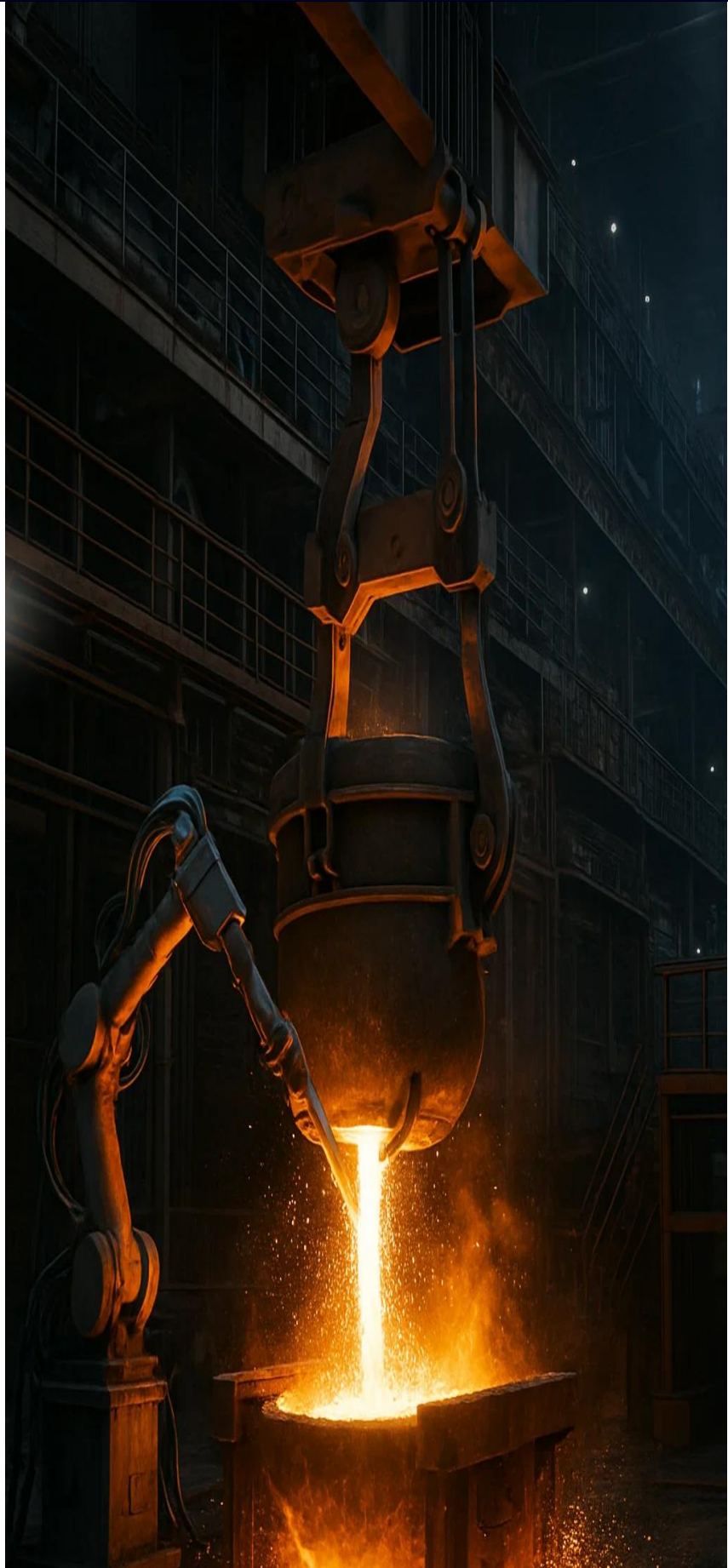


AI adoption in Metallurgy

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BORGX

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"AI has brought the Fourth Industrial Revolution to an inflection point, and manufacturers must choose a path forward: innovate, accelerate, or follow fast."
McKinsey reviews [1]

Introduction

The metallurgical industry stands at the threshold of a technological revolution. As one of humanity's oldest and most fundamental industries, metallurgy has traditionally relied on empirical knowledge, decades of experience, and incremental process improvements. However, the convergence of artificial intelligence, machine learning, and advanced data analytics is fundamentally transforming how metals are discovered, processed, manufactured, and optimized.

Modern metallurgical operations generate vast amounts of data from sensors, monitoring systems, quality control processes, and production equipment. This data deluge, once considered merely operational overhead, now represents an unprecedented opportunity to unlock new levels of efficiency, quality, and innovation. Artificial intelligence technologies are emerging as the key to harnessing this information, enabling metallurgists to move beyond reactive decision-making toward predictive, prescriptive, and autonomous process control.

This technological transformation is driven by several converging factors: the increasing complexity of manufacturing requirements, growing pressure for environmental sustainability and energy efficiency, the need for faster time-to-market in materials development, and the imperative to maintain competitive advantage in a global marketplace. Traditional trial-and-error approaches to metallurgical problem-solving are giving way to data-driven methodologies that can accelerate innovation cycles and improve outcomes. However, the integration of AI into metallurgical practices is not without challenges. The industry must navigate issues of data quality and standardization, address the need for domain-specific AI models, overcome resistance to change in traditionally conservative operations, and ensure that AI systems can operate reliably in harsh industrial environments. Additionally, the successful adoption of AI requires a workforce equipped with new skills that bridge metallurgical expertise with data science capabilities.

This white paper summarizes the current state of AI adoption in metallurgy, analyzes potential impact and the barriers to AI implementation, provides some case studies and discusses future trajectory of this technological convergence.

Global trends 2020-2025

The period from 2020 to 2025 has marked a transformative era for artificial intelligence (AI) applications in metallurgy, characterized by accelerated adoption, technological breakthroughs, and fundamental shifts in how metals are produced, processed, and managed globally. This transformation has been accelerated by several converging factors, including digital transformation imperatives, sustainability pressures, and the need for enhanced operational efficiency in an increasingly competitive global market.

The COVID-19 pandemic served as an unexpected catalyst for digital transformation in the metallurgy sector. In March 2020, the pandemic triggered acute declines in metals prices due to collapsed demand, forcing companies to rapidly adopt AI-driven solutions to maintain competitiveness and operational efficiency [2]. The crisis accelerated digitalization efforts that might have otherwise taken years to implement, as companies sought to reduce dependency on manual labor and improve resilience against future disruptions [3]. Steel manufacturers faced unprecedented challenges with lockdowns affecting both supply and demand, leading to a 10% reduction in global exploration budgets and significant supply chain disruptions [2]. This environment created urgency for AI adoption as companies recognized the need for predictive analytics, automated quality control, and remote monitoring capabilities to navigate operational uncertainties [3].

The initial phase of AI adoption in metallurgy (2020-2021) was characterized by experimentation and pilot projects focusing on specific operational challenges [4]. Steel companies began implementing AI-powered systems for basic applications such as quality control and predictive maintenance, with early adopters achieving significant results including raw material input cost reductions of more than 5% and throughput improvements at bottlenecks by more than 6% [4]. The industry recognized that implementing AI was a journey requiring capabilities and experience to be built over time, as steel remained largely an analog industry with deeply entrenched cultures and processes dating back over a century [4]. Challenges included data availability from older plant equipment and the need to connect newer machinery in ways that enabled accurate and consistent data tracking [4].

The period 2022-2024 saw a shift from isolated AI applications to integrated smart manufacturing systems, with technology suppliers focusing on solutions that addressed safety, sustainability, and productivity as the three primary objectives [5]. The latest trend in all industries is the development of complex integrated solution involving generative AI and large language models. Global AI adoption surged to exceed 378 million users in 2025, representing a 20% increase from the previous year, with manufacturing being one of the leading sectors driving this growth [6]. Companies began implementing AI-powered systems for complex decision-making, autonomous process control, and predictive modelling with unprecedented accuracy.

Primary Application Domains

Materials Discovery and Design. The integration of AI in materials research has accelerated significantly since 2020, with data-driven approaches enabling faster discovery and optimization of new alloys and processing techniques. Advanced algorithms now support the prediction of material properties and performance characteristics, reducing traditional trial-and-error approaches that historically dominated metallurgical research and development [7].

Predictive Maintenance emerged as one of the most successful AI applications in metallurgy, with the global predictive maintenance market projected to reach \$107.3 billion by 2033 at a CAGR of 28.5% [8]. Steel manufacturers adopted AI-driven systems that analyze vibration, temperature, and acoustic data from critical equipment to anticipate failures before they occur [9]. Companies implement predictive maintenance technologies to forecast and mitigate potential machinery failures, ensuring continuous operation and significantly reducing accident rates.

Quality Control and Process Optimization. AI-powered quality control systems revolutionized steel production by analyzing sensor data in real-time to identify deviations in temperature, pressure, and composition [10]. ArcelorMittal demonstrated the dramatic impact of these technologies, implementing AI-powered systems that resulted in a 15% reduction in product defects and annual savings of \$5 million through optimized raw material mixes [11]. Advanced AI algorithms enabled manufacturers to optimize raw material procurement by analyzing market trends and historical production data, with tools like Impactive AI achieving high accuracy in price forecasting for key materials, which allowed companies to make smarter procurement decisions and manage inventory more effectively.

Energy Efficiency and Sustainability. AI played a crucial role in addressing environmental concerns and energy consumption in metallurgy. Companies implemented AI algorithms to optimize energy consumption throughout manufacturing processes, significantly lowering costs and reducing environmental impact [12]. AI-driven process optimization enabled real-time adjustments to reduce carbon emissions and energy use, supporting the industry's transition toward sustainable production methods [13]. The integration of AI into sustainability initiatives helped companies reduce their carbon footprint by up to 25% through precision extraction and energy optimization, while also enhancing recycling rates and supporting circular economy goals. Advanced data analytics and machine learning improved scrap management and recycling processes, contributing to waste reduction and resource efficiency.

Additive manufacturing. AI is revolutionizing design optimization for additive manufacturing through automated, physics-informed approaches. AI tools can reduce simulation times from hours to seconds using deep learning to evaluate and modify part geometry within user-defined bounds. These systems can

simulate and evaluate hundreds of thousands of design candidates in significantly less time than traditional methods [14,15].

Market view

The AI in metallurgy and metal production market is poised for explosive growth, driven by the sector's critical need for enhanced efficiency, sustainability, and product quality. With a projected CAGR of over 40% in the broader manufacturing AI market and strong growth in specialized areas like material informatics, AI technologies are becoming indispensable tools for metallurgical companies aiming to compete globally and meet evolving regulatory and market demands.

The global artificial intelligence in manufacturing market was valued at approximately \$5.3 billion in 2024 and is projected to reach nearly \$47.9 billion by 2030, growing at a compound annual growth rate (CAGR) of 46.5% between 2025 and 2030 [16]. While this figure encompasses all manufacturing sectors, metallurgy and metal production are key contributors due to the industry's strong push toward automation, quality control, and predictive maintenance.

The niche of Material Informatics is a fast-growing segment, which applies AI to accelerate materials discovery and process optimization in metallurgy. The global material informatics market is expected to grow from \$170 million in 2025 to over \$410 million by 2030, at a CAGR of 19.2% [17]. Predictive maintenance, which dominated about 25% of AI manufacturing market share in 2024 [18]. Europe is investing heavily in AI-driven smart factory initiatives, supported by multi-billion euro programs to maintain leadership in AI innovation while ensuring ethical and human-centric AI use [19]. 3D-printing market grows very fast not least due to leveragin the AI and digital technologies [20]. North America and Asia-Pacific regions are also major markets, with significant government and private sector investments fueling AI adoption in metallurgy.

Key highlights

- Industrial AI market growing at up to 54% annually
- Predictive maintenance as a primary application
- AI revolutionizing steel processing, quality control, distribution, and inventory management
- 3D printing metal market valued at \$1.0 billion in 2024, growing at 17.3% CAGR

Regional Trends

US, Europe and Asia are at the forefront of integrating AI into metal production and metallurgy, driven by a combination of industrial needs, ambitious sustainability targets, and coordinated research. AI is central to the green steel initiatives, optimizing energy use and reducing emissions in real time. Projects like AID4GREENEST (EU-China collaboration) focus on sustainable steel production through AI-driven process control and recycling optimization. Indian and Korean companies also use AI to enhance scrap recycling and develop low-carbon steel products aligned with national environmental goals. Beyond the major hubs of the USA, Europe, China, India, South Korea, and Japan, artificial intelligence (AI) adoption in metal production is gaining momentum across other regions of the world, notably Africa and Latin America.



Europe

AI initiatives in Europe are largely focused on sustainability issues, green steel, steel scrap optimisation and AI-driven predictive maintenance. AID4GREENEST Project (Horizon Europe) is a major European project (2023–2026) developing AI-based characterization and modeling tools to advance sustainable “green” steel production. The goal is to replace traditional trial-and-error approaches with AI-driven innovation, reducing waste, lowering emissions, and saving costs. The project involves companies like Reinsa Forgings and Castings (Spain), OCAS NV, and ePotentia (Belgium), and collaborates with leading academic and research institutions. Outcomes include enhanced material quality, reduced carbon emissions, and less waste. The project also aims to set best practices and new standards for the EU steel sector [21,22].

European manufacturers are using AI-driven predictive maintenance to minimize downtime and optimize compaction and process simulation in powder metallurgy. Digital twins and machine learning algorithms are improving process control and efficiency, while also addressing challenges such as skill shortages and integration complexity [25].

AI4Electropolishing Project by GPAINNOVA, a Spanish technology group, is applying AI to metal surface finishing. Their EU-funded initiative uses digital twins and virtual sensors to detect anomalies in dry electropolishing, enabling automated process optimization and quality control [24]

ArcelorMittal implemented AI-powered sensor data analysis throughout the steelmaking process, resulting in a 15% reduction in product defects and significant cost savings. AI also optimizes raw material mixes, leading to annual savings of \$5 million without compromising quality (see more about examples from ArcelorMittal in the next section).

The Table summaries some of European industiral AI- projects.

<i>Company/Project</i>	<i>Application</i>	<i>Outcome</i>	<i>Ref</i>
<i>AID4GREENEST (EU Project)</i>	<i>AI modeling, rapid characterizati on</i>	<i>Reduced waste, emissions, improved quality</i>	<u>[21]</u> <u>[22]</u>
<i>ArcelorMittal</i>	<i>Sensor data analysis, raw material mix</i>	<i>15% defect reduction, \$5M/year cost savings</i>	<u>[23]</u>

GPAINNOVA (AI4Electropolishing)	Digital twins, anomaly detection	Automated optimization, quality control	[24]
Powder Metallurgy (Europe)	Digital twins, predictive maintenance	Reduced downtime, improved simulation	[25]
Scrap Optimization (Research)	Self- supervised learning, simulation	Automated scrap workflow, cost reduction	[26]

North America

The U.S. government's strategic focus on AI is evident through legislation such as the National Artificial Intelligence Initiative Act and significant funding via the Department of Energy's Advanced Manufacturing Office. These initiatives support AI research, workforce development, and public-private partnerships, fostering innovation in metallurgy and manufacturing [27]. National labs like Oak Ridge and Argonne collaborate with industry and academia to develop AI-driven digital twins and process models, accelerating the adoption of smart manufacturing technologies.

U.S. Steel has partnered with Google Cloud to deploy generative AI solutions that streamline maintenance workflows. Their AI system reduces work order times by up to 20%, enabling faster diagnostics and repair scheduling [28]. This AI-driven predictive maintenance minimizes unplanned downtime and enhances equipment reliability, a critical factor in continuous steel production.

Tata Steel, a global steel producer with operations in the U.S., uses AI to monitor rolling mills by analyzing vibration and temperature data, predicting machinery failures before they occur. This has led to a 15% reduction in unplanned downtime and significant maintenance cost savings (see more about examples from Tata Steel in the next section). AI also optimizes furnace parameters, improving energy efficiency and product quality.

Epiroc, a Swedish manufacturer with operations in the U.S., uses Microsoft Azure AI services to predict steel density, hardness, and flexibility for drilling tools. AI models ensure precise reproduction of over 3,500 steel grades, preventing structural fatigue and failure [29]. This capability supports high-quality, customized steel products.

Wesco implemented an AI-guided process that improved productivity and sustainability for a U.S. steel company client. The AI system optimized

production parameters, reducing waste and energy consumption, resulting in significant financial gains [30].

The U.S. metals sector increasingly integrates AI-powered robotics for welding, cutting, material handling, and inspection. Nvidia's Groot AI model enables robots to learn diverse manufacturing tasks autonomously, improving flexibility and productivity. Robotics reduce human exposure to hazardous tasks, improve quality consistency, and accelerate production cycles. Autonomous vehicles manage internal logistics, while AI-driven machine vision systems inspect products in real time, detecting defects beyond human capability [23].

Additionally, AI is actively being adopted in additive manufacturing, for sustainable and green manufacturing and workforce transformation and skills development [27].

The Table summarized some industrial AI-projects.

<i>Company/Project</i>	<i>Application</i>	<i>Outcome</i>	<i>Ref</i>
<i>U.S. Steel MineMind™</i>	<i>GenAI for maintenance</i>	<i>20% productivity improvement; cost reduction</i>	[27]
<i>Nucor Corporation</i>	<i>Predictive maintenance; digital twins</i>	<i>Reduced downtime; enhanced quality control</i>	<i>[23]</i>
<i>ArcelorMittal</i>	<i>AI sensor data analysis; raw material optimization</i>	<i>15% defect reduction; \$5M annual savings</i>	<i>[11]</i>
<i>Desktop Metal</i>	<i>AI-driven additive manufacturing</i>	<i>Improved process control; defect reduction</i>	<i>[31]</i>
<i>Surveil</i>	<i>AI safety monitoring</i>	<i>24/7 safety alerts; reduced workplace incidents</i>	<i>[32]</i>

Asia

The industrial policy in **China**, especially "Made in China 2025" (MIC25), has catalyzed rapid digital transformation and AI adoption across manufacturing, including metals and metallurgy [33]. Large AI models are being deployed in traditional steel hubs such as Hebei province, which produces about 20% of China's crude steel [34]. Xinxing Ductile Iron Pipes Co in Wu'an, Handan, has implemented 38 AI-driven scenarios, including a coal blending model that reduced coke costs by 9.4 yuan/ton. Their AI models use big data to optimize coal blending, replacing manual, trial-and-error approaches and improving both cost and quality [34]. HBIS Group Co developed the WeShyper Iron and Steel Large Model, an advanced AI system for the steel industry that streamlines information processing, decision-making, and operational management. The company identified 142 AI scenarios to enhance 12 industrial procedures with digital intelligence [34]. Hebei Taihang Steel AI Management System: Developed by a consortium of 39 steel enterprises and 13 AI firms to address production challenges using AI [34].

Additionally, AI-Integrated Smart Factory Solutions [35], Robotics and Embodied AI [36] and AI-driven Additive Manufacturing are rapidly developing.

The **Indian** steel industry is rapidly integrating AI to optimize production, improve quality, and enhance safety [37]. Tata Steel is a leader, having developed over 550 AI models in the past 5–6 years. These models address yield, energy efficiency, throughput, quality, productivity, safety, and sustainability. Tata Steel's investments in generative AI platforms are powering automated insights, conversational interfaces, and advanced analytics that directly support business KPIs (see examples from Tata Steel in the next section).

Jindal Steel and Power Limited (JSPL) has appointed a Chief AI Officer to lead its AI transformation, focusing on operational efficiency, quality improvement, safety, and sustainability. JSPL's strategy aligns with India's Ministry of Steel, which is actively encouraging AI adoption for process optimization, asset management, and environmental impact assessment [38].

AI in metal production in **South Korea** is financed by the state within the launched \$7.5 billion push for AI manufacturing modernization [39]. Korean steel giants like POSCO and Hyundai Steel are actively adopting AI for predictive maintenance of blast furnaces and rolling mills, AI-driven quality inspection and defect detection (using computer vision and deep learning), process optimization for energy savings and emissions reduction, smart factory initiatives integrating IoT, big data, and AI for real-time monitoring and control.

Japan is at the forefront of integrating AI into precision component processing and metallurgy, addressing both skill shortages and the need for greater efficiency [40–43]. ARUM Inc. has developed ARUMCODE, an AI-based software that automatically generates complex machining programs, reducing reliance on skilled technicians and enabling high-mix, low-volume production. By 2025, ARUM Inc. expects to expand its AI solutions to hundreds of manufacturers in Japan and abroad [40]. JFE Steel and Hitachi have jointly implemented AI-driven cold-rolling flatness control systems, which learn from skilled operators and automate high-

quality shape control. This has led to improved yields, higher utilization rates, and stabilized product quality [41]. Japanese powder metallurgy firms leverage AI and machine learning for alloy design, process simulation, and predictive maintenance, achieving efficiency gains and cost reductions [42]. Morikawa Foundry uses DISA's Monitizer® AI platform to target a 40% reduction in scrap, optimize casting conditions, and improve quality and profitability [43].

The Table summarises some projects run in China, India, South Korea and Japan.

Country	Company/Project	Application	Outcome	Ref
China	China Baowu Steel Group	Large AI models for steel production	15% cost reduction; 30% R&D efficiency increase	[44][45]
China	HBIS Group	AI-driven coal blending and process control	Reduced coke costs by 9.4 yuan/ton; improved quality	[45]
South Korea	POSCO	Predictive maintenance; AI vision systems	Reduced accidents; improved safety and efficiency	[44][45]
South Korea	Hyundai Steel	Smart Enterprise system; AI-based production	Improved process control and energy efficiency	[45]
India	Tata Steel	550+ AI models for yield, safety, sustainability	Enhanced operational efficiency and safety	[45]
India	JSPL	AI strategy led by Chief AI Officer	Driving operational and sustainability goals	[45]
Japan	ARUM Inc.	AI-based automated machining program generation	Reduced skilled labor dependency; improved precision	[45]

<i>Japan</i>	<i>JFE Steel & Hitachi</i>	<i>AI-driven flatness control in cold rolling</i>	<i>Improved product quality; labor productivity gains</i>	<u>[45]</u>
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Rest of the world

Beyond the major hubs of the USA, Europe, China, India, South Korea, and Japan, artificial intelligence (AI) adoption in metal production is gaining momentum across other regions of the world, notably Africa, Latin America. In Brazil, the international companies develop several AI-driven projects that makes Brazil a leader in AI adoption in the South America (see the next section for examples). In Africa much effort focuses on bringing AI into mining. African Mining Week 2025, held in Cape Town, showcases how AI is revolutionizing mining operations across the continent. Over 60% of major African mining companies now incorporate AI tools to enhance exploration and production efficiency, reflecting a shift from traditional practices to data-driven decision-making [46,47].

Industrial Examples

ArcelorMittal

Use Case 1: Predictive maintenance

Technology: Machine learning platform (*Sentinel Platform*) [48]

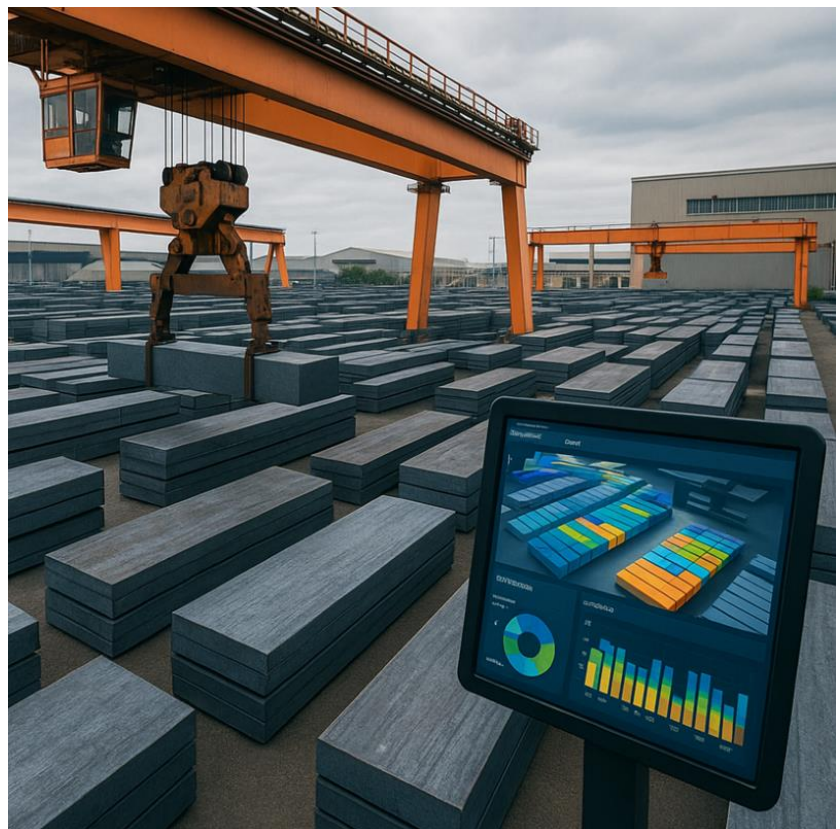
ArcelorMittal developed *Sentinel*, a machine learning platform designed to predict equipment failures before they occur. Initially used offline to monitor motors and hydraulic actuators, the platform learned from sensor data to accurately forecast potential breakdowns. Pilots in Canada and northern France achieved 100% prediction accuracy, with no unanticipated failures. Following its success, *Sentinel* was deployed online and is currently being tested in Brazil. The project, ongoing throughout the 2020s, supports proactive maintenance strategies and enhances equipment reliability across the company's global operations.



Use Case 2: Slab Yard Optimization

Technology: Machine learning-driven decision system (Slab Yard Optimisation Brain) [49]

ArcelorMittal, in collaboration with AM/NS Calvert in Alabama, developed the *Slab Yard Optimisation Brain*, a machine learning system that manages slab inventory and crane operations in the steel mill's slab yard. The system ingests real-time data to optimize the movement, stacking, and retrieval of over 17,000 steel slabs using 10 cranes. Replacing manual planning with AI-driven decisions, the platform dynamically adjusts logistics to improve flow and productivity. Since its deployment in 2021–2022, the system has delivered record operational performance and multimillion-dollar savings. In recognition of its impact, the project won the IDC Future Enterprise Award for Operations in 2022, highlighting ArcelorMittal's leadership in smart logistics and industrial AI.



Use Case 3: Computer vision for manufacturing automation

Technology: AI-powered image recognition and measurement systems [50,51]

Project 1 – Weld-Release Detection (Canada)

At the Dofasco hot-rolling mill in Canada, ArcelorMittal implemented an AI-driven image recognition system to automate *weld release* decisions. Cameras monitor welded joints, and a deep-learning model identifies the precise moment to separate steel coils. This system, operational since the early 2020s, reduces manual intervention, saves operator time, and increases production throughput.

Project 2 – Cold-Coil Width Measurement (Brazil)

In Brazilian rolling mills, an AI-based vision system was introduced to automatically measure the width of cold-rolled steel coils. Replacing manual caliper checks, the system uses laser and camera data analyzed by AI to deliver real-time, high-precision measurements. Trained on thousands of images, the solution improves accuracy and quality control. The project began around 2021–2022.

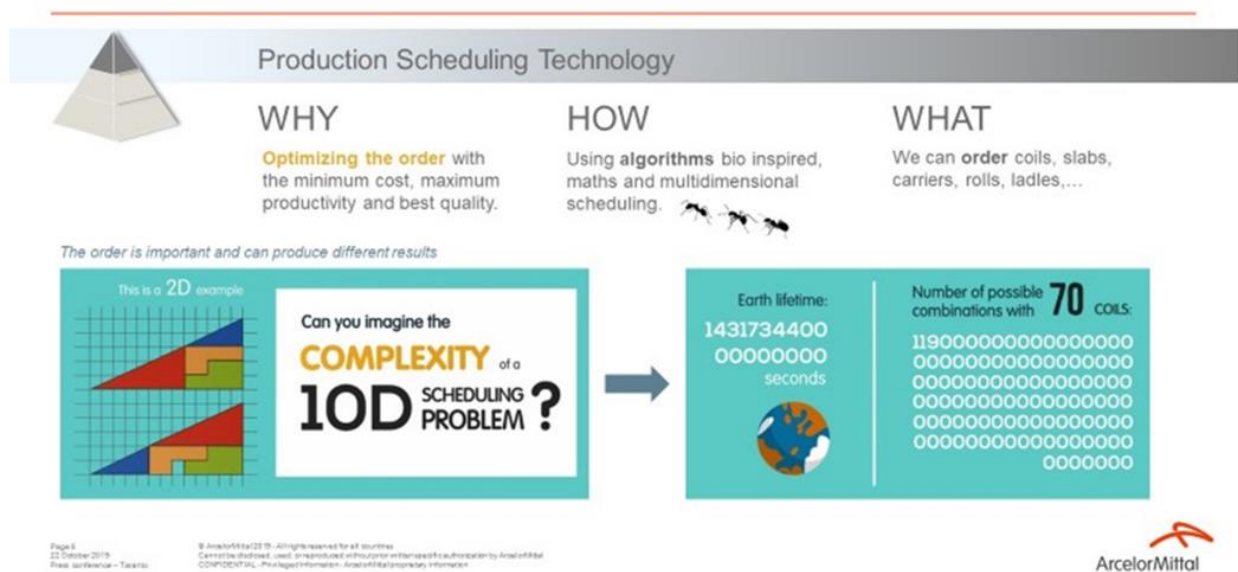
Project 3 - Environmental emissions grading (Brazil)

Also in Brazil, an AI image-analysis solution was implemented to “automatically grade” environmental emissions (e.g. smoke, dust) from plant stacks. Video feeds were processed by computer-vision algorithms trained to classify emissions levels, helping sites monitor and control pollution. This project (started in the early 2020s) aims to improve environmental performance and reporting by automating emissions inspection.



Technology: Ant Colony Optimization (ACO) algorithm (bio-inspired AI) [52]

ArceLorMittal's Global R&D team deployed an AI-powered scheduling system based on the Ant Colony Optimization algorithm to optimize the sequencing of steel coil and plate production. This dramatically reduced planning time from hours to minutes, improved throughput, and significantly increased yield. One hot-dip galvanizing line alone reported annual savings of nearly \$1 million. Initially deployed in the early 2020s, the system has now been adopted across multiple finishing lines and steel mills globally.



Use Case 5: AI in Quality Control for Automotive Steel

Technology: AI-based defect detection via image and video analytics [53]

ArcelorMittal's R&D teams developed proprietary AI models to automatically detect surface and structural defects in high-strength automotive steel. Using advanced image and video analytics, the system identifies flaws during production—such as cracks, dents, or surface anomalies—before products reach customers. This innovation significantly reduces scrap risk and enhances quality control. The technology was matured throughout the 2020s and has since been integrated into ArcelorMittal's Global Product Quality System (GPQS). By 2023, GPQS and its AI inspection capabilities were deployed across dozens of galvanizing lines, standardizing and strengthening quality assurance across the company's global operations.

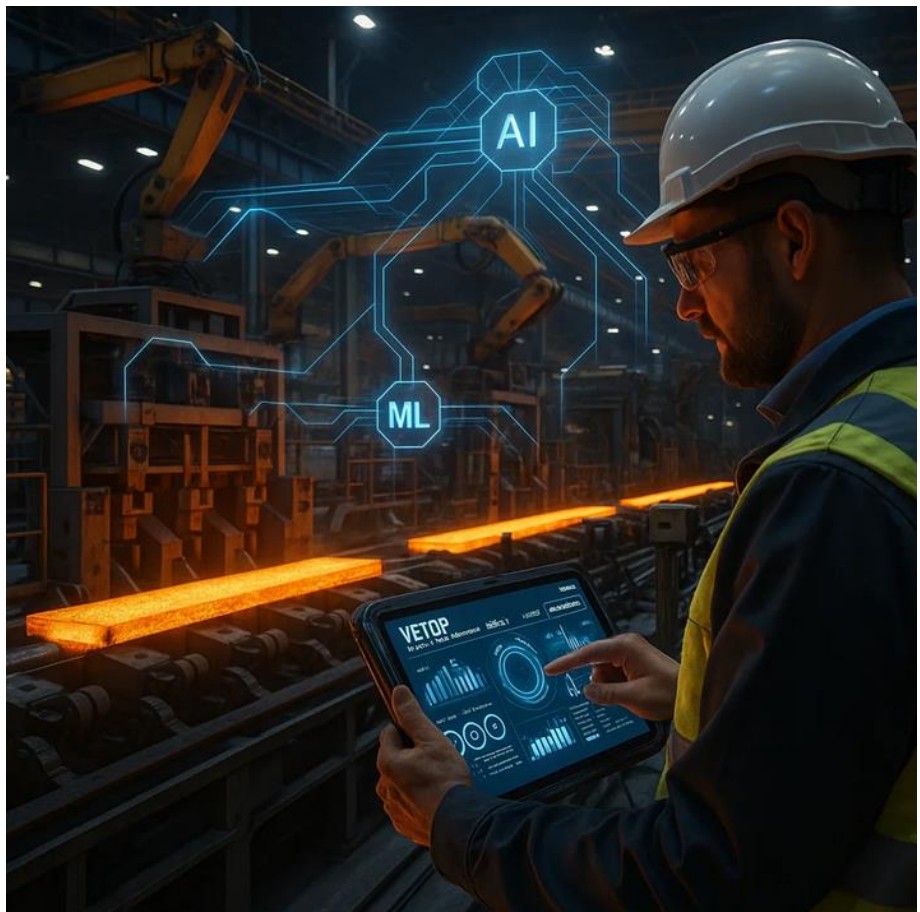


TATA Steel

Use Case 1: AI/ML for Process Optimization in Steelmaking

Technology: 550+ machine learning models for predictive control and decision support [54]

Between 2020 and 2024, Tata Steel developed and deployed over 550 AI and machine learning models to optimize critical steelmaking and rolling processes. These models focus on improving Yield, Energy, Throughput, Quality, and Productivity (YETQP) across the production value chain. By analyzing large volumes of real-time process data, the AI systems provide predictive insights and automated decision support, leading to improved operational efficiency and product quality. This large-scale AI integration has positioned Tata Steel as a leader in intelligent manufacturing, as detailed in their Integrated Report 2023–24.



Use Case 2: Logistics & Raw Material Handling Automation

Technology: AI-enabled robotic arm for railway wagon tippler operation [55]

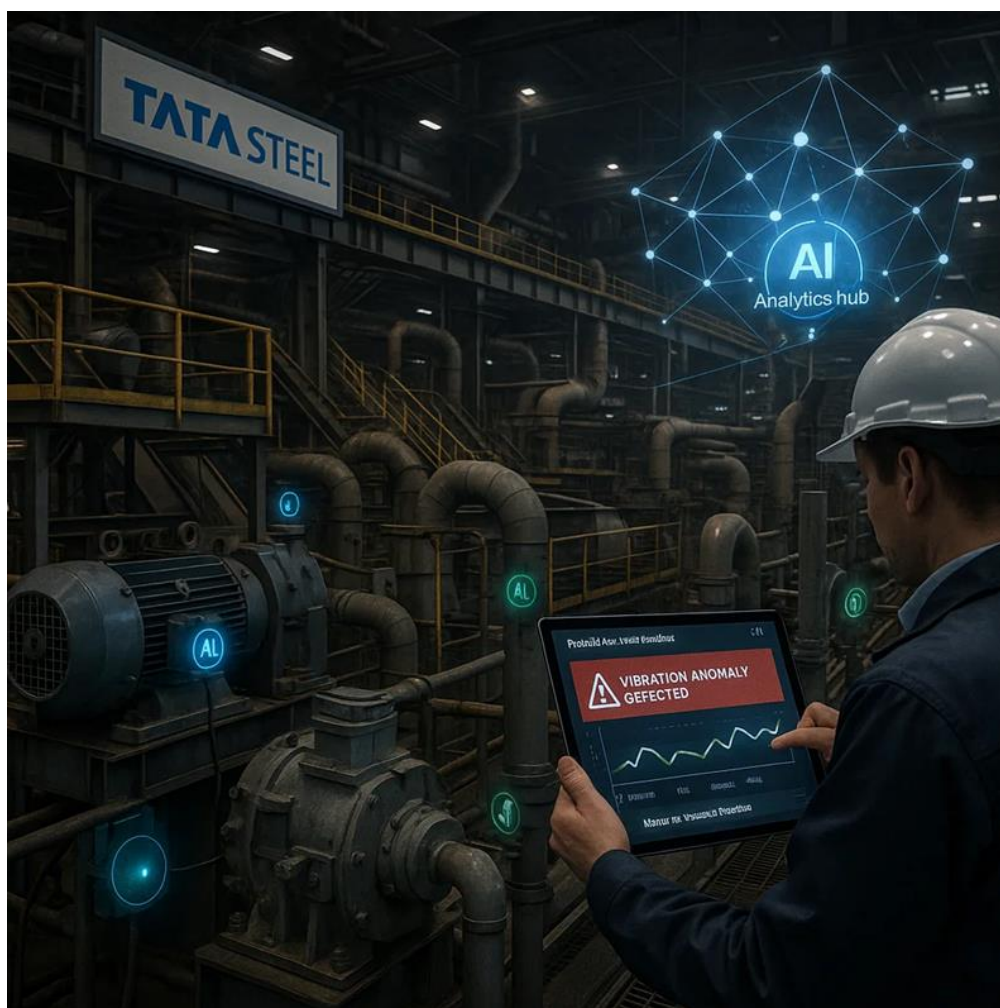
In July 2021, Tata Steel's Kalinganagar plant deployed a robotic wagon tippler system to automate the inspection and alignment of railway wagon couplers. Powered by AI, the robotic arm performs real-time post-tipping checks and executes automatic decoupling and coupling, eliminating the need for manual intervention. This innovation not only enhances operator safety but also boosts throughput and efficiency in the raw-material handling process. The solution reflects Tata Steel's commitment to using industrial automation for safer and smarter logistics, as highlighted in its 2021 press release.

In Nov 2022, Tata Steel deployed a fully automated "man-less" wagon-tippler system at Meramandali. Advanced robots and sensors now handle the entire unloading and tipping operation with no human-machine interface. This AI-driven automation eliminates safety risks from manual coupling and boosts productivity by shortening unloading cycles



Use Case 3: Predictive Maintenance & Operational Reliability
Technology: AI-powered sensor network with machine learning analytics [54]

Tata Steel's Connected Assets platform leverages a network of AI-enabled sensors and machine learning algorithms to predict equipment failures before they occur. In FY2023–24, the system successfully prevented over 1,350 hours of unplanned downtime by continuously analyzing machine health data and scheduling maintenance proactively. This predictive approach enhances equipment reliability, minimizes disruptions, and supports cost-efficient operations. The initiative exemplifies Tata Steel's broader strategy to integrate smart technologies across its industrial infrastructure.



Alcoa

Use Case 1: Safety Automation via Robotic Inspections

Technology: Four-legged robotic “dogs” with AI-based sensors and autonomy [56]

In 2024, Alcoa began trialling robotic inspection dogs across its mining, refining, and smelting operations, including the Huntly mine, Wagerup refinery, and Portland smelter. These four-legged robots are designed to handle repetitive or hazardous inspection tasks—such as conveyor checks, pipe and pump monitoring, and confined space evaluations—that would otherwise put human workers at risk.

Initially operated remotely, the robotic platforms are being developed to function autonomously using onboard sensors, cameras, and AI. Once matured, they will navigate complex environments, collect visual and thermal data, and proactively alert operators to maintenance needs. The initiative aims to enhance worker safety, ensure inspection consistency, and reduce unplanned downtime. Currently in the testing phase, the program will inform future deployment across Alcoa’s global operations.



Use Case 2: Furnace Automation & Operator Safety

Technology: Automated Robotic Furnace Tending (ARFT) with camera-guided precision [57]

In September 2023, Alcoa announced the deployment of an Automated Robotic Furnace Tending (ARFT) system at its Deschambault aluminum smelter in Quebec. Developed in partnership with technology collaborators, the ARFT robot automates high-risk furnace operations, such as molten metal siphoning, skimming, and casting preparation, traditionally performed by human operators. The goal is to reduce worker exposure to extreme heat and explosion risks, while improving process consistency and safety.

The ARFT system is part of Alcoa's broader Industry 4.0 roadmap. It integrates advanced mechanical manipulators, a camera-based guidance system, and automated control algorithms to deliver precise, repeatable furnace handling tasks. While not fully AI-driven, the system incorporates smart automation features that enhance decision-making and operational accuracy. Originally initiated in 2016, the ARFT entered its testing phase in late 2023. Full installation and commissioning are planned for this year (2025), backed by government and Alcoa funding.

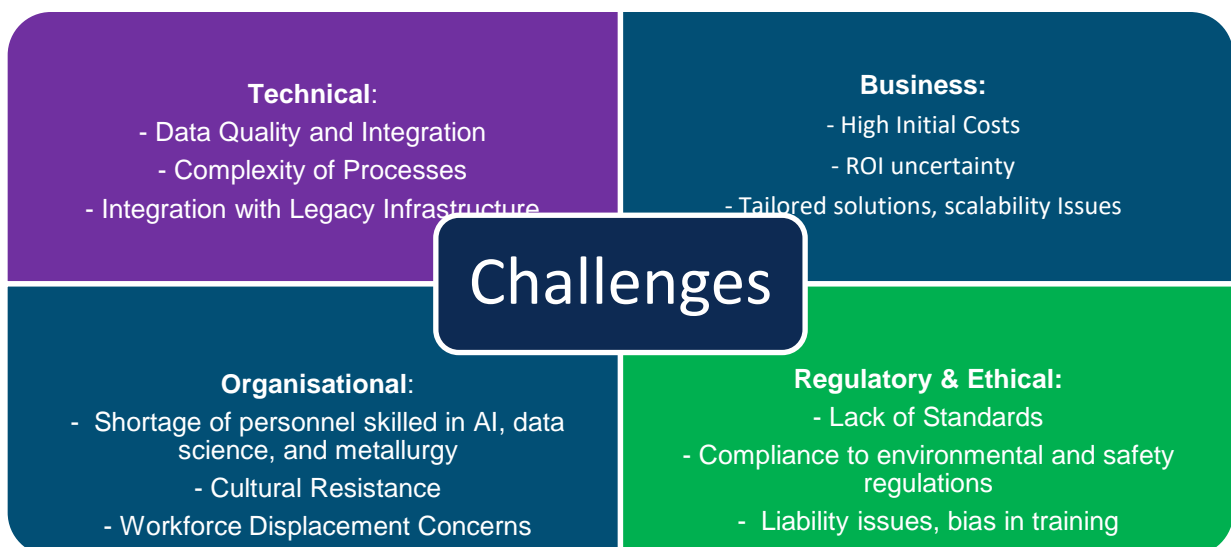


Challenges and Limitations

Adopting AI in metallurgy offers significant potential, but it also presents a complex landscape of organizational, technical, business, and regulatory challenges. A critical barrier is the shortage of **skilled personnel who can bridge expertise across AI, data science, and metallurgical processes**. Many companies also face cultural resistance, especially in traditional manufacturing environments where digital transformation is seen as disruptive. This resistance is compounded by workforce displacement concerns, as employees worry that automation will replace jobs rather than augment them, leading to hesitancy in adoption.

On the technical side, AI deployment in metallurgy is hampered by poor data quality and fragmented systems, especially in plants where legacy infrastructure lacks the digital readiness for seamless integration. The inherent complexity of metallurgical processes, which are nonlinear, variable, and dependent on subtle physical-chemical interactions that adds to the challenge of building reliable, interpretable models. Business-wise, high upfront costs, coupled with uncertain return on investment (ROI), often stall decision-making. Many solutions need to be customized to specific plant conditions, raising scalability issues for broader industrial rollout.

From a regulatory and ethical standpoint, there is a lack of standardized frameworks guiding AI use in heavy industry. Ensuring compliance with environmental and safety regulations becomes more complex when decision-making is automated. Moreover, liability concerns, particularly in the event of system failures, and potential bias in training data raise ethical questions about trust and accountability. Without clear guidelines, companies risk regulatory exposure, reputational damage, or implementation delays. Overcoming these obstacles requires not just technical innovation, but also strategic alignment, reskilling initiatives, and cross-functional collaboration.



Future Prospects

Looking toward the remainder of 2025 and beyond, AI adoption in metallurgy is expected to continue accelerating. The convergence of AI with other advanced technologies such as robotics, 5G, and blockchain is creating new possibilities for innovation and value creation . Advanced manufacturers are increasingly using AI for predictive maintenance, quality control, and automation of production processes, with expectations for fully autonomous manufacturing systems in the near future.

Looking ahead, the next decade will likely see AI move beyond isolated pilot projects toward **fully integrated, plant-wide systems** that support real-time optimization, autonomous process control, and predictive decision-making across the value chain.

Emerging trends such as **physics-informed machine learning**, **digital twins**, and **edge AI** are set to enhance the reliability and interpretability of AI models in complex metallurgical environments. These technologies will bridge the gap between empirical data and metallurgical science, enabling more accurate modeling of high-temperature reactions, phase transformations, and microstructural evolution. As **sensor networks** and **industrial IoT platforms** become more pervasive, real-time data will feed continuous learning loops, allowing AI systems to adapt dynamically to process variability.

From an organizational standpoint, companies will need to invest not only in technology but also in **human capital** developing hybrid roles that combine domain expertise with digital fluency. Cross-disciplinary collaboration between metallurgists, data scientists, and operators will become standard practice. Meanwhile, industry-wide efforts to establish **AI governance standards**, promote **interoperability**, and ensure **regulatory compliance** will be crucial for scaling solutions responsibly.

Conclusions

Based on current industry developments and proven applications, metallurgical companies should prioritize AI adoption in three critical areas: predictive maintenance systems for equipment optimization, real-time process control for quality assurance, and computer vision systems for automated inspection and defect detection. The urgency is underscored by the rapid market growth and competitive advantages already demonstrated by early adopters.

The convergence of AI technologies with metallurgical processes represents a fundamental shift toward intelligent manufacturing. Organizations that delay adoption risk falling behind competitors who are already realizing significant operational improvements and cost savings through AI implementation. The technology has moved beyond experimental stages to become an essential component of modern metallurgical operations.

If you want to have regular updates, analysis or coaching about recent AI technologies, new developments and adoption status in different industries, follow us: www.borgx.eu

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