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Development of a Statistical Benchmarking Methodology for Black Mass Quality Standards Using a Capacity-Reliability-Weighted Mean

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Research Article

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Abstract

The rapid growth of lithium-ion battery recycling emphasizes the need for standardized black mass (BM) quality criteria to ensure process stability and trading transparency. This study proposes an industrial benchmarking framework using data from three major South Korean recyclers, covering 58% of national capacity. We developed a novel Capacity-Reliability-Weighted Mean (CRWM) model that integrates facility scale with statistical consistency. Evaluation through sensitivity analysis confirms that CRWM provides more stable benchmarks than conventional methods, especially for impurity parameters like fluorine and copper. While valuable metal content varies by battery chemistry, impurity thresholds serve as reliable indicators for quality control. These benchmarks offer practical guidance for optimizing hydrometallurgical processes, reducing reagent consumption, and improving product purity. Ultimately, this framework establishes a technical foundation for global quality standards for intermediate recycling materials, enhancing communication and reliability within the battery recycling market.

1. Introduction

The rapid expansion of the electric vehicle (EV) market driven by global carbon neutrality initiatives has led to a significant increase in the demand for lithium-ion batteries (LIBs) (Ralls et al., 2023). Consequently, the volume of end-of-life LIBs is expected to grow substantially, intensifying global interest in battery recycling as a strategy for both resource circularity and the recovery of critical raw materials such as lithium (Li), nickel (Ni), and cobalt (Co) (Zhang et al., 2025). In response, regulatory frameworks such as the European Battery Regulation have established ambitious recovery targets, further accelerating the development of efficient recycling technologies (European Commission, 2023; Bird et al., 2022; Windisch-Kern et al., 2022).

During the recycling of LIBs, mechanical pretreatment processes such as crushing and separation generate black mass (BM), a fine powder composed primarily of cathode and anode materials. Owing to its high metal content, BM serves as the principal feedstock for downstream hydrometallurgical recovery processes. However, BM is not a pure material and contains a wide range of impurity elements originating from battery components and processing steps. In practical recycling markets, the absence of standardized BM quality benchmarks creates significant uncertainty in feedstock trading. Variations in quality specifications across suppliers often result in mismatches with refinery requirements, leading to unstable process performance, increased reagent consumption, and potential equipment degradation. This lack of harmonized criteria also limits the development of transparent pricing mechanisms for BM, thereby constraining the scalability of global battery recycling supply chains. As a result, establishing representative and industry-relevant BM quality benchmarks has become a critical prerequisite for improving both process efficiency and market transparency in battery recycling systems.

Typical impurities include aluminum (Al) and copper (Cu) from current collectors, iron (Fe) from casings and equipment abrasion, and fluorine (F) derived from electrolyte and binder materials such as $LiPF_6$ and polyvinylidene fluoride (PVDF) (Krüger et al., 2014; Wang et al., 2023).

These impurity elements play a critical role in determining the efficiency and stability of hydrometallurgical recycling processes. For example, Al and Cu can increase acid consumption and interfere with precipitation and separation processes, thereby reducing recovery efficiency (Chernyaev et al., 2021; Or et al., 2020). Fluorine is particularly problematic due to its association with corrosion of process equipment, degradation of extractants during solvent extraction, and contamination of lithium products (Demirel et al., 2022; Windisch-Kern et al., 2022; Doose et al., 2021). In addition, iron may influence redox reactions in leaching systems, while other contaminants introduced during processing can further affect solution chemistry and process performance (Lombardo et al., 2020; Xu et al., 2021). These characteristics indicate that BM quality is inherently linked not only to valuable metal content but also to impurity levels that reflect process constraints.

Accordingly, industrial BM quality specifications are typically defined based on both economic value and process feasibility. However, existing approaches to defining BM quality standards vary significantly across countries. In China, a national standard (GB/T 45203 – 2024) incorporates a wide range of chemical parameters, including process-related indicators such as water-soluble fluorine and molar ratios, and classifies BM as a product when the criteria are satisfied. In Japan, the Battery Association for Circular Systems (BACS) has developed a classification scheme based on key compositional criteria, although BM is still regulated as waste. In South Korea, regulatory efforts focus on recycling requirements, including minimum metal content(Ni 10%) and leaching limits for hazardous substances, with additional requirements for solvent removal.

These differences demonstrate that BM quality standards are largely shaped by policy objectives and process requirements, resulting in significant variability across regions. Despite the growing importance of BM as a key intermediate in battery recycling, there remains a lack of systematic and academically grounded methodologies for deriving representative quality benchmarks that reflect industrial practice.

To address this gap, this study proposes a statistical framework for deriving industry-representative BM quality benchmarks based on industrial specifications. Quality management data from major recycling facilities were integrated using a capacity-weighted approach to reflect the structure of industrial processing capacity. By incorporating industrial operational characteristics into the analysis, this study aims to provide a more realistic representation of BM quality requirements compared with conventional averaging methods.

The contributions of this study are threefold. First, the role of key impurity elements in hydrometallurgical processes is examined. Second, representative BM quality benchmarks are derived using industrial data and a capacity-weighted framework. Third, the applicability of the proposed benchmarks is evaluated using literature-reported BM composition data, providing a basis for their broader industrial relevance.

2. Methodology

2.1 Proposed Industrial Benchmarking Framework

The existing literature on BM has predominantly focused on laboratory-scale chemical characterization, providing valuable insights into material composition (Pourmohammad et al., 2025). However, industrial recycling facilities determine feedstock suitability based on operational specifications that ensure process stability and equipment longevity in large-scale hydrometallurgical systems. This creates a critical discrepancy between theoretical laboratory data and the practical quality thresholds applied in industry. Furthermore, since these specifications vary across facilities depending on processing capacity and technology configurations (Latini et al., 2022), benchmarks derived from a single facility lack industry-wide representativeness.

To bridge this gap, this study proposes an industrial benchmarking framework that integrates facility-level specifications through statistical aggregation and robustness evaluation. The framework aims to establish representative quality thresholds grounded in actual industrial practice. The analytical workflow is structured into four primary stages, as illustrated in Fig. 2.

Stage 1: Data Collection and Pre-processing The first stage involves the collection of industrial BM quality specifications from major recycling facilities. By comparing these specifications, the study identifies the key parameters used in feedstock management, providing the empirical basis for defining the quality control metrics essential for industrial operations.

Stage 2: Data Integration and Statistical Analysis To derive representative benchmarks, a capacity-weighted mean (CWM) approach is applied to the collected specifications. Since large-scale facilities process a dominant share of the national BM feedstock, their operational criteria exert a more significant influence on effective industry standards (Wang, X., et al., 2014). In addition to weighted averages, the framework incorporates statistical measures, including standard deviations and confidence intervals, to quantify the distribution and reliability of the integrated data.

Stage 3: Robustness and Sensitivity Evaluation The third stage assesses the stability of the derived benchmarks through variability and sensitivity analyses (Saltelli, A., et al., 2019). By systematically excluding individual facility datasets (Leave-one-out approach) and recalculating the thresholds, the analysis evaluates whether the benchmarks are overly sensitive to specific facility conditions, thereby ensuring the robustness of the proposed framework.

Stage 4: Validation and Industrial Implications Finally, the applicability of the established benchmarks is evaluated by comparing them with independent literature data on BM composition. This validation step confirms whether the derived thresholds remain consistent with broader material characteristics. Based on these results, the study provides practical implications for BM quality management, defining acceptable concentrations for valuable metals and maximum limits for critical impurities in downstream processes.

2.2 Collecting Data

To ensure the reliability of the analysis, this study collected industrial BM quality specification data from three major lithium-ion battery recycling companies operating hydrometallurgical facilities in South

Korea. The internal quality specifications of companies (A, B, and C) were collected and used as the primary dataset.

While the dataset comprises three primary recycling entities, these facilities collectively account for 58% of South Korea's total national hydrometallurgical processing capacity (388 out of 668.7 ton/day).

The collected specifications include impurity limits and minimum valuable metal contents defined for BM feedstock prior to hydrometallurgical processing.

In cases where composition limits were presented as ranges, the midpoint value was adopted as the representative value for statistical analysis. This approach minimizes potential bias that may arise when selecting either the minimum or maximum values and provides a balanced estimate of the typical operational thresholds applied in industrial facilities.

Smaller facilities were excluded from the analysis because many of them operate pilot-scale or mixed recycling processes where standardized BM quality specifications are not formally established.

Although the dataset is limited to three facilities, these companies represent a highly concentrated segment of the domestic hydrometallurgical recycling industry. Their combined processing capacity accounts for approximately 58% of the national total, indicating that their operational practices strongly influence industry-level standards. Therefore, the derived benchmarks reflect the operational tendencies of dominant industrial players rather than representing a statistically complete population.

However, given the limited number of facilities, the results should be interpreted as an exploratory industrial benchmark rather than a fully generalized industry standard. Despite the limited sample size, the dataset captures a highly concentrated segment of the industry in which a small number of large-scale facilities dominate material processing capacity. In such industrial structures, representativeness is more strongly determined by capacity share than by the number of entities, supporting the validity of capacity-weighted aggregation in this context. Therefore, the objective of this study is not to achieve statistical generalization in a conventional sense, but to reflect the operational reality of dominant industrial players whose specifications effectively define de facto industry standards.

2.3 Methodology development for quality standard

2.3.1 Capacity-Weighted mean(CWM)

Because hydrometallurgical recycling facilities differ substantially in their processing capacities, their operational specifications do not contribute equally to the effective industrial practice (Marsh et al., 2025).

Large-scale facilities process a significantly larger share of national BM feedstock, and therefore their quality specifications exert a stronger influence on the practical operational benchmark of the industry (Marsh et al., 2025).

In many comparative studies, specification values from multiple facilities are integrated using a simple arithmetic mean. However, this approach implicitly assumes that all facilities contribute equally to the industry-level operational conditions(Beaudet, A. et al. 2020). In reality, recycling plants vary widely in their processing capacities, and treating small pilot-scale facilities and large industrial plants equally may introduce statistical bias.

To address this limitation, this study adopts a capacity-weighted estimator in which the contribution of each facility is proportional to its processing capacity (Beskorovainyi, D. et al., 2025; Sands, A. et al., 2025). This approach allows facilities with larger processing throughput to exert a greater influence on the derived benchmark values, thereby reflecting the actual industrial structure of BM processing.

The weight of each facility was defined as:

$$W_i = \frac{C_i}{\sum C_i}$$

1

Where,

- W_i is the weight of facility i
- C_i is the daily BM processing capacity of facility i

The capacity-weighted average for each component was calculated as

$$X_w = \sum W_i \times S_i$$

2

Where,

- X_w is the capacity-weighted threshold
- S_i is the specification value reported by facility i

To further justify the use of the capacity-weighted approach, the results were compared with those obtained using a simple arithmetic mean. While the arithmetic mean assumes equal contribution of all facilities, CWM method accounts for the dominance of large-scale operations, thereby providing a more realistic representation of industrial practice. This distinction is particularly important in industries where processing capacity is unevenly distributed.

2.3.2 Capacity-Reliability-Weighted Mean(CRWM)

To derive industry-relevant benchmarks from a limited number of industrial specifications, this study proposes a heuristic weighting approach termed the Capacity-Reliability-Weighted Mean (CRWM), which

integrates elements of scale-based weighting and robust central tendency estimation. This method calculates the final weight ($W_{i,j}$) for each facility i regarding quality parameter j by integrating two distinct factors: the Scale Factor (S_i) and the Reliability Factor ($R_{i,j}$).

(1) Scale Factor (S_i)

To account for the operational dominance of large-scale facilities while preventing the statistical bias caused by extreme capacity variances. The logarithmic transformation is applied to mitigate the disproportionate influence of extremely large facilities, a common issue in skewed industrial datasets, while preserving the relative dominance structure. a logarithmic transformation is applied to the capacity (C_i) of each facility:

$$S_i = In(C_i + 1)$$

3

This transformation compresses the weight distribution, ensuring that while the influence of major recycling plants is maintained, the data from smaller facilities are not numerically marginalized.

(2) Reliability Factor ($R_{i,j}$)

The reliability factor is designed to reflect the degree of agreement with the central tendency of the dataset. By using the median as a robust estimator of central tendency, this approach reduces the influence of extreme or facility-specific specifications, consistent with principles used in robust statistics. It is defined as the inverse of the absolute deviation between an individual specification ($x_{i,j}$) and the industrial median ($Median_j$) for parameter j:

$$R_{i,j} = \frac{1}{|x_{i,j} - Median_j| + \epsilon}$$

4

where Є is a small smoothing constant (ε = 0.1) is introduced to avoid division instability and to prevent excessive weight concentration. Sensitivity to this parameter was tested and found to have negligible influence on the final benchmark values.

(3) Final Benchmark Derivation

The integrated weight ($W_{i,j}$) is determined by the product of the scale and reliability factors. The final representative benchmark (B_j) for each quality parameter is then calculated as the weighted average:

$$W_{i,j} = S_i \times R_{i,j}$$

5

$$B_j = \frac{\sum_{i=1}^{n}(x_{i,j} \times W_{i,j})}{\sum_{i=1}^{n} W_{i,j}}$$

6

This dual-layered approach econtributes to improving the robustness of the resulting benchmarks against both monopolistic data dominance by a single large firm and idiosyncratic outliers from smaller pilot-scale operations.

It should be noted that the CRWM is not intended as a mathematically optimal estimator, but rather as a pragmatic approach to integrate industrial specifications under conditions of limited data availability. Nevertheless, its validity lies in its ability to capture both industrial dominance and statistical consistency, which are not simultaneously addressed by conventional estimators. The proposed CRWM can be conceptually aligned with robust statistical estimation approaches, where the influence of extreme or facility-specific values is moderated through deviation-based weighting. In contrast to conventional estimators such as arithmetic mean or capacity-weighted averaging, which are sensitive to dominance or skewness, the CRWM introduces a reliability adjustment based on proximity to the median, thereby enhancing resistance to outliers while preserving industrial representativeness. Therefore, the CRWM can be interpreted as a pragmatic yet theoretically informed estimator designed for industrial datasets where both operational dominance and data variability must be considered simultaneously.

2.4 Variability analysis

2.4.1 Leave-one-out sensitive

The robustness of the framework was rigorously validated through leave-one-out sensitivity analysis(Chen et al., 2015). The results demonstrated that even when excluding the largest facility, the fluctuation in critical impurity thresholds remained negligible, confirming that the derived benchmarks are stable and not overly reliant on a single data source

To quantitatively evaluate the stability of benchmark values derived from different aggregation methods, a sensitivity variability analysis was performed. First, the benchmark values were recalculated using a leave-one-out procedure in which one facility dataset was excluded at a time. This generated three benchmark scenarios (A + B, A + C, and B + C) for both the arithmetic mean and CWM approaches.

2.4.2 Variability analysis

For each parameter, the variability of the benchmark estimates was calculated based on the relative fluctuation of the values obtained from the leave-one-out scenarios. Specifically, variability was defined as the normalized range of the benchmark estimates according to the following Eq. (7) (Townsend and Colonius 2025):

$$Variability\,(\%) = \frac{X_{max} - X_{min}}{X_{mean}} \times 100$$

7

where X_{max} and X_{min} represent the maximum and minimum benchmark values obtained from the leave-one-out combinations, and X_{mean} represents the average of the benchmark values across the sensitivity scenarios.

This procedure was applied independently to both the arithmetic mean and CWM benchmarks for all evaluated parameters. The resulting variability values were then compared to assess the robustness of the two aggregation methods. Lower variability indicates that the benchmark values remain stable even when individual facility datasets are excluded, thereby suggesting greater statistical robustness and reduced sensitivity to sample composition. The calculated variability values were subsequently visualized to illustrate the difference in stability between the arithmetic and capacity-weighted estimation approaches.

2.5 Quantitative Validation Using Literature Data

To evaluate the practical applicability and global relevance of the proposed capacity-weighted benchmarks, a comprehensive literature-based validation was performed. This stage evaluates the consistency between the proposed benchmark values and previously reported BM compositions in the literature. Rather than a binary pass/fail assessment, this analysis quantifies the degree of agreement between model-derived thresholds and independent datasets.

To provide a quantitative evaluation, two complementary metrics were applied. First, the deviation between literature-reported values and benchmark thresholds was calculated for each parameter. Second, the proportion of data falling within acceptable deviation ranges was analyzed to assess consistency across different statistical models.

3. Results and Discussion

3.1 Quality Specifications of BM in Major Domestic Recycling Companies

The internal BM quality specifications collected from three major recycling companies are summarized in Table 1. The results show that all companies define minimum content thresholds for valuable metals and upper limits for impurity elements that may interfere with hydrometallurgical processing.

The industrial specifications collected in this study reflect these process-related considerations. For valuable metals, Company B and Company C require a minimum Ni content of ≥ 15 wt%, whereas Company A allows a wider range of 10–50 wt%. A notable difference was observed for Co content: Company C requires ≥ 10 wt% Co, while Company B only specifies ≥ 2 wt%. This difference suggests that

Company C preferentially processes high-nickel battery scrap, which typically contains higher concentrations of nickel.

Impurity limits also showed significant variation among companies. For example, the allowable Fe concentration ranged from ≤ 0.5 wt% in Company A to ≤ 3.0 wt% in Company B, while Company C maintained an intermediate threshold of ≤ 1.3 wt%. Copper limits were similarly variable, ranging from ≤ 3.5 wt% to ≤ 5.0 wt%. These differences likely reflect variations in hydrometallurgical process configurations and tolerance levels for impurity elements during leaching stages.

Halogen elements were also controlled in the specifications. Fluorine limits were relatively consistent across companies (≤ 2.0–2.1 wt%). This consistency suggests that the industry has reached a consensus on minimum pretreatment standards. The limit implies that all suppliers are expected to perform at least a basic level of thermal treatment (pyrolysis) or advanced mechanical separation to remove a portion of the electrolyte and PVDF before the BM reaches the leaching stage.

Chlorine was explicitly regulated only by Company C (≤ 0.01 wt%), suggesting stricter corrosion control requirements in that facility.

Water content limits ranged from ≤ 5 wt% to ≤ 20 wt%. Interestingly, the largest facility (Company C) allowed higher water content compared with the other companies. This may indicate the presence of more advanced drying or thermal pretreatment systems capable of handling wetter feedstock materials.

Overall, the observed variation in BM quality specifications among companies highlights the lack of standardized feedstock quality criteria in the recycling industry. These differences provide a strong rationale for applying the capacity-weighted statistical approach proposed in this study to derive representative industrial benchmark values for BM quality management.

Table 1
Industrial BM quality specifications from three recycling companies

(Unit: wt%)			
Parameter	**Company A**	**Company B**	**Company C**
Ni	10–50	≥ 15	≥ 15
Co	3–9	≥ 2	≥ 10
Fe	≤ 0.5	≤ 3.0	≤ 1.3
P	≤ 0.6	≤ 1.0	≤ 1.1
Li	≥ 3	≥ 3.0	≥ 3.0
F	≤ 2.0	≤ 2.0	≤ 2.1
Mn	≥ 4	≤ 10	≤ 9
Cu	≤ 4	≤ 5.0	≤ 3.5
Al	≤ 3	≤ 3.0	≤ 3.2
Mg	≤ 0.3	≤ 0.5	≤ 0.2
K	≤ 0.4	≤ 0.1	–
Si	–	≤ 0.5	–
Ca	–	≤ 0.5	≤ 1.7
Cl	–	–	≤ 0.01
water	≤ 5	≤ 7	≤ 20
Zn	–	≤ 1.0	≤ 5.5
Pb	–	–	≤ 0.1
Cd	–	–	≤ 0.01

3.2 Quality standard

Figure 3 presents a comparison of BM quality benchmarks derived from three different statistical methods: Arithmetic Mean, CWM, and the proposed CRWM. The results indicate that the choice of methodology significantly influences the resulting thresholds, reflecting different assumptions about industrial representation.

For valuable metals, the three methods yielded distinct results. The arithmetic mean produced the highest Ni content (20.00 wt%), while the CWM and CRWM provided more conservative estimates (18.48 wt% and 17.78 wt%, respectively). Conversely, for Co, the CRWM (6.05 wt%) and arithmetic mean (6.00

wt%) showed high alignment, whereas the simple CWM (8.70 wt%) was significantly higher, being heavily influenced by the specific requirements of the largest processing facility. This divergence suggests that while the CWM captures operational dominance, the CRWM effectively moderates this influence by incorporating a reliability factor, preventing the benchmark from being skewed by a single facility's unique feedstock profile.

A similar trend was observed for impurity elements. For Fe and Cu, the CRWM provided the most stringent thresholds (1.09 wt% and 3.97 wt%, respectively) compared to the arithmetic mean (1.60 wt% and 4.17 wt%). This indicates that large-scale facilities with advanced purification systems often apply stricter impurity controls, and the CRWM further refines these limits by identifying the consensus across high-reliability data sources. In contrast, for stable parameters such as Li, F, and Al, the differences between the three methods were minimal, confirming that these elements have reached a degree of "industrial consensus" regardless of the facility scale or statistical weighting.

Overall, the comparison demonstrates that the CRWM does not merely provide a numerical average but serves as a "balanced industrial benchmark." While the arithmetic mean assumes equal importance across all facilities and the CWM reflects pure capacity dominance, the CRWM integrates both scale and data reliability. This tripartite analysis confirms that the CRWM provides a more robust and representative standard, essential for stabilizing quality requirements in the increasingly complex global BM market. From an operational perspective, the proposed benchmark thresholds can be directly linked to key hydrometallurgical performance indicators. For instance, maintaining fluorine concentrations below approximately 2 wt% is essential to minimize HF generation and prevent extractant degradation during solvent extraction processes. Similarly, strict control of iron and copper concentrations reduces co-precipitation and impurity carryover, thereby improving metal recovery efficiency and product purity while lowering sludge generation.

3.3 Variability analysis

To evaluate the statistical robustness of the proposed framework, a variability analysis was conducted comparing the arithmetic mean and CRWM. As illustrated in Fig. 4, the integrated weighting approach which accounts for both facility processing capacity and data reliability significantly stabilizes the benchmark estimates.

The most pronounced reduction in variability was observed for high-value metals; specifically, the variability for Co and Mn decreased from 67% to 9% and 78% to 24%, respectively. By incorporating a reliability factor that penalizes idiosyncratic outliers through median deviation, the CRWM ensures that the resulting benchmarks are not only representative of large-scale operations but also statistically consistent across the industry. On average, the proposed CRWM method achieved a 35% in parameter variability.

3.5 Applicability Validation of Industrial Benchmarks

Figure 5 presents a comparative analysis of literature-reported BM compositions against the thresholds derived from the three statistical models: Arithmetic Mean, CWM, and the proposed CRWM. The box-and-whisker plots visualize the inherent variability in academic data (n = 14), while the horizontal lines represent the derived industrial benchmarks.

Overall, the CRWM model demonstrated superior robustness in bridging the gap between highly variable literature data and industrial requirements. As shown in Fig. 5, for critical valuable metals such as Ni and Co, literature values exhibit extreme dispersion (2.1–38.2 wt% for Ni), reflecting diverse battery chemistries. While the arithmetic mean (blue dashed line) is easily skewed by high-nickel outliers, the CRWM establishes a more conservative and realistic benchmark (17.78 wt% for Ni) by prioritizing high-reliability industrial specifications.

The effectiveness of the CRWM is most evident in impurity management. For Fe and P, despite the presence of significant outliers in literature (e.g., Ref 4 at 6.1 wt% Fe), the CRWM remained stable at 1.09 wt%, aligning with the stringent requirements of hydrometallurgical refineries for corrosion and precipitation control. Similarly, for F and Li, the CRWM benchmark passes through the densest concentration of literature data, suggesting a strong consensus between academic observations and industrial quality standards.

In contrast to the simple CWM, which can be disproportionately influenced by the specific feedstock of a single dominant facility, the CRWM incorporates a reliability factor that effectively filters out idiosyncratic data. This results in a "balanced industrial consensus" that is less sensitive to sample composition.

The high pass rates for impurity-related parameters (Fe: 89%, Al: 80%) confirm that these thresholds are highly compatible with current recycling operations. These results indicate that the CRWM-derived benchmarks provide a statistically grounded and practically applicable framework for the global standardization of BM quality, facilitating more transparent and stable feedstock trading in the battery recycling market.

3.6 Limitation

Although the proposed BM quality benchmarks were derived from industrial specifications of major recycling companies, several limitations should be acknowledged.

First, the proposed benchmark primarily reflects BM generated from nickel-based lithium-ion batteries such as NCM and NCA chemistries. These battery types are currently the dominant feedstock for hydrometallurgical recycling processes due to their high content of valuable metals such as Ni and Co. However, lithium iron phosphate (LFP) batteries, which have recently experienced rapid growth in market share, were not sufficiently represented in the dataset because clear industrial quality specifications for LFP-derived BM are not yet widely established in domestic recycling facilities. Since the metal composition of LFP BM differs substantially from that of nickel-based batteries, future research should consider developing dedicated benchmark criteria for LFP-derived recycling streams.

Second, the industrial dataset used in this study was limited to quality specifications from three major recycling companies. Although these facilities represent a substantial portion of the national hydrometallurgical processing capacity, the dataset does not encompass all domestic or international recycling operators. In practice, acceptable impurity thresholds may vary depending on the specific hydrometallurgical processes employed, such as leaching conditions, solvent extraction systems, or purification technologies. Therefore, while the proposed benchmark provides a useful reference framework, its application in different industrial contexts may require minor adjustments depending on process-specific operational conditions.

Future studies may also consider integrating dynamic market data such as metal price fluctuations or feedstock composition variability when defining industrial BM quality benchmarks.

4. Conclusion

This study developed an industrial benchmarking framework for evaluating the quality of BM, the primary feedstock used in hydrometallurgical recycling of lithium-ion batteries. By integrating industrial quality specifications with facility processing capacity, a capacity-based statistical approach was employed to derive representative benchmark values that reflect actual industrial practices.

The analysis incorporated internal quality specifications from three major recycling companies, representing approximately 58% of the national hydrometallurgical processing capacity. Based on this dataset, the study established representative benchmark values for key BM quality parameters, including minimum thresholds for valuable metals and maximum limits for critical impurities. Compared to conventional arithmetic averaging, CWM provided a more realistic representation of industrial conditions by accounting for the structural dominance of large-scale facilities.

To further improve robustness, this study proposed CRWM, which integrates both scale effects and statistical consistency. The results demonstrated that the CRWM effectively reduces sensitivity to outliers while maintaining industrial representativeness, particularly for impurity-related parameters. The variability analysis confirmed that the proposed method significantly enhances the stability of benchmark estimates compared to conventional approaches.

The applicability validation using literature-reported BM compositions showed that impurity-related thresholds exhibit relatively high consistency across datasets, whereas valuable metal contents are more strongly influenced by battery chemistry and feedstock variability. This finding suggests that impurity thresholds may serve as more reliable indicators for industrial quality control in hydrometallurgical recycling processes.

From a practical perspective, the proposed benchmark values provide actionable guidance for both upstream and downstream operations. Specifically, impurity thresholds can support process optimization by reducing operational instability, minimizing reagent consumption, and improving product purity. In addition, the establishment of standardized quality criteria can enhance communication

between BM suppliers and recycling facilities, thereby reducing the risk of feedstock mismatch and improving transaction reliability.

Beyond process-level implications, this study also highlights the potential role of industrial benchmarking in supporting regulatory and market development. The proposed framework can contribute to defining objective quality criteria for intermediate recycling materials, facilitating the distinction between product-grade BM and waste streams. This is particularly relevant in the context of emerging regulatory frameworks such as the EU Battery Regulation, where traceability, material classification, and recycling efficiency are becoming critical considerations.

Overall, the proposed framework provides a transparent and practically grounded methodology for establishing industry-representative BM quality benchmarks. By bridging the gap between laboratory-based characterization and industrial operational requirements, this study contributes to improving both process efficiency and market transparency in the rapidly expanding battery recycling sector.

Future research should expand the dataset to include a broader range of recycling facilities and battery chemistries, particularly lithium iron phosphate (LFP) systems. In addition, integrating dynamic factors such as market conditions and feedstock variability may further enhance the applicability of industrial benchmarking approaches in circular economy systems.

Declarations

Author Contribution

Dowan Kim: Conceptualization, Methodology, Software, Data Curation, Formal Analysis, Investigation, Validation, Visualization, Writing - Original Draft, Writing - Review & Editing.

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Figures

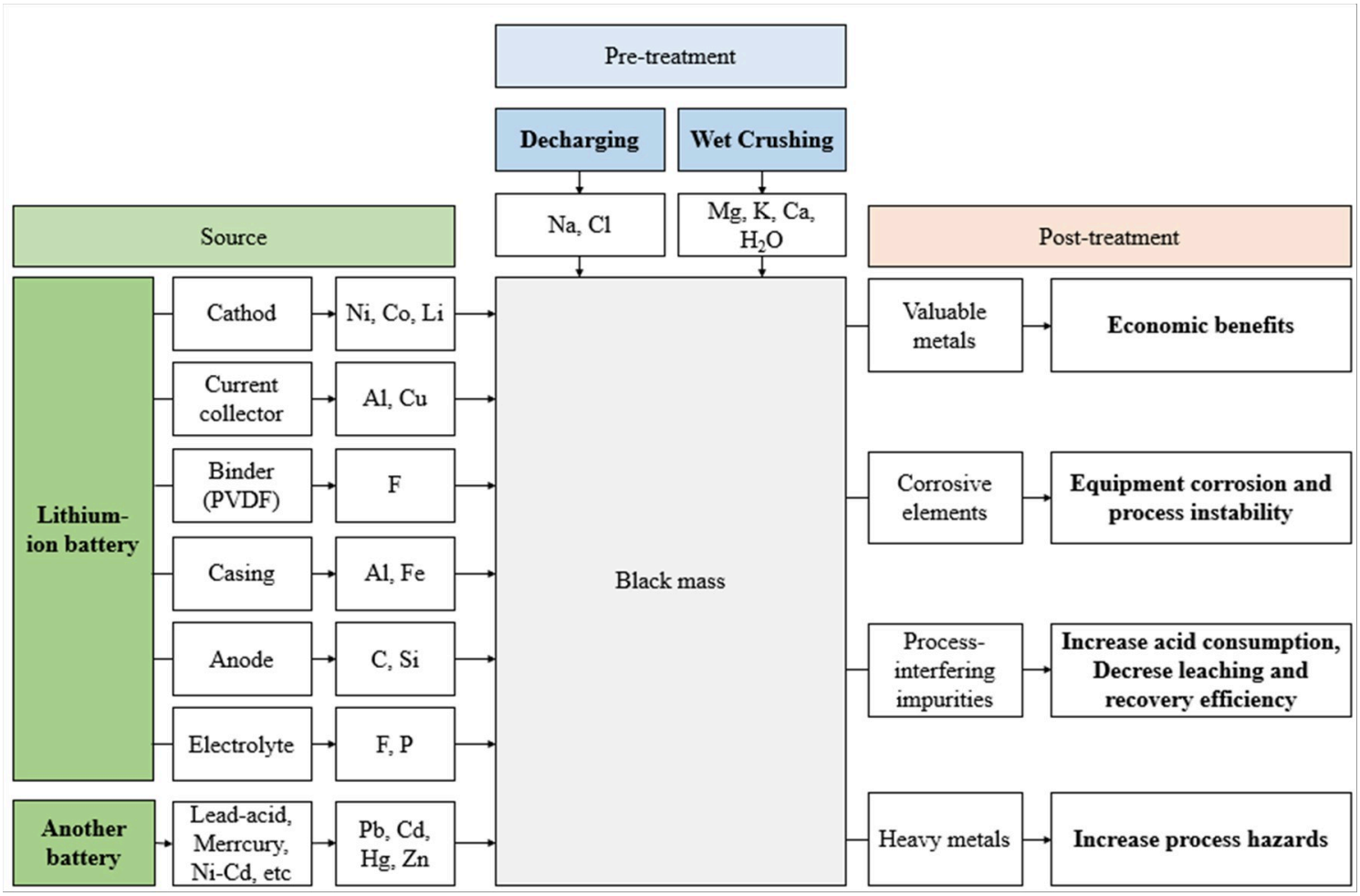


Figure 1

Inflow pathways of BM components and their functional classification based on impacts on hydrometallurgical recycling processes

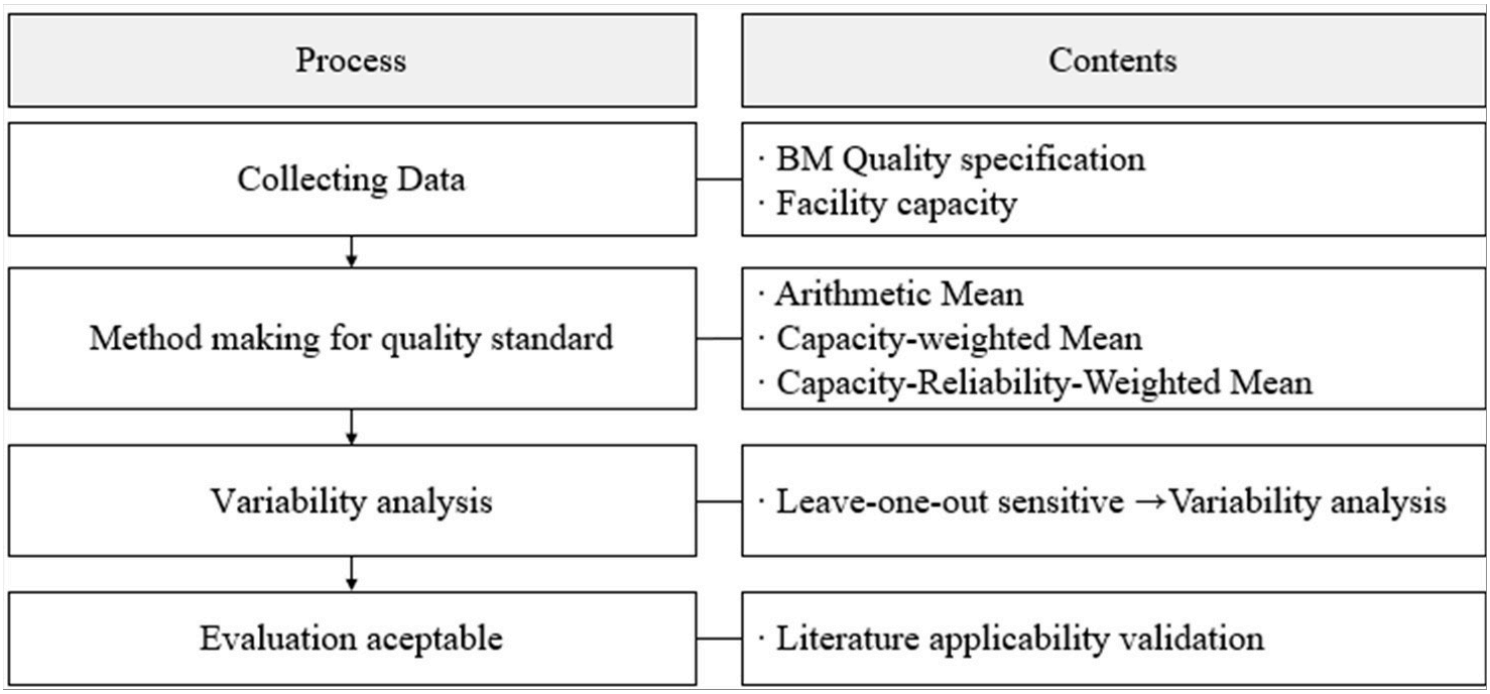
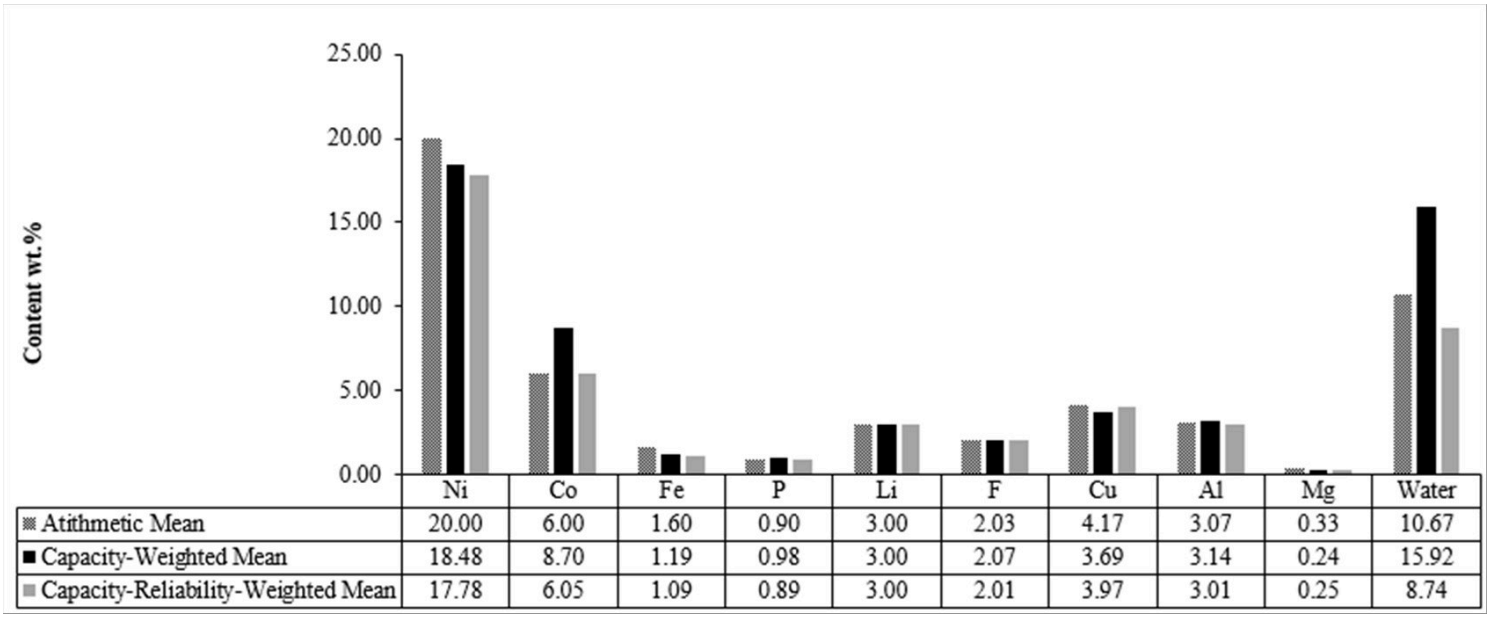


Figure 2

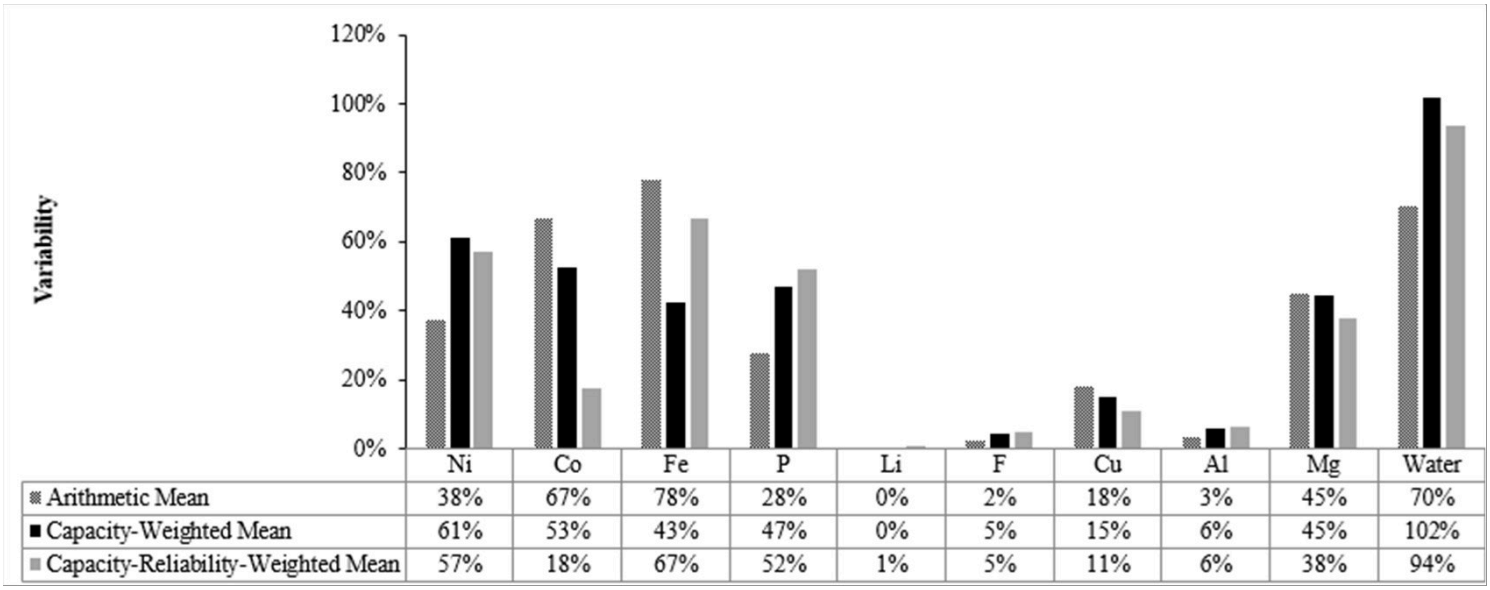
Framework for deriving and validating method BM quality benchmarks based on industrial specifications.



	Ni	Co	Fe	P	Li	F	Cu	Al	Mg	Water
Atithmetic Mean	20.00	6.00	1.60	0.90	3.00	2.03	4.17	3.07	0.33	10.67
Capacity-Weighted Mean	18.48	8.70	1.19	0.98	3.00	2.07	3.69	3.14	0.24	15.92
Capacity-Reliability-Weighted Mean	17.78	6.05	1.09	0.89	3.00	2.01	3.97	3.01	0.25	8.74

Figure 3

Comparison of benchmark values for BM quality parameters by method.



	Ni	Co	Fe	P	Li	F	Cu	Al	Mg	Water
Arithmetic Mean	38%	67%	78%	28%	0%	2%	18%	3%	45%	70%
Capacity-Weighted Mean	61%	53%	43%	47%	0%	5%	15%	6%	45%	102%
Capacity-Reliability-Weighted Mean	57%	18%	67%	52%	1%	5%	11%	6%	38%	94%

Figure 4

Comparative variability of BM quality parameters between arithmetic and Capacity-Reliability-Weighted Mean (CRWM) estimation. The proposed CRWM model, which integrates facility scale and data reliability factors, achieves a substantially lower sensitivity to sample composition

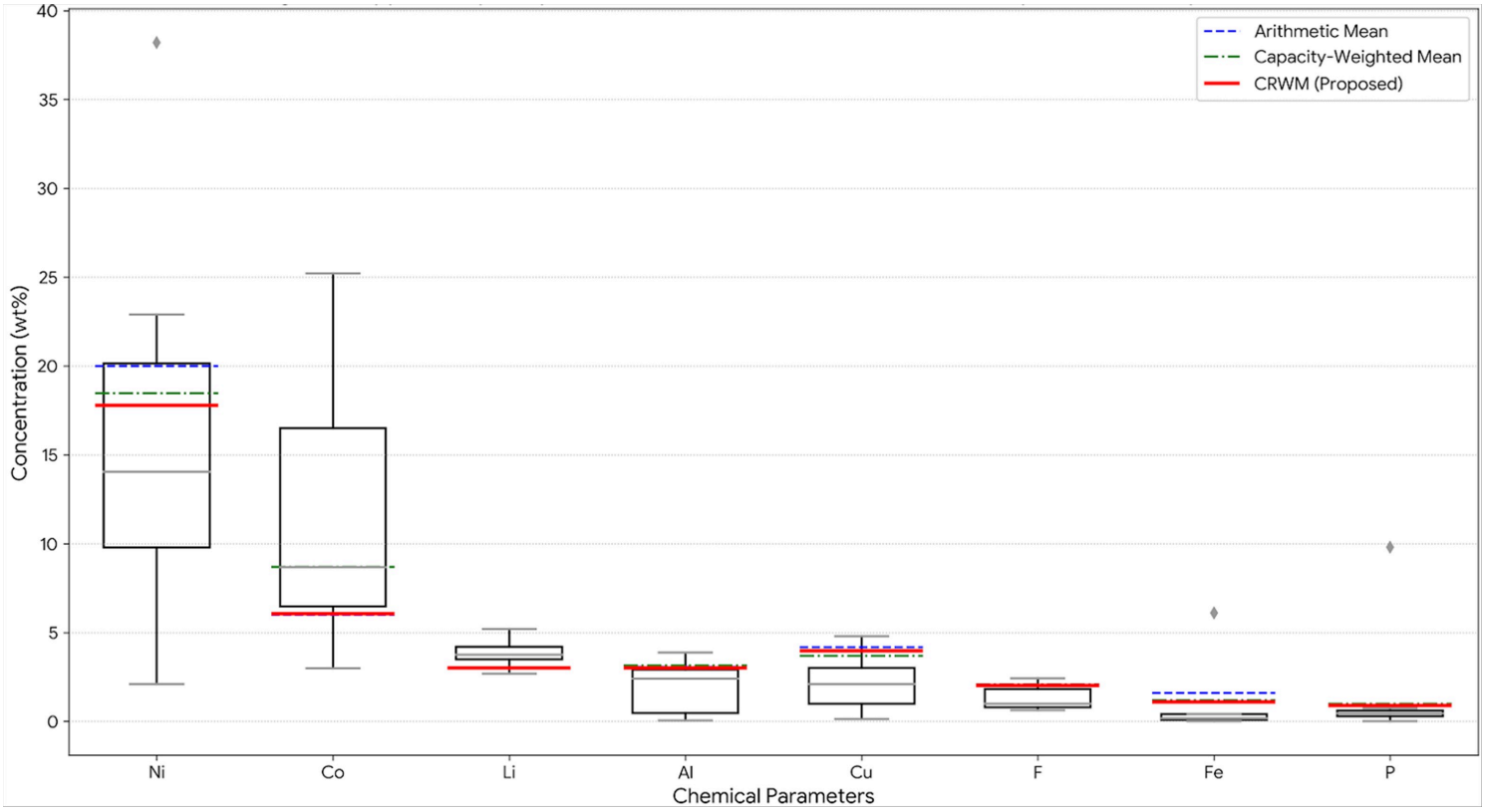


Figure 5

Applicability validation of the proposed industrial benchmarks using literature-reported BM compositions. The box-and-whisker plots represent the distribution and variability of chemical

parameters across 14 literature sources, while the horizontal lines indicate the benchmarks derived from different statistical models: Arithmetic Mean (blue dashed), Capacity-Weighted Mean (green dash-dotted), and the proposed Capacity-Reliability-Weighted Mean (CRWM, red solid). The CRWM demonstrates superior robustness by aligning with the industrial consensus while effectively filtering out academic outliers, particularly for impurity elements (Fe, P, and F).

Supplementary Files

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