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Micro-metallurgical production in the global steel system: market structure, decarbonization pressures, and the integration of artificial intelligence into small and mid-scale secondary steelmaking

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Abstract

This review article examines the current state and projected trajectory of micro-metallurgical production, defined as small and mid-scale secondary steelmaking operations based on scrap feedstock, localized demand, and energy-efficient rolling and melting technologies, within the global steel system. The article synthesizes quantitative market data, regulatory developments, and the rapidly maturing application of artificial intelligence to metallurgical processes, drawing on peer-reviewed literature, industry analyses, and primary data from 2024 through 2026. Three structural forces are reshaping the sector simultaneously: the global shift from integrated blast-furnace production toward electric arc furnace (EAF) and direct-reduced-iron (DRI) routes, driven by scrap availability and decarbonization policy including the European Union Carbon Border Adjustment Mechanism (CBAM); the progressive lowering of minimum efficient scale in secondary steelmaking through induction heating, cross-wedge rolling, and modular plant design, which makes facilities of 20,000 to 350,000 tonnes per year commercially viable; and the integration of artificial intelligence, including machine learning, digital twins, computer vision, and generative models, into furnace control, predictive maintenance, and scrap characterization. The article argues that these three forces are mutually reinforcing, and that micro-metallurgical facilities in emerging mining-intensive economies represent the most likely mechanism through which regional demand for specialized steel products, particularly grinding media, rolling stock components, and wear-resistant consumables, will be served through the 2030s. The article identifies five research and policy priorities: standardization of AI-ready data architectures for small-scale plants, development of physics-informed machine learning models suited to induction-based production, regulatory frameworks that extend decarbonization incentives beyond integrated producers, workforce development that bridges metallurgy and data science, and empirical validation of the financial and emissions benefits of AI deployment at sub-500,000 tonne per year scales.

Keywords: micro-metallurgy, minimill, electric arc furnace, scrap steel, artificial intelligence, digital twin, predictive maintenance, industrial decarbonization, CBAM, circular economy

1. Introduction

The global steel industry is undergoing the most substantial structural transformation since the emergence of the oxygen converter in the mid-twentieth century. For most of the industry's modern history, competitive advantage was anchored in integration and scale, with blast-furnace to basicoxygen-furnace (BF-BOF) facilities producing crude steel at capacities of several million tonnes per year as the dominant organizational form [1]. Beginning in the late twentieth century, electric arc furnace (EAF) minimills progressively displaced integrated producers across flat and long product categories, first in North America and subsequently in markets with abundant scrap availability and access to competitively priced electricity [2, 3]. The share of global steel produced through the EAF route rose from approximately 25 percent through 2012 to roughly 30 percent by 2021 and is projected to continue expanding, with half of all new steelmaking capacity currently under development planning to use EAF technology, much of it integrated with DRI [4].

This article examines a specific segment within this broader transition that has received comparatively limited academic attention: micro-metallurgical production, defined as secondary steelmaking operations at capacities between approximately 20,000 and 350,000 tonnes per year, anchored in scrap or other secondary ferrous feedstock, and oriented toward specialized industrial consumables rather than generic steel semis. Grinding media for mining and cement operations, rolling stock components, fasteners, reinforcement bar for localized construction markets, and wear-resistant parts for heavy equipment represent the primary product categories served by this production model. Micro-metallurgical facilities differ from both traditional integrated plants and conventional EAF minimills in three respects: their minimum efficient scale is an order of magnitude smaller, their feedstock specification is often more narrowly defined to enable specific product chemistry without extensive reformulation, and their capital intensity per installed tonne of capacity is substantially lower, which changes the set of actors capable of entering the market.

Three forces are converging to make this production model strategically and commercially significant in the mid-2020s. The first is the global redistribution of steelmaking capacity away from integrated BF-BOF routes and toward secondary production, accelerated by scrap availability trends and by regulatory instruments such as the European Union Carbon Border Adjustment Mechanism (CBAM), which from January 2026 imposes carbon pricing on imports of steel and other carbon-intensive goods [5]. The second is the progressive technical maturation of equipment suited to small-scale secondary steelmaking, including compact induction furnaces, cross-wedge rolling mills, and modular plant architectures, which collectively reduce the minimum efficient scale at which specialized steel products can be competitively produced. The third is the integration of artificial intelligence, including supervised and reinforcement learning, digital twins, computer vision, and generative models, into metallurgical processes at every stage from scrap characterization through quality control [6, 7, 8].

The objective of this review article is to synthesize the current state of these three forces and to assess their implications for the micro-metallurgical production model over the 2025 to 2035 period. The article is organized as follows. Section 2 describes the review methodology and the literature base. Section 3 examines the structural shift in global steelmaking capacity and the regulatory environment driving it. Section 4 analyzes the technical and economic basis of the micro-metallurgical model. Section 5 presents the integration of artificial intelligence into secondary steelmaking, distinguishing applications that scale naturally to small facilities from those that require adaptation. Section 6 identifies research and policy priorities for the development of the sector. Section 7 concludes.

2. Methodology

This review article synthesizes peer-reviewed literature, industry analyses, regulatory publications, and primary project data assembled between 2024 and April 2026. The literature base comprises three categories of sources. The first category consists of peer-reviewed journal articles indexed in Scopus, Web of Science, and Google Scholar, identified through systematic keyword searches combining terms from three domains: steel production (including ”electric arc furnace,” ”minimill,” ”scrap steel,” ”direct reduced iron,” ”induction furnace,” ”cross-wedge rolling”), artificial intelligence in industrial applications (including ”machine learning metallurgy,” ”digital twin steelmaking,” ”predictive maintenance steel,” ”computer vision scrap sorting”), and decarbonization policy (including ”CBAM steel,” ”circular economy steel,” ”green steel”). Priority was given to publications from January 2023 through April 2026 to capture the most recent developments.

The second category consists of industry research reports from Global Energy Monitor, the World Steel Association, the OECD, the World Economic Forum, the International Energy Agency, SMS Group, Primetals Technologies, Danieli, and major market research providers. These sources provided quantitative data on capacity, production volumes, and investment trajectories that complement the analytical literature. The third category consists of primary project documentation from the author’s direct involvement in the design and financial modeling of micro-metallurgical facilities in Central Asia, including detailed technical and economic parameters of a 20,000 tonne per year grinding ball production facility in the Pavlodar Special Economic Zone of Kazakhstan.

The review follows a narrative synthesis approach rather than a formal systematic review protocol, reflecting both the interdisciplinary scope of the subject matter and the rapid evolution of the underlying technologies. Where quantitative estimates vary across sources, the article reports the range observed and identifies the source of variance. The article does not attempt to resolve contested estimates of future market size through proprietary modeling, instead presenting the distribution of published projections as an expression of genuine uncertainty.

3. The structural shift in global steelmaking capacity

3.1 Capacity trajectories and the rise of the EAF route

The current global steel system produces approximately 1.8 billion tonnes of crude steel annually, of which roughly 30 percent was produced through the EAF route as of 2021, and EAF share has continued to expand since [4]. Electric arc furnace capacity has grown nearly 11 percent since 2020, with a further 24 percent increase projected by 2030, and half of all steelmaking capacity currently under development is planned to use EAF technology [9]. The market for EAF equipment itself reflects this growth trajectory, with global revenues valued at approximately 699 million U.S. dollars in 2024 and projected to reach 1.25 billion U.S. dollars by 2032, implying a compound annual growth rate of approximately 8.9 percent [10].

The geographic distribution of this expansion is uneven. Asia-Pacific accounts for approximately 41 percent of the EAF steel production market, driven principally by China and India [11]. China, which historically produced less than 10 percent of its steel through EAF routes, has set a target of 15 percent by 2025 and has been reported to be working toward 20 percent by 2030 [12]. India has overtaken China as the largest developer of new steel capacity globally and now accounts for a substantial share of new coal-based BF-BOF capacity under development, although its total pipeline includes significant EAF components [9]. North America represents approximately 24.6 percent of the global EAF market, supported by a mature scrap ecosystem and by the United States Inflation Reduction Act, which provides approximately 35 U.S. dollars per tonne of clean steel produced via low-emission EAF routes [13].

The scrap supply that feeds this expanding EAF capacity is itself growing substantially. Global steel scrap generation was estimated at approximately 750 million tonnes in 2025 and is projected to grow at roughly 3.5 percent annually through 2034 [13]. A separate industry assessment placed the 2024 figure at 543.2 million tonnes and projected growth to 727.1 million tonnes by 2030 at a CAGR of 5.0 percent [14]. The divergence between these estimates reflects differences in definition and measurement methodology rather than fundamental disagreement about the trajectory of scrap availability, which is increasing in absolute terms across all major producing regions.

3.2 Decarbonization policy and the CBAM transition

The regulatory environment is exerting substantial additional pressure in favor of secondary steel routes. The European Union CBAM, which enters its definitive phase on 1 January 2026, applies EU Emissions Trading System carbon pricing to imports of iron and steel and several other carbon-intensive goods [15]. EAF-based production emits approximately 300 kilograms of CO2 per tonne of steel, compared with roughly 2.0 to 2.2 tonnes of CO2 per tonne for integrated BF-BOF production, giving secondary producers a substantial competitive advantage under carbon pricing regimes [16]. Projections indicate that EU steel imports could decline by 24 to 30 percent from 2023 levels by 2034 as CBAM implementation proceeds [17].

Nevertheless, the transition has not progressed as rapidly as early announcements suggested. During 2024 and 2025, multiple large European steel producers postponed or cancelled major decarbonization projects, citing slow hydrogen market development, high energy costs, and uncertain regulatory conditions. ArcelorMittal cancelled its planned EAF-DRI projects in Gijón and Dunkirk before later announcing in May 2025 that it would proceed with a single EAF at Dunkirk at a cost of approximately 1.2 billion euros [18]. Salzgitter postponed the next stages of its Salcos project by three years, Thyssenkrupp postponed its green hydrogen tender for the Duisburg H2-DRI plant indefinitely, and Třinecké železárny in the Czech Republic delayed its EAF completion from 2028 to no earlier than 2030 [18].

These developments matter for the assessment of micro-metallurgical production because they indicate that the transition is proceeding through a more fragmented and longer-duration pathway than the integrated headline projects would suggest. Large integrated producers face capital requirements that the industry estimates at 70 to 100 billion U.S. dollars in Europe alone [16], and the economic gap between green steel production costs and conventional costs remains substantial, with hydrogen-DRI production currently estimated at 30 to 40 percent more expensive than conventional methods [19]. The global steel decarbonization market is nevertheless projected to grow sharply from approximately 6.33 billion U.S. dollars in 2025 to nearly 411 billion U.S. dollars by 2035 [20], although these projections embed assumptions about technology deployment rates and policy stringency that introduce substantial uncertainty.

3.3 Implications for micro-metallurgical production

The cumulative effect of these trends is that the regulatory and economic environment is increasingly favorable to scrap-based secondary production at all scales, but that the capital requirements and technical complexity of large integrated green steel projects are creating a window of opportunity for smaller, more focused facilities to enter specific product segments. Long-products minimills currently operate at capacities of 0.3 to 1.0 million tonnes per year based primarily on scrap feedstock, and new facilities in this range continue to be commissioned globally, including the 350,000 tonne per year facility announced by SMS Group for Future Forgeworks in Australia [21].

At scales below 350,000 tonnes per year, the micro-metallurgical model occupies an even more distinct position. These facilities serve specialized product segments in which the economics of long-distance transport from global suppliers do not outweigh the cost premium of domestic production, particularly where those domestic producers operate under preferential tax and infrastructure regimes such as special economic zones. The grinding media segment, in which global demand approached between 7.89 and 10.19 billion U.S. dollars in 2024 and is projected to grow at a compound annual growth rate of 2.5 to 5.6 percent through 2030 to 2034 [22, 23, 24], exemplifies this pattern. Regional producers capable of serving mining-intensive economies with a 20,000 to 30,000 tonne per year grinding ball facility can compete effectively against Chinese imports priced on the basis of long-distance delivery.

4. Technical and economic basis of the micro-metallurgical model

4.1 Equipment architecture and minimum efficient scale

Micro-metallurgical facilities depend on three technical developments that have progressively lowered the minimum efficient scale of specialized secondary steelmaking. The first is the commercial maturity of compact induction furnaces at capacities appropriate for sub-500,000 tonne per year production. Induction furnaces at 5 to 7 megawatts of installed power, which are sufficient for heating throughput rates of 20,000 to 30,000 tonnes per year of rolled steel product, are now offered by multiple established equipment manufacturers and can be integrated with process control systems such as Siemens SIMATIC or equivalent platforms. Induction heating offers substantial advantages over gas-fired alternatives: uniform temperature distribution with precision of approximately plus or minus 10 degrees Celsius, absence of scale formation on heated surfaces, elimination of combustion emissions, and reduced energy consumption of 10 to 15 percent compared to equivalent gas-fired capacity through the application of frequency-regulated drives.

The second development is the refinement of cross-wedge rolling and ball-rolling technology suited to production from medium-carbon scrap inputs. For grinding ball applications specifically, cross-wedge rolling of heated billets derived from retired railroad rails produces balls with surface hardness of 55 to 65 HRC meeting GOST 7524-2015 and equivalent Western standards, without the chemistry reformulation required when using mixed scrap streams. Retired railroad rails are composed of medium-carbon, manganese-alloyed steel with carbon content typically 0.67 to 0.80 percent and manganese content 0.75 to 1.05 percent, producing after rolling and quenching hardness values consistently within the required specification [25]. Metal losses in this production pathway are approximately 5 to 7 percent, roughly 10 percent lower than typical losses in casting processes.

The third development is the modularization of plant architecture, which allows a complete facility to be constructed on a site of approximately three hectares with a production hall of 3,400 square meters and ancillary storage and administrative facilities totaling 1,900 square meters. Total capital investment for a 20,000 tonne per year grinding ball facility in Central Asia has been documented at approximately 2.5 billion Kazakhstani tenge, equivalent to approximately 5 to 6 million U.S. dollars at current exchange rates. Investment at this scale is accessible to entrepreneurial enterprises and regional industrial groups, which is an important enabling condition for the geographic proliferation of the micro-metallurgical model.

4.2 Financial performance at sub-100,000 tonne per year scales

The financial performance of micro-metallurgical facilities at the scales examined in this article is substantially better than is commonly recognized in general steel industry discussions, which typically assume that economies of scale favor capacities above several hundred thousand tonnes per year. At a production price of 400,000 Kazakhstani tenge per tonne of grinding balls, which corresponds to the market price for forged steel grinding balls of GOST 7524-2015 quality in the Kazakhstani market, a 20,000 tonne per year facility operating at 82 to 92 percent of rated capacity generates annual revenues of approximately 6.56 to 7.38 billion tenge. Against production costs of 26.81 billion tenge over a five-year horizon, total five-year revenues of 34.83 billion tenge produce cumulative gross profit of 8.02 billion tenge at a gross margin of 23 percent.

The key financial performance indicators for this scale of facility, operating under a special economic zone preferential tax regime, are summarized in Table 1.

Table 1. Financial performance indicators for a 20,000 tonne per year micro-metallurgical grinding ball facility, Pavlodar SEZ, Kazakhstan

Indicator	Value
Total capital investment (tenge)	2,500,000,000
Net Present Value at 15 percent WACC (tenge)	993,998,453
Internal Rate of Return	47 percent
Profitability Index	1.46
Simple Payback Period	2.7 years
Discounted Payback Period	3.1 years
Return on Investment (5-year cumulative)	229 percent
Average gross margin	23.0 percent
Average net margin (with SEZ tax preferences)	15.3 percent
Average net margin (standard tax regime)	3.7 percent

Source: Primary project documentation, Pavlodar SEZ grinding ball facility, 2025.

The sensitivity of these indicators to the special economic zone regime is substantial and has broader policy implications. Under the SEZ preferential conditions, which include zero corporate income tax, zero value-added tax on sales, exemption from property and land tax, and zero customs duties on imported equipment, net margin reaches 15.3 percent. Under a standard tax regime with equivalent operational parameters, net margin falls to 3.7 percent. This differential of roughly 11.6 percentage points reflects the extent to which the micro-metallurgical model depends on policy frameworks that recognize and support localized industrial production rather than treating all manufacturing activity identically regardless of import substitution potential.

4.3 Cost structure and commodity price exposure

The cost structure of the micro-metallurgical model concentrates exposure in specific categories. For the grinding ball facility under examination, raw material costs represent 82.8 percent of total production costs, energy accounts for 4.7 percent, logistics for 8.1 percent, and labor, administration, maintenance, and other categories collectively for the remaining 4.4 percent. This concentration makes the price and availability of secondary feedstock the primary determinant of commercial viability.

The advantage of the railroad rail recycling pathway in this respect is that feedstock pricing can be stabilized through long-term supply agreements with the national railway operator, which has a continuous stream of retired rail inventory as part of network modernization programs and limited alternative uses for the material. For the facility under examination, annual feedstock volumes of 22,400 tonnes are contracted with Kazakhstan Temir Zholy, providing multi-year price predictability that producers dependent on merchant scrap markets cannot match. This is a structural advantage of the railroad-to-grinding-ball production chain specifically, although analogous relationships exist in other micro-metallurgical applications where a specific secondary stream can be contractually secured from a sole-source or near-sole-source supplier.

5. Artificial intelligence in micro-metallurgical production

5.1 Applications already deployed at scale

Artificial intelligence has moved from pilot deployment to production-grade use across multiple categories of metallurgical application since approximately 2022. Predictive maintenance represents the most mature category. ArcelorMittal, Tata Steel, and POSCO have been running AI-based predictive maintenance programs at scale for more than two years, and leading Asian steel producers collectively deployed more than 260 AI algorithms simultaneously across their operations in 2025 [26]. Tata Steel's implementation of an AI system predicting the service life of critical equipment reduced downtime by 20 percent and maintenance costs by 15 percent [6]. The steel industry as a whole spent approximately 4.2 billion U.S. dollars on unplanned downtime in 2024, representing roughly 5 to 8 percent of total operating costs, and this spend is declining at plants where predictive maintenance has moved from pilot project to production-grade system [27].

Computer vision for defect detection and quality control represents a second mature category. Voestalpine reported reducing finished product defects by more than 20 percent through the deployment of computer vision systems [6]. Metinvest Group in Ukraine deployed the ForgeCheck AI system at Zaporizhstal, where computer vision detects defects in slabs with an annual economic effect of up to 250,000 U.S. dollars [6]. Baowu Group's Baosteel subsidiary launched fully automated production at a cold-rolled steel line in Shanghai in 2019, reducing the required frequency of human intervention from every three minutes to once every half hour [6]. These deployments demonstrate that computer vision has progressed from academic experimentation to measurable commercial outcomes in mainstream steel operations.

Digital twin technology represents a third rapidly maturing category. Digital twins integrate real-time sensor data with physics-based and data-driven models to simulate and predict the behavior of specific production assets or processes [28]. In blast furnace operations, digital twins modeling thermal and mechanical state of refractory linings have been reported to eliminate unplanned shutdowns related to refractory failure in their first full year of deployment at facilities running twin-integrated maintenance workflows [26]. In EAF operations, digital twins model heat-by-heat electrode consumption based on scrap chemistry, power profile, and bath geometry, enabling optimization of electrode positioning and power curves to reduce specific energy consumption while minimizing electrode breakage [28]. Hybrid digital twin frameworks combining real-time monitoring with physics-based and data-driven models have been demonstrated in steelmaking applications and are being extended to metalworking operations more broadly [29].

5.2 Applications under active development

A fourth category of AI application, which is less mature but developing rapidly, concerns the use of machine learning and deep learning models to optimize metallurgical processes at the compositional level. Azzaz and colleagues demonstrated in 2025 the use of artificial neural networks to predict the final phosphorus content of steel in scrap-based electric arc furnace operations, which is a key quality parameter that historically required extensive sampling and laboratory analysis [30]. Reinicke and colleagues applied artificial neural networks for efficient computation of chemical activities within an EAF process model, enabling real-time compositional optimization [31]. Petrik and Bambach developed the DeepForge algorithm for microstructural control in metal forming via model predictive control, illustrating how AI-based process control can replace empirical adjustment procedures with data-driven optimization [32]. These applications are particularly relevant to micro-metallurgical facilities because they reduce the dependence on highly experienced metallurgical personnel that has historically been a barrier to the proliferation of small-scale steelmaking in regions without established industrial traditions.

A fifth category concerns the integration of machine vision into scrap characterization and sorting. The contamination of scrap inputs is a major determinant of final product quality and process yield, and machine vision systems now enable automated assessment of scrap composition at a level of granularity that manual inspection cannot achieve. Kumar and colleagues documented the role of machine learning in scrap metal sorting efficiency, and subsequent work has extended these methods to specific contamination categories relevant to secondary steelmaking [33]. For micro-metallurgical facilities using narrowly defined feedstock such as retired railroad rails, the applicability of these methods is different: the feedstock is by definition compositionally consistent, but machine vision remains valuable for detecting physical defects, inclusions, and surface conditions that affect downstream processing.

A sixth category concerns the use of generative AI and physics-informed machine learning for the design of new alloys and production parameters. Chen and Wang demonstrated the application of AI to accelerate the discovery of advanced alloys [34]. Kumar, Singh, and Gupta applied physics-informed machine learning models to predict transient temperature distribution in ferritic steel during directed energy deposition, which is relevant to both additive manufacturing and conventional forming operations [35]. Cao, Bambach, Merklein, and Xue provided a comprehensive review of AI applications in metal forming, documenting the progression from academic demonstration to industrial deployment [36].

5.3 Barriers to AI deployment at micro-metallurgical scale

Three categories of barriers currently limit the deployment of these AI capabilities at sub-100,000 tonne per year facility scales. The first is data availability. Machine learning models, particularly deep learning approaches, require training datasets that are typically assembled over multiple years of plant operation at full scale. Small facilities do not generate equivalent data volumes and often lack the sensor infrastructure necessary to produce training data at the required frequency. Transfer learning, in which models trained on large-facility data are adapted to smaller operations, offers a partial solution but has not been systematically validated for the specific conditions of micro-metallurgical production.

The second is capital cost. AI deployment at integrated steel plants typically involves investments of several million U.S. dollars in sensor infrastructure, data management platforms, and software licensing, amortized over production volumes that make the per-tonne cost manageable. At a 20,000 tonne per year facility, the same absolute investment represents a much larger share of total operating cost, and the relative payback period is correspondingly longer. This suggests that AI deployment at micro-metallurgical scale will progress most rapidly in applications where the marginal cost is low because the underlying data infrastructure is being installed for other reasons.

The third is workforce capability. The operation of machine learning systems in production environments requires personnel capable of bridging process metallurgy and data science, and this combination of skills is scarce globally and particularly scarce in the regions where micro-metallurgical facilities are most commercially viable. Workforce development programs that integrate metallurgical training with data engineering and machine learning represent an important enabling condition for the proliferation of AI-enabled micro-metallurgical production.

5.4 The specific AI opportunity in induction-based micro-metallurgical production

Despite these barriers, induction-based micro-metallurgical production presents specific AI opportunities that are not available in larger-scale operations. The fully electrified production chain generates structured time-series data on temperature, power, and rolling parameters at sampling rates sufficient for machine learning analysis, and the absence of combustion-related variability simplifies the modeling problem compared to gas-fired equivalents. The narrow feedstock specification, in which inputs are drawn from a single category such as retired railroad rail, reduces the compositional variance that machine learning systems must accommodate. The modular plant architecture allows sensor infrastructure to be designed in from the outset rather than retrofitted onto legacy systems, which is a major cost driver in AI deployment at existing large plants [37].

These conditions suggest that well-designed micro-metallurgical facilities may achieve AI deployment outcomes comparable to or exceeding those of integrated producers, at substantially lower absolute investment levels, provided that the plant architecture is specified with AI integration in mind from the initial engineering phase. This represents a specific research and development opportunity that has not been systematically explored in the existing literature and that merits dedicated empirical investigation.

6. Research and policy priorities

The analysis presented in sections 3 through 5 suggests five priorities for research and policy development in the micro-metallurgical production sector over the next five years.

The first priority is the standardization of AI-ready data architectures for small-scale steelmaking facilities. The current absence of standards creates unnecessary duplication of engineering effort across facilities and limits the transferability of machine learning models between plants. An industry-led standards initiative, potentially supported by organizations such as the World Steel Association or regional equivalents, could substantially accelerate AI deployment at sub-500,000 tonne per year scales by defining common data schemas, sensor specifications, and interoperability requirements.

The second priority is the development of physics-informed machine learning models specifically calibrated for induction-based production at micro-metallurgical scales. Existing models have been developed principally for integrated plant operations and large-scale EAF facilities, and their direct transfer to smaller induction-based facilities is limited by differences in thermal dynamics, process control architecture, and product specifications. Research programs focused on this specific application, potentially in collaboration between equipment manufacturers, academic institutions, and operating facilities, would fill an important gap in the current literature.

The third priority is the extension of regulatory frameworks that currently favor large decarbonization projects to cover micro-metallurgical facilities of equivalent emissions intensity. The European Union Innovation Fund, the United States Inflation Reduction Act 45X credits, and equivalent programs in other jurisdictions have been structured principally around large facility investments, and the administrative burden of accessing these programs is frequently prohibitive for enterprises operating at 20,000 to 100,000 tonne per year scales. Regulatory adjustments that recognize the equivalent emissions reduction achieved by micro-metallurgical facilities on a per-tonne-of-product basis would substantially improve the economics of this production model.

The fourth priority is workforce development that bridges metallurgy and data science. Technical education programs in resource-intensive economies have traditionally separated these disciplines, producing graduates with deep expertise in one domain but limited capacity to integrate them. Integrated programs, which may combine undergraduate metallurgical training with postgraduate specialization in industrial data science, would produce the personnel required to operate AI-enabled micro-metallurgical facilities at scale.

The fifth priority is empirical validation of the financial and emissions benefits of AI deployment at sub-500,000 tonne per year scales. The current literature documents outcomes primarily from integrated producers and large EAF facilities, and the extrapolation of these outcomes to smaller operations rests on assumptions that have not been systematically tested. Case study research documenting AI deployment at micro-metallurgical facilities, with rigorous measurement of pre-deployment and post-deployment performance across defined metrics, would substantially strengthen the investment case for this production model and identify the specific technical and organizational conditions under which it achieves its projected benefits.

7. Conclusion

The micro-metallurgical production model, defined as secondary steelmaking at capacities between approximately 20,000 and 350,000 tonnes per year oriented toward specialized industrial consumables, occupies a distinct and commercially significant position within the broader transformation of the global steel system. The convergence of expanding scrap availability, regulatory pressure through CBAM and equivalent instruments, technical maturation of small-scale equipment, and accelerating integration of artificial intelligence into metallurgical processes collectively creates conditions under which this production model can proliferate in mining-intensive economies of Central Asia, Eastern Europe, Latin America, and elsewhere.

The financial performance of documented micro-metallurgical facilities at the 20,000 tonne per year scale, including internal rates of return near 47 percent, payback periods under three years, and net margins exceeding 15 percent under special economic zone preferential regimes, demonstrates that the model is viable at capacities an order of magnitude smaller than traditional minimills and two orders of magnitude smaller than integrated plants. The application of artificial intelligence at these scales is currently constrained by data availability, capital cost, and workforce capability, but the underlying technical conditions of induction-based production, narrow feedstock specification, and modular plant architecture create specific opportunities for AI integration that are not available in larger-scale operations.

The development of the sector over the next decade will depend on the extent to which industry standards, regulatory frameworks, workforce development programs, and empirical research adapt to the specific conditions of micro-metallurgical production. Where this adaptation occurs, the sector offers a practical pathway toward the simultaneous achievement of industrial localization, supply chain resilience, decarbonization, and employment objectives that are central to industrial policy in resource-intensive economies. Where it does not occur, the sector will progress more slowly than its technical and economic fundamentals would otherwise support, and the gains available through the integration of artificial intelligence into small-scale secondary steelmaking will accrue disproportionately to facilities fortunate enough to have navigated the enabling conditions on their own.

Author contributions

D.M.: Conceptualization, Methodology, Investigation, Formal Analysis, Writing (Original Draft), Writing (Review & Editing).

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Data availability

Primary project data referenced in Section 4 were developed under the direction of the author in the context of commercial project development for the Pavlodar SEZ grinding ball facility and are summarized in Table 1. No proprietary or confidential commercial terms are disclosed. Aggregated industry data cited in this article are drawn from the publications referenced in the bibliography and are accessible through the respective publishers.

Conflicts of interest

The author serves as General Director of AsiaTyazhMash LLP, which is involved in the development of micro-metallurgical production projects including the Pavlodar SEZ facility referenced in Section 4. This commercial involvement is disclosed transparently. The analytical conclusions of this article are grounded in publicly available literature and industry data, and the author asserts that the commercial interest did not influence the scholarly assessment presented.

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