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Voices

Next steps for battery diagnostics

Batteries are a cornerstone of expanding sustainable infrastructure. Battery behavior has an impact on consumers recharging their electric vehicles, industries designing battery-powered equipment, large-scale electric grid performance, warranties for electronics, and safety for everyday users. Correctly planning, executing, and succeeding in battery deployment relies on an accurate understanding of how batteries function and fail. We sought out researchers on the leading edge of battery diagnostic and prognostic techniques to describe where the field is headed. In this Voices piece, they provide their expert opinions—including evolving definitions, data as a key resource, future battery formats, and diagnostics motivating industry investment—to portray the future of battery diagnostics and prognostics.

Dongzhen Lyu
Wenzhou University

Open-ended definitions and proactive prediction

As the field of battery diagnostics and prognostics evolves, it's time to rethink how we define and predict battery lifetime. Traditional metrics like cycle life (charge-discharge cycles) and calendar life (elapsed service time) have been foundational, but they often fail to capture the diverse and dynamic ways batteries are used across industries. To advance the field, we need more open-ended and practical definitions of battery cumulative lifetime—ones that reflect real-world usage and operational demands. Instead of limiting ourselves to cycle life and calendar life, we should consider a flexible framework based on accumulated usage metrics that directly tie the battery's performance to the work it enables. For example, mileage lifetime (the total distance a battery powers an electric vehicle [EV] to travel), mechanical work lifetime (the total volume of earth a battery enables an electric excavator to move), or practical work lifetime (the total number of rotations a battery drives an electric drill to perform) could serve as more meaningful indicators in specific applications. By adopting these open-ended definitions, we can better align lifetime metrics with the unique demands of different applications, ensuring that battery-lifetime predictions are more relevant and actionable. This shift could open new avenues for research and innovation, enabling more accurate and context-aware lifetime predictions.

However, predicting battery lifetime is only the first step. The true goal of prognostics should be not just to foresee the future but to shape it. Imagine if we could predict our fate but lacked the power to change it—how despairing and tragic that would be. I would not wish for such a predictive ability. The same applies to battery-lifetime prediction. If we can predict a battery's remaining useful life but lack the means to influence it, our efforts fall short. The next frontier in battery prognostics must focus on proactive lifespan management—actively managing and extending battery life based on predictive insights. This requires identifying key influencing factors, such as temperature, charging patterns, depth of discharge, or environmental conditions as well as developing adaptive strategies to mitigate their impact. For instance, smart charging algorithms could optimize charging rates to minimize stress, or thermal management systems could maintain optimal operating temperatures. By integrating prediction with proactive management, we can transform battery prognostics from a passive observational tool into an active driver of longevity and performance. This, I believe, is the true mission of lifetime prediction—not just to foresee the future but to shape it in ways that maximize the value and sustainability of battery technologies.

About the author: Dongzhen Lyu is an assistant professor at Wenzhou University, Wenzhou, China. He received his PhD in thermal-power engineering from Huazhong University of Science and Technology, Wuhan, China in 2023. His research interests focus on the fault diagnosis and prognostics of lithium-ion batteries, and he is working to transform battery cycle lifetime through advancements in cumulative battery lifetime.

Simona Onori
Stanford University

Data-driven diagnostics as a cornerstone for sustainable energy

As batteries become central to EVs, grid storage, and next-generation energy systems, the development of robust diagnostic and prognostic tools is essential. Diagnostics are critical for monitoring health during operation and identifying faults and failures—a process known as fault detection and isolation (FDI). FDI enables granular insight at the cell and module level, supporting early, localized fault detection and timely intervention.

This is enabled by the Digital Twin—a high-fidelity, physics-informed virtual replica of a battery system that evolves with real-time data. Digital Twins integrate model-based predictions with sensor measurements to support condition monitoring, degradation tracking, and early anomaly detection, even under uncertain conditions. They provide a scalable framework for translating diagnostics and prognostics into practical, deployable tools. In our lab, we develop Digital Twins for lithium nickel manganese cobalt oxide chemistries used in EVs, enabling real-time FDI strategies under dynamic operating conditions.

For lithium iron phosphate (LFP), dominant in grid storage and increasingly adopted in EVs, we address the challenge of accurate state-of-charge and state-of-health estimations, complicated by the chemistry's flat open-circuit voltage profile. To tackle this, we use a blended approach combining modeling, control strategies, optimization, online adaptation, and data-driven methods. We are also pioneering efforts in sodium-ion batteries, developing one of the first battery-management system architectures grounded in physics-based electrochemical models for this emerging technology.

Beyond technical performance, diagnostics and life prediction are also strategic enablers for investment. As battery systems scale, utilities, investors, and regulators rely on health monitoring to assess reliability, support warranty structuring, and manage financial risk—making diagnostics a cornerstone of sustainable energy deployment.

About the author: Simona Onori is an associate professor in energy science and engineering at Stanford University, where she also holds a courtesy appointment in electrical engineering. She is the director of the Stanford Energy Control Lab and a senior fellow at the Precourt Institute for Energy. Her lab develops models to improve, monitor, and control the performance of cutting-edge energy-storage devices.

Shengyu Tao
Tsinghua University
University of California, Berkeley

Facing data frontiers in battery diagnostics and prognostics

As battery diagnostics and prognostics grow increasingly critical for sustainable energy systems, the limitations of data have become a defining challenge for the field. Although data-driven methods promise accurate and scalable solutions, their performance is fundamentally constrained by data quality, quantity, and accessibility.

Despite decades of lithium-ion battery deployment, publicly available datasets remain surprisingly limited, amounting to fewer cells than a single EV contains. This scarcity is compounded by heterogeneity in material systems, physical formats, capacity designs, testing protocols, and missing historical metadata. Efforts to generate more data are often hindered by the high cost and time demands of battery cycling, as well as data privacy and commercial confidentiality barriers.

Addressing these constraints calls for new paradigms in how diagnostic and prognostic systems are developed. Rather than assuming unlimited high-quality data, future approaches must explicitly account for data scarcity and heterogeneity. Emerging solutions include privacy-preserving learning to enable secure trustworthy collaboration, generative models that augment sparse physical measurements, and physics-informed methods that leverage domain knowledge to compensate for data gaps.

Ultimately, overcoming these data bottlenecks is essential for ensuring diagnostic and prognostic models are accurate, generalizable, and sustainable. Doing so will accelerate safe integration of batteries into grid-level energy storage by dynamic status monitoring, enable cost-effective critical material recycling through quick condition assessment, and support the development of novel battery chemistries that require robust quality validation. Data are no longer just a tool but a resource to be preserved, engineered, standardized, and equitably shared to fulfill their full potential to provide accurate, generalizable, and accessible battery diagnostic and prognostic information.

About the author: Shengyu Tao (陶晟宇) recently received his PhD degree in electrical engineering from Tsinghua University, working with Dr. Xuan Zhang and Dr. Guangmin Zhou. He was a visiting doctoral researcher at the Energy, Controls, and Applications Lab at UC Berkeley with Dr. Scott Moura. His research includes data-driven applications for sustainable utilization of retired EV batteries, e.g., reusing, recycling, and remanufacturing, with special attention paid to battery diagnostics and prognostics under limited and heterogeneous data availability. Additionally, he works with material scientists on AI for Science topics.

David A. Howey
University of Oxford

Open challenges met with multifaceted techniques

Understanding and predicting battery lifetime and health, typically referring to capacity fade and resistance growth, are critical for informing warranties, asset operation, and maintenance strategies. This challenge can be divided into two core tasks: first, assessing the current health of a battery system, and second, forecasting how that health will evolve under expected future usage. Diagnosing health without disrupting regular operation—for example, during grid energy-storage trading—requires high-quality sensor data and prior system knowledge (e.g., open-circuit voltage curves) and is complicated by non-uniform degradation in large-scale systems. Some chemistries, like LFP, introduce further challenges due to flat voltage curves and hysteresis, making accurate estimation of state of charge and health particularly difficult.

Predicting lifetime under diverse real-world conditions remains an open challenge. Solutions range from electrochemical models to purely data-driven techniques, but for parameterization they all require extensive, high-quality data across a wide range of conditions (e.g., temperature, cycling rates). Model validation is especially difficult, because collecting representative long-term degradation data can take years, often outpaced by evolving developments in battery manufacturing and changes to internal chemistry. Additionally, manufacturing variability demands repeated testing across many cells to ensure generality.

Although there are no easy solutions, advances in statistical methods and machine learning (ML) are helping us to identify the most informative tests, and field data offer a major opportunity to improve diagnostics and lifetime prediction. In the future, combining lab and field data with robust, adaptable models could unlock real-time, large-scale prognostics for a range of battery technologies and applications.

About the author: David Howey is a professor of engineering science at the University of Oxford specializing in batteries and energy systems. He has published extensively, holds several patents, co-founded Brill Power and the Oxford Battery Modeling Symposium, and has received funding from major UK and international bodies.

Bin Zhang
University of South Carolina

Adapting to diverse conditions with new techniques

Battery diagnostics and prognostics hinge on overcoming key challenges while embracing emerging technologies. As batteries provide power for systems from EVs to grid storage, accurate and scalable diagnosis (battery-state estimation) and prognosis (battery-life predication) are critical. Research currently focuses on estimation and prediction of state of health, state of charge, state of power, and early faults, all of which could lead to battery failure or even fire. However, the growing diversity of battery chemistries and materials and manufacturing processes, including different thermodynamics, complicates battery modeling and makes parameter identification and adaptation challenging. This requires new techniques in modeling, data-processing, and diagnostic/prognostic methods as well as cooperation with industries. To build more generic battery models, including electrochemical models and thermal models, emerging techniques like ML/AI need to be developed for modeling. Additionally, more metrics that directly reflect battery longevity and safety need to be developed.

Another major challenge lies in real-time and large-scale diagnostics, where data processing and sensor integration face computational and cost barriers. New data-processing techniques are required to deal with real-world data with random and irregular charging and discharging conditions. For instance, cumulative life and Lebesgue-sampling based prognosis can be integrated. Cumulative lifetime sampling makes the random charge/discharge data more consistent, whereas Lebesgue sampling can be combined with ML/AI to greatly reduce the computational burden. The combination can handle complicated cases with variable operating conditions and degradation mechanisms. This technique is promising in offering high-quality and unified methods for battery diagnosis and prognosis.

To integrate academic research with industrial, some work needs to be done in embedded sensing and AI-driven analytics. Such techniques enable dynamic adjustments in battery-management systems, which can provide real-time feedback for managing charging and discharge profiles to not only optimize the energy but also maximize the battery lifetime. Given these research topics, interdisciplinary efforts can be developed to bridge gaps in modeling, sensing, and scalability, ensuring safer, more efficient energy-storage systems.

About the author: Bin Zhang is an associate professor in the Department of Electrical Engineering at the University of South Carolina. He obtained his PhD degree in electrical engineering at Nanyang Technological University, Singapore. His lab has over 20 years of experience in prognostics and health management, intelligent systems and control, robotics, and machine learning. Now, his lab is leveraging and applying these techniques to condition monitoring, control, and resilience in power grids and batteries, among other applications.

Katharina L. Quade
RWTH Aachen University

Extending knowledge to next-generation batteries

Even the most promising cell is only as valuable as our ability to understand and manage it in real-world operation. Therefore, as academia and industry explore emerging cell technologies to complement existing lithium-ion systems, our diagnostic and prognostic methods must evolve accordingly.

As we have researched lithium-ion systems for decades, I am particularly interested in how this knowledge can be transferred to new technologies like sodium-ion cells. We need to understand where established diagnostic approaches still apply and where adjustments are needed. Encouragingly, sodium-ion chemistries, especially those based on layered transition-metal oxide cathodes with hard carbon anodes, offer a broader voltage operating range. This benefits both model-based and direct diagnostic methods, paving the way for accurate and reliable real-time monitoring, which remains a significant limitation for the widely used LFP/C cells.

Aging prognostics for sodium-ion cells, however, is a more challenging endeavor. Early commercial cells already show fundamentally different aging behavior compared to well-established lithium-ion counterparts. To develop reliable prognostic methods that reflect these differences, broader datasets covering diverse cell types and operating conditions are needed, especially at this early stage of development. In my opinion, to unlock the full potential of prognostics, collaboration across multiple disciplines is essential: understanding the fundamental electrochemical differences requires expertise from materials science and electrochemistry, and integrating this knowledge into reliable tools depends on data science and ML. Equally important is incorporating insights from real-world application data to capture aging behavior under practical operating conditions. To facilitate this task, we need data. Open, shared datasets of electrochemical and postmortem sodium-ion data will be essential to enable diagnostics and prognostics to support the successful integration of sodium-ion cells into future energy systems.

About the author: Katharina Quade is a doctoral researcher at the Center for Aging, Reliability, and Lifetime Prediction of Electrochemical and Power Electronic Systems at RWTH Aachen University, Germany with a background in electrical engineering. Her research focuses on aging diagnostics and prognostics for lithium-ion and sodium-ion batteries through experimental analysis and data-based methods.

Matthieu Dubarry
University of Hawaii

Achieving enough accuracy

Battery diagnosis and prognosis are complex tasks, and there are still multiple challenges to overcome, especially when considering large deployed systems. Among those, a lot of the complexity arises from path dependence, where batteries exposed to different environments will likely experience a unique mix of degradation mechanisms, even within the same battery pack. This implies that prognosis cannot be predetermined and thus must be recalculated at every occasion. Although tracking signals like voltage, current, and temperature might be enough to provide a real-time state of safety, that is not the case for state of health without significant processing. One silver lining is that real time might not be necessary as, with batteries lasting close to a decade with less than 20% capacity loss, the monthly degradation is already below reasonable resolution. Therefore, I would argue that state-of-health estimation should only be performed sporadically when auspicious conditions are met, which in turn open the gate for more accurate, but calculation-intensive, model-based methodologies.

The accuracy of battery models will depend on the data used to parameterize and the data that is gatherable during usage. Tracking capacity and power will not provide enough information to detect knee points, and intrusive methodologies cannot be applied to deployed systems. An intermediate is possible with the degradation-mode approach where quantifying how much lithium or material is lost, or whether the kinetic changed, could enable diagnosis and prognosis *in situ* or *in operando* from voltage time series. This could be eased by data-driven methods, but algorithm training must be performed on representative data, which poses the problem of accelerated aging. Increasing current and temperature does introduce faster capacity losses but might degrade the cells differently and thus provide inaccurate information. This could be circumvented by generating synthetic datasets covering every possible degradation, which should remove the path-dependence barrier and allow for more consistent onboard diagnosis and prognosis.

About the author: Matthieu Dubarry, a professor at University of Hawaii at Manoa/Hawaii Natural Energy Institute, has helped to pioneer the use of data-driven techniques for the non-destructive analysis of the degradation of lithium- and sodium-ion cells and has developed numerous software tools facilitating the prognosis of battery degradation both at the single-cell and the battery-pack level. His model, ‘alawa, received significant accolades from the community and is used worldwide by universities and the industry alike.

Billy Wu
Imperial College London

Harder, better, faster, stronger

Next-generation batteries need next-generation diagnostic and prognostic techniques. Approaches to improving battery performance are numerous and often come with new challenges. Silicon-containing anodes lead to significant volume change and pressure evolution, while large-format cells amplify heterogeneous phenomena like electrolyte redistribution and localized dry-out/plating.

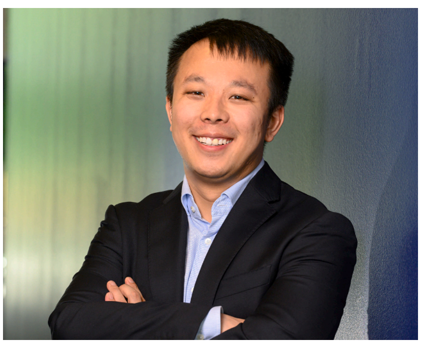
Therefore, future diagnostic and prognostic strategies must incorporate additional physical mechanisms introduced by these design changes. For instance, this could involve use of pressure or ultrasonic sensors to probe mechanical effects, though cost and integration constraints highlight the growing value of virtual sensing approaches. Ensuring that the most relevant states are being probed is also critical. Although state of health and remaining useful lifetime are among the most extensively studied states, significant gaps remain in our ability to estimate and forecast the state of safety (SOS).

Cell-scale heterogeneity will also become more pronounced with larger formats, yet many diagnostic frameworks still assume lumped or uniform behavior. Thus, methods that can detect, quantify, and model spatial heterogeneities are essential. These insights should, in turn, feed into physically informed prognostic models capable of making probabilistic forecasts, moving away from deterministic predictions.

Translating these insights into deployable solutions requires consideration of computational efficiency and state observability under real-world conditions. Emerging methods, such as ML-accelerated surrogates and hybrid physics-data-driven methods, offer promising pathways, though robust uncertainty quantification remains a critical research need.

In my view, the future of battery diagnostics and prognostics lies in accounting for new physical states, especially mechanical ones, capturing heterogeneous effects and developing efficient, multi-dimensional, and multi-physics models with due consideration of safety. Virtual sensing and hybrid physics-data ML are likely to be key enablers realizing these capabilities at scale. Exciting conceptual advances in other fields highlight the value of interdisciplinary approaches, which should be actively encouraged in the development of next-generation battery diagnostics and prognostics.

About the author: Billy Wu is an associate professor in electrochemical engineering at Imperial College London. His research bridges fundamental science and engineering applications of electrochemical devices with a focus on diagnostics, multi-scale modeling, thermal management, and control.



Weihan Li
RWTH Aachen University

Data at the core to unite physics and AI

Battery aging, safety, and reliability remain key concerns in advancing battery technology. Effective battery management is essential for ensuring reliable and efficient operation. The future of battery management is shifting from localized control by individual embedded systems to cloud-based management of numerous battery systems. This shift brings both new opportunities and significant challenges.

Future diagnostics and prognostics will rely on combining physical models with ML to extract insights from large-scale field data covering electrical, thermal, and mechanical behaviors. As sensor technologies for monitoring internal temperature and pressure become more affordable, they will be increasingly integrated into battery systems, expanding the scale and richness of data available for management. As data volumes grow, so does complexity, due to issues like data gaps, low sampling rates, and noisy signals. In such scenarios, ML, particularly deep learning, shows strong potential to uncover hidden patterns and correlations that traditional physical models might not capture effectively. Nonetheless, improving the interpretability of ML models by incorporating physical constraints remains a key focus, as it can enhance model robustness and generalization.

On the other hand, physics-based models continue to prove valuable, especially when data are limited, such as in laboratory testing. These models are increasingly being adapted for field applications, supported by control algorithms and AI techniques for parameter tuning. A key challenge for physics-based approaches is enhancing model accuracy for large-format battery cells used in both automotive and stationary energy-storage systems, where cell-level inhomogeneity cannot be overlooked.

Ultimately, data will be a decisive factor in delivering battery products with high reliability and long service life. Establishing strong connections between data from cell production, system integration, and real-world operation will unlock further possibilities and innovations.

About the author: Weihan Li is a junior professor of artificial intelligence and digitalization for batteries at RWTH Aachen University. His research integrates AI and physics to advance the digital transformation of battery technology. He has authored over 50 journal publications, holds several patents, and has received multiple honors, including recognition as a Clarivate Highly Cited Researcher and the BMBF BattFutur Starting Grant.

DECLARATION OF INTERESTS

The authors declare no competing interests.