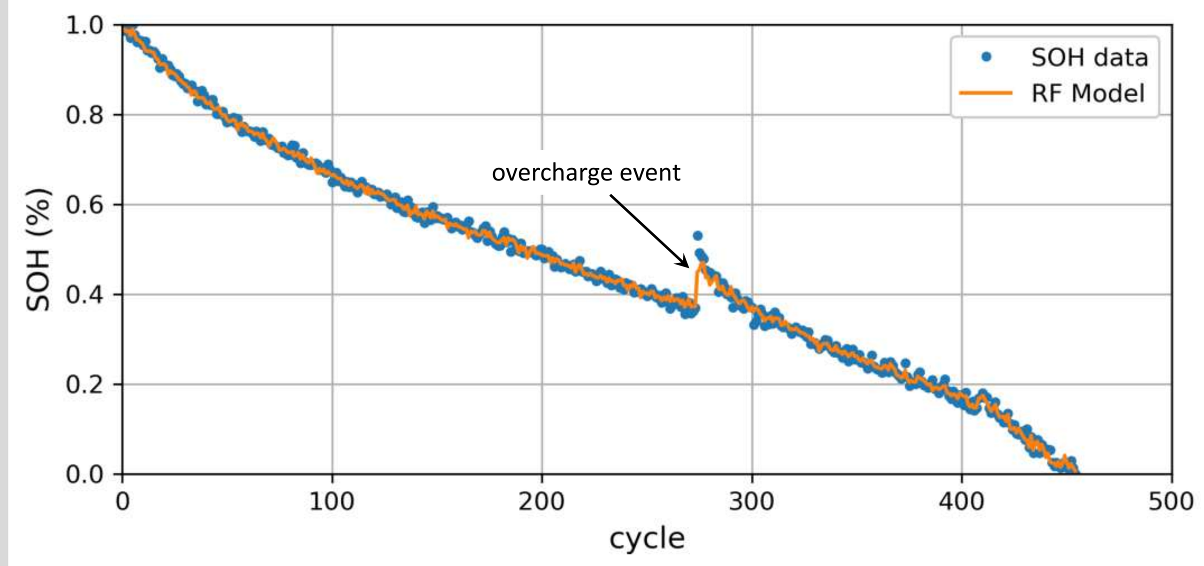
Random Forest regression (100 trees, max depth 10) achieved:

- R^2 = 0.9949
- MAE = 0.0151
- MSE = 0.00035
- RMSE = 0.0187

Predictions closely follow experimental SOH trajectories.

SOH computed each cycle using:

SOH = 100 × (Q_measured / Q_rated)



Comparison of measured SOH data and Random Forest predictions over cycling, showing close agreement across 0–450 cycles.

Conclusions

- Strain-derived features provide strong, interpretable indicators of battery degradation.
- Decomposition into offset, slope, and residual components isolates meaningful mechanical behavior.
- Machine-learning models trained on strain features can accurately estimate SOH without relying solely on electrical measurements.
- This approach supports future integration of strain sensing into battery management systems for enhanced safety and reliability.

References

Flemming, G. Anthony, R. L. Limbaugh, and A. R. J. Downey, "Exploratory analysis of strain-derived features for machine-learning estimation of state of health in 18650 lithium-ion cells," 2026.