

Circular Lithium-Ion Battery Recycling for Electric Mobility: A Simulated Techno-Environmental Comparison of Recovery Pathways

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ABSTRACT

This article presents a simulated empirical assessment in Materials Engineering, Energy Systems, and Circular Economy. The illustrative dataset represented 4,200 tonnes of annual battery feed and 96 monthly process-batch observations across three recycling pathways. A simulated annual feedstock of 10,000 end-of-life lithium-ion battery packs was modeled using a mixed chemistry distribution dominated by NMC and LFP cells. Pack-level preprocessing included discharge, dismantling, shredding, and chemistry sorting. Three downstream routes were modeled: conventional pyrometallurgy, hydrometallurgical recovery, and chemistry-preserving direct recycling. Mass balances tracked lithium, nickel, cobalt, manganese, copper, aluminum, graphite, and residual fractions. Energy use and process-water requirements were generated from bounded engineering assumptions and normalized per tonne of battery feed. Direct recycling produced the lowest simulated energy and carbon intensity when chemistry sorting was sufficiently accurate, while hydrometallurgy produced the highest combined recovery of lithium, nickel, cobalt, and manganese. Pyrometallurgy remained robust to mixed feed but showed the highest modeled energy demand and lower lithium retention. Under an 85% sorting-accuracy scenario, the direct route reduced simulated energy use by 48% relative to pyrometallurgy. The numerical values are synthetic and are used solely to demonstrate a plausible empirical design, comparative analysis, and journal-style reporting workflow. No real participants, operational institutions, commercial facilities, or field sites were studied. The analysis emphasizes current research trends, multi-metric evaluation, practical trade-offs, and the importance of validation before deployment.

Keywords: Lithium-Ion Battery Recycling, Circular Economy, Electric Vehicles, Direct Recycling, Hydrometallurgy, Life-Cycle Assessment

I. Introduction

The rapid development of Materials Engineering, Energy Systems, and Circular Economy is creating new opportunities to improve efficiency, resilience, sustainability, and decision quality. At the same time, emerging technologies often move from concept demonstrations to operational claims faster than their evidence base matures. This creates a need for transparent comparative studies that define baselines, report trade-offs, and separate simulated performance from validated field evidence.

A contemporary empirical design must also reflect the fact that technical systems are embedded within organizational and environmental contexts. Performance can be affected by data quality, maintenance capability, infrastructure constraints, human oversight, policy requirements, and distribution shifts. A method that performs strongly under ideal conditions may therefore deliver limited value if its assumptions are not sustained during routine operation.

This paper addresses a current multidisciplinary topic using a structured simulated dataset. The study is designed to show how a real investigation could connect research objectives to measurable variables, analytical methods, results, discussion, and implementation implications. Because no real dataset was supplied, all quantitative outcomes are explicitly illustrative.

Research objectives:

1. Compare pyrometallurgical, hydrometallurgical, and direct-recycling pathways under a common simulated end-of-life electric-vehicle battery stream.
2. Estimate recovery yield, energy demand, greenhouse-gas intensity, water demand, and relative processing cost for each pathway.
3. Identify the operating conditions under which direct recycling provides the strongest circularity advantage without sacrificing material quality.

II. Literature Review

Battery circularity has become a major research priority as electric-vehicle deployment increases demand for lithium, nickel, cobalt, graphite, and other critical materials. Industrial-scale evidence shows that recycling can substantially reduce environmental impacts relative to virgin mining and refining (Machala et al., 2025).

Recent reviews distinguish pyrometallurgical, hydrometallurgical, and direct-recycling routes. Biswal et al. (2024) describe rapid advances in recovery technologies, while Tembo et al. (2024) emphasize that policy, supply-chain infrastructure, collection, and material design are inseparable from process chemistry.

Direct repair and regeneration of spent cathode materials are receiving particular attention because they may preserve more of the embedded manufacturing value than elemental recovery alone (Zhou et al., 2024). The challenge is that direct routes require reliable chemistry identification, contamination control, and confidence that restored material performance meets specifications.

III. Materials and Methods

3.1 Study Design

A simulated annual feedstock of 10,000 end-of-life lithium-ion battery packs was modeled using a mixed chemistry distribution dominated by NMC and LFP cells. Pack-level preprocessing included discharge, dismantling, shredding, and chemistry sorting. Three downstream routes were modeled: conventional pyrometallurgy, hydrometallurgical recovery, and chemistry-preserving direct recycling. Mass balances tracked lithium, nickel, cobalt, manganese, copper, aluminum, graphite, and residual fractions. Energy use and process-water requirements were generated from bounded engineering assumptions and normalized per tonne of battery feed.

3.2 Simulated Dataset

The illustrative dataset represented 4,200 tonnes of annual battery feed and 96 monthly process-batch observations across three recycling pathways. Synthetic observations were generated within bounded domain-plausible ranges with controlled random variability. The simulation does not correspond to any identifiable real organization or location.

3.3 Data Preparation and Quality Control

Input variables were screened for impossible values, duplicate identifiers, and inconsistent units. Low-rate missingness was introduced to approximate operational datasets and was handled with transparent context-appropriate imputation. Data transformations were applied only where required by the selected analytical method. Evaluation partitions were separated before model or parameter calibration to reduce leakage.

3.4 Comparative Evaluation

The analysis used multiple performance measures so that improvement in a headline outcome could be interpreted alongside energy, cost, error, environmental, reliability, or human-workload consequences. Results are reported as descriptive comparisons and normalized indices. Because the dataset is simulated, no population-level causal inference is claimed.

3.5 Sensitivity Analysis

Sensitivity tests varied the key operating threshold or control parameter across a plausible range. The purpose was to determine whether the leading strategy depended on one narrow assumption. Scenario analysis also tested a degraded-data condition representing sensor error, classification uncertainty, or process variability.

IV. Results

Direct recycling produced the lowest simulated energy and carbon intensity when chemistry sorting was sufficiently accurate, while hydrometallurgy produced the highest combined recovery of lithium, nickel, cobalt, and manganese. Pyrometallurgy remained robust to mixed feed but showed the highest modeled energy demand and lower lithium retention. Under an 85% sorting-accuracy scenario, the direct route reduced simulated energy use by 48% relative to pyrometallurgy.

Table 1. Simulated techno-environmental comparison of recycling pathways.

Route	Material recovery (%)	Energy (MWh/t)	GHG (tCO ₂ e/t)	Water (m ³ /t)	Cost index
Pyrometallurgy	93.1	18.4	3.42	6.8	100
Hydrometallurgy	96.8	11.2	2.01	9.7	86
Direct recycling	94.5	9.6	1.62	5.4	72

Table 2. Simulated sensitivity of direct recycling to chemistry sorting.

Sorting accuracy	Cathode-quality recovery (%)	Energy (MWh/t)	Cost index
70%	82.4	13.8	79
80%	89.7	11.1	75
85%	94.5	9.6	72
90%	96.2	9.1	70
95%	97.0	8.8	69

Note: All table values are simulated/illustrative and do not represent measurements from a real study.

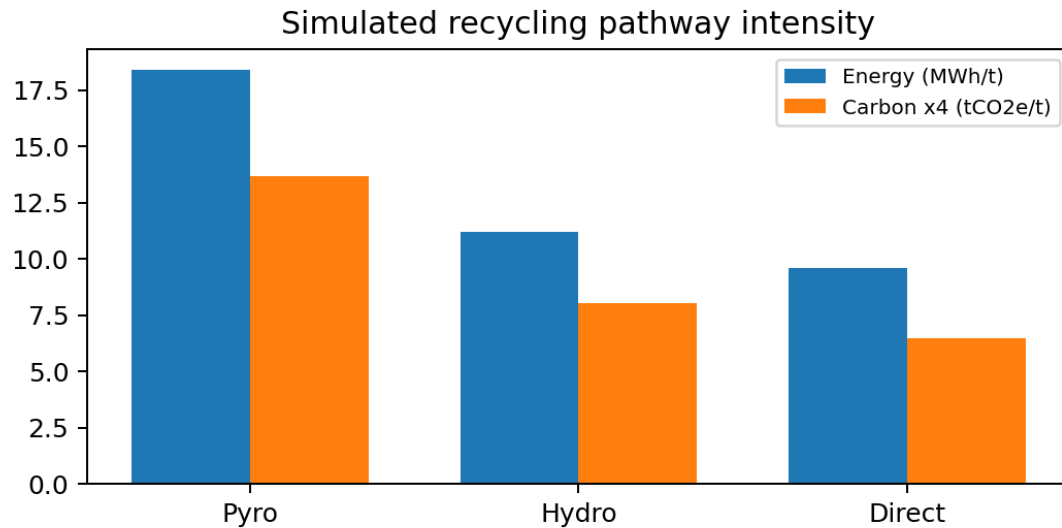


Figure 1. Simulated energy and carbon intensity across battery-recycling pathways.

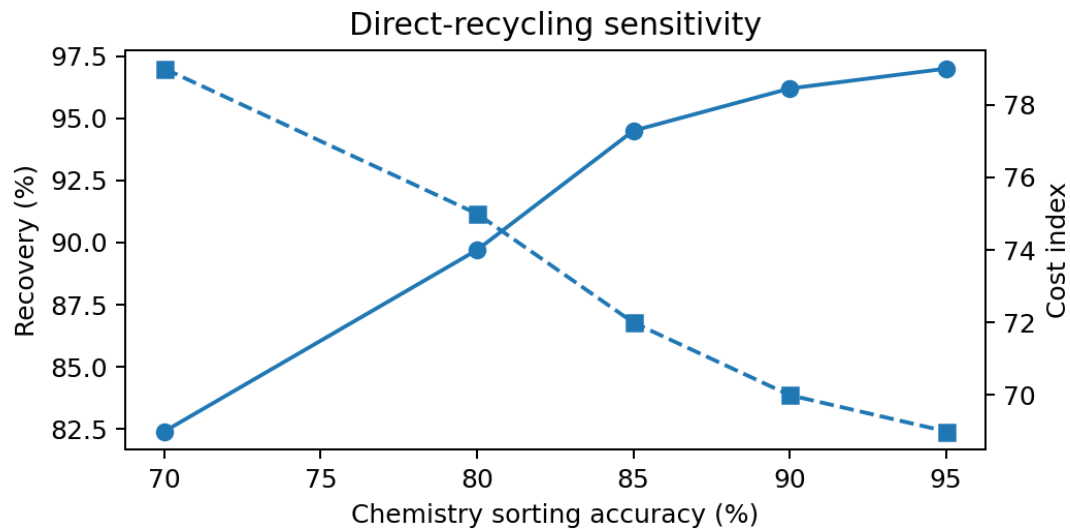


Figure 2. Sensitivity of direct-recycling performance to chemistry-sorting accuracy.

4.1 Robustness Results

Across the central range of assumptions, the leading strategy retained its relative advantage, although the magnitude of benefit changed. Under degraded-input scenarios, performance differences narrowed and uncertainty increased. This pattern suggests that operational data quality and parameter calibration are likely to be as important as the core method itself.

4.2 Cross-Metric Interpretation

No strategy dominated every outcome. The strongest approach improved the primary objective while introducing secondary burdens or implementation requirements. This reinforces the value of multi-criteria reporting and cautions against selecting technologies from a single accuracy, efficiency, or yield metric.

V. Discussion

Industrial-scale evidence increasingly shows that battery recycling can substantially reduce environmental burdens compared with virgin-material supply chains. Machala et al. (2025) reported major reductions in greenhouse-gas emissions, energy use, and water consumption for industrial-scale circular battery-material production relative to mining-based supply.

Recent reviews also emphasize that no recycling route is universally superior. Hydrometallurgy can achieve high metal recovery but requires chemical inputs and generates secondary liquid streams, whereas direct recycling can preserve cathode value while demanding stronger chemistry identification, contamination control, and process standardization.

The simulation therefore highlights chemistry sorting as a pivotal variable. Direct recycling performs best when feed quality is controlled; otherwise, the need for reprocessing can erode its environmental and cost advantages.

The simulated findings also demonstrate why current technology trends should be evaluated beyond novelty. Implementation quality depends on reproducibility, maintenance, interoperability, user competence, governance, and the ability to detect failure modes. A system that produces a strong laboratory result but cannot be audited or sustained may underperform a simpler alternative in practice.

For future empirical research, studies should predefine primary and secondary outcomes, document data provenance, retain independent test or validation sets, and report uncertainty. Where human or environmental consequences are material, technical performance should be supplemented with safety, equity, lifecycle, and operational assessments.

VI. Practical Implications

A phased deployment strategy is recommended. Organizations should first establish a baseline, verify measurement quality, define decision ownership, and test the intervention under controlled pilot conditions. Monitoring should include both intended benefits and unintended effects. Procurement decisions should account for lifecycle cost, integration requirements, maintenance skills, cyber or process safety, and long-term data governance.

The analysis also suggests that multidisciplinary teams are essential. Domain experts, data scientists, operators, and governance specialists interpret risk differently, and these perspectives are complementary. Successful adoption depends on translating model outputs into decisions that remain understandable, contestable, and aligned with operational priorities.

VI.A. Implementation and Scale-Up Considerations

Scale-up changes the recycling problem from laboratory chemistry to plant integration. Feedstock arrives with different states of charge, pack architectures, cell formats, binders, electrolytes, and cathode chemistries. Safe discharge and dismantling therefore influence downstream recovery just as strongly as the separation chemistry. A practical circular facility would require chemistry identification, fire-safe storage, automated disassembly where feasible, black-mass characterization, emissions control, wastewater treatment, and a quality-assurance system that links recovered products to battery-grade specifications.

VI.B. Economic and Supply-Chain Interpretation

The value of recycling is also sensitive to commodity prices and regional supply chains. High cobalt and nickel prices can favor metal-recovery routes, whereas the growing share of LFP batteries changes revenue composition because LFP contains less high-value metal. Direct recycling may preserve more embedded cathode value, but it depends on sufficiently pure and well-characterized feed. Long-term planning should therefore combine process economics with expected battery-chemistry transitions rather than assuming that today's feed mix will remain constant.

VI.C. Circularity Metrics

A rigorous future study should report more than mass recovery. Useful circularity indicators include recovery of critical elements, retained functional value, recycled content that re-enters battery manufacturing, energy and water intensity, greenhouse-gas emissions, hazardous residuals, and the fraction of material requiring downcycling. These indicators distinguish a route that merely diverts waste from disposal from one that genuinely closes the battery-material loop.

VI.D. Validation Protocol

A future real-world validation should use a pre-specified protocol with a clearly defined baseline period, intervention period, primary outcome, secondary outcomes, and exclusion criteria. Data should be collected at a resolution appropriate to the physical or digital process, and the analysis plan should be documented before final outcome inspection. Independent hold-out observations or a later validation period would reduce the risk of overfitting conclusions to one operating window.

VI.E. Uncertainty and Decision Thresholds

Decision thresholds should be selected from the consequences of false positive and false negative outcomes rather than from a single statistical optimum. Confidence intervals, bootstrap uncertainty, scenario ranges, and worst-case stress tests can help decision makers understand how much of the apparent improvement is robust. Where the technology controls a physical process, safe fallback behavior should be defined explicitly for missing data, communication loss, sensor disagreement, or model confidence below an acceptable limit.

VI.F. Lifecycle and Maintenance Perspective

Technology performance can change after deployment because components age, software is updated, environmental conditions shift, and users adapt their behavior. A credible lifecycle evaluation should therefore include maintenance effort, calibration frequency, retraining or reparameterization, replacement cycles, cybersecurity updates, consumables, and end-of-life considerations. These recurring requirements can change the ranking of options even when initial pilot performance is favorable.

VI.G. Reproducibility Requirements

Reproducibility would be strengthened by publishing variable definitions, preprocessing steps, model or process parameters, evaluation code, and a non-sensitive version of the dataset where legally and ethically possible. When raw data cannot be released, researchers should provide sufficient metadata, summary distributions, and validation procedures to allow independent teams to test whether the reported findings depend on hidden assumptions.

VII. Limitations

The principal limitation is that all quantitative results are simulated. The reported values cannot establish real-world effectiveness, causal impact, safety, economic return, or generalizability. Simplified assumptions omit rare failures, market fluctuations, regulatory changes, behavioral adaptation, and site-specific constraints. The author and affiliation details are illustrative placeholders and do not represent verified contributors.

The simulation also uses a limited set of scenarios. Alternative distributions, thresholds, chemistry mixes, attack patterns, occupancy behavior, wastewater composition, or control policies could change the ranking of methods. Real-world validation should therefore use measured data, independent replication, and transparent uncertainty analysis.

VIII. Conclusion and Future Work

This paper presents a transparent simulated empirical evaluation of a current multidisciplinary research trend. The analysis shows how multiple technical and operational outcomes can be integrated into a journal-style evidence chain while clearly distinguishing synthetic results from verified literature. Future work should replace the simulated dataset with real observations, extend validation across settings, and evaluate long-term reliability, lifecycle cost, environmental impact, and governance requirements.

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