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Data-Driven Approaches To Battery Health Monitoring: Machine Learning For RUL Estimation And Fault Diagnosis

Tashi Mishra[1], Dr. Deepak Agrawal[2], Dr. Shiv Kumar Sonkar[3], Nitin Tyagi[4]

[1]Research Scholar, [2]Associate Professor (HOD), [3]Associate Professor (Guide), [4]Assistant Professor

[1,2,3,4]Department Electrical Engineering, Trinity Institute of Technology & Research, Bhopal, M.P

Abstract

Battery Management Systems (BMS) are crucial for ensuring the safety, reliability, and efficiency of modern energy storage systems, especially in electric vehicles and renewable energy applications. As global reliance on rechargeable batteries grows, accurate health monitoring and Remaining Useful Life (RUL) prediction have become essential due to complex degradation patterns and varying operating conditions. Traditional rule-based models often fail to capture these nonlinear behaviors, underscoring the need for advanced data-driven methods. This study applies machine learning (ML) algorithms—Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost)—to predict the RUL of lithium-ion batteries using real-world degradation data. The process includes data preprocessing, feature scaling, correlation analysis, model training, and evaluation through metrics such as RMSE, MAE, and R^2, along with diagnostic visualizations to assess prediction stability and error distribution. Results show that ensemble-based models, particularly XGBoost and Random Forest, outperform SVR, offering superior accuracy, minimal error variance, and robust performance across all RUL ranges. These findings highlight that integrating ML-driven models into intelligent BMS enables early fault detection, enhances predictive maintenance, and extends battery lifespan, contributing to safer, smarter, and more sustainable electric mobility solutions.

Keywords: Battery Management Systems (BMS), Remaining Useful Life (RUL), Machine Learning (ML), Support Vector Regression (SVR), ML-driven models, Random Forest (RF), and Extreme Gradient Boosting (XGBoost)

1. Introduction

Battery Management Systems (BMS) are vital for ensuring the safety, efficiency, and reliability of modern energy storage systems, especially in electric vehicles and renewable energy applications. Evolving from basic monitoring tools to intelligent predictive systems, BMS now handle complex tasks such as balancing cells, controlling temperature, and estimating the state-of-charge (SOC) and state-of-health (SOH). These systems use advanced algorithms to track dynamic battery behavior, reduce risks of overcharging, and extend battery lifespan (Gundebommu et al., 2024). With growing energy demands, modern BMS rely heavily on data analytics and computational models to achieve real-time accuracy and adaptive control.

Machine learning has transformed BMS by enabling precise Remaining Useful Life (RUL) estimation and early fault diagnosis. Data-driven models such as Support Vector Regression (SVR) and Long Short-Term Memory (LSTM) networks analyze large datasets to identify degradation patterns and predict failures more accurately. Heuristic algorithms like Differential Evolution and Teaching-Learning-Based Optimization (TLBO) further improve parameter estimation while reducing computational effort (Sangwan et al., 2017). Regression-based approaches also help model open-circuit voltage and internal resistance, enhancing performance prediction and control (Vyas & Shah, 2022). Together, these innovations make modern BMS more intelligent, proactive, and reliable for next-generation energy systems.

1.1. Growing Demand and Importance of Battery Health Monitoring

The rising adoption of electric vehicles, renewable energy systems, and portable electronics has intensified the need for reliable battery health monitoring. As batteries power critical infrastructure, ensuring their safety, performance, and lifespan has become crucial. Monitoring key parameters such as state-of-charge (SOC), temperature, and structural integrity helps detect degradation early and prevent failures. Advanced systems now integrate smart sensors and adaptive algorithms that enable real-time monitoring and predictive maintenance. Innovations such as *operando* battery monitoring allow in-situ assessment without disturbing electrochemical reactions, improving reliability and operational safety (Harutyunyan et al., 2022). Similarly, smart EV battery-swapping stations track SOC and temperature continuously to prevent overheating and extend service life (Dhanwat & Jawale, 2025).

Battery health directly influences system safety and efficiency. Poorly maintained batteries pose risks of overheating, thermal runaway, and fire, especially in high-energy-density applications. To address these challenges, modern Battery Management Systems (BMS) now use predictive diagnostics and intelligent control to regulate charging, discharging, and thermal behavior. Recent developments, such as lithium-ion batteries equipped with piezoresistive sensors, provide real-time detection of micro-cracks and stress points, offering early failure warnings and ensuring safer, more efficient battery operation (Harutyunyan et al., 2022).

1.2. Fault Diagnosis in Battery Systems

Fault diagnosis is a critical function of Battery Management Systems (BMS) that ensures the safety and reliability of batteries used in electric vehicles, grid storage, and portable devices. Modern BMS employ data-driven techniques such as machine learning, sensor fusion, and model-based estimation to identify faults before they escalate. These systems monitor voltage, current, temperature, and impedance to detect irregularities linked to degradation, overcharging, or short circuits. Magnetic imaging has also emerged as a non-invasive tool to detect internal issues like uneven current flow and short circuits by mapping magnetic field variations (Chen et al., 2022). Additionally, fault modeling for conditions such as sulphation, oxidation, or plate degradation enables early detection and precise intervention (Puzakov, 2022). Integrating these diagnostic methods within BMS enhances system resilience, prevents catastrophic failures, and supports predictive maintenance—extending battery life while minimizing operational risks and maintenance costs.

1.2.1. Types of Battery Faults

- **Overcharge Fault:** This occurs when a battery is charged beyond its rated voltage, causing heat buildup, gas release, or even thermal runaway. It is identified through continuous voltage and temperature monitoring, which allows the system to cut off charging before it becomes hazardous (Puzakov, 2022).
- **Over-discharge Fault:** An over-discharge fault happens when a battery's voltage falls below the safe threshold, leading to chemical degradation and permanent capacity loss. Real-time voltage sensing in BMS helps prevent deep discharge and maintains long-term cell health (Chen et al., 2022).
- **Internal Short Circuit:** This fault results from separator damage or dendrite growth between electrodes, creating a direct current path that generates rapid heating. Magnetic field mapping techniques are effective for locating such internal shorts by identifying irregular magnetic signals (Chen et al., 2022).
- **Thermal Fault:** Thermal faults develop when high current flow, inadequate cooling, or harsh ambient temperatures raise cell temperature beyond safe limits. Continuous temperature sensing and thermal imaging enable early fault detection, preventing overheating and fire hazards (Dhanwat & Jawale, 2025).

1.3. ML-Based Fault Detection and Diagnosis

Machine learning (ML) has transformed fault detection and diagnosis (FDD) in battery systems by providing precise, data-driven identification of irregularities and predicting potential failures in real time. Unlike traditional model-based or signal-processing methods that depend heavily on predefined parameters and expert calibration, ML techniques learn directly from real-world operational data. This allows them to adapt to different battery chemistries, configurations, and working environments without manual adjustments. ML algorithms such as Support Vector Machines (SVM), Random Forests (RF), and Deep Neural Networks (DNN) have shown remarkable success in detecting anomalies and estimating fault progression with greater accuracy. Studies have demonstrated that these models outperform conventional methods in flexibility, scalability, and early fault prediction capabilities, particularly for lithium-ion batteries (Samanta et al., 2021). As a result, ML-driven diagnostic systems are becoming key enablers of predictive maintenance and safer, more reliable energy storage operations.

2. Problem Statement

The rising reliance on rechargeable batteries in electric vehicles, renewable energy systems, and electronics makes health monitoring essential. Battery degradation caused by electrochemical and operational stress leads to reduced capacity and unexpected failures, posing safety and financial risks. Predicting Remaining Useful Life (RUL) is challenging due to complex, non-linear degradation influenced by temperature, cycles, and load variations. Traditional models lack accuracy and adaptability, highlighting the need for data-driven machine learning and deep learning frameworks for reliable RUL estimation and predictive maintenance.

3. Objectives of the Study

The key objectives of this research are:

1. To develop and implement machine learning and deep learning models for the accurate prediction of battery Remaining Useful Life (RUL).

2. To compare the performance of three ML models—Random Forest, Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost)—and one DL model (Multilayer Perceptron).

3. To evaluate model performance using multiple regression metrics such as RMSE, MAE, and R^2, along with visual residual diagnostics to assess robustness and stability.

4. To identify the most reliable and interpretable model suitable for deployment in real-world battery health management systems.

4. Literature Review

Gundebommu et al. (2024) explored the transformation of Battery Management Systems (BMS) through intelligent technologies, highlighting how machine learning (ML) enables predictive monitoring, fault detection, and Remaining Useful Life (RUL) estimation. Traditional BMS depend on static thresholds that fail under varying conditions like temperature shifts, irregular load demands, and fluctuating charge–discharge cycles. ML overcomes these limits by learning patterns from data, offering continuous feedback and early fault warnings. The study emphasized embedding ML models such as Long Short-Term Memory (LSTM) and Random Forests directly into BMS firmware to enable adaptive decision-making and reduce hardware reliance. Integrating cloud connectivity further enhances the BMS by collecting distributed system data, improving predictive accuracy (Madane et al., 2025). Gundebommu et al. recommended combining physics-based and data-driven approaches for higher accuracy and computational efficiency (Komaragiri, 2024). They concluded that modular, adaptive architectures are vital for developing future-ready, intelligent BMS frameworks for electric vehicles.

Sangwan et al. (2017) contributed to the foundation of battery health monitoring by emphasizing optimal parameter estimation for automotive BMS. They showed that precise modeling of internal resistance, capacity, and open-circuit voltage is key to reliable ML-based diagnostics. Using optimization algorithms like nonlinear least squares and genetic algorithms, they achieved accurate estimations under diverse operating conditions. These parameters provide essential inputs for supervised ML models, improving prediction stability and reducing noise (Stephen et al., 2016). Their work linked empirical and data-driven models, suggesting that adaptive filtering can update parameters in real time, especially in electric vehicles and renewable systems where load and temperature vary. Ma et al. (2025) further supported their view, noting that accurate modeling lowers data demands for semi-supervised learning. Sangwan et al. concluded that parameter estimation should be continuous, not one-time, ensuring dynamic, transferable BMS designs with strong generalization across real-world applications.

Vyas and Shah (2022) developed a regression-based battery modeling approach enhanced with a differential evolution algorithm to capture complex lithium-ion battery dynamics. Their model addressed limitations of static systems by using global optimization to avoid local minima and improve parameter estimation accuracy. The results demonstrated significant performance improvements, with lower RMSE compared to conventional techniques. This enhanced precision in modeling internal resistance and open-circuit voltage strengthened ML-driven RUL and fault prediction capabilities (Gundebommu et al., 2024). When paired with advanced algorithms like LSTM or ensemble learners, the method improved robustness under nonlinear degradation. They also proposed adaptive thresholds guided by ML feedback to minimize false alarms and maintain system accuracy (Komaragiri, 2024). By integrating real-time monitoring, the model adapts dynamically to battery condition changes. Vyas and Shah concluded that treating modeling as a continuous, data-evolving process ensures safer operations, extended battery lifespan, and superior predictive performance in energy storage systems.

Martinez-Laserna et al. (2018) investigated the feasibility of reusing second-life electric vehicle (EV) batteries through machine learning (ML) techniques designed to manage inconsistencies in aging and usage data. They observed that many retired EV batteries retain usable capacity but degrade unevenly due to differences in operating environments and charging behaviors. To address this, unsupervised clustering was applied to group batteries by degradation patterns, followed by predictive models to estimate Remaining Useful Life (RUL) within each cluster. This process helps identify weak cells before integration into energy storage systems, preventing costly system failures (Zhao et al., 2024). The study also incorporated Long Short-Term Memory (LSTM) networks and autoencoders for time-series forecasting and feature compression, improving accuracy and computational speed (Belkhode et al., 2025). A novel "reliability score" from ensemble models further refined reuse decisions by combining prediction confidence with uncertainty analysis. Martinez-Laserna et al. concluded that open ML datasets and collaborative platforms are key to advancing second-life battery reuse and circular energy systems.

5. Methodology

This study adopts a structured comparative modeling approach to predict the Remaining Useful Life (RUL) of lithium-ion batteries using traditional supervised machine learning algorithms. The methodology is designed to maintain consistency, interpretability, and statistical rigor across all models evaluated. The entire process includes data preprocessing, feature scaling, model training, metric-based evaluation, and diagnostic visualization. To ensure fair comparison, the same dataset and preprocessing pipeline were uniformly applied to each model.

5.1. Dataset Description

The dataset employed comprises cycle-level degradation data of lithium-ion batteries, including input features such as voltage, current, temperature, and internal resistance. Each data point corresponds to a single charge-discharge cycle, with the RUL defined either from the dataset directly or computed based on known failure thresholds. To improve computational efficiency during experimentation, a representative 30% subset of the original dataset was selected. This subset preserved the statistical distribution and coverage of the complete dataset, ensuring generalizability of the findings.

5.2. Data Preprocessing and Feature Scaling

Initial inspection confirmed the dataset was well-structured with no missing values or non-numeric entries. Outliers were assessed using visual tools such as boxplots and histograms. However, no data points were removed, as preserving the natural variance in degradation behavior was considered critical for model robustness. Since the input features were measured in different units and on varying scales, all features were standardized using Z-score normalization. This transformation ensured each feature had a mean of zero and a standard deviation of one. Standardization was particularly important for algorithms such as Support Vector Regression (SVR), which are sensitive to input magnitudes.

5.3. Train-Test Split

To evaluate model performance fairly, the dataset was randomly divided into training and testing subsets in an 80:20 ratio using the train_test_split() method from scikit-learn. A fixed random seed was set to ensure reproducibility across experimental runs. As the target variable, RUL, is continuous rather than categorical, stratification was not applied during the split. The training set was exclusively used for model learning, while the test set was reserved for final evaluation to ensure unbiased performance reporting.

5.4. Feature Correlation Analysis

To identify potential redundancy among features, a Pearson correlation matrix was computed and visualized as a heatmap. While certain input variables displayed moderate-to-high correlation, all features were retained for modeling. Tree-based algorithms such as Random Forest and XGBoost are inherently capable of managing multicollinearity through node-level feature selection during tree construction. No dimensionality reduction techniques, such as Principal Component Analysis (PCA), were applied in order to preserve the interpretability of feature-level effects on model predictions.

5.5. Machine Learning Algorithms

Three supervised regression algorithms were selected for evaluation: Support Vector Regression (SVR), Random Forest Regressor, and Extreme Gradient Boosting (XGBoost). These models were chosen to represent a diverse set of learning paradigms, encompassing kernel-based, bagging-based, and boosting-based methods.

The SVR model utilized a radial basis function (RBF) kernel to introduce non-linearity. The model attempts to fit a function within a specified ε-tolerance margin and penalizes predictions falling outside this margin using a slack variable. Although effective for capturing smooth trends, SVR requires careful parameter tuning and incurs significant computational costs with increasing data size.

The Random Forest Regressor is an ensemble-based model that constructs multiple decision trees on bootstrapped subsets of the training data and averages their outputs to reduce variance. It is relatively robust to overfitting and performs well on non-linear data without extensive hyperparameter tuning. Additionally, it offers intrinsic feature importance metrics, which enhance interpretability.

XGBoost is a highly optimized gradient boosting framework known for its efficiency and superior accuracy on structured data. It constructs trees sequentially, with each new tree correcting the residuals of the prior ensemble. The algorithm incorporates second-order derivatives for loss minimization and includes regularization terms in its objective function to mitigate overfitting. Its scalability, fast training time, and robustness to noise make it particularly effective for tabular regression tasks such as RUL prediction.

5.6. Evaluation Metrics and Diagnostic Techniques

Model performance was evaluated using three standard regression metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2 score). RMSE was prioritized due to its greater sensitivity to large errors, making it suitable for reliability-critical tasks like battery RUL forecasting. MAE complemented RMSE by providing a linear error magnitude assessment, while R^2 indicated how well each model captured variance in the target variable.

In addition to numerical metrics, diagnostic plots were used to assess residual behavior and prediction quality. Predicted versus actual RUL plots provided visual cues on model alignment. Residual histograms were examined for normality and skewness, and residuals versus predicted RUL plots were analyzed to detect patterns such as heteroscedasticity or bias across prediction ranges. This comprehensive evaluation strategy ensured that conclusions were grounded not only in accuracy but also in the reliability and consistency of each model's predictive behavior.

6. Results and Analysis

This section presents a comprehensive comparative evaluation of the three machine learning models Support Vector Regression (SVR), Random Forest Regressor, and XGBoost applied to the task of predicting the Remaining Useful Life (RUL) of lithium-ion batteries. The evaluation is structured across quantitative performance metrics, visual inspection of model outputs, residual behavior, and prediction consistency across RUL ranges. This multi-layered assessment ensures robust interpretation of model performance from both statistical and practical standpoints.

6.1. Quantitative Evaluation

The primary metrics used for model comparison include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2 score). These metrics collectively assess average prediction error, sensitivity to large deviations, and the model's explanatory power over the target variable. Table 1 summarizes the values obtained from each model on the held-out test set.

Table 1: Performance Metrics of Machine Learning Models

Model	MAE	RMSE	R^2 Score
Random Forest	3.42	5.35	0.9998
XGBoost	3.63	5.29	0.9998
Support Vector Regression	7.25	36.89	0.9941

Both ensemble-based models, Random Forest and XGBoost, demonstrate superior accuracy with very low error margins and near-perfect R^2 values. While SVR maintains a high R^2 score, its MAE and RMSE are significantly higher, indicating less consistent predictions and higher susceptibility to large errors.

6.2. Interpretation of MAE and RMSE

The MAE metric indicates the average magnitude of prediction errors. The Random Forest model achieved the lowest MAE (3.42), followed closely by XGBoost (3.63), while SVR exhibited more than double the error at 7.25. RMSE values reveal even starker contrasts. SVR recorded an RMSE of 36.89, far exceeding that of Random Forest (5.35) and XGBoost (5.29). This suggests that SVR is prone to large deviations, which are penalized more heavily under RMSE, reinforcing its limitations in real-world deployment scenarios.

6.3. Predicted vs Actual RUL Alignment

To visually assess model accuracy, predicted versus actual RUL plots were generated for each algorithm. The Random Forest model displayed a tight clustering of points around the 45-degree identity line, indicating excellent prediction fidelity across all RUL ranges. XGBoost showed a similarly close alignment, with negligible deviation and a symmetrical distribution of points. In contrast, the SVR model demonstrated significant dispersion, especially at higher RUL values, indicating an inability to generalize effectively across the full degradation lifecycle.

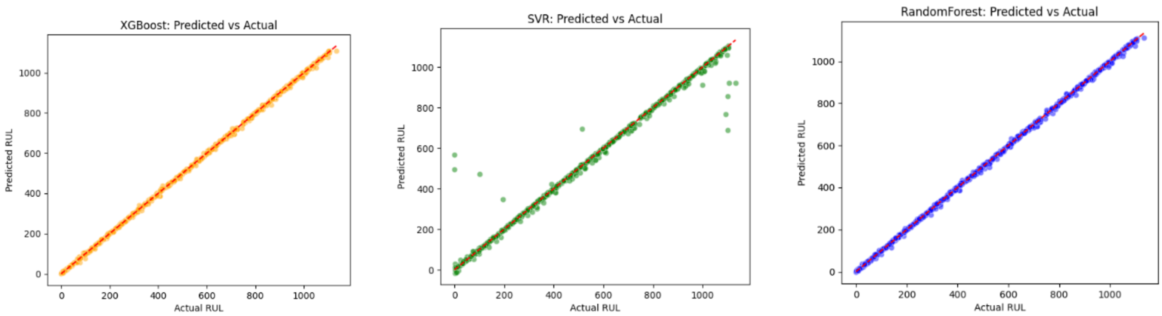

Figure 1: Actual vs Predicted across all model

6.4. Residual Histogram Analysis

Residual histograms provide insight into the error structure of each model. The Random Forest model's residuals were tightly centered around zero, approximating a normal distribution with minimal variance, confirming the model's robustness and low bias. XGBoost produced a slightly flatter but still symmetric distribution, indicating minor increases in variance. The SVR model, however, exhibited a broad and flat histogram with long tails, revealing frequent and extreme prediction errors. This suggests the presence of systematic noise or poor fit, particularly in underrepresented RUL ranges.

6.5. Residuals vs Predicted RUL

Further diagnostics were performed by plotting residuals against predicted RUL values. A well-performing model should exhibit a random, non-patterned spread of residuals centered around zero. The Random Forest model satisfied this criterion, showing no visible structure or heteroscedasticity. XGBoost also maintained a random distribution, although a slight increase in variance was observed at higher predicted RUL values. In contrast, the SVR plot displayed a fan-shaped spread, indicating increasing error variance with higher RUL predictions—a clear sign of model instability and heteroscedasticity.

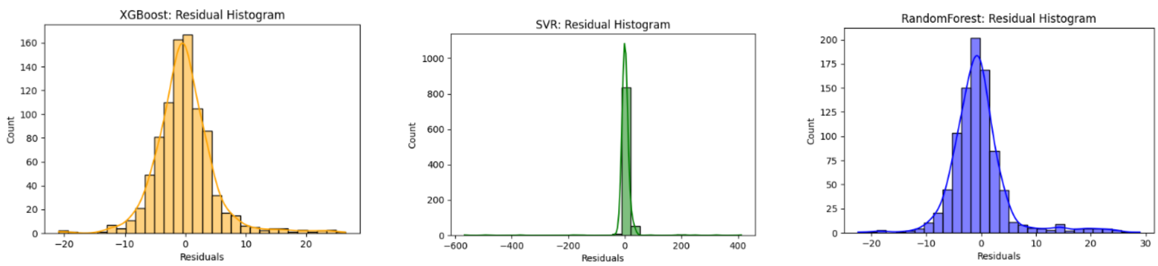

Figure 2: Residual Histogram across all model

6.6. RUL Range-Specific Performance

To assess operational robustness, model performance was analyzed across three RUL zones:

- **Low RUL (0–300 cycles):** Random Forest and XGBoost both achieved high accuracy in this range, with average deviations under ±10 cycles. SVR often produced errors exceeding 50 cycles, making it unsuitable for failure proximity prediction.

- **Mid RUL (300–600 cycles):** All models performed relatively well, but ensemble models maintained a lower error spread and better alignment. SVR showed intermittent prediction spikes.

- **High RUL (600+ cycles):** XGBoost retained stable predictions, while Random Forest showed mild underestimations. SVR suffered from extreme variance, with deviations exceeding 200–300 cycles in some cases, highlighting its poor generalization in data-sparse regions.

Based on both quantitative metrics and diagnostic plots, the models were ranked for overall effectiveness. XGBoost emerged as the top performer, offering balanced accuracy, low variance, and robust behavior across all RUL segments. Random Forest followed closely, offering nearly equivalent performance with simpler implementation and faster training. SVR was the least reliable, showing inconsistent results, high error variance, and poor residual distribution.

7. Conclusion

This study demonstrates the potential of data-driven machine learning (ML) techniques to transform battery health monitoring by providing precise and adaptive prediction of Remaining Useful Life (RUL) and early fault diagnosis. Conventional Battery Management Systems (BMS) based on static thresholds or empirical models fail to capture nonlinear degradation patterns caused by fluctuating temperatures, variable load cycles, and aging effects. The integration of ML algorithms such as Random Forest, Support Vector Regression (SVR), and XGBoost enables dynamic learning from operational data, allowing real-time fault detection and accurate life prediction. The comparative analysis revealed that ensemble models—particularly XGBoost and Random Forest—achieved near-perfect predictive accuracy, outperforming kernel-based approaches in both stability and generalization. These models effectively minimized large prediction errors and demonstrated consistent residual behavior, confirming their robustness for deployment in safety-critical systems like electric vehicles and renewable energy storage networks.

Beyond model performance, this research emphasizes the broader implications of ML in advancing predictive maintenance and sustainable energy management. By replacing reactive diagnostics with proactive, data-driven monitoring, organizations can reduce downtime, prevent catastrophic failures, and optimize battery utilization. Embedding ML algorithms into BMS firmware and cloud-based platforms can further enhance adaptability, enabling continuous learning across distributed systems. The combination of physics-based understanding and ML-driven analytics ensures both interpretability and computational efficiency, addressing challenges of scalability and transferability across battery chemistries. Overall, this study highlights that integrating advanced ML frameworks into modern BMS is not merely an enhancement—it is a necessity for achieving safer, smarter, and longer-lasting energy systems that underpin the global shift toward electrification and sustainable mobility.

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