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Scrap Selection and Charge Design for Foundry Alloys: A Critical Review of Classification Criteria, Metallurgical Constraints, and Industrial Practices

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Abstract

Scrap-based melting is essential to the decarbonization of foundry production, but scrap selection is still often treated as a purchasing decision rather than as an integrated metallurgical design problem. This structured critical narrative review—not a systematic review or meta-analysis—evaluates an audited corpus of 105 publications published from 2020 to August 2026. The corpus was assembled through iterative Google Scholar searches, targeted publisher searches, and citation chaining, and then retrospectively audited using explicit eligibility, thematic coding, and evidence appraisal fields. Because the original discovery-stage hit lists, export files, and screened-result counts were not retained, corpus completeness cannot be independently verified before the 105-record audit stage. All screening, coding, and evidence-tier assignments were performed by a single reviewer without independent calibration or inter-rater reliability testing. Evidence coding identified 40 aluminum-focused studies, 25 steel-focused studies, 7 cast-iron studies, 7 copper-alloy studies, 1 nickel-base study, and 25 cross-cutting contributions. Only 15 studies were industrial or pilot demonstrations, whereas 55 were laboratory studies and 35 were models, reviews, or contextual analyses. Nominal chemistry alone was consistently insufficient to determine scrap fitness: origin, size distribution, bulk density, coatings, oxide load, entrained contaminants, sampling uncertainty, and furnace-specific response jointly controlled metallic yield, energy demand, melt cleanliness, residual-element accumulation, emissions, and off-specification risk. Quantitative sensor studies reported laboratory classification metrics ranging from approximately 84% F1 for three commercial aluminum fractions to 99–100% for narrower cast/wrought or controlled-grade tasks; however, one magnetic-induction study fell from 89.66% recovery and 94.96% purity in static laboratory testing to 63.89% recovery and 60% purity in an industrial trial. The review proposes a normalized mass-balance formulation, probabilistic chemistry constraints, a cost-per-tonne-of-conforming-metal objective,

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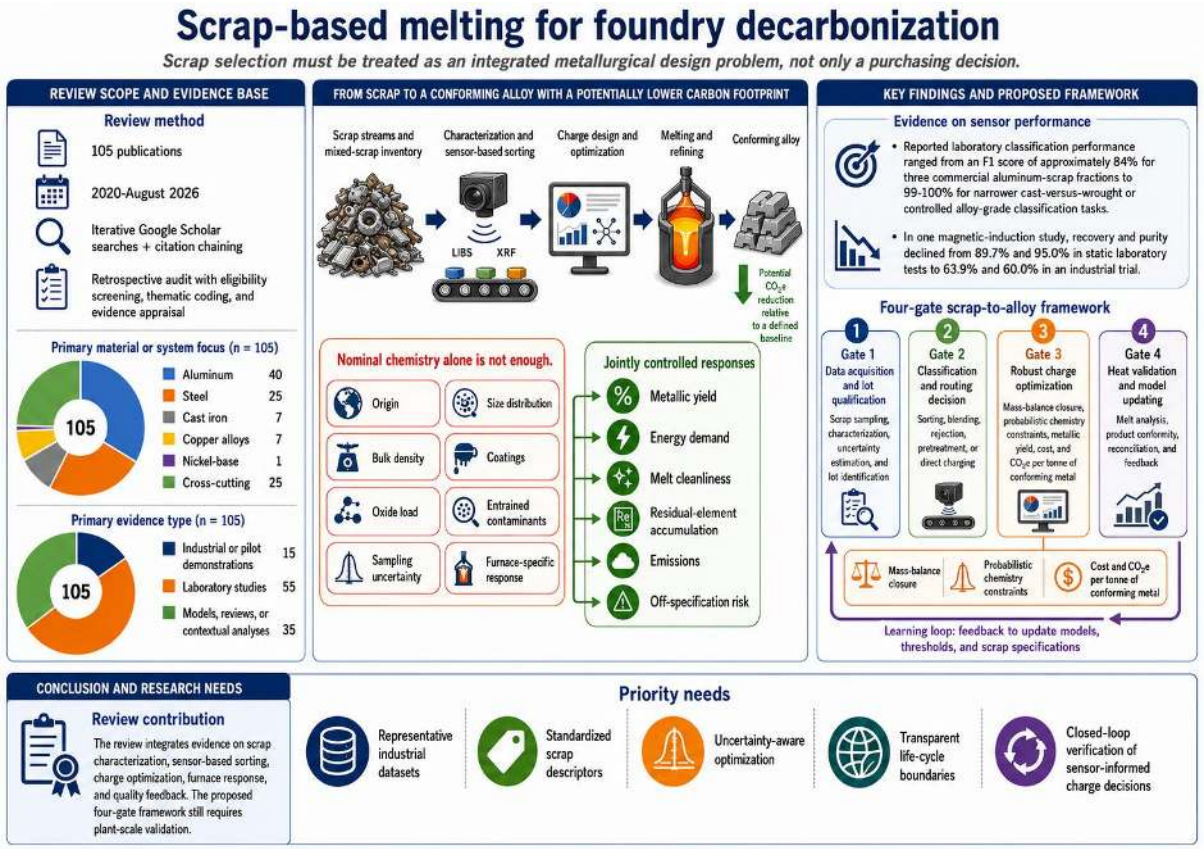
and a four-gate scrap-to-alloy framework. These contributions are conceptual, direct evidence for zinc- and magnesium-based foundries remains limited, and plant-scale validation is required. Priority needs are representative industrial datasets, standardized scrap descriptors, uncertainty-aware optimization, transparent life-cycle boundaries, and closed-loop verification of sensor-informed charge decisions.

Keywords: Foundry scrap; Charge optimization; Residual elements; Scrap-based metallurgy; Sensor sorting; Circular foundry.

Highlights

- Scrap suitability depends jointly on chemistry, geometry, contamination, and furnace response.
- Deterministic charge recipes underestimate compositional uncertainty and cumulative residual elements.
- Sensor-based sorting creates value only when its data are connected to alloy and process decisions.
- A risk-adjusted charge framework can align quality, cost, yield, energy use, and circularity.

Graphical abstract



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1. Introduction

Foundries are increasingly expected to increase recycled metallic content while simultaneously meeting tighter requirements for composition, cleanliness, mechanical performance, energy efficiency, and product consistency. This dual pressure makes scrap a strategic raw material rather than a homogeneous substitute for primary metal. Recent work on low-carbon casting alloys, aluminum and steel circularity, and environmental process modeling consistently frames recycling as indispensable to decarbonization, but also emphasizes that the benefits depend on the quality and process compatibility of the secondary feedstock (Armstrong et al., 2026; Colla et al., 2026; Hannula et al., 2020; Jarfors, 2025; Raabe et al., 2022; Raabe et al., 2024; Sajjad et al., 2025; Tshipama et al., 2023).

A foundry charge may combine primary metal, secondary ingot, internal returns, industrial production scrap, and post-consumer material. These categories differ in chemical uncertainty, surface condition, geometry, traceability, and the likelihood of cumulative residual elements. Internal gates, risers, rejected castings, and machining returns are usually compositionally close to the target alloy, but may carry oxides, sand, lubricants, or mixed grades. Post-consumer streams offer the largest circularity potential but present the greatest heterogeneity, as demonstrated by studies of end-of-life aluminum flows, vehicle scrap, copper recycling, and scrap-based steel production (Bulei et al., 2023; Compañero et al., 2021; Compañero et al., 2023; Loibl & Tercero Espinoza, 2021; Shankar et al., 2025; Tu & Hertwich, 2022; Van den Eynde et al., 2022; Yu et al., 2026).

The conventional purchasing description of scrap—such as “clean cast,” “mixed turnings,” “shredded aluminum,” or a nominal ferrous grade—does not fully describe metallurgical fitness. A low-priced scrap can create disproportionate cost through oxidation, dross, slag, refractory attack, excessive holding time, energy consumption, refining additions, emissions treatment, downgraded product, or complete heat rejection. Conversely, a higher-priced, well-characterized scrap may permit a larger recycled fraction, narrower correction margins, and reduced primary-metal consumption. The central economic object is therefore not the purchase price per tonne, but the risk-adjusted cost per tonne of conforming molten alloy. Circular foundry

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performance should therefore be assessed through retained alloy function, not recycled mass alone.

The technical difficulty varies by alloy family. In aluminum, iron and copper accumulation, oxide films, inclusions, and hydrogen-related melt quality can constrain closed-loop recycling, while certain secondary die-casting compositions are intentionally redesigned to tolerate broader impurity windows (Al-Helal et al., 2021; Cinkilic et al., 2022; Garcia et al., 2025; Garcia et al., 2026; Nunes et al., 2023; Piątkowski et al., 2026; Pogatscher & Samberger, 2024; Raabe et al., 2022). In steel, copper, tin, and other tramp elements can accumulate because they are difficult to remove by conventional oxidation refining; at the same time, alloy design can sometimes convert a residual element into a functional addition (Kalhor et al., 2026; Raabe et al., 2024; Wu et al., 2022; Yeşiltepe & Şeşen, 2021). In cast irons, the balance among steel scrap, pig iron, returns, carburizers, and alloy additions affects carbon equivalent, graphite morphology, chill tendency, matrix formation, and mechanical properties (Almanza et al., 2021; Hossain, 2021; Mishra et al., 2023; Mishra et al., 2024; Mojisola et al., 2022; Pribulová et al., 2020). Copper and brass charges similarly require control of zinc, lead, tin, iron, and cross-alloy mixing (Abdelmoneim et al., 2026; Anyszkiewicz et al., 2025; Flamme et al., 2024; Liu et al., 2020; Loibl & Tercero Espinoza, 2021; Malec et al., 2023; Sakallı & Birgören, 2020).

Charge design is often performed with deterministic spreadsheets or operator rules based on average analyses. Such methods are practical, but they obscure the fact that scrap composition is a distribution rather than a single value. The same nominal grade may vary by supplier, collection route, particle-size fraction, coating condition, or sampling protocol. Optimization studies and models for foundry batching, brass casting, electric furnaces, and scrap-based steelmaking show the value of formal calculation, yet their usefulness depends on realistic constraints and reliable incoming data (Carlsson et al., 2020; Ghezzi et al., 2023; Jafari-Ramiani et al., 2022; Kannisto et al., 2024; M. Li et al., 2026; Mapelli et al., 2025; Mombelli et al., 2021; Moskal et al., 2022; Reimann et al., 2021; Sakallı & Birgören, 2020; Xue et al., 2026).

The rapid development of handheld and in-line analytical technologies changes the information available for charge decisions. X-ray fluorescence (XRF), laser-

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induced breakdown spectroscopy (LIBS), machine vision, hyperspectral imaging, RGB-depth sensing, and magnetic-induction methods can classify or quantify scrap at much higher resolution than traditional visual grading (Akram et al., 2023; Anyszkiewicz et al., 2025; Badowski et al., 2026; Brooks & Gaustad, 2021; Chen et al., 2026; de la Peña et al., 2023; Díaz-Romero et al., 2022a; Díaz-Romero et al., 2022b; Díaz-Romero et al., 2023; Efe et al., 2025; Huang et al., 2022; Jurtsch et al., 2024; Koinig et al., 2026; X. Li et al., 2026; Lin et al., 2024; Quan et al., 2026; Seidel et al., 2021; Williams et al., 2023; Xu et al., 2024; Zhang et al., 2026). Nevertheless, classification accuracy alone is not equivalent to metallurgical value. A sensor system creates value only when its output changes routing, blending, pretreatment, furnace operation, or quality-control decisions.

This article therefore treats scrap selection as a coupled decision problem involving raw-material classification, alloy thermodynamics, microstructural tolerance, surface contamination, furnace behavior, quality assurance, economics, and environmental performance. The objective is not merely to catalogue scrap types, but to define how information should be converted into a robust charge decision. The review asks four questions: which scrap descriptors are technically decisive; how do alloy and furnace constraints modify scrap suitability; how should uncertainty enter charge calculation; and which emerging technologies can close the gap between incoming inspection and melt performance?

Foundational foundry metallurgy provides the underlying basis for this decision logic: charge cleanliness, oxide and inclusion control, solidification behavior, melt treatment, and alloy-specific tolerance determine whether recycled metal retains its intended function, while many undesirable elements cannot be removed economically during melting (ASM International, 2008; Campbell, 2015; Davis, 1993; Stefanescu, 2015). These foundational sources are cited for metallurgical context and are not included in the 105-record evidence counts.

The scope is deliberately centered on foundry alloys and foundry melting. Evidence from integrated steelworks and electric-arc-furnace steelmaking is retained only when it addresses transferable mechanisms—sampling, tramp-element control, melting dynamics, energy prediction, or uncertainty-aware batching—and is labelled

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as analog evidence rather than direct foundry validation. The main contribution is an integrated scrap-to-alloy framework for aluminum, cast-iron, steel-casting, copper-alloy, and selected specialty-alloy foundries. The framework supports supplier qualification, pretreatment, charge calculation, furnace routing, and post-heat learning, while explicitly distinguishing conclusions supported by the literature from author-developed, not-yet-validated propositions.

2. Review Methodology and Evidence Appraisal

2.1. Corpus construction and retrospective audit

The article is a structured critical narrative review, not a systematic review or meta-analysis. The research corpus was assembled through iterative Google Scholar searches, citation chaining, and targeted publisher searches in July–August 2026; the last search and metadata audit occurred on 2 August 2026. The original Google Scholar hit lists, export data, number of result pages screened, and discovery-stage exclusion counts were not retained, so the initial record count and completeness of the discovery stage cannot be reconstructed. This limitation is reported explicitly rather than replaced by an artificial PRISMA-style count.

The reconstructed search logic combined five concept blocks: (1) “scrap selection,” “scrap classification,” “scrap sorting,” or “scrap quality”; (2) “charge design,” “charge calculation,” “batching optimization,” or “charge mix”; (3) “foundry,” “casting,” “induction furnace,” “electric arc furnace,” or “remelting”; (4) alloy terms including aluminum/aluminium, steel, cast iron, copper/brass, zinc, magnesium, and nickel-base; and (5) technology or outcome terms including LIBS, XRF, machine vision, hyperspectral imaging, residual elements, metallic yield, dross/slag, energy, cost, LCA, and carbon footprint. The exact reconstructed Boolean strings, field definitions, and coding rules are provided in Supplementary Methodological Note S2; Supplementary Table S1 provides the study-level audit matrix.

Records were eligible if published in English from January 2020 to August 2026 and included evidence on scrap identification, alloy compatibility, pretreatment, melting, charge calculation, quality control, economics, environmental performance, or digital integration. Early-online 2026 records were kept only with complete

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metadata, DOI or publisher record, and sufficient full-text or coding info. Exclusions included patents, vendor claims, waste sorting, preprints, records lacking metadata, and studies not related to metallic charge decisions. One e-waste study was used as evidence for machine-learning-assisted LIBS transferability. Duplicate checks used normalized title, first author, year, and DOI.

The audit started with 105 unique research records, all meeting eligibility criteria. Four normative/regulatory documents and four metallurgy sources were analyzed separately and not counted among the 105 studies. Figure 1 shows the audit stage and highlights unavailable discovery-stage counts.

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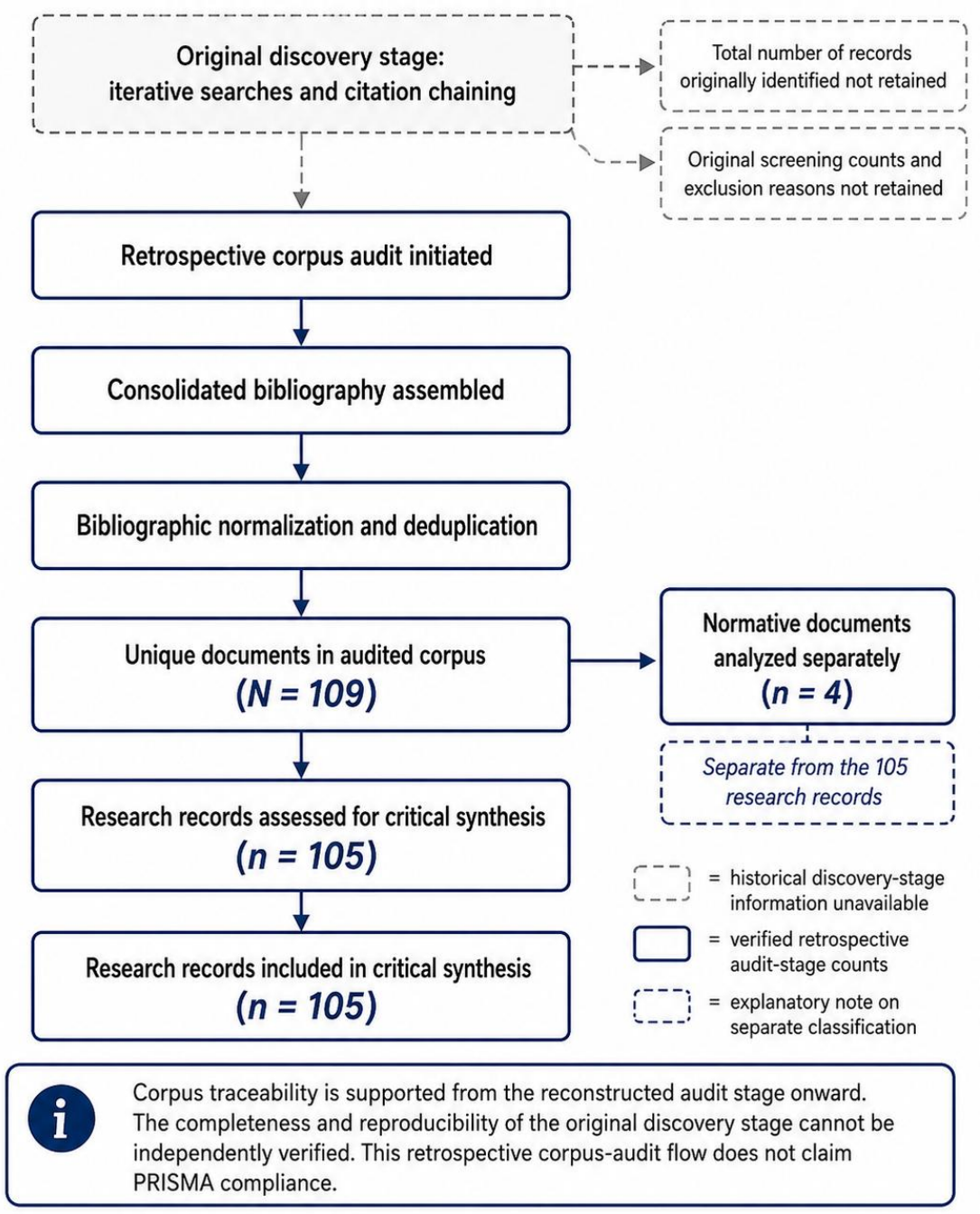

Figure 1. Retrospective corpus-audit flow: iterative searches and citation chaining; original hit count not retained; 105 unique records assessed; 105 research records included; four normative documents analyzed separately.
Author's conceptual synthesis based on the retrospective audit protocol. The figure distinguishes unavailable historical discovery-stage information from verified audit-stage counts and does not claim PRISMA compliance.

Figure 1 shows that the corpus is auditable from the 105-record retrospective stage onward, while the completeness and reproducibility of the original discovery stage cannot be independently verified.

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2.2. Data extraction and evidence coding

Each record was coded for bibliographic type, alloy or material family, scrap origin, process or technology, evidence scale, material representativeness, principal metric, directness of linkage to charge or process decisions, and the dominant limitation. Evidence scale was classified as laboratory/bench, pilot/demonstration, industrial/plant, model/data study, or review/context. Representativeness distinguished prepared or controlled materials, commercial heterogeneous scrap, plant/process-representative feeds, modeled data, and review evidence. Decision linkage was classified as direct, partial/direct, or indirect when classification accuracy was the terminal outcome.

A five-tier evidence scheme was used: Tier A, reliable industrial evidence; Tier B, pilot or industrial demonstration with partial validation; Tier C, laboratory work with commercial scrap; Tier D, laboratory work with prepared materials; and Tier E, models, reviews, or contextual analyses. The 105-source coding matrix is supplied as Supplementary Table S1 so that the material-family, scale, representativeness, decision-linkage, theme, and tier assignments can be audited.

All screening, coding, and evidence-tier assignments were completed by one reviewer. No independent calibration, duplicate coding, or inter-rater reliability coefficient was available; therefore, the classifications are transparent and auditable reviewer judgments but are not independently validated measurements.

The synthesis follows a decision-science logic rather than a meta-analytic logic: heterogeneous engineering evidence is organized according to the decisions it can support, the boundary conditions that restrict transfer, and the uncertainty attached to each claim; effect sizes are not pooled.

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Table 1 summarizes the quantitative profile of the corpus.

Table 1. Quantitative profile of the 105-study evidence corpus

Coding dimension	Category	Number of studies	Interpretive implication
Material family	Aluminum / steel / cast iron / copper alloys / nickel-base / cross-cutting	40 / 25 / 7 / 7 / 1 / 25	The corpus is dominated by aluminum and steel; zinc and magnesium charge design remain direct evidence gaps.
Evidence scale	Laboratory / pilot / industrial / model-data / review-context	55 / 5 / 10 / 20 / 15	Only 15 studies reached pilot or industrial scale; most conclusions require scale-transfer caution.
Representativeness	Prepared / commercial heterogeneous / plant-representative / modeled / review	44 / 17 / 10 / 20 / 14	Prepared specimens remain the largest single category, limiting direct transfer to mixed incoming lots.
Decision linkage	Direct / partial-direct / indirect classification endpoint	75 / 5 / 25	One quarter of the corpus stops mainly at sensing or classification rather than heat-level outcomes.
Evidence tier	A / B / C / D / E	9 / 6 / 12 / 43 / 35	High-confidence industrial evidence is a minority; Tier D and E evidence dominates.
Primary theme	Alloy compatibility / sensing / charge-furnace / pretreatment / economics-environment / digital-governance	33 / 30 / 16 / 9 / 11 / 6	Technical sensing is well represented, but integrated economics, governance, and plant validation are thinner.

Note. Author's synthesis from the study-level coding reported in Supplementary Table S1. Counts are descriptive and non-mutually interpretive; each study received one primary category per coding field.

The coding supports three review-level conclusions. First, laboratory performance cannot be treated as an industrial performance guarantee. Second, steelmaking evidence is useful mainly as analog evidence for mechanisms and optimization and should not be interpreted as direct validation for foundry furnaces. Third, claims of cost or environmental superiority require a common functional unit and explicit treatment of metallic yield and product conformity.

3. Scrap Taxonomy and Quality Attributes

3.1. Classification by origin and information quality

Origin is the first useful classification axis because it predicts both compositional uncertainty and traceability. Internal returns are generated within the foundry and normally have the strongest link to a known alloy family, heat, mold line, and process

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history. Their principal risks are grade mixing, sand or refractory attachment, oxide accumulation, and repeated recirculation. Industrial scrap from stamping, extrusion, machining, or component manufacture is often chemically narrow but may include lubricants, coatings, mixed tooling materials, or batch-to-batch variation. Post-consumer scrap has the highest potential circular benefit and the lowest intrinsic traceability, especially after shredding or commingling (Bulei et al., 2023; Compañero et al., 2021; Compañero et al., 2023; Langan et al., 2024; Loibl & Tercero Espinoza, 2021; Shankar et al., 2025; Tu & Hertwich, 2022; Van den Eynde et al., 2022).

Secondary ingots are an intermediate form, not just scrap at the furnace door but involving upstream collection, sorting, refining, and blending. They offer a guaranteed or certified composition and are designed for melting, but the foundry pays for upstream processing and may lose sight of the original scrap. The best strategy distinguishes certified secondary metal from heterogeneous scrap and applies different inspection levels.

3.2. Physical classification

Physical form controls charging density, heat transfer, oxidation exposure, bridge formation, bath penetration, and handling safety. Large dense pieces have low specific surface area but may melt slowly or mechanically interfere with furnace loading. Thin sheet, turnings, and shredded fractions melt rapidly when submerged, yet are highly susceptible to oxidation and entrainment in slag or dross. Bale density, chip compaction, particle-size distribution, and the presence of fines can therefore affect metallic recovery as strongly as nominal chemistry. Representative sampling and fractionation studies further show that composition itself may vary with particle size, making physical and chemical classification inseparable (Bhaskar et al., 2022; Djurdjevic et al., 2026; Mapelli et al., 2025; Shankar et al., 2025; Steglich et al., 2020; Wibner et al., 2020).

3.3. Chemical and surface-condition classification

A metallurgically useful scrap description should include major alloying elements, critical residuals, uncertainty ranges, and surface-condition indicators. Average composition is insufficient when the probability of a high-residual fragment controls

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heat risk. For steel, copper-bearing or high-alloy pieces may dominate tramp-element exposure; for aluminum, a small fraction of wrought or cast grades with incompatible copper, zinc, magnesium, or iron can shift the melt outside the target window. Studies of steel-scrap purity, copper-containing fragments, post-consumer aluminum chemistry, and representative sampling all point to the need for lot-level distributions rather than isolated measurements (Bulei et al., 2023; Dobosz et al., 2024; Janiszewski, 2021; Jurtsch et al., 2024; Koinig et al., 2026; Quan et al., 2026; Wibner et al., 2020).

Table 2 converts the conventional scrap categories into a decision-oriented "scrap fingerprint."

Table 2. Decision-oriented scrap fingerprint for foundry charge selection

Attribute	Typical descriptors	Metallurgical relevance	Minimum control response
Origin and history	Internal return, industrial, post-consumer, secondary ingot; known alloy or mixed stream	Predicts traceability, prior thermal cycles, and mixing risk	Supplier/lot identification and segregation rules
Chemical composition	Major alloying elements; critical residuals; mean, range, and outliers	Determines dilution requirement, residual accumulation, and correction capacity	Representative sampling plus rapid or laboratory analysis
Geometry	Piece size, thickness, aspect ratio, bulk density, compaction	Controls charging, melting time, oxidation, and bridge risk	Size specification and furnace-specific routing
Surface condition	Oxide, paint, oil, polymer, salt, sand, refractory, moisture	Controls gas generation, dross/slag, inclusions, emissions, and safety	Visual inspection, moisture limits, cleaning or rejection
Information quality	Certificate, sensor classification, historical variability, sample count	Controls confidence in the charge calculation	Uncertainty band and risk class
Economic quality	Purchase price, yield, preparation cost, energy, correction and rejection risk	Determines cost per tonne of conforming melt	Total-cost calculation rather than purchase-price comparison

Note. Author's synthesis based on (Brooks & Gaustad, 2021; Bulei et al., 2023; Compañero et al., 2021; Compañero et al., 2023; Dobosz et al., 2024; Janiszewski, 2021; Langan et al., 2024; Loibl & Tercero Espinoza, 2021; Shankar et al., 2025; Tu & Hertwich, 2022; Van den Eynde et al., 2022; Wibner et al., 2020; Yu et al., 2026).

The critical implication is that commercial descriptions should be treated as an initial routing label rather than a complete metallurgical specification. Two lots sold under the same trade grade can require different dilution, pretreatment, or furnace

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sequence. The foundry should therefore maintain an internal quality class that combines supplier information with measured chemistry, physical form, and historical melt performance.

Figure 2 translates the scrap fingerprint into a pre-furnace routing decision.

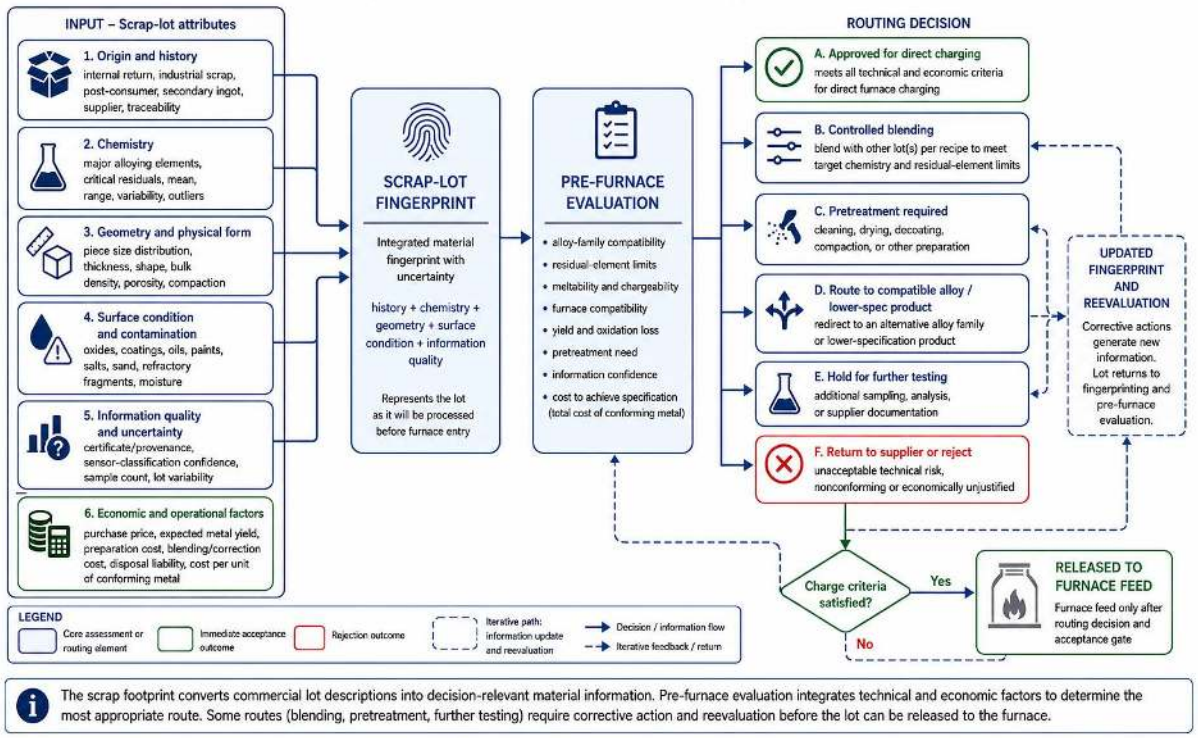

Figure 2. Scrap fingerprint linking origin, chemistry, geometry, contamination, uncertainty, and total cost to charge routing.
Author's conceptual synthesis based on the classification and information-value concepts discussed by Compañero et al. (2021, 2023), Brooks and Gaustad (2021), Bulei et al. (2023), Shankar et al. (2025), Tu and Hertwich (2022), Van den Eynde et al. (2022), and Wibner et al. (2020).

The figure makes explicit that classification should end in an action: direct charging, controlled blending, pretreatment, downgrade to another alloy family, return to supplier, or rejection.

4. Metallurgical Compatibility Across Alloy Families

4.1. General compatibility logic

Metallurgical compatibility is governed by four distinct questions. First, is the element required in the target alloy? Second, can an excess be removed by the available refining route? Third, can the excess be diluted economically without violating other limits? Fourth, what microstructural or processing consequence follows

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if the element remains? These questions separate desirable alloying additions from tolerable residuals and from cumulative tramp elements. The same element may move among these categories depending on alloy family, product geometry, heat treatment, and property requirements.

Practical danger is asymmetric correction. Deficiencies in elements like silicon or magnesium can often be fixed by adding alloys or metals. However, excess copper in steel or iron in aluminum, or contamination among alloys can be hard or impossible to remove in melting. Charge design should focus on controlling non-removable elements rather than just hitting average targets.

4.2. Aluminum foundry alloys

Aluminum recycling illustrates the tension between impurity avoidance and impurity-tolerant alloy design. Studies on end-of-life vehicle scrap, secondary casting alloys, recycled structural die-casting alloys, and “dirty” alloy science show two complementary strategies: improve sorting to preserve alloy families, or redesign alloy windows and microstructures so that a broader scrap mix can be used without unacceptable properties (Al-Helal et al., 2021; Cinkilic et al., 2022; Garcia et al., 2025; Garcia et al., 2026; Nunes et al., 2023; Piątkowski et al., 2026; Pogatscher & Samberger, 2024; Raabe et al., 2022; Tangsuksan et al., 2025). Neither strategy eliminates the need for control. Broader tolerance must be validated against phase formation, castability, porosity, heat-treatment response, corrosion, and product-specific requirements.

Iron is a central constraint in Al–Si foundry alloys because it tends to accumulate and promotes Fe-rich intermetallics whose morphology and volume fraction can impair ductility, feeding, and machinability. The significance of iron depends on silicon, manganese, cooling rate, modification practice, and the permitted property envelope. Copper, zinc, magnesium, nickel, and trace elements can be beneficial in one grade and harmful in another. The reported effects of return additions, recycled 6000-series material, trace copper, shrinkage porosity, and quality variation in incoming AlSi9Mn-type material demonstrate that the problem is alloy-specific rather than reducible to a universal “recycled content” limit (De Caro et al., 2023; Gyarmati et al., 2024; Medrano et al., 2021; Mrówka-Nowotnik et al., 2021; Piątkowski et al., 2026; Šmalc et al., 2023).

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Machining chips and thin scrap create an additional quality layer, as oxidation and contamination can dominate recovery even when the chemistry is compatible. Recycling of aluminum chips, motor scrap, and loose machining waste shows the importance of preparation, compaction, and process route (Bazhin et al., 2025; Bhaskar et al., 2022; Djurdjevic et al., 2026; Gökelma et al., 2023). Charge rules should therefore distinguish chemical compatibility from compatibility with recoverable metal.

4.3. Steel and cast iron

In scrap-based steelmaking, copper and tin are archetypal residuals because they are not readily removed under conventional oxidizing conditions. Copper can contribute to hot shortness and surface defects, although controlled composition and processing may allow it to serve as a functional alloying element. This duality is captured by recent work on copper in steels, circular-steel metallurgy, scrap reuse, and heat treatment of copper-containing carbon steel (Kalhor et al., 2026; Raabe et al., 2024; Wu et al., 2022; Yeşiltepe & Şeşen, 2021). The correct conclusion is not that copper is always unacceptable, but that its allowable range must be coupled to steel grade and downstream thermomechanical processing.

Steel scrap grade also affects yield, energy consumption, slag generation, and the need for dilution with direct-reduced iron, hot metal, or pig iron. Plant and modeling studies indicate that bulk density, size, gangue, and metallic purity influence both the mass balance and furnace dynamics (Carlsson et al., 2020; Chen et al., 2022; Dobosz et al., 2024; Janiszewski, 2021; M. Li et al., 2026; Mapelli et al., 2025; Mombelli et al., 2021; Moskal et al., 2022; Reimann et al., 2021). High-alloy scrap can be a valuable source of nickel, chromium, and molybdenum when correctly identified, but a severe contamination risk when routed to plain-carbon steel.

Cast iron charge design has a related but distinct logic. Steel scrap supplies relatively low-carbon iron units and may require carburizer and silicon correction; pig iron provides carbon, silicon, and favorable nucleation behavior but can raise cost and embodied impact; returns provide compositionally close metal but accumulate treatment history and inclusions. Foundry studies on ductile and gray iron show that charge composition and additions of cobalt, copper, tin, and other elements modify

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matrix, graphite, strength, hardness, and casting behavior (Almanza et al., 2021; Hossain, 2021; Mishra et al., 2023; Mishra et al., 2024; Mojisola et al., 2022; Pribulová et al., 2020). Consequently, the “maximum scrap” charge is not necessarily the technically or economically optimal charge.

4.4. Copper, brass, zinc, and magnesium systems

Copper-alloy scrap has high intrinsic value, making precise segregation economically attractive. However, the large number of brass, bronze, and specialty copper families poses a severe risk of cross-contamination. XRF characterization, sorting of mixed foundry residues, preparation of post-production chips, and optimization of brass casting demonstrate the need to control zinc, lead, tin, nickel, iron, and other alloy-family markers (Abdelmoneim et al., 2026; Anyszkiewicz et al., 2025; Flamme et al., 2024; Liu et al., 2020; Loibl & Tercero Espinoza, 2021; Malec et al., 2023; Sakallı & Birgören, 2020). Closed-loop return is generally preferable, while mixed copper scrap requires analytical routing or upstream refining.

Specialty nickel-base casting alloys require an even tighter closed-loop strategy because revert additions can alter creep-critical microstructures and minor-element balances. Evidence from Inconel 713LC return-material studies indicates that the acceptable revert fraction must be validated against the microstructure and high-temperature performance, rather than defined solely by bulk chemistry (Farahani et al., 2025).

The corpus offers limited direct evidence on charge design for zinc- and magnesium-based foundry alloys, which differ in oxidation, vaporization, contamination, and safety. Instead of extrapolating from aluminum or copper, the review identifies zinc and magnesium as research gaps, recommending alloy-specific validation before applying a general framework.

The cross-alloy comparison is summarized in Table 3.

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Table 3. Metallurgical interpretation of scrap-borne elements in major foundry alloy families

Alloy family	High-priority elements or attributes	Why they matter	Charge-design response
Aluminum casting alloys	Fe, Cu, Zn, Mg, Ni, oxides, coatings, moisture	Intermetallic phases, heat-treatment response, porosity, inclusions, dross	Separate cast/wrought families where needed; control upper bounds; use tolerant secondary grades only with validation
Steel	Cu, Sn, Ni, Cr, Mo, nonmetallics, density	Tramp accumulation, hot shortness, grade contamination, energy and slag	Positive identification of high-alloy pieces; dilution or grade routing; combine with DRI/hot metal where justified
Gray and ductile iron	C, Si, Mn, S, P, Cu, Sn, Cr, return history	Carbon equivalent, graphite morphology, chill, matrix and mechanical properties	Balance steel scrap, pig iron and returns; account for inoculation and treatment practice
Copper and brass	Zn, Pb, Sn, Ni, Fe, Al, mixed-alloy fragments	Vaporization, phase balance, conductivity, hot workability, product compliance	Closed-loop segregation, XRF/LIBS routing, controlled chip preparation and refining
Zinc and magnesium	Oxide condition, cross-alloy contamination, moisture, volatile or reactive contaminants	Metal loss, fumes, inclusions and safety	Use alloy-specific acceptance rules; avoid direct transfer of limits from other alloy systems

Note. Author's synthesis based on (Abdelmoneim et al., 2026; Al-Helal et al., 2021; Almanza et al., 2021; Anyszkiewicz et al., 2025; Cinkilic et al., 2022; De Caro et al., 2023; Garcia et al., 2025; Garcia et al., 2026; Gyarmati et al., 2024; Hossain, 2021; Kalhor et al., 2026; Liu et al., 2020; Loibl & Tercero Espinoza, 2021; Malec et al., 2023; Medrano et al., 2021; Mishra et al., 2023; Mishra et al., 2024; Mojisola et al., 2022; Mrówka-Nowotnik et al., 2021; Piątkowski et al., 2026; Pogatscher & Samberger, 2024; Pribulová et al., 2020; Raabe et al., 2022; Raabe et al., 2024; Sakallı & Birgören, 2020; Šmalc et al., 2023; Tangsuksan et al., 2025; Wu et al., 2022; Yeşiltepe & Şeşen, 2021).

Table 3 reinforces a key rule: the foundry should classify each element as correctable, dilutable, routable, or non-removable under its actual process. Upper-bound constraints for non-removable residuals should carry a larger safety margin than lower-bound constraints for elements that can be added at the furnace.

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5. Surface Condition, Contamination, and Pretreatment

5.1. Contamination pathways and consequences

Surface contamination changes the effective chemistry and thermal behavior of scrap. Oils, greases, paints, polymers, and moisture can generate smoke, volatile organic compounds, hydrogen-bearing gases, flames, pressure events, or unstable furnace operation. Oxides, corrosion products, sand, refractories, salts, and dirt increase slag or dross, entrain metal, and introduce inclusions. The consequence is a chain of effects rather than a single penalty: slower charging, lower metallic yield, higher flux or treatment demand, greater off-gas load, longer holding, and increased variability in melt quality.

The severity is strongly related to surface-area-to-mass ratio. Loose chips, thin-gauge scrap, and shredded fractions expose more area to oxidation and carry larger amounts of lubricant or coating per unit of metal. Studies on aluminum chips, loose machining waste, beverage-can bales, thin complex scrap, and dross minimization show that geometry, pretreatment, and charging practice interact (Bhaskar et al., 2022; Djurdjevic et al., 2026; Melwyn et al., 2023; Sathiyaseelan et al., 2025; Steglich et al., 2020; Vicario et al., 2022). A chemically clean chip stream may still have poor recovery if it is wet, oily, oxidized, or charged onto an oxidizing surface rather than rapidly submerged.

Coatings also interfere with sensor performance. Painted or oxidized surfaces can cause analytical mismatch between surface measurement and bulk composition. In-situ laser cleaning has been proposed to improve LIBS classification of painted metal scrap, illustrating that analytical preparation is part of the measurement system rather than a separate concern (Lee et al., 2025; Seidel et al., 2021).

5.2. Pretreatment options

Pretreatment should be selected according to the dominant loss mechanism. Mechanical sorting removes foreign materials and separates size fractions. Cutting and shredding improve handling and sensor access but may increase fines and oxidation. Briquetting or compaction improves bulk density and submergence of chips, provided moisture and volatile contaminants are controlled. Thermal de-coating or

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drying removes organics and water but requires off-gas treatment and can oxidize metal if temperature and atmosphere are poorly controlled. Chemical washing may remove specific contaminants but introduces effluent and drying requirements. Flux treatment can assist oxide separation but adds salt management and residue-generation obligations.

Process-specific investigations illustrate the range of options: preparation of copper-alloy chips for continuous casting, XRF sorting of mixed foundry residues, boric-acid washing of Twitch aluminum scrap, treatment of thin complex aluminum scrap, refining-flux characterization, and multistage recovery from aluminum casting slags (Flamme et al., 2024; Kulikov et al., 2026; Malec et al., 2023; Sathiyaseelan et al., 2025; Vicario et al., 2022; Wan et al., 2020). These studies should not be read as universal recipes. The correct pretreatment is the least-cost sequence that reduces the limiting risk for a defined scrap–alloy–furnace combination.

Table 4 links common scrap conditions to pretreatment objectives and possible failure modes.

Table 4. Pretreatment routes for contaminated or physically difficult scrap

Scrap condition	Preferred objective	Potential route	Critical control or failure mode
Oily or wet chips	Remove volatiles and improve submergence	Drain, centrifuge, dry, compact or briquette	Fire/explosion risk, re-oxidation, trapped moisture
Painted or polymer-coated scrap	Reduce gas and off-gas load; expose metal for sensing	Mechanical removal, controlled thermal de-coating, laser cleaning for analysis	Organic emissions, ash, oxidation, incomplete coating removal
Thin sheet or low-density shred	Increase furnace productivity and metallic recovery	Baling, compaction, controlled charging below bath surface	Oxidation during delay, bridge formation, trapped nonmetallics
Sand/refractory-contaminated returns	Reduce inclusions and slag volume	Shot blasting, tumbling, mechanical cleaning, segregation	Embedded refractory, excessive metal loss during cleaning
Mixed metallic residues	Separate alloy families and foreign metals	XRF/LIBS/vision sorting, magnetic or density separation	Sampling bias, surface effects, insufficient sensor resolution
Oxidized dross or slag-rich material	Recover entrained metal or regenerate flux where justified	Hot processing, crushing/classification, remelting, salt-flux recovery	Salt residue, energy demand, low net recovery

Note. Author's synthesis based on (Bhaskar et al., 2022; Djurdjevic et al., 2026; Flamme et al., 2024; Kulikov et al., 2026; Lee et al., 2025; Malec et al., 2023; Melwyn et al., 2023;

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Sathiyaseelan et al., 2025; Seidel et al., 2021; Steglich et al., 2020; Vicario et al., 2022; Wan et al., 2020).

The economic decision should compare pretreatment costs with avoided metal loss, reduced energy and holding time, lower emissions, improved analytical accuracy, and reduced off-specification risk. Pretreatment is justified when it changes the total cost of conforming metal, not simply when it produces visibly cleaner scrap.

Figure 3 illustrates the causal chain between surface condition and foundry outcomes.

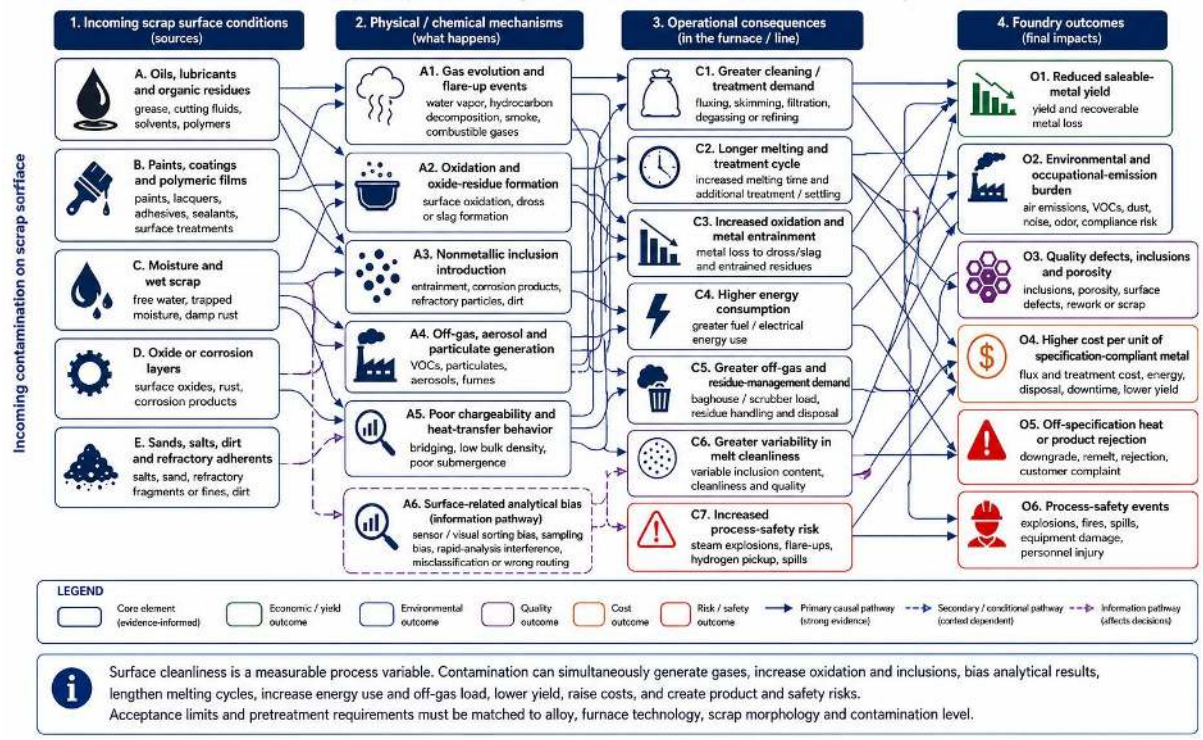

Figure 3. Contamination pathway from scrap surface condition to gas generation, oxidation, inclusions, yield loss, emissions, and product risk.
Author's conceptual synthesis based on the process relationships discussed by Bhaskar et al. (2022), Djurdjevic et al. (2026), Flamme et al. (2024), Lee et al. (2025), Melwyn et al. (2023), Sathiyaseelan et al. (2025), Steglich et al. (2020), Vicario et al. (2022), and Wan et al. (2020).

The pathway highlights why incoming cleanliness specifications should be linked to measurable outcomes such as moisture, nonmetallic fraction, melt loss, dross rate, smoke events, and inclusion-related rejection rather than relying exclusively on visual descriptors.

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6. Charge Mix Design: From Deterministic Balances to Risk-Adjusted Optimization

6.1. Yield-normalized elemental balance

A charge model must distinguish total metallic yield from the transfer of each element. Let m_i be the charged mass of material i (kg), Y_i its recovered-metal yield (kg metal per kg charged), C_ij the mass fraction of element j in material i, R_ij the fraction of element j transferred to the molten metal, M_j^add the mass of element j deliberately added, and M_k^add the gross mass of addition k. The predicted melt concentration is therefore normalized by the recovered metal mass rather than by the nominal charge mass:

$$C_j^{melt} = [\Sigma_i(m_i C_{ij} R_{ij}) + M_j^{add}] / [\Sigma_i(m_i Y_i) + \Sigma_k(M_k^{add})] \quad (1)$$

All masses are expressed in kilograms and concentrations as mass fractions or consistently converted weight percentages. R_ij may differ from Y_i when an element oxidizes, volatilizes, partitions to slag or dross, or is intentionally refined. The elemental constraints are $L_j \le C_j^{melt} \le U_j$, where L_j and U_j are the product-specific lower and upper limits. This formulation corrects the dimensional ambiguity of a charge-fraction equation and makes yield loss explicit.

Decision variables are the masses m_i and additions M_k^add. Minimum and maximum lot use, material availability, furnace capacity, bulk density or volume constraints, mandatory heel mass, charge sequence, maximum fines or coated fraction, and supplier allocation rules can be represented as linear, nonlinear, or logical constraints. Foundry practice remains essential because a chemically feasible solution can be physically unchargeable or operationally unsafe.

6.2. Uncertainty and objective function

For heterogeneous scrap, C_ij and sometimes Y_i are random variables rather than constants. A probabilistic formulation requires the chemistry limits to be satisfied at a chosen confidence level. For an upper-bound residual element, the chance constraint is:

$$P(C_j^{melt} \le U_j) \ge 1 - \alpha_j \quad (2)$$

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Here, α_j is the accepted probability of exceeding the upper specification limit for element j. A robust model can replace the probability distribution with bounded uncertainty sets; a stochastic model can minimize expected cost over scenarios. The risk level should be product-specific: safety-critical or low-residual alloys justify smaller α_j than broad-tolerance secondary casting grades. Industrial scrap distributions may be skewed, multimodal, supplier-clustered, outlier-prone, and correlated across elements. Accordingly, empirical distributions, non-parametric or bootstrap models, Bayesian updating, and scenario-based robust optimization may be preferable to independent normal approximations when plant data are available.

The objective should be the expected cost per tonne of conforming molten metal rather than purchase cost per tonne charged. For one heat, a dimensionally explicit formulation is:

$$c_{conf} = [C_{mat} + C_{prep} + C_{energy} + C_{treat} + C_{add} + E(C_{nonconf})] / M_{conf} \quad (3)$$

C_mat, C_prep, C_energy, C_treat, and C_add are batch costs in currency per heat; E(C_nonconf) is the expected cost of correction, dilution, downgrade, rework, or rejection; and M_conf is the expected mass of conforming molten metal in tonnes. A multiobjective formulation may add energy, carbon, throughput, or inventory penalties, but units and weighting factors must be disclosed.

Table 5 summarizes the minimum set of components for a defensible charge-optimization model.

Table 5. Minimum formulation for risk-adjusted foundry charge optimization

Model component	Required representation	Typical variables or data	Failure if omitted
Objective	Expected cost per tonne of conforming molten metal; optional energy/carbon terms	Material, preparation, energy, treatment, additions, correction, downgrade and rejection costs	Low-price scrap can be selected despite poor yield or high quality risk.
Chemical balance	Yield-normalized element transfer and additions	m_i, C_ij, R_ij, Y_i, M_j^add, L_j, U_j	Bath composition is biased when materials have different yields or element losses.
Uncertainty	Robust bounds, scenarios, or probability distributions	Within-lot and between-lot distributions; sensor uncertainty; α_j	Edge-of-specification deterministic solutions create hidden nonconformance risk.

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Model component	Required representation	Typical variables or data	Failure if omitted
Availability and logistics	Lot limits, inventory, supplier and segregation rules	Minimum/maximum use, stock, delivery and storage capacity	The mathematical recipe cannot be executed with available lots.
Furnace constraints	Capacity, volume, density, heel, sequence, refining and treatment capability	Bulk density, maximum fines/coated fraction, charge order, melt rate	A chemically valid recipe can bridge, oxidize excessively, or exceed off-gas capacity.
Feedback	Update distributions using actual heat outcomes	Final chemistry, yield, energy, dross/slag, quality, supplier and lot IDs	The model does not learn and uncertainty remains generic.

Note. Author's synthesis based on charge-calculation, stochastic optimization, model-predictive control, and furnace-modeling studies (Carlsson et al., 2020; Compañero et al., 2023; Ghezzi et al., 2023; Jafari-Ramiani et al., 2022; Kannisto et al., 2024; M. Li et al., 2026; Mapelli et al., 2025; Mombelli et al., 2021; Moskal et al., 2022; Reimann et al., 2021; Sakallı & Birgören, 2020; Xue et al., 2026).

6.3. Illustrative comparison of deterministic and robust solutions

Because the reviewed corpus lacks a common plant dataset, the following example is illustrative and not experimental validation. A 1000-kg aluminum charge is assembled from stable scrap A, lower-cost variable scrap B, and primary metal. Fe is treated as a non-removable residual with an upper limit of 1.00 wt.%. The assumed Fe means, standard deviations, metallic yields, and prices are shown in the table note.

Table 6. Illustrative deterministic versus risk-adjusted aluminum charge

Result	Deterministic low-purchase-cost solution	Risk-adjusted solution	Interpretation
Charge mix, kg	A = 100; B = 700; primary = 200	A = 550; B = 250; primary = 200	The robust solution substitutes stable scrap A for highly variable scrap B.
Recovered molten metal, kg	947.0	969.5	Higher yield partly offsets the higher purchase price.
Predicted mean Fe, wt.%	0.958	0.692	Both mean values are below 1.00 wt.%, so a mean-only balance accepts both.

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Result	Deterministic low-purchase-cost solution	Risk-adjusted solution	Interpretation
One-sided 95th-percentile Fe, wt.%	1.185	0.800	The deterministic solution violates the risk-adjusted upper bound.
Estimated P(Fe > 1.00 wt.%)	38.0%	0.00013%	Uncertainty changes the preferred solution even though both means conform.
Material cost per kg molten metal	1.505	1.679	The robust recipe has the higher direct material cost.
Expected cost with nonconformance penalty	Can exceed robust cost when correction/rejection exceeds 0.46 currency units per kg off-spec metal	Stable near 1.679 before other operating savings	The economically preferred solution depends on the measured consequence of nonconformance.

Note. Author-developed numerical illustration. Assumptions: Fe mean ± standard deviation: A = 0.65 ± 0.08 wt.%, B = 1.25 ± 0.20 wt.%, primary = 0.15 ± 0.02 wt.%; metallic yields: 0.98, 0.93 and 0.99; purchase prices: 1.55, 1.10 and 2.50 currency units kg−1, respectively; independent normal uncertainty; Fe transfer equal to metallic yield. Values are pedagogical and require plant-specific replacement.

The example demonstrates the difference between a literature-supported principle and an author-developed framework. The literature supports optimization, uncertainty treatment, and the value of composition information; the specific numerical solution is illustrative. Plant validation should compare deterministic and risk-adjusted recipes over repeated heats, reporting chemistry, yield, energy, correction, throughput, and total conforming-metal cost.

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Figure 4 is included to illustrate the proposed risk-adjusted information flow.

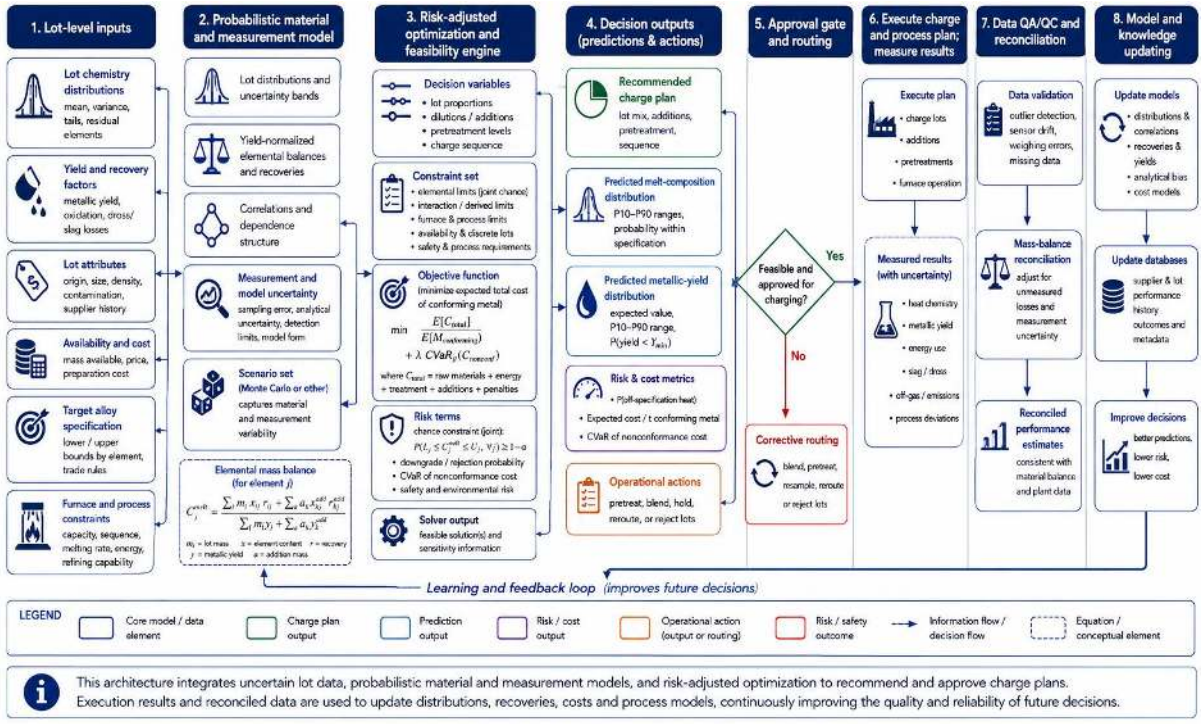

Figure 4. Risk-adjusted charge-design architecture linking lot distributions, yield-normalized balances, furnace constraints, expected nonconformance cost, and post-heat updating. *Author's conceptual synthesis based on* the author-developed framework informed by Carlsson et al. (2020), Ghezzi et al. (2023), Jafari-Ramiani et al. (2022), Kannisto et al. (2024), M. M. Li et al. (2026), Mapelli et al. (2025), Mombelli et al. (2021), Reimann et al. (2021), Sakallı and Birgören (2020), and Xue et al. (2026).

Figure 4 distinguishes decision variables, uncertain inputs, constraints, calculated outputs, and measured feedback, while explicitly identifying the architecture as author-developed and not yet industrially validated.

7. Furnace and Process Constraints

7.1. Melting mechanism and refining capacity

Scrap suitability is furnace-specific because furnaces differ in heat-transfer mode, bath agitation, atmosphere, slag practice, charging access, and refining capacity. An induction furnace offers clean and efficient melting with strong electromagnetic stirring, but limited chemical refining and sensitivity to bulky or poorly packed charge. Electric arc furnaces can melt heterogeneous ferrous charges and support slag refining, yet scrap density, size, gangue, and sequence affect arc stability, energy, oxidation, and tap-to-tap time. Reverberatory and rotary furnaces can accommodate broad aluminum

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scrap streams, but oxidation and dross formation depend strongly on surface exposure, burner atmosphere, salt or flux practice, and submergence.

Numerical and plant studies of EAF melting are used here as analog evidence rather than direct foundry validation; they demonstrate that scrap behavior cannot be represented by chemistry alone. CFD, heat-transfer, energy-demand, and charge-loss models link piece size, charge mix, and furnace operation to melting time and metallic loss (Carlsson et al., 2020; Chen et al., 2022; Hassan et al., 2025; Hay et al., 2021; M. Li et al., 2026; Mapelli et al., 2025; Mombelli et al., 2021; Moskal et al., 2022; Reimann et al., 2021). Induction-furnace modeling similarly highlights electromagnetic force and heat distribution as constraints on charge arrangement and melt circulation (Ibrahim et al., 2026).

7.2. Charge sequence and process window

Charge sequence can be used to protect high-surface-area scrap, promote submergence, stabilize the heel, and prevent bridging. Dense clean metal may establish a molten bath before chips or thin scrap are introduced. Contaminated or coated materials may require controlled feed rates to avoid excessive off-gas peaks. High-alloy or high-residual scrap should be distributed according to the chemistry plan rather than concentrated in one local region of the furnace. Continuous charging can improve productivity but may increase oxidation exposure if feed size and bath coverage are poorly controlled.

The furnace also determines which correction actions are realistic. Dilution and alloy additions are widely available. Oxidation refining can remove some elements in steel or copper systems, but may cause valuable-metal loss and cannot remove all tramp elements. Degassing, filtration, fluxing, and settling can improve aluminum melt quality without correcting an incompatible bulk composition. Electroslag remelting or other secondary routes can upgrade selected high-alloy scrap, but these are specialized processes rather than general foundry corrections (Al-Helal et al., 2021; Wu et al., 2022).

Table 7 provides a furnace-oriented compatibility matrix and labels the evidentiary basis of each row. Electric-arc-furnace studies serve as analog evidence for

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transferable mechanisms, whereas the aluminum, cast-iron, induction, and specialty-remelting rows draw on direct foundry or closely related process evidence.

Table 7. Furnace constraints relevant to scrap selection and charge design

Furnace/process	Scrap-related advantages	Primary constraints	Charge-design implications
Induction melting (direct foundry/specialty-remelting evidence)	Clean heat source, high efficiency, strong bath stirring	Limited refining; packing and bridge sensitivity; difficult bulky charge	Require compatible chemistry; control size and density; establish safe melt heel where applicable
Electric arc furnace (analog steelmaking evidence)	Flexible ferrous charge; slag refining; large throughput	Energy and yield sensitive to density, gangue, size, and sequence; tramp elements persist	Model energy, slag, metallic loss, and residual limits; identify high-alloy pieces
Reverberatory/side-well aluminum (direct or adjacent foundry evidence)	Can process mixed shapes and continuous feeds	Surface oxidation, dross, burner atmosphere, long exposure	Prioritize clean dense scrap or rapid submergence; account for oxide and coating load
Rotary/salt-assisted aluminum (direct secondary-aluminum evidence)	Effective for contaminated or oxidized secondary feed	Salt residue, flux consumption, emissions, metal entrainment	Use only when recovery exceeds treatment and residue cost; control salt balance
Cupola/iron melting (direct foundry evidence)	High productivity and tolerance for varied ferrous units	Coke/slag balance, chemistry control, sulfur and thermal regime	Balance pig iron, steel scrap, returns, flux and carbon sources
Secondary refining/remelting (specialty-process evidence)	Can upgrade selected alloy streams and remove inclusions	Additional energy, yield loss, capital and product-specific constraints	Reserve for high-value streams where recovered alloy value justifies extra processing

Note. Author's synthesis based on (Al-Helal et al., 2021; Carlsson et al., 2020; Chen et al., 2022; Hassan et al., 2025; Hay et al., 2021; Ibrahim et al., 2026; Jarfors, 2025; M. Li et al., 2026; Mapelli et al., 2025; Mombelli et al., 2021; Moskal et al., 2022; Reimann et al., 2021; Wu et al., 2022).

A robust charge model should therefore include furnace-specific acceptance rules. The same scrap may be directly chargeable in one unit, acceptable only after preparation in another, and unsuitable in a third. Corporate scrap specifications that ignore furnace configuration can unintentionally transfer risk from procurement to operations.

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8. Quality Control, Sensor Sorting, and Traceability

8.1. Sampling before instrumentation

Quality control starts with sampling. Heterogeneous lots vary in pieces, size fractions, surfaces, and containers; analyzing a non-representative fragment can falsely increase confidence without more information. Lot protocols should specify the sampling unit, observation count and placement, treatment of fines and oversize, surface prep, replicates, and escalation criteria. Supporting studies include fractionation, melting, ingot, and scrap assessments (Dobosz et al., 2024; Gyarmati et al., 2024; Seidel et al., 2021; Wibner et al., 2020).

Analytical uncertainty must be separated from sampling uncertainty. Repeated measurements on one clean coupon estimate instrumental repeatability, whereas repeated sampling across a commercial lot estimates the uncertainty relevant to charge design. Both should be propagated into the composition distribution used in Section 6.

8.2. Quantitative performance and scale transfer

The literature reports high performance for many sensing tasks, but metrics are not directly comparable due to differences in material classes, surface preparation, train/test splitting, sample prevalence, and industrial throughput. Table 8 shows representative values with conditions that limit interpretation, not pooled accuracy.

Table 8. Representative quantitative results for scrap characterization and sorting

Study and technology	Material and sample	Reported performance	Validation level	Charge-design implication
Huang et al. (2022), RGB/ResNet18	Three prepared aluminum grades: 1060, 5052 and 6061	Final classification accuracy reached 100% after hyperparameter optimization	Laboratory; narrow class set and controlled image conditions	Demonstrates potential for discrimination but does not establish performance on dirty mixed scrap.
Díaz-Romero et al. (2022a), real-time LIBS + ML/DL	Post-consumer aluminum divided into three commercial fractions	Classwise precision reported up to 96% and recall above 94%	Pilot-oriented moving-scrap system; calibration and surface effects remain	Useful for routing only when spectral quality control and melt verification are linked.

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Study and technology	Material and sample	Reported performance	Validation level	Charge-design implication
Díaz-Romero et al. (2023), LIBS + RGB-D fusion	773 post-consumer aluminum pieces; cast/wrought and three-fraction tasks	Cast/wrought precision, recall and F1 = 99%; three-fraction precision 86%, recall 83%, F1 84%	Laboratory/pilot dataset with real pieces; no heat-level economic validation	Task complexity materially lowers performance; class definition must reflect alloy-routing value.
Lin et al. (2024), LIBS + two-step clustering	Automotive scrap metal under three experimental conditions	Average classification accuracy = 98.25%	Laboratory experimental conditions	High accuracy requires confirmation under supplier, coating and equipment drift.
Williams et al. (2023), magnetic-induction spectroscopy	Wrought versus cast aluminum in Twitch	Static: F1 0.9222, recovery 89.66%, purity 94.96%; industrial trial: recovery 63.89%, purity 60%	Both laboratory and industrial trial	The performance loss quantifies the scale-transfer problem and the importance of orientation and sensor coverage.
Anyszkiewicz et al. (2025) and Flamme et al. (2024), XRF	Copper scrap and mixed foundry residues	Quantitative composition and improved alloy-family routing; study-specific metrics	Laboratory to applied residue sorting	XRF adds value where surface state and light-element limitations do not control the decision.

Note. Author's synthesis based on (Ali et al., 2025; Anyszkiewicz et al., 2025; Díaz-Romero et al., 2022a; Díaz-Romero et al., 2023; Flamme et al., 2024; Huang et al., 2022; Lin et al., 2024; Williams et al., 2023). Metrics are reproduced only where reported in accessible study metadata or full text; they are not pooled because tasks and validation conditions differ.

The strongest cross-study finding is not that one sensor is universally superior, but that task definition and validation level dominate apparent performance. Narrow controlled-grade tasks can approach 100%, while broader commercial fractions and industrial conveyors introduce class overlap, orientation, coatings, partial sensor coverage, and domain shift.

8.3. Traceability and decision integration

Each accepted lot should retain supplier, date, source category, sampling plan, raw and processed sensor data, uncertainty class, preparation route, charged heat, final chemistry, yield, energy, dross or slag, and quality outcome. The highest-value sensor output is therefore not merely a class label; it is an updated probability

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distribution for charge-relevant attributes connected to a documented routing or blending action (Compañero et al., 2021; Compañero et al., 2023; Kannisto et al., 2024; Langan et al., 2024; Uyan et al., 2023; Wang et al., 2026).

Sensor-based sorting should be justified through a value-of-information test: the measurement must reduce expected correction, dilution, downgrade, rejection, or primary-metal use by more than its capital and operating cost. Supplier incentives should reward stable composition, cleanliness, and data completeness so that the organization investing in measurement can capture part of the downstream value.

Illustrative decision-economics example. Suppose an in-line sensor costs 4 currency units per tonne of scrap processed, reduces the false-acceptance probability from 8% to 2%, and each false-accepted tonne creates an average downstream correction or downgrade penalty of 180 currency units. If false rejection affects 3% of acceptable material and replacement costs 40 currency units per affected tonne, the net expected value of information is $(0.08 - 0.02) \times 180 - 0.03 \times 40 - 4 = 5.6$ currency units per tonne processed. The example is illustrative; plant decisions require measured class prevalence, asymmetric error costs, throughput, maintenance, and avoided primary metal use.

Figure 5 maps the required digital integration from lot identity and sampling through furnace execution and post-heat learning.

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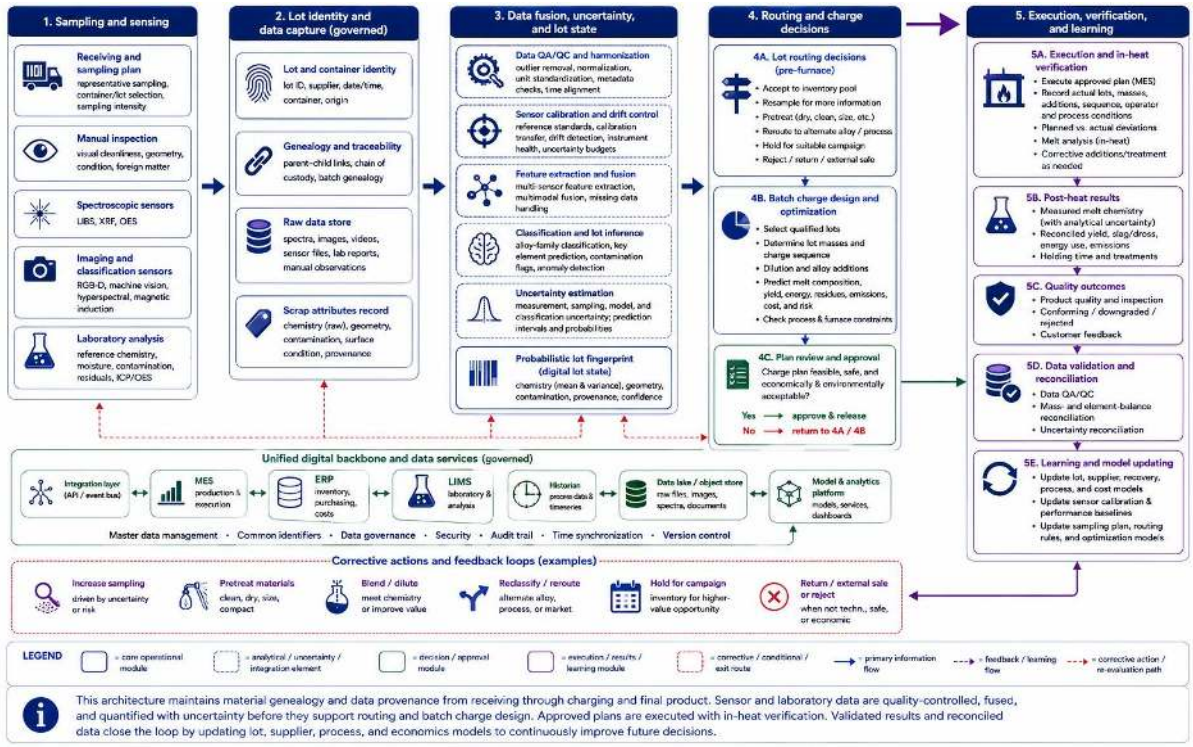

Figure 5. Digital scrap-to-heat architecture linking sampling, sensors, lot identity, uncertainty estimation, routing, charge optimization, furnace execution, melt analysis, and quality feedback.

Author's conceptual synthesis based on the author-developed integration model informed by Akram et al. (2023), Díaz-Romero et al. (2022a, 2022b, 2023), de la Peña et al. (2023), Efe et al. (2025), Kannisto et al. (2024), Kolev and Simeonova (2026), Langan et al. (2024), Uyan et al. (2023), Wang et al. (2026), and Zhang et al. (2026).

Figure 5 emphasizes data lineage, uncertainty propagation, and closed-loop feedback without duplicating the four-gate decision framework in Figure 6.

9. Economic and Environmental Performance

9.1. Cost per tonne of conforming molten metal

The relevant economic quantity is not the quoted scrap price but the expected cost per tonne of conforming molten metal defined in Equation (3). The calculation must use one heat or one tonne as an explicit basis and include transport, sampling, sorting, drying or de-coating, compaction, furnace energy, fluxes, alloy additions, metallic loss, off-gas and residue treatment, productivity, final inspection, correction, downgrade, and rejection. Cost terms should be reported per heat before normalization by the expected conforming-metal mass.

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The value of composition information can then be quantified as the reduction in expected nonconformance and safety-margin costs minus the cost of measurement. This framework explains why a more expensive but stable scrap lot may be economically preferable, and why a low-priced high-surface-area or poorly characterized lot may become expensive after yield and risk are included (Compañero et al., 2023; Djurdjevic et al., 2026; Jarfors, 2025; Mapelli et al., 2025; Mombelli et al., 2021; Sakallı & Birgören, 2020).

9.2. Environmental comparability and quality retention

Higher recycled content reduces reliance on primary extraction, but comparisons are meaningful only when functional units and boundaries align. A tonne of scrap, charged metal, molten metal, and conforming casting are not equivalent when yields and downgrades differ. The preferred functional unit for joint assessment is one tonne of conforming molten alloy or conforming product if downstream rejection is significant.

Closed-loop recycling preserves alloy identity and generally minimizes correction, whereas open-loop recycling can transfer residual-element burdens to lower-grade products. Environmental claims should therefore disclose metallic yield, product quality, fate of dross or slag, avoided-primary-metal credit, allocation method, electricity mix, transport, and whether downgrade is counted as equivalent recycling (Colla et al., 2026; Hannula et al., 2020; Loibl & Tercero Espinoza, 2021; Nunes et al., 2023; Padamata et al., 2021; Pereira, 2025; Raabe et al., 2022; Raabe et al., 2024; Sajjad et al., 2025; Tu & Hertwich, 2022; Van den Eynde et al., 2022; Yu et al., 2026).

Table 9 defines the minimum reporting fields required for critical comparison of environmental studies.

Table 9. Minimum normalization fields for environmental comparison of scrap-based melting

Field	Required disclosure	Reason for comparability
Functional unit	t scrap, t charged metal, t molten metal, or t conforming product	Different denominators can reverse apparent environmental rankings.
System boundary	Gate-to-gate, cradle-to-gate, collection-to-casting, or other	Sorting, pretreatment and residue treatment may be inside or outside the boundary.
Metallic yield	Recovered molten metal as a percentage of charged metallic feed	Low yield increases primary replacement and residue burden.

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Field	Required disclosure	Reason for comparability
Quality and downgrade	Alloy compliance, property retention, rejected or cascaded output	A recycled tonne is not functionally equivalent if quality is lost.
Avoided-primary credit	Substitution ratio and displaced primary-metal route	Credit assumptions often dominate the result.
Energy and electricity mix	Fuel/electricity use, country, year and marginal or average mix	Carbon intensity varies strongly by energy source and time.
Dross/slag and emissions treatment	Included processes, recovery credits, disposal and salt management	Residues can materially alter both mass balance and impact.
Transport and allocation	Distance, mode, co-product allocation or system expansion	Logistics and allocation affect cross-study comparability.

Note. Author's synthesis based on exergy, LCA, process-simulation and carbon-footprint studies (Colla et al., 2026; Hannula et al., 2020; Jarfors, 2025; Loibl & Tercero Espinoza, 2021; Raabe et al., 2024; Sajjad et al., 2025; Tu & Hertwich, 2022; Van den Eynde et al., 2022; Yu et al., 2026).

The reviewed environmental evidence is therefore directionally supportive of greater high-quality recycling, but too heterogeneous for a pooled carbon value. Future work should publish reconciled mass and energy balances and should report both recycled content and retained alloy function.

10. Standards, Specifications, and Industrial Practice

Scrap transactions are governed by a layered specification system: commercial grade descriptions, national or international standards, supplier certificates, customer alloy requirements, and internal foundry acceptance rules. These layers do not always use the same terminology or measure the same attributes. Commercial specifications often emphasize visible contamination and broad material class, whereas the foundry needs residual-element distributions, physical density, moisture, nonmetallic fraction, and lot traceability.

The reviewed literature reveals this gap indirectly. Studies of scrap purity, incoming aluminum-ingot quality, ferrous-scrap grade, charge composition in operating foundries, and representative sampling show that nominal grades do not guarantee a stable process response (Dobosz et al., 2024; Gyarmati et al., 2024; Janiszewski, 2021; Pribulová et al., 2020; Wibner et al., 2020). The difference between normative compliance and metallurgical fitness becomes especially important near tight residual limits.

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An effective internal specification should define both acceptance limits and the inspection method. A limit without a sampling plan is not enforceable; a sensor classification without a decision rule is not operational; and a chemical certificate without lot identity is not traceable. Comparative elemental-analysis studies emphasize the need to understand method capability and agreement before using measurements interchangeably (Anyszkiewicz et al., 2025; Brooks & Gaustad, 2021; Seidel et al., 2021).

Supplier incentives also matter. If clean, well-characterized scrap is paid as an undifferentiated commodity, the supply chain has little reason to invest in segregation or data. Circular-steel research shows that information and actor incentives influence recyclability and the practical value of compositional data (Compañero et al., 2021; Compañero et al., 2023). Long-term contracts can therefore include quality premiums, penalties, shared sampling protocols, and data exchange.

Table 10 distinguishes the function of external standards and commercial specifications from the additional controls required for metallurgical charge design. The documents are complementary rather than interchangeable: sampling standards govern how a sample is obtained, end-of-waste rules address legal and quality-management status, and trade specifications provide commercial descriptions; none alone defines furnace-specific alloy fitness.

Table 10. External standards and specifications relevant to foundry scrap governance

Document or system	Principal scope	Useful control for foundries	Limitation for charge design
ASTM B985-24	Sampling aluminum ingots, billets, castings, and wrought products for compositional analysis	Requires a defined sampling practice before compositional acceptance	Does not establish scrap-grade chemistry, contamination limits, or furnace-specific suitability
ISO 14284:2022	Sampling and sample preparation of steel and iron for chemical-composition determination	Supports representative laboratory sampling and traceable preparation	Does not prescribe commercial scrap classes or probabilistic charge limits

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Document or system	Principal scope	Useful control for foundries	Limitation for charge design
Council Regulation (EU) No 333/2011	End-of-waste criteria for iron, steel, and aluminum scrap, including quality-management and specified impurity/contamination conditions	Provides a regulatory acceptance floor and documented quality system	Legal end-of-waste status does not demonstrate compatibility with a particular alloy or furnace
ReMA Scrap Specifications Circular	Commercial definitions and transaction terminology for recycled commodity grades	Provides common purchasing language and dispute reference	Trade-grade descriptions may be broader than residual-element, geometry, and uncertainty needs
Internal foundry performance specification	Lot identity, chemistry distributions, geometry, surface condition, uncertainty, and routing action	Connects procurement acceptance directly to charge calculation and heat performance	Requires plant data, periodic revision, and supplier-specific validation

Note. Author's comparison based on ASTM International (2024), Council of the European Union (2011), International Organization for Standardization (2022), Recycled Materials Association (2022), and the industrial-governance evidence in (Anyszkiewicz et al., 2025; Brooks & Gaustad, 2021; Compañero et al., 2021; Compañero et al., 2023; Dobosz et al., 2024; Gyarmati et al., 2024; Janiszewski, 2021; Pribulová et al., 2020; Seidel et al., 2021; Wibner et al., 2020; Yu et al., 2026).

Table 11 translates this layered governance system into a minimum internal scrap-lot specification for foundry use.

Table 11. Minimum internal scrap-lot specification for foundry use

Specification field	Required content	Verification	Decision use
Lot identity and provenance	Supplier, source process, collection date, container, declared alloy family	Document and barcode/RFID check	Traceability and supplier performance
Chemical limits	Major elements, critical residual upper bounds, prohibited alloy families	Defined sampling plan plus XRF/LIBS/laboratory method	Charge calculation and routing
Physical form	Size range, thickness, bulk density, fines and compaction	Visual/physical measurement and mass-volume check	Furnace compatibility and productivity
Surface condition	Moisture, oil, paint, polymer, corrosion, sand/refractory, foreign material	Visual grading plus quantitative tests where critical	Safety, pretreatment and yield prediction
Uncertainty class	Historical standard deviation, sample count, outlier frequency	Lot database and periodic audit	Optimization safety margin

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Specification field	Required content	Verification	Decision use
Acceptance action	Direct charge, blend limit, pretreat, downgrade, return or reject	Approved decision matrix	Consistent procurement–operations response

Note. Author's synthesis based on (Anyszkiewicz et al., 2025; Brooks & Gaustad, 2021; Compañero et al., 2021; Compañero et al., 2023; Dobosz et al., 2024; Gyarmati et al., 2024; Janiszewski, 2021; Pribulová et al., 2020; Seidel et al., 2021; Wibner et al., 2020; Yu et al., 2026).

The proposed specification is intentionally performance-oriented and creates a common language among procurement, laboratory, yard, melting, quality, and environmental teams. Responsibility should be distributed rather than transferred downstream: procurement controls supplier qualification and contractual limits; the yard verifies identity, physical condition, and segregation; the laboratory owns sampling and analytical validity; melting defines furnace-specific caps and sequence; quality verifies final conformity; and environmental personnel close emissions and residue balances. A lot should not be accepted by procurement alone when its metallurgical, safety, or environmental consequences are borne elsewhere. The specification should be revised to reflect actual heat outcomes rather than remain a static purchasing document.

11. Digitalization and Emerging Technologies

11.1. From automated sorting to adaptive charge control

The technology frontier is moving from single-sensor classification toward integrated, adaptive systems. Recent research combines LIBS spectra with images, uses deep learning for metal recognition, applies hyperspectral imaging to automated upgrading, estimates mass and class together, and develops chute-based high-throughput sorting (Badowski et al., 2026; Chen et al., 2026; Chen et al., 2021; de la Peña et al., 2023; Díaz-Romero et al., 2022a; Díaz-Romero et al., 2022b; Díaz-Romero et al., 2023; Huang et al., 2022; X. Li et al., 2026; Li et al., 2021; Lin et al., 2024; Zhang et al., 2026). These systems can transform heterogeneous scrap into narrower, more valuable streams, but only if the classification classes correspond to actual foundry decisions.

Artificial intelligence is also entering the field of furnace and process control. Model-predictive control, resilient self-configuring AI pipelines, digital tools for

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aluminum processing, and smart manufacturing reviews indicate a progression from descriptive dashboards to prescriptive decision-making (Ghezzi et al., 2023; Kannisto et al., 2024; Kolev & Simeonova, 2026; Wang et al., 2026). For charge design, the most useful AI function is not a black-box recipe. It is a transparent recommendation that reports confidence, limiting residuals, expected cost, and the consequences of alternative routing.

11.2. Sensor fusion, domain adaptation, and data quality

Domain adaptation is a critical, emerging topic because models trained on standard or single-supplier populations may fail on dirty, painted, fragmented, or compositionally shifted scrap. Adversarial domain adaptation and data augmentation have been explored for LIBS-based identification (Srivastava et al., 2022; Srivastava et al., 2023). The industrial research priority is to test whether such approaches maintain accuracy under seasonal, supplier, coating, and equipment changes.

Sensor fusion can reduce ambiguity by linking chemistry, appearance, geometry, and mass. Optical alloy-selective sorting, RGB-D and LIBS fusion, magnetic-induction spectroscopy, and image-guided tramp-material detection demonstrate complementary pathways (Díaz-Romero et al., 2023; Efe et al., 2025; Quan et al., 2026; Williams et al., 2023). Future systems should output a scrap fingerprint with uncertainty rather than a single hard class.

11.3. Technology-readiness considerations

Technology readiness should be judged by a sequence of gates: analytical validity; representative sampling; throughput; maintainability; calibration stability; integration with material handling; decision linkage; and verified economic benefit. Case studies on sensor-based sorting, industrial AI, and foundry data management show that software accuracy is only one element of deployment (Jurtsch et al., 2024; Koinig et al., 2026; Langan et al., 2024; Tischberger-Aldrian et al., 2026; Uyan et al., 2023; Wang et al., 2025; Xu et al., 2024).

A practical deployment can begin with targeted high-value problems: separating cast from wrought aluminum, identifying copper-bearing ferrous fragments, distinguishing high-alloy steel, cleaning painted measurement spots, or qualifying a

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stable supplier stream. Broader autonomous control should follow only after these use cases produce reliable mass balances and financial results.

These digital elements are integrated into the four-gate framework presented later in Figure 6 rather than repeated in a separate future-state diagram. The final framework retains human supervision for abnormal lots and safety-critical decisions; explainable constraints, audit trails, and manual override are essential because the cost of a false acceptance can exceed the value of many correct classifications.

12. Critical Synthesis, Decision Framework, and Research Agenda

12.1. What is supported, inferred, and proposed

The evidence matrix permits a clearer separation of claim types. Directly supported conclusions are that scrap chemistry, geometry and contamination interact with yield and quality; residual elements with limited removability require upper-bound control; sampling and surface condition affect sensor performance; and furnace response depends on charge form and sequence. These conclusions recur across alloy, melting, sensing and modeling studies.

The inference that plant-scale validation is scarce is quantitatively supported: only 10 studies were coded as industrial/plant and 5 as pilot/demonstration, compared with 55 laboratory studies and 35 model, review or contextual sources. Likewise, 44 studies used prepared or controlled material, while 17 used commercial heterogeneous scrap and 10 used plant/process-representative feeds. The evidence therefore supports caution when transferring high laboratory accuracy or controlled alloy-property results to incoming scrap lots.

The scrap fingerprint, yield-normalized probabilistic optimizer, cost-per-tonne-of-conforming-metal objective, and four-gate framework are author-developed syntheses. They are consistent with the reviewed evidence but have not been validated as an integrated system. Their status is therefore a testable conceptual contribution rather than an established industrial best practice.

12.2. Four-gate implementation framework

Gate 1 addresses safety and basic acceptance: moisture, sealed items, hazardous attachments, excessive organics, prohibited foreign materials, and

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applicable regulatory controls. Gate 2 addresses chemical compatibility: major alloying elements, non-removable residuals, uncertainty, and dilution or refining capacity. Gate 3 addresses physical and process compatibility: size, density, surface condition, preparation, furnace route, sequence, and expected yield. Gate 4 addresses economic and environmental value: expected conforming-metal cost, productivity, residues, emissions, product quality, and future recyclability.

Much should progress only when uncertainty aligns with failure consequences. Broad-tolerance secondary alloys might allow lower-resolution classification; safety-critical structural alloys or low-residual products need certified metal, more sampling, or piece-level sorting. The same scrap can be acceptable for one product–furnace combination but not another.

The consolidated framework is summarized in Table 12.

Table 12. Scrap-to-alloy decision gates and minimum evidence

Gate	Decision question	Minimum evidence	Typical action
1. Safety and legal acceptance	Can the material be stored, handled and charged safely and legally?	Moisture, sealed items, organics, hazardous attachments, radiation/prohibited-material checks where applicable	Accept, isolate, clean, return or reject.
2. Chemical compatibility	Will major and residual elements satisfy a risk-adjusted alloy window?	Representative analyses, distributions, sensor uncertainty, removability and dilution capacity	Direct route, blending cap, downgrade, refine or reject.
3. Physical/process compatibility	Will the material melt with acceptable yield, time, emissions and melt quality?	Size, density, surface condition, preparation need, furnace model and historical yield	Resize, compact, de-coat, alter sequence or route to another furnace.
4. Economic/environmental value	Does the lot reduce expected cost and impact per tonne of conforming output?	Purchase/preparation cost, energy, yield, nonconformance, residues, functional unit and boundary	Approve optimized fraction, renegotiate, invest in sorting, substitute feed or reject.

Note. Author-developed synthesis informed by the full evidence corpus, particularly (Al-Helal et al., 2021; Armstrong et al., 2026; Colla et al., 2026; Compañero et al., 2023; Garcia et al., 2025; Garcia et al., 2026; Hannula et al., 2020; Kalhor et al., 2026; Loibl & Tercero Espinoza, 2021; Nunes et al., 2023; Padamata et al., 2021; Pereira, 2025; Raabe et al.,

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2022; Raabe et al., 2024; Sajjad et al., 2025; Shankar et al., 2025; Tshipama et al., 2023; Tu & Hertwich, 2022; Van den Eynde et al., 2022).

Figure 6 presents the four gates, rejection or rerouting exits, and the feedback loop from heat outcomes to lot and supplier models. It is deliberately differentiated from Figure 4, which formalizes optimization variables, and Figure 5, which maps digital data integration.

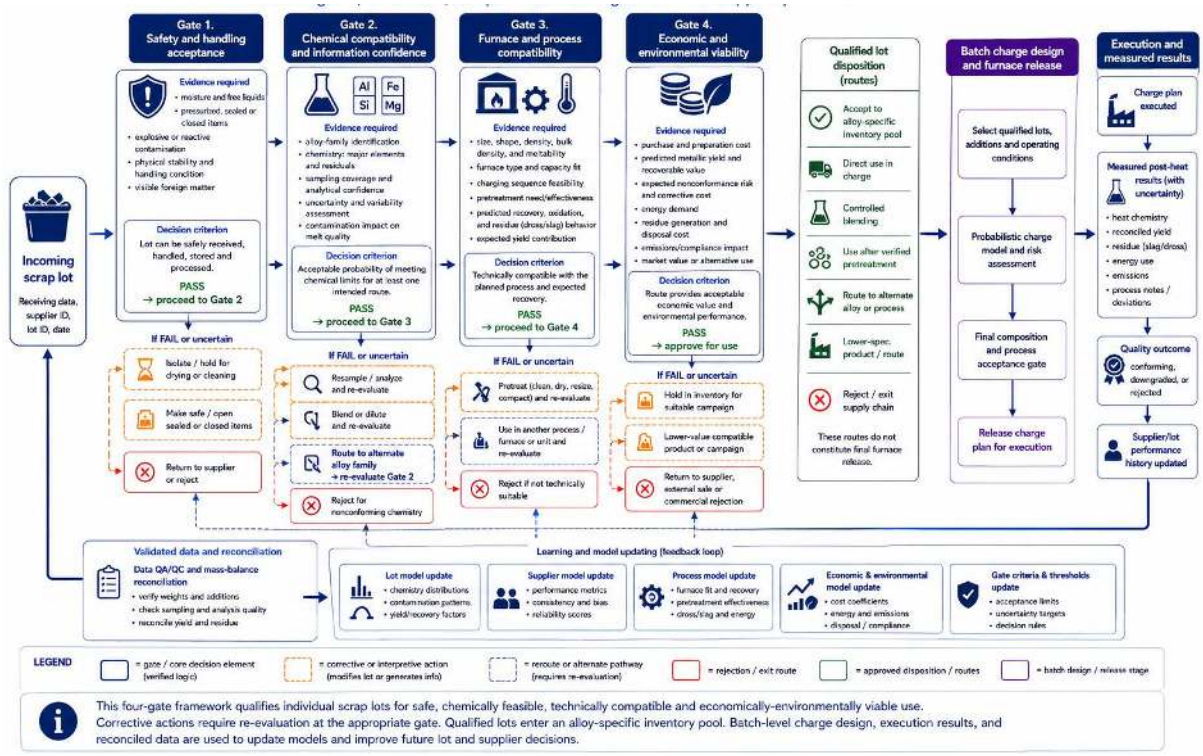

Figure 6. Four-gate scrap-to-alloy decision framework with rejection/rerouting exits and post-heat feedback to lot and supplier models.
Author's conceptual synthesis based on the author-developed synthesis in this review. The final graphic should differentiate safety, chemistry, process compatibility, and economic/environmental value and show the evidence required at each gate.

Figure 6 serves as the integrative graphical conclusion, while Figures 4 and 5 represent the mathematical and digital architectures, respectively.

Validation status. The four-gate framework is an author-developed, evidence-informed conceptual synthesis. It should not be treated as a prescriptive industrial standard until it has been tested through repeated plant heats across multiple alloy families and furnace types, using predefined endpoints for chemistry, metallic yield, energy, emissions, correction, cycle time, product quality, and total conforming metal cost.

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12.3. Priority research agenda

First, plant trials should publish reconciled lot-to-heat datasets containing scrap distributions, sampling design, sensor outputs, charged masses, final chemistry, metallic yield, energy, dross or slag, correction, cycle time, product quality, and total cost. Repeated heats are required to estimate uncertainty and validate the risk levels in Equation (2).

Second, benchmark studies should compare sensors on the same commercial scrap population using piece-level and lot-level metrics, class prevalence, surface condition, throughput, false-acceptance cost, and subsequent melt validation. Accuracy alone is insufficient when the cost of a false acceptance is asymmetric.

Third, alloy-specific residual windows should be reported with product geometry, cooling rate, heat treatment, and property requirements. Universal contaminant limits are generally not defensible; the useful output is a conditional response surface or validated acceptance window.

Fourth, pretreatment studies should close metal, energy, emissions, residue, and cost balances and identify the threshold at which drying, de-coating, washing, compaction, or flux treatment becomes favorable.

Fifth, environmental studies should use the normalization fields in Table 9 and report quality retention and downgrade. Digital and governance research should also address identifiers, data ownership, cybersecurity, operator override, and distribution of value across suppliers, recyclers, and foundries.

Finally, direct evidence is needed for zinc, magnesium, and specialty foundry systems. Their oxidation, vaporization, safety, and contamination behavior should not be inferred uncritically from aluminum, copper, or steel.

Limitations and boundary conditions

The review has six principal limitations. First, the corpus was reconstructed retrospectively, and the original discovery-stage hit lists, screened-result counts, and Google Scholar page counts were not retained; completeness cannot therefore be independently verified before the 105-record audit stage. Second, all screening and coding were performed by one reviewer without independent calibration or inter-rater

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reliability testing. Third, English-language and Google-Scholar-centered retrieval may underrepresent regional, proprietary, and non-indexed industrial evidence.

Fourth, the evidence base is uneven: aluminum and steel dominate; only 15 studies reached pilot or industrial scale; and direct evidence from zinc and magnesium foundries is sparse. Fifth, studies of electric arc furnace steelmaking are used only as analog evidence for transferable mechanisms and do not directly validate foundry furnaces. Sixth, the numerical example assumes independent normal uncertainty, and the scrap fingerprint, probabilistic optimizer, cost objective, digital architecture, and four-gate framework remain conceptual until validated with repeated plant heats.

These limitations do not negate the integrated decision logic, but they constrain claim strength, generalizability, and prescriptive use. Supplementary Table S1 and Supplementary Methodological Note S2 are provided to make the single-reviewer audit as transparent as the retained records allow.

13. Conclusions

Scrap selection and charge design are inseparable metallurgical decisions. A scrap lot cannot be judged solely by its nominal alloy family or purchase price because chemistry, geometry, contamination, information quality, and furnace response jointly determine whether the material becomes conforming metal, recoverable residue, or avoidable loss.

The review shows that non-removable residual elements require the most conservative control. Deficiencies can often be corrected with additions, whereas excess residuals may require dilution, downgrade, alternative routing, or rejection. This asymmetry should shape sampling intensity, uncertainty margins, and supplier specifications.

Charge calculation should evolve from average-value recipes toward risk-adjusted optimization. Empirical knowledge remains valuable, but it should be expressed as transparent constraints and updated with lot-level and heat-level data. The model should predict not only chemistry, but also yield, energy, preparation needs, correction, and the probability and cost of off-specification metal.

Advanced sensing and artificial intelligence can materially improve scrap utilization, particularly through rapid alloy identification, contaminant detection, mass

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estimation, and sensor fusion. Their success, however, depends on representative sampling, calibration stability, industrial throughput, traceability, and direct connection to routing and charge decisions. Classification accuracy without decision integration is an incomplete performance measure.

The proposed four-gate framework—safety, chemical compatibility, physical/process compatibility, and economic/environmental value—provides a practical basis for aligning procurement, yard operations, laboratory control, melting, quality, and sustainability. It can be implemented progressively and adapted to different alloy families and furnace types.

Future progress requires plant-scale datasets that close mass, energy, quality, cost, and environmental balances; standardized scrap descriptors; uncertainty-aware models; and stronger feedback between suppliers and foundries. The conclusions should be interpreted within the retrospective-search, single-reviewer, alloy-family-imbalance, and plant-validation limitations stated above. The technically sustainable objective is not the maximum possible scrap fraction in isolation, but the maximum reliable use of secondary metal that preserves product function, process stability, and future recyclability.

Declarations

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Conflict of interest: No conflict of interest is declared.

Data availability: No new experimental dataset was generated. The study-level evidence coding for the 105-source corpus is provided as Supplementary Table S1; the numerical example in Section 6.3 is illustrative and fully parameterized in the manuscript.

Author contributions: Removed from the double-blind review version and to be restored after editorial acceptance.

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