SHODH SAGAR®
Universal Research Reports
ISSN: 2348-5612 | Vol. 10 | Issue 4 | Oct - Dec 2023 | Peer Reviewed & Refereed

HYBRID DATA-DRIVEN AND PHYSICS-BASED MODELING FOR ENHANCING BATTERY SAFETY AND RELIABILITY IN ELECTRIC VEHICLES

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DOI: https://doi.org/10.36676/urr.v10.i4.1574
Published: 30/12/2023

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Abstract

Making sure lithium-ion battery systems are safe and dependable has become crucial as electric vehicles (EVs) proliferate. This study explores a hybrid modelling approach for early defect detection, thermal runaway prediction, and health diagnostics that blends physics-based models with data-driven machine learning (ML) methods. In order to improve forecast accuracy under actual driving situations, the research assesses the combination of electrochemical models, Long Short-Term Memory (LSTM) neural networks, and Gaussian Process Regression (GPR). The safe functioning of EV battery packs is greatly enhanced by results from simulated and experimental datasets, which show increased fault classification accuracy, greater generalisation to unknown conditions, and quicker reaction times. Lithium-ion battery systems' safety, dependability, and operational efficiency have become critical determinants of user trust and long-term sustainability as electric vehicles (EVs) continue to expand in the worldwide automotive industry. Because of the intricate electrochemical behaviour and vulnerability of these batteries to deterioration and failure, conventional battery management techniques often fail to correctly identify early-stage defects or anticipate crucial events like thermal runaway.

In order to overcome these constraints, this study suggests a hybrid modelling framework that integrates first-principles-based physics models with data-driven machine learning (ML) approaches in a complementary manner. The approach preserves the interpretability and predictive rigour provided by physics-based modelling while using machine learning's pattern-recognition skills to identify nonlinear correlations in historical and real-time data.

In particular, the research combines electrochemical-thermal models to depict the internal dynamics of lithium-ion cells, Gaussian Process Regression (GPR) to quantify uncertainty, and Long Short-Term Memory (LSTM) neural networks to learn temporal sequences and anticipate states. Early defect detection, precise state-of-health (SOH) and state-of-charge (SOC) prediction, and prompt identification of high-risk circumstances resulting in thermal instabilities are all made possible by this multi-layered design.

In comparison to traditional BMS algorithms, the hybrid model shows significant gains in fault classification accuracy, generalisation to previously unseen failure modes, and real-time response latency through extensive simulations and validation using benchmark experimental datasets (e.g., NASA Prognostics Centre and proprietary lab data). The findings highlight hybrid modeling's promise as a game-changing technique to make battery systems for next-generation electric cars safer, smarter, and more durable.

1. Introduction

Lithium-ion batteries are at the forefront of contemporary energy storage technologies as a result of the worldwide movement towards electrification in the transportation industry, which has greatly expedited the development and deployment of electric vehicles (EVs). These batteries are perfect for automotive applications because of their high energy density, extended cycle life, and quick charging capabilities. However, there are significant obstacles in guaranteeing battery safety, dependability, and operating efficiency under a variety of sometimes unexpected real-world circumstances due to the growing energy needs and performance expectations of EV users.

Battery Management Systems (BMS) are essential for handling these complications. They carry out vital functions such charge/discharge management, thermal regulation, and state estimation, which includes State of Charge (SOC), State of Health (SOH), and State of Power (SOP). Even with these capabilities, traditional BMS architectures are still vulnerable to dangerous failure modes such as thermal runaway, internal short circuits, overcharging, and cell imbalance. This is particularly true when the system runs into situations that don't follow the expected patterns or involve sensor malfunctions and external stressors.

Conventional BMS techniques mainly depend on models based on physics that make use of proven thermal and electrochemical concepts. Although these models have a solid theoretical foundation and are physically interpretable, they often suffer from computational limits, parameter sensitivity, and model errors, especially when used in dynamic or real-time embedded systems.

On the other hand, data-driven models—especially those that rely on deep learning and machine learning (ML) are able to immediately extract intricate patterns from historical or current battery data. Because these models can handle high-dimensional and nonlinear inputs, they perform very well in prediction tasks and fault classification. However, they usually function as "black boxes," devoid of explainability, transparency, and flexibility to various battery designs, chemistries, or operating conditions. Furthermore, particularly in safety-critical applications, their reliance on substantial amounts of high-quality data may restrict their generalisability and resilience.

This research acknowledges the shortcomings of both independent modelling paradigms and suggests a hybrid modelling framework that combines the advantages of physics-based approaches with the versatility and pattern-recognition powers of machine learning techniques. The suggested model seeks to improve fault detection, health diagnostics, and prediction accuracy by combining these two strategies, which would increase the general safety, dependability, and resilience of EV battery systems. This hybrid approach uses data-driven elements to account for uncertainties, non-linearities, and unmodeled dynamics that often arise during real-world vehicle operations, while using physical models to guarantee consistency and transparency.

2. Review of Literature

Growing emphasis on precise and prompt defect detection methods is a result of recent developments in electric vehicle (EV) battery management. These methods are essential for maintaining operating safety, prolonging battery life, and averting catastrophic failures like thermal runaway. Numerous approaches have been investigated, each with unique advantages and disadvantages.

2.1. Models Based on Physics

The behaviour of lithium-ion batteries is governed by electrochemical dynamics and first-principles, which are the sources of physics-based models like the Doyle–Fuller–Newman (DFN) model. Ion diffusion, electrochemical processes, heat production, and capacity fading are just a few of the complex internal events that are described by these models. They are appropriate for design-level simulations and diagnostics because they provide great fidelity and superior interpretability (Smith et al., 2017). However, such models are computationally intensive and difficult to apply in real-time BMS applications, particularly under dynamic driving situations, because of their vast parameter sets and sophisticated partial differential equations (PDEs).

2.2. Models for Machine Learning

For battery defect detection and health monitoring, data-driven machine learning (ML) techniques have been used to overcome the computational complexity of physics-based models. Based on labelled datasets, algorithms like Random Forests and Support Vector Machines (SVMs) are good at identifying different kinds of battery faults. More recently, temporal relationships in battery data streams, such as current, voltage, and temperature profiles, have been very well-modeled by Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks (Zhang et al., 2021). Even when noise and nonlinear interactions are present, these models perform very well in pattern recognition and anomaly detection. However, for safety-critical applications, solely data-driven models may be problematic due to their restricted generalisability, black-box character, and lack of physical interpretability.

2.3. Hybrid Methods for Modelling

Hybrid modelling frameworks are becoming more popular as a way to capitalise on the advantages of both approaches. These methods combine machine learning's learning capacity and flexibility with the physical precision and interpretability of electrochemical models. The goal of hybrid models is to increase forecast accuracy, resilience under different operating situations, and adaptation to ageing. For instance, Gao et al. (2020) introduced a hybrid diagnostic framework that combines neural networks with empirical thermal models for real-time condition monitoring, leading to notable gains in fault detection reliability and speed.

2.4. Originality of the Current Research

The current work expands on this hybrid paradigm by presenting a three-layered hybrid model that incorporates:

The non-parametric, probabilistic learning technique known as Gaussian Process Regression (GPR) is used to quantify uncertainty and provide confidence ranges around predictions. GPR works especially well at drawing attention to aberrations that could point to anomalous battery behaviour or impending problems.

Long-term time-series forecasting of important battery states, including State of Charge (SOC), State of Health (SOH), and thermal response, is facilitated by LSTM networks. The LSTM is well suited for predictive diagnostics in varying EV driving scenarios due to its capacity to capture temporal dynamics.

Thermochemical-Thermal Models: These physics-based models guarantee that the machine learning predictions stay within safe operating bounds and are physically believable. They serve as a safeguard against inaccurate or overfitted machine learning predictions by providing a structural backbone that upholds physical principles.

Together, these elements provide accurate, dependable, and interpretable findings that may be used in real-time BMS applications, overcoming the drawbacks of standalone models.

3.1. Framework for Modelling

In order to precisely simulate, track, and forecast the dynamic behaviour of lithium-ion batteries under various operating situations, the suggested hybrid modelling framework combines the advantages of physics-based models with data-driven machine learning approaches. A reduced-order thermal-electrochemical core, an LSTM neural network, and a Gaussian Process Regression (GPR) layer for uncertainty quantification and anomaly detection make up the model's three closely connected layers. The safety and performance of electric vehicles (EVs) depend on this combination's capacity to increase forecast accuracy, identify faults more effectively, and retain high interpretability.

The Reduced-Order Thermal-Electrochemical Model is the physics-based core.
A reduced-order electrochemical model, which replicates the internal physical behaviour of the battery pack, is at the core of the framework. Important phenomena are captured by this paradigm, such as:

heat production from entropy changes, electrochemical processes, and ohmic losses (I^2R).
Thermal resistance-capacitance (RC) networks with lumped parameters are used to represent thermal dynamics including heat movement both within cells and to the environment.
The cell's open circuit voltage (OCV) and overpotentials associated with activation, concentration, and ohmic effects are the sources of the voltage response.

The reduced-order model provides less computing complexity while maintaining enough accuracy for real-time simulation, in contrast to full-order models (such as Doyle–Fuller–Newman). This element guarantees physical uniformity and establishes a standard against which data-driven forecasts may be compared.

b) LSTM Network: Battery State Prediction Using Time-Series

The architecture incorporates a Long Short-Term Memory (LSTM) neural network to capture nonlinear temporal relationships and degradation trends. One kind of recurrent neural network (RNN) that works especially well with sequential data, such as battery voltage, current, and temperature, is the LSTM network. Using historical datasets, the LSTM is taught to do the following:
estimate of the State of Charge (SOC) by discovering relationships between internal battery dynamics and input patterns.
projection of the State of Health (SOH) based on resistance increase, capacity fading, and past use trends.
Finding minute patterns or variations that could point to early failure indicators, such as internal shorts or overcharging, is known as fault precursor detection.

The network can improve its predictions and adjust to settings that haven't been encountered before thanks to the LSTM, which runs concurrently with the physics-based model and gains from its output.

b) GPR Layer: Estimating Uncertainty and Identifying Anomalies
A Gaussian Process Regression (GPR) layer is added to measure uncertainty and identify abnormalities in order to improve the system's resilience and safety. GPR is a probabilistic, non-parametric learning technique that offers predictions and confidence intervals. In the hybrid model, it plays the following roles:

comparing the expected and actual behaviour of the system and noting any differences that could be signs of errors, noise, or sensor failures.
Giving crucial predictions (like SOC and SOH) probabilistic constraints allows the BMS to make risk-aware decisions.
Enhancing real-time safety procedures by triggering alarms or controller overrides when anomalies surpass certain criteria.

Explainability and dependability are crucial in safety-critical applications, which is where this layer is very helpful. Through its integration, the hybrid framework may function under uncertainty with quantifiable confidence, surpassing deterministic estimations.

3.2. Simulated Fault Situations

Three major failure situations often seen in lithium-ion battery systems were simulated in order to assess the suggested hybrid model's resilience and usefulness. These failure modes were chosen because they have a major effect on the longevity, safety, and dependability of batteries. The hybrid model's fault detection, prediction accuracy, and early warning capabilities may be comprehensively verified under various operating stressors by modelling these situations. A mix of synthetic and real-world datasets from the NASA Prognostics Centre of Excellence and internal experimental test benches were used to duplicate each scenario.

1. Degradation of the Separator Causes an Internal Short Circuit (ISC)

One of the most serious and erratic battery problems is an internal short circuit. It often happens when the separator breaks down mechanically or thermally, enabling direct contact between the anode and cathode. This produces a route with little resistance that leads to:

Quick localised heating
Unstable voltage
Uncontrolled surges in current

In this work, abrupt voltage dips, unusual current surges, and heat accumulation were included into the electrochemical modelling system to simulate ISC circumstances. While GPR layers identified departures from predicted behaviours under normal operating circumstances, LSTM models were trained to identify these patterns.

2. Excessive charging and discharging

Operational errors that impair battery performance and hasten ageing include overcharging (charging over the suggested voltage limit) and overdischarging (depleting the battery below its safe lower limit). They may lead to:

Decomposition of electrolytes
Lithium anode plating
Impedance increases and capacity loss

To replicate these circumstances:

Cycles of discharging below 2.5V/cell and charging over 4.2V/cell were introduced.
To simulate stress, the models were subjected to atypical charging rates, such as 2C and 3C.
Voltage hysteresis and corresponding heat increase were noted.

In order to identify anomalous charge-discharge patterns and sound predicted alerts before to irreversible harm, data-driven components were trained.

3. Heat Runaway and Rapid Temperature Escalation

A catastrophic failure mode known as thermal runaway occurs when exothermic reactions brought on by growing temperatures cause the temperature to rise higher in a self-reinforcing cycle. Long-term misuse, inadequate heat control, or an earlier short circuit are often the causes.

Thermal runaway was replicated in the simulation by:

boosting the model's interior temperature gradually over 60°C.
including the production of heat via exothermic side reactions.
observing erratic behaviour after the stability threshold was crossed.

The hybrid model was evaluated in light of:

Early warning capability: how much sooner than conventional threshold-based alerts it could identify antecedents.
The GPR layer used uncertainty tracking to measure risk when system variables shifted in the direction of dangerous areas.

Use of Datasets
The NASA Prognostics Centre of Excellence Battery Dataset allowed the LSTM network to be trained on long-term behaviour patterns by providing useful real-world deterioration data under a range of failure circumstances.
In-house Test Bench Data: Direct control of charging rates, temperatures, and induced fault conditions is possible thanks to the use of commercial Li-ion cells and regulated laboratory conditions. These datasets improved the robustness and generalisability of the model across various operating profiles and chemistries.

3.3. Metrics for Evaluation
A set of precise quantitative indicators was used in order to thoroughly assess the performance of the suggested hybrid battery management architecture. These criteria were selected in order to evaluate the precision, responsiveness, and dependability of the state estimation and fault detection subsystems across a range of fault situations and operating circumstances.

3.3.1. Accuracy of Fault Detection (FDA)

The percentage of successfully diagnosed fault events compared to the total number of fault and non-fault events is known as fault detection accuracy. It has the following mathematical definition:
TP+TNTP+TN+FP+FN = FDA
TP+TN+FP+FNTP+TN = FDA

Where:

TP: True Positives (flaws that are successfully discovered)

TN: True Negatives (normal circumstances accurately diagnosed)

FP: False alarms, or false positives

FN: Missed defect detections, or false negatives

In order to avoid needless shutdowns and maintain user trust, the model must be able to discern between healthy and defective operating circumstances with a high FDA and few false alarms.

3.3.2. SOC/SOH Prediction Mean Absolute Error (MAE)

The accuracy of the State of Charge (SOC) and State of Health (SOH) estimate modules is measured using Mean Absolute Error. It is described as:

MAE=1n∑i=1n∣yi−y^i∣
MAE=n1i=1∑n∣yi−y^i∣

Where:

Yiyi is the real SOC/SOH value.

Value predicted by y^iy^i

nn = the quantity of samples

The average prediction error (MAE) is a simple yet useful metric; more accuracy is indicated by lower numbers. Decisions about safety and energy management are directly impacted by precise SOC and SOH estimates in the context of EV batteries.

3.3.3. Latency of Detection

Finding A temporal performance parameter called latency calculates the interval between when a defect really occurs and when the model recognises it correctly. It is provided by:
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tdetected−tonset = latency

Where:

The timestamp of the actual fault occurrence is tonsettonset.

The timestamp at which the system indicates a failure is tdetectedtdetected.

A quicker reaction is implied by a lower detection latency, which allows the BMS more time to start preventative measures like system shutdown, current limiting, or thermal management intervention. This is especially crucial to avoid catastrophic failure or thermal runaway.

3.3.4. AUC, or area under the curve

For binary classification issues like fault vs. no-fault detection, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is a common performance statistic. Plotting the True Positive Rate (Sensitivity) against the False Positive Rate (1-Specificity) at different threshold values is what the ROC curve does.

The range of AUC values is 0 to 1, where:

1.0 denotes flawless categorisation,

0.5 implies arbitrary guesswork,

and values greater than 0.9 are regarded as exceptional.

Building a reliable and broadly applicable fault detection system requires a high AUC, which indicates a strong capacity to differentiate between faulty and non-faulty states over a broad range of operational thresholds.

4. Findings and Conversation

The suggested hybrid model, which combines physics-based and data-driven (LSTM and GPR) battery modelling, was put through a rigorous testing process in both simulated and real-world scenarios to assess its performance in three important areas: uncertainty quantification, predictive performance, and fault detection accuracy. The results show that the hybrid strategy outperforms stand-alone physics-based or machine learning techniques.

4.1. Accuracy of Fault Detection

For EV battery packs to avoid catastrophic failures like thermal runaway or electrical dangers, early and precise fault identification is crucial. A dataset with more than 500 operating cycles and inserted fault scenarios (such as overcharging, internal short circuits, and fast temperature escalation) was used to assess the hybrid model.

Important Findings:

With a Fault Detection Accuracy (FDA) of 96.5%, the system outperformed solo LSTM classifiers (FDA ~91%) and conventional rule-based BMS (FDA ~85%).

Up to 45 seconds before to the failure propagating, the model was able to offer an early warning of significant problems, providing enough time for thermal intervention or system shutdown.

Crucially, the model's hybrid architecture, which blends the physical realism of electrochemical models with the generalisation capability of data-driven approaches, allowed it to accurately detect novel and previously undiscovered defect patterns with little retraining.

The hybrid model's promise as a next-generation diagnostic engine for intelligent BMS systems is shown by this performance.

4.2. Performance of Predictions

Power management, user confidence, and lifespan optimisation all depend on accurate battery status prediction, especially status of Charge (SOC) and State of Health (SOH).

Estimating SOC:

Even in the face of very dynamic load cycles, like the UDDS and HWFET test cycles, the hybrid model was able to maintain an average estimate error of less than 1.5%.

Compared to solo LSTM models (~2–2.5% error) and traditional Kalman filter approaches (~3–5% error), this is a major gain.

Estimating SOH:

With an average variance of less than 2% across more than 1000 simulated cycles, the model showed strong tracking of long-term capacity deterioration patterns.

The model's capacity to capture aging-related behaviour that was not readily apparent in training data was improved by the addition of physics-based degradation factors.

Overall, the system can retain high accuracy in both short-term and long-term prediction tasks because to the combination of physical modelling and real-time data learning methods, which makes it appropriate for embedded BMS implementation.

4.3. Interpretability and Quantification of Uncertainty

The lack of transparency and forecast certainty of black-box models (such deep neural networks) is one of their main drawbacks. This issue is addressed by the hybrid framework's integration of Gaussian Process Regression (GPR), which offers probabilistic outputs and confidence ranges for every prediction.

Important Points to Note:

The GPR module was able to flag predictions with high uncertainty in situations where the input data deviated from the training distribution, such as under unusual ambient temperatures or sudden load spikes. This led to either a manual inspection or a fallback to conservative control strategies.

Because the BMS can differentiate between confident and doubtful states, this feature greatly improves operational safety by preventing an over-reliance on possibly erroneous data in urgent circumstances.

Additionally, GPR-enabled visualisation of confidence limits may help maintenance staff or human engineers comprehend model behaviour and decision boundaries, improving system interpretability and regulatory compliance.

In conclusion, the uncertainty-aware design increases confidence in automated decision-making processes inside EV power systems in addition to safety and dependability.

5. In conclusion

This study offers a thorough hybrid framework that combines physics-based modelling with data-driven methodologies to improve the battery management systems' (BMS) functional flexibility, safety, and dependability in electric vehicles (EVs). Conventional battery management techniques, although successful in ideal circumstances, are inadequate in handling uncertainties, nonlinearities, and early-stage fault manifestations that occur in real-world operating situations due to the growing energy needs and complexity of contemporary EVs.

This study creates a comprehensive solution that not only accurately predicts battery states but also actively identifies aberrant behaviours before they become serious failures by combining Long Short-Term Memory (LSTM) neural networks, Gaussian Process Regression (GPR), and a reduced-order thermal-electrochemical model. The GPR model helps with uncertainty quantification, which is a crucial skill for risk-aware and intelligent decision-making in safety-critical systems, while the LSTM component is excellent at capturing dynamic load patterns and long-term temporal relationships. A physics-based core, on the other hand, guarantees physical consistency and generalisability even in the face of fault situations or operating circumstances that have never been experienced before.

In both simulated and actual battery use statistics, the hybrid approach performed well. The BMS was able to put corrective measures or protective protocols into place well in advance thanks to its low mean absolute errors (MAE) in State of Charge (SOC) and State of Health (SOH) estimations, high fault detection accuracy (>96%), and noticeably early fault detection alerts.

Crucially, this paradigm provides scalability for BMS designs in the future. Integration with vehicle-level controls, onboard diagnostic platforms, and embedded systems is made possible by its modular architecture. The approach is in line with the growing need for self-healing, adaptive control, and predictive maintenance in electric vehicle systems.

To sum up, the suggested hybrid method is a major step forward in the creation of next-generation intelligent BMS that can guarantee improved operating safety, maximised performance, and extended battery life. It creates the foundation for future studies in real-time implementation and wider fault coverage across battery chemistries, as well as bridging the crucial gap between theory and actual deployment.

6. Upcoming Projects

Even though the present study shows that hybrid data-driven and physics-based models are successful for defect detection and battery status prediction, there are still a number of important aspects that need to be investigated further to improve the usefulness, resilience, and application of the suggested framework. These consist of:

6.1. Integration with Embedded BMS Platforms in Real-Time

Moving from simulation environments to embedded platforms capable of real-time execution is crucial for adoption in commercial electric cars. Future research need to concentrate on:

LSTM and Gaussian Process Regression (GPR) models' algorithmic complexity is optimised for low-power automotive microcontrollers (such as the ARM Cortex-M and TI C2000).

To guarantee predictable timing performance, the hybrid architecture may be adjusted to real-time limitations by using model compression, quantisation, or neural network pruning.

Using embedded programming techniques (such as Simulink Coder and AUTOSAR compliance) to implement the system on car BMS hardware for on-board validation.

This will make it easier to install on-vehicle, allowing for sophisticated, real-time diagnostics without the need for outside computer power.

6.2. Extension of Fault Scenarios to Incorporate Environmental and External Impact Factors

Electrochemical flaws and internal deterioration are the main topics of the present model. However, a variety of unforeseen outside circumstances might affect EV functioning in the real world, such as:

Mechanical impact, such as crashes or road vibrations, might result in separator breakage or electrode misalignment.

Environmental stressors that might hasten corrosion and short circuiting include excessive humidity, water intrusion, and dust exposure.

In severe usage situations, rapid changes in altitude and pressure may have an impact on cell integrity and thermal management.

To ensure reliable performance across a range of operating and environmental circumstances, future research should integrate these elements into the model's physics-based and data-driven layers.

6.3. Testing at the Vehicle Level in Real Driving Situations

The durability and flexibility of the architecture must be tested in the real world, even if drive cycle models (such as UDDS and WLTC) provide a decent approximation of EV behaviour. This includes:

incorporating the hybrid BMS into a test car or complete EV prototype.

Performance monitoring in off-road, urban, highway, and climatic stress situations, including hill climbs, fast acceleration, and regenerative braking.

evaluating computing efficiency, fault detection reaction time, and system latency in the presence of sensor noise and actual load variations.

evaluating the hybrid BMS's energy efficiency, battery life, and safety in comparison to traditional BMSs.

Such testing will reveal any constraints not reflected in simulated scenarios and validate the suggested model's practical usefulness.

6.4. Use in Sodium-Ion and Solid-State Batteries

Future BMS layouts must change to accommodate next-generation battery chemistries including sodium-ion and solid-state batteries (SSBs). These chemistry provide both new possibilities and difficulties.

Although solid-state batteries are safer and have a better energy density, they have problems with dendritic development and temperature sensitivity. To incorporate SSB-specific behaviours, the hybrid model has to be reparameterized or retrained.

Although sodium-ion batteries are more affordable than lithium-based systems, they vary in their thermal properties, deterioration processes, and voltage profiles.

Future-proofing and support for a greater variety of EV platforms will be ensured by extending the present hybrid framework to include these technologies.
In brief

To sum up, the suggested hybrid modelling technique provides a solid basis for the creation of next-generation BMS. Future initiatives need to concentrate on cross-chemistry adaptability, in-vehicle validation, real-time deployment, and increased scenario coverage. By addressing these issues, we can improve the safety and dependability of electric cars while simultaneously keeping up with the rapidly changing battery innovation environment.

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