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The role of machine learning enabled diagnostics in a circular battery economy

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SUMMARY

Machine learning-enabled battery diagnostics transform scarce and heterogeneous field battery data into reliable state indicators, enabling informed decision-making across reuse, recycling, and remanufacturing stages. By linking safety, economic value, and environmental performance, diagnostics function as critical information infrastructure for an efficient, scalable and sustainable battery circular economy.

INTRODUCTION AND CONTEXT

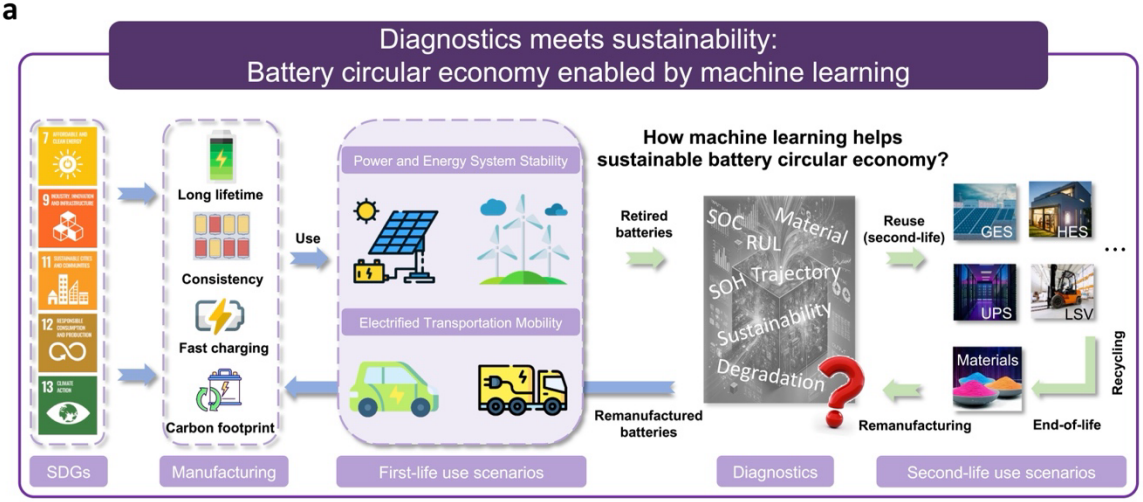
Batteries enable high penetration of variable renewables, underpin the shift to electric mobility, and support resilient power supply in critical infrastructures.[1] At the same time, large-scale deployment of batteries has exposed a set of tightly coupled sustainability concerns: constrained mineral supply chains, geographically uneven refining capacity, energy-intensive manufacturing, safety incidents during use, and a looming wave of retired packs from electric vehicles and stationary storage. [2-4]

These pressures turn the sustainability question from end-of-life mitigation into a genuinely full-lifecycle systems problem. Decisions taken at one stage of the lifecycle, such as manufacturing quality control, first-life operating conditions in electric vehicles, or the route design of reuse and recycling technology, strongly shape the environmental and economic performance of their downstream stages. However, these decisions are often made with only partial, or even missing knowledge of a battery's internal state and degradation history. Such partial knowledge of a battery can be attributed to the inaccessibility of historical battery data, as they are typically found, stored and estimated in the battery management system, which is highly confidential due to commercial or safety considerations. The inaccessibility of battery data, as well as the data in their applications, remains a critical challenge to informed decision-making across battery reuse, recycling, and remanufacturing stages. This data accessibility gap propagates along the battery lifecycle chain, leading to conservative operation, premature retirement, and sub-optimal selection of reuse or recycling pathways. [5,6]

Figure 1A further demonstrates this data accessibility gap: material and service flows follow a well-defined path, while battery data flows are currently fragmented and incomplete. Where state information is rich and reliable, stakeholders can operate batteries closer to their true capability, allocate them to appropriate second-life uses, and choose recycling routes that match their material composition and remaining value. Where information is poor, they revert to simple rules such as fixed lifetime thresholds, undifferentiated recycling processes, or even landfilling. In this context, battery diagnostics, the ability to infer internal states and degradation characteristics from accessible field signals (i.e., the field available electrical testing data instead of the privacy- or safety sensitive historical operation data) is not just a technical function but a structural enabler of battery lifecycle circularity.

The central argument of this Commentary is that machine learning-enabled diagnostics framework can act as critical information infrastructure for the decision-making in a circular economy of batteries, by turning scarce, heterogeneous, incomplete field data into decision-relevant indicators, which further connects safety, economic value, and environmental performance of batteries and can be used as a decision support in their lifecycle management.

a



b

Lifetime stage	SOC	SOH	RUL	Trajectory	Degradation	Material	Sustainability
1st Manufacturing	√	√	√	√	√		√
2nd First-life use	√	√	√		√		√
3rd Second-life use	√	√	√		√	√	√
4th Recycling use					√	√	√

Figure 1: The conceptualization of machine learning (ML) enabled battery circular economy. (A) The role of ML in the battery circular economy, i.e., using data and ML to diagnose retired batteries to inform safety- and commercial value-aware circular allocation across lifecycle. (B) The ML tasks in battery lifecycle.
SOC: State of charge; SOH: State of health; RUL: Remaining useful life; Trajectory: Capacity decay trajectory; Degradation: Aging modes (such as lithium plating, loss of lithium inventory, loss of active materials); Material: Material chemistry type; Sustainability: Economic and environmental impact; GES: Grid energy storage; HES: Household energy storage; UPS: Uninterrupted power supply; LSV: Low speed vehicle.

Battery management tasks across the lifecycle

To understand how machine learning-enabled diagnostics links to battery lifecycle sustainability, it is useful to decompose battery lifecycle management into a set of recurring tasks (Figure 1B). Each task occurs at specific stages, uses specific data streams, and informs specific decisions.

At the most basic level, state-of-charge (SOC) estimation is required across all stages, expect for recycling since at this stage the charge energy is no longer concerned. SOC governs immediate operational safety and usability; inaccurate SOC can cause over-charge, over-discharge, or unnecessary curtailment of usable capacity. SOC estimation typically relies on current integration, voltage models, or data-driven mappings between time-series measurements and stored charge.[7] Building on SOC, state-of-health (SOH) estimation assesses how much of the initial functionality, often quantified as capacity or power capability, remains available. In first-life use, SOH informs warranty enforcement, predictive maintenance, and residual value calculations. In second-life and recycling contexts, SOH acts as a gatekeeper: cells with sufficient SOH may be repurposed for less demanding applications, whereas severely degraded cells are sent directly to recycling.[6]

Remaining useful life (RUL) prediction extends SOH into the future. Instead of asking “how healthy is the battery today?”, RUL asks “how long can this battery continue to operate safely and usefully under expected conditions?”. RUL is crucial for planning fleet replacements, sizing maintenance resources, negotiating

second-life contracts, and designing business models such as battery leasing and pay-per-use schemes, especially under cross-operation conditions.[8]

While SOC, SOH, and RUL capture macroscopic performance, degradation trajectory and mechanism identification seek to understand how performance is changing and why. Trajectory prediction uses early-life patterns to anticipate long-term behavior; mechanism identification aims to distinguish, for example, between loss of lithium inventory, loss of active materials, and impedance growth.[9] Such distinctions matter because different mechanisms have different implications for safety, recoverable value, and appropriate intervention. In parallel, material classification becomes vital at the end of life. Recycling processes are often cathode-specific: mixing chemistries can reduce recovery efficiency, contaminate products, and increase environmental burdens. Identifying cathode material, and ideally even more detailed compositional information, enables tailored recycling routes and supports emerging practices such as direct regeneration.[10]

Finally, sustainability evaluation integrates diagnostic outputs with techno-economic and environmental models. Given distributions of SOH, RUL, and material composition, one can compare alternative pathways, such as extended first-life use, repurposing into grid storage or low-speed vehicles, or immediate recycling via different technologies, in terms of cost, carbon footprint, and resource efficiency.[2] Diagnostics thus provide the input data that make lifecycle optimization and policy design possible.

Sustainability implications of machine learning-enabled battery diagnostics

On the economic side, more accurate and granular diagnostics enable better asset valuation. Batteries with sufficient remaining capacity and benign degradation patterns can be confidently allocated to demanding second-life applications such as grid-connected storage, while marginal cells can be directed to less critical uses or immediate recycling.[2,6] This targeted allocation increases the overall utilization of manufactured materials and improves the business feasibility for reuse.[11]

A prominent example is the use of history-free state estimation, which is enabled by pulse-based testing and machine learning regression to rapidly assess the health of retired batteries only using field electrical current injections. Studies show that such approaches can reduce diagnostic time by more than 70%, decrease electricity consumption by up to 65 kg CO_2-eq per ton of batteries processed, and lower pretreatment costs by more than $200 per ton. These reductions strengthen the economic competitiveness of second-life pathways by increasing throughput and reducing the overhead traditionally associated with retirement sorting and evaluation.[12]

On the environmental side, reducing the need for long testing campaigns decreases electricity consumption and associated emissions. The use of generative learning for SOC- and SOH-agnostic diagnosis has been shown to substantially improve the deployability of reused batteries. Analysis of more than 2,700 retired cells covering multiple chemistries and physical format factors demonstrates that generative models can reconstruct missing voltage responses across unseen SOC levels using sparse field-tested voltage response signals, enabling robust SOH estimation even under random, uncontrolled retirement conditions. Techno-economic projections estimate that, if deployed globally by 2030, these methods could reduce electricity consumption for laboratory-based characterization by the equivalent of 4.9 billion USD in avoided testing energy costs and prevent approximately 35.8 billion kilograms of CO_2 emissions. These findings highlight that generative learning not only solves data scarcity challenges but also directly contributes to sustainability goals by reducing the need for energy-intensive experimental procedures.[13]

Improved sorting and material classification raise the efficiency and yield of recycling processes, lowering the environmental footprint per unit of recovered metal. In recycling ecosystems where data privacy has historically prevented cross-facility collaboration, federated learning allows recyclers and repurposing companies to jointly train material sorting and degradation classification models only using the field available data instead of their privacy-sensitive historical records. Experiments across multiple manufacturers and five cathode chemistries show that federated models can achieve material

misclassification rates as low as 1-3%, which in turn increases the yield of direct cathode regeneration processes and stabilizes the purity of recovered materials. This improved material stream quality enhances profitability and reduces chemical waste, strengthening the environmental and economic case for advanced recycling technologies.[10]

Additionally, physics-informed learning augments remanufacturing workflows by enabling early detection of manufacturing variability and end-of-life degradation modes. By extracting latent electrochemical parameters from short electrical excitation sequences that is available at the battery remanufacturing field, these models support the identification of cells that are suitable for module-level remanufacturing or those that require disassembly into individual cells. This intelligence can prevent the inclusion of high-risk or defect-prone cells in rebuilt modules, thereby reducing safety incidents and lowering warranty costs. Techno-economic analyses of such approaches demonstrate that early detection of failure-prone cells can reduce module-level scrap rates and save millions of dollars annually in large-scale remanufacturing facilities.[9]

From a societal perspective, robust diagnostics enhance safety by identifying cells and packs at risk of thermal runaway or sudden failure, both in first- and second-life contexts.[14] In regions with limited grid infrastructure, reliable second-life batteries can support decentralized energy access; accurate diagnostics are essential to ensure this is done accessibly and fairly.[15] Moreover, transparent and verifiable state information can build trust among consumers, regulators, and investors, facilitating wider adoption of battery-based solutions. It is important to emphasize that these benefits do not arise automatically from improved prediction accuracy alone. They materialize only when diagnostic insights are embedded in operational policies, market contracts, and regulatory frameworks that explicitly value long-term performance and circularity. Machine learning provides new capabilities, but their sustainability impact depends on how institutions choose to use them.

Toward a machine learning-native circular ecosystem for battery circular economy

Looking ahead, several research and implementation directions could strengthen the role of diagnostics in battery sustainability. First, there is a need for standardized data schemas and exchange protocols that span the lifecycle. Without a minimum level of interoperability, even the most sophisticated machine learning models will remain siloed. Efforts such as digital product passports and battery data spaces should therefore be co-designed with diagnostic researchers to ensure that the consistently formatted data and field-available data, including both raw signals and derived state estimates, can flow into the decision-making process where they are needed. Second, future models must incorporate uncertainty quantification and robustness guarantees. Decision-makers need to know not only a point estimate of SOH or RUL, but also how confident the model is, how it might fail under distributional shifts, and what safety margins are appropriate. Third, as new chemistries and architectures emerge, including sodium-ion, solid-state, and hybrid systems, diagnostic frameworks must generalize beyond today's battery landscape. Transferable representations that capture universal aspects of electrochemical storage, combined with physics-informed components, may help maintain continuity across technological transitions. Fourth, closer coupling between diagnostic models and system-level optimization is needed. Instead of treating diagnostics as a standalone module, battery management systems, energy dispatch algorithms, and lifecycle planning tools should explicitly account for diagnostic outputs and their uncertainties. This integration would align the objectives of machine learning developers, system operators, and sustainability analysts. Finally, the community must carefully consider ethical and governance aspects, for example, who owns battery diagnostic data and models given the ownership change and data privacy issue in second-life? How are errors or biases handled? How can we prevent diagnostic tools from exacerbating inequities, for example, by steering high-quality second-life batteries away from underserved communities? Addressing these questions is part of making diagnostics truly supportive of sustainable and just energy transitions underpinned by battery technologies .

Conclusions

Machine learning-enabled diagnostics is becoming a decisive lever for sustainable battery lifecycle management. By generating reliable estimates of battery states from heterogeneous and often scarce field data, machine learning provides the quantitative inputs required for sustainability assessments, including carbon footprint calculations, resource-efficiency modeling, and techno-economic optimization of reuse and recycling pathways. This integration transforms circular battery management from heuristic decision-making into analytically grounded, economically viable, and environmentally optimized practice.

To fully realize these benefits, future progress must focus on (i) establishing interoperable data standards linking diagnostic outputs with techno-economic models, (ii) developing uncertainty-aware methods to ensure safe and verifiable lifecycle decisions, (iii) enabling cross-stakeholder collaboration to break data silos across manufacturing, operation, repurposing, and recycling, and (iv) embedding diagnostic-informed sustainability metrics directly into policy mechanisms such as battery passports, extended producer responsibility schemes, and circularity incentives. By advancing these actionable directions, machine learning-enabled diagnostics can function as the information backbone of a circular battery economy, ensuring that every battery is accurately characterized, efficiently reused, and responsibly recycled, while delivering measurable reductions in cost, carbon emissions, and material waste.

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AUTHOR CONTRIBUTIONS

Conceptualization, S.T., X.Z. and C.Z.; methodology, S.T., X.Z. and C.Z.; investigation, S.T., X.Z. and C.Z.; writing—original draft, S.T., X.Z. and C.Z.; writing—review & editing, S.T., X.Z. and C.Z.; funding acquisition, S.T., X.Z. and C.Z.; resources, S.T., X.Z. and C.Z.; supervision, S.T., X.Z. and C.Z.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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