Artificial Intelligence in Metallurgical Engineering: Paradigms, Applications, and Future Prospects A Comprehensive Review

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***Abstract*—Artificial Intelligence (AI) encompassing expert systems, fuzzy logic, evolutionary algorithms, machine learning, deep learning, computer vision, natural language processing, and digital twin technologies is reshaping every sub-discipline of metallurgical engineering. This review provides a systematic and comprehensive examination of AI paradigms as applied to materials design, ironmaking and steelmaking process control, casting and solidification, deformation processing, heat treatment, corrosion science, failure analysis, non-destructive evaluation, and sustainable metallurgy. Unlike narrower reviews focused on individual algorithms or unit operations, this paper spans the full AI technology spectrum across the entire metallurgical value chain. A total of 140 peer-reviewed publications from 2010 to 2025 are critically evaluated, encompassing industrial deployments at integrated steel plants, academic proof-of-concept studies, and benchmark comparisons across AI methodologies. The review identifies the evolutionary trajectory from rule-based expert systems of the 1980s to today's physics-informed neural networks and generative AI tools for alloy design. Key findings include: (i) hybrid AI-physics models consistently outperform purely data-driven approaches in extrapolation scenarios; (ii) computer vision has achieved superhuman accuracy in microstructure classification and defect detection; (iii) digital twins enabled by AI are delivering 15–30% energy savings in blast furnace operations; and (iv) generative AI (variational autoencoders, generative adversarial networks) opens entirely new routes for inverse alloy design. The review concludes with a structured research agenda addressing data sovereignty, AI explainability in safety-critical applications, and the role of AI in decarbonising the global steel industry.**

***Index Terms*—Artificial Intelligence; Expert Systems; Deep Learning; Computer Vision; Digital Twin; Alloy Design; Steelmaking; Failure Analysis; Sustainable Metallurgy; Generative AI**

I. INTRODUCTION

Metallurgical engineering the science and engineering of extracting, processing, and shaping metals and alloys stands at a pivotal intersection with Artificial Intelligence (AI). The discipline spans centuries of empirical knowledge codified in phase diagrams, metallurgical thermodynamics, kinetic models, and process engineering practice. Yet the complexity of modern metallurgical challenges designing multicomponent alloys with simultaneous requirements for strength, ductility, corrosion resistance, and manufacturability; controlling blast furnaces with thousands of process variables; predicting failure modes in structurally critical components exceeds what human intuition and classical physics-based models alone can efficiently navigate [1, 2].

AI, in its broadest definition, encompasses any computational system that mimics cognitive functions such as learning, reasoning, problem-solving, perception, and language understanding. The history of AI in metallurgy is longer than commonly appreciated. Expert systems encoding the heuristic knowledge of experienced metallurgists in IF-THEN rule bases were deployed in blast furnace advisory systems and alloy selection tools as early as the 1980s [3]. Fuzzy logic controllers, capable of handling imprecise process measurements, were implemented in rolling mill control and continuous casting by the 1990s [4]. The modern machine learning revolution, enabled by big data and GPU computing, added a new and powerful layer that has fundamentally shifted the AI-metallurgy interface since approximately 2015 [5].

The global steel industry alone produces 1.9 billion tonnes annually, employing over six million people worldwide, and accounts for approximately 7–9% of global CO_2 emissions [6]. Even marginal improvements in process efficiency, yield, and product quality enabled by AI translate to enormous economic and environmental impact. Simultaneously, the demand for advanced materials in aerospace, automotive electrification, biomedical implants, and clean energy infrastructure is driving alloy development at a pace that traditional trial-and-error experimentation cannot sustain. AI offers the computational leverage to explore vast compositional and processing spaces rapidly, systematically, and at a fraction of the cost of purely experimental approaches [7].

Despite this enormous potential, the metallurgical community faces specific barriers to AI adoption that distinguish it from other engineering fields: the scarcity and proprietary nature of high-quality process data; the need for AI outputs to conform to thermodynamic and physical constraints; the high cost of misapplication in safety-critical components; and the cultural gap between metallurgists trained in physics-based reasoning and AI practitioners trained in statistical optimisation. Bridging these barriers requires not just technical innovation but also a community-wide understanding of AI principles and their appropriate application [8].

This review addresses this need by providing a comprehensive, multi-paradigm survey of AI across the metallurgical engineering domain. Uniquely, it covers the full spectrum of AI approaches from expert systems and evolutionary algorithms to convolutional neural networks, transformer architectures, and generative AI and traces their application across the entire metallurgical value chain. The paper is structured as follows: Section 2 describes the review methodology; Section 3 provides a taxonomy of AI paradigms; Sections 4–12 examine AI applications by metallurgical domain; Section 13 addresses cross-cutting challenges; Section 14 presents a future research roadmap; and Section 15 concludes.

II. REVIEW METHODOLOGY AND SCOPE

The literature survey was conducted across Scopus, Web of Science Core Collection, Google Scholar, and the ACM Digital Library. Search terms combined AI paradigm keywords ("expert system", "fuzzy logic", "genetic algorithm", "neural network", "deep learning", "convolutional neural network", "generative adversarial network", "digital twin") with metallurgical domain terms ("steel", "cast iron", "aluminium alloy", "titanium", "superalloy", "blast furnace", "steelmaking", "heat treatment", "corrosion", "fatigue", "microstructure", "NDT"). The search covered 2010–2025, yielding 487 initial results. After de-duplication and applying inclusion criteria (peer-reviewed, English, direct AI application), 140 articles were retained. Table 1 summarises the distribution.

Table 1. Summary Of Reviewed Ai Applications Across Metallurgical Domains

	Papers Reviewed	Dominant AI Paradigm	Maturity Level
Ironmaking / Blast Furnace	19	DNN, LSTM, Fuzzy Control, RL	Industrial deployment
Steelmaking (BOF/EAF)	18	ANN, XGBoost, Expert Systems	Industrial deployment
Casting & Solidification	14	CNN, Expert Systems, GA	Pilot / semi-industrial
Deformation Processing	11	ANN, FEM-ML hybrid, Fuzzy	Industrial deployment
Heat Treatment	13	ANN, Bayesian Opt., DNN	Pilot / semi-industrial
Alloy Design (Inverse)	16	GAN, VAE, BO, GNN	Research / emerging
Corrosion & Degradation	12	RF, SVM, CNN, ANN	Research stage
Failure Analysis & NDT	15	CNN, SVM, Autoencoder	Pilot / industrial
Microstructure Analysis	12	CNN, U-Net, Transfer Learning	Pilot / industrial
Sustainable / Green Metallurgy	10	RL, DNN, LCA-ML hybrid	Research / emerging
Total	140	—	—

III. A TAXONOMY OF AI PARADIGMS IN METALLURGICAL ENGINEERING

AI is not a monolithic technology but a family of diverse computational approaches, each with distinct strengths and suitability for different metallurgical problems. Figure 1 (described below) presents a taxonomy of AI paradigms organised hierarchically.

A. Symbolic AI: Expert Systems and Rule-Based Reasoning

Expert systems, the dominant AI paradigm in metallurgy from the 1980s to the early 2000s, encode domain expertise as formal IF-THEN rules within an inference engine. The XCON system at DEC (1980) validated the commercial viability of this approach [9]. In metallurgy, pioneering applications included METALS ADVISOR for alloy selection [10], CASCAST for casting defect diagnosis [11], and multiple blast furnace advisory systems developed by Nippon Steel and Posco [3]. Strengths: transparent reasoning, no training data required, excellent for well-codified domains. Limitations: knowledge acquisition bottleneck, poor handling of uncertainty, inability to learn from new data.

B. Computational Intelligence: Fuzzy Logic and Evolutionary Algorithms

Fuzzy logic systems handle the inherent imprecision of metallurgical measurements (e.g., "the silicon content is slightly high") by mapping linguistic variables to membership functions. Fuzzy controllers have been widely deployed in rolling mill speed control, ladle temperature regulation, and sinter plant control, where they outperform classical PID controllers in handling non-linear, time-varying process dynamics [4]. Genetic Algorithms (GAs) and Evolutionary Strategies, inspired by Darwinian evolution, optimise metallurgical problems defined by objective functions alloy composition for minimum cost at target strength, heat treatment schedule for maximum toughness, rolling mill pass schedule for minimum power consumption [12]. Particle Swarm Optimisation (PSO) and Differential Evolution (DE) have found application in heat treatment sequence optimisation for nickel superalloys [13].

C. Machine Learning: Statistical Pattern Recognition

The core of modern AI in metallurgy supervised, unsupervised, and reinforcement learning algorithms trained on historical process and property data is covered in depth in the application sections. Key algorithms include: Artificial Neural Networks (ANNs) for continuous property prediction; Random Forests (RF) and Gradient Boosting (XGBoost, LightGBM) for tabular metallurgical datasets; Support Vector Machines (SVM) for classification with small datasets; Gaussian Process Regression (GPR) for uncertainty-aware property prediction and Bayesian optimisation; and Long Short-Term Memory (LSTM) networks for time-series blast furnace and rolling mill data [14, 15].

D. Deep Learning: Representation Learning from Raw Data

Deep neural networks with multiple hidden layers learn hierarchical feature representations directly from raw data eliminating the need for hand-crafted feature engineering. Convolutional Neural Networks (CNNs) process grid-structured data (micrograph images, EBSD maps, X-ray films) with unmatched accuracy for microstructure classification and defect detection. Recurrent architectures (LSTM, GRU, Transformer) model sequential process data from blast furnaces and rolling mills. Encoder-decoder networks (U-Net) perform pixel-wise semantic segmentation of grain boundaries and phases in microscopy images [16, 17].

E. Generative AI: Creating Novel Materials by Design

Generative AI models Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and transformer-based large language models represent the newest frontier of AI in metallurgy. Rather than predicting properties of known materials, generative models synthesise entirely new alloy compositions or microstructure configurations with targeted property profiles. This inverse design capability "given the desired properties, generate the composition" fundamentally inverts the traditional materials development paradigm [18, 19].

F. Digital Twins: AI-Enabled Virtual Process Replicas

A digital twin is a continuously updated virtual replica of a physical process, asset, or system that uses real-time sensor data, physics-based models, and ML algorithms to predict current state, forecast future behaviour, and optimise operating conditions. In metallurgy, digital twins have been implemented for blast furnaces, continuous casting machines, rolling mills, and heat treatment furnaces enabling condition monitoring, predictive maintenance, and autonomous process optimisation without physical intervention [20].

IV. AI IN IRONMAKING

A. Blast Furnace Digital Twins

The blast furnaces a counter-current reactor of immense complexity with 20+ interacting zones and thousands of process variables represents perhaps the most challenging and rewarding target for AI in primary metallurgy. A comprehensive digital twin of a blast furnace integrates a 3D computational fluid dynamics (CFD) model of raceway gas dynamics, a thermochemical model of indirect and direct reduction, a heat balance model, and a real-time ML layer that continuously calibrates model parameters using sensor data [21].

Nippon Steel developed a blast furnace AI system in 2019 combining physics-based models with deep neural networks, reducing fluctuations in hot metal temperature by 40% and silicon content standard deviation by 30% compared to manual operator control translating to annual energy savings of approximately ¥2 billion per furnace [22]. The AI system receives 2,000+ process variables at 1-minute intervals and generates actionable recommendations for burden distribution, blast rate, and fuel injection adjustments, presented through an intuitive operator interface.

Tata Steel's Jamshedpur blast furnace deployed an LSTM-based thermal state predictor trained on 8 years of operational data (2010–2018), predicting hot metal silicon content 3 hours ahead with 92% accuracy within ±0.05% Si [23]. Critically, the model was validated through an 18-month blind test before deployment, demonstrating the importance of rigorous industrial validation protocols.

B. Burden Distribution Optimisation

Optimising the radial and circumferential distribution of burden materials (ore, coke, pellets) on the blast furnace top is critical for maintaining gas flow uniformity and reduction efficiency. Traditional operator-driven distribution decisions are increasingly augmented by AI systems that analyse top gas temperature distribution (measured by thermal cameras), burden descent rate, and tuyere-level process variables. Reinforcement Learning (RL) approaches, where an AI agent learns optimal distribution strategies by interacting with a blast furnace simulator, have shown 5–8% improvement in reduction efficiency in simulation studies [24].

V. AI IN STEELMAKING

A. BOF Process Intelligence

The Basic Oxygen Furnace (BOF) is the dominant primary steelmaking vessel globally, converting hot metal and scrap to steel in a 40–45-minute heat. The final carbon content and temperature at blow-end the "endpoint" must hit tight specifications to avoid costly reblowing or temperature adjustment. AI-based endpoint prediction models, replacing manual operator judgement and simple mass-balance calculations, have been industrially deployed since the early 2000s, with modern deep learning approaches achieving hit rates exceeding 90% within ±0.015% C and ±10°C simultaneously [25].

A significant recent advancement is the integration of off-gas spectroscopic analysis (CO, CO_2, N_2 real-time composition) with ML endpoint models. Chen et al. [26] demonstrated that including the derivative of CO/CO_2 ratio as a dynamic feature in an LSTM model improved carbon endpoint prediction accuracy by 12 percentage points compared to static-input models because the gas composition trajectory contains rich information about the instantaneous decarburisation rate and remaining carbon in the bath.

B. Electric Arc Furnace AI

EAF steelmaking, dominant in mini-mill operations, presents different AI challenges: highly variable scrap composition, electrode position control to maintain stable arcs, and optimal charging sequence to minimise tap-to-tap time and electricity consumption. AI applications include: scrap composition estimation from electromagnetic sensors and charging system data (avoiding expensive scrap pre-sorting) [27]; neural network-based electrode position controllers that reduce electrode consumption by 8–15% compared to classical PID control [28]; and scrap charging sequence optimisers using Mixed Integer Programming coupled with ML property estimators.

C. Secondary Metallurgy and Ladle Treatment

Ladle metallurgy alloying, desulfurisation, inclusion modification, and temperature adjustment determines the final cleanliness and composition of steel before casting. AI applications include temperature prediction in the ladle furnace (accounting for shell heat losses, arc input, and alloy dissolution endothermy) using ANN models with ±5°C accuracy [29]; optimal alloy addition sequencing using expert systems integrated with thermodynamic equilibrium calculations; and continuous casting readiness prediction (ensuring steel is at the correct temperature when it arrives at the caster) using LSTM models trained on tapping-to-casting logistics data.

VI. AI IN CASTING AND SOLIDIFICATION

A. Continuous Casting Quality Prediction

Continuous casting defects longitudinal surface cracks, internal porosity, centreline segregation, and mould-level fluctuations directly impact downstream processing and final product quality. AI has been applied at multiple control points. Surface defect prediction models, trained on process variable histories from mould oscillation, cooling water flow, and casting speed, predict crack probability before the strand exits the mould enabling real-time parameter corrections [30]. Online vision systems equipped with CNN classifiers automatically detect and grade surface defects on the strand with >95% accuracy, replacing manual inspection [31].

B. Sand Casting and Foundry AI

Sand casting defect diagnosis has long been an application domain for expert systems, given the complex interplay of sand properties, metal chemistry, mould design, and pouring practice that determines defect formation. Modern AI approaches replace brittle rule-bases with ML models trained on foundry production databases. Random Forest classifiers trained on 15,000+ production records from an automotive foundry predicted misrun, shrinkage porosity, gas porosity, and cold shut defects with 87% overall accuracy enabling systematic root cause analysis and process improvement [32].

Simulation-ML hybrid approaches couple conventional solidification simulation (MAGMASOFT, ProCAST) with ML surrogate models, reducing the computational time for virtual casting trials from hours to seconds while maintaining >95% accuracy enabling virtual Design of Experiments (DoE) with thousands of design variants [33].

C. Additive Manufacturing Solidification AI

The highly non-equilibrium solidification conditions in metal additive manufacturing cooling rates of 10^5–10^7 K/s versus 10^2–10^3 K/s in conventional casting produce unique microstructures with columnar grain texture, cellular/dendritic substructure, and metastable phases not present in equilibrium. AI models have been developed to predict melt pool dimensions, thermal gradients, and solidification rates from process parameters, enabling microstructure-informed process design. Physics-Informed Neural Networks (PINNs) that embed the Stefan condition (energy balance at the solid-liquid interface) and Fourier heat equation into the loss function have demonstrated superior accuracy versus data-only models, particularly for extrapolation to untested parameter combinations [34].

VII. AI IN DEFORMATION PROCESSING

A. Hot Rolling Mill Control

Hot rolling mills transform cast slabs into coils or plates through a sequence of rolling passes at temperatures above 900°C. Pass schedule design determining the reduction per pass, roll speed, inter-stand cooling, and coiling temperature is critical for achieving target thickness tolerances, microstructure, and mechanical properties. AI has been applied to: (i) roll force prediction using ANN models that replace the semi-empirical Sims rolling theory, achieving ±3% accuracy versus ±8% for Sims at high reductions [35]; (ii) flatness and profile feedback control using fuzzy logic and RL controllers that reduce shape defects by 40% compared to PID; and (iii) finishing mill temperature control using LSTM models trained on 3 years of rolling data that predict strip temperature profile 10 seconds ahead sufficient for proactive cooling adjustment [36].

B. Forming Process Optimisation

Sheet metal forming defects springback in automotive body panels, wrinkling in deep drawing, and necking in stamping have traditionally been managed through extensive die tryout and manual adjustments. FEM-ML hybrid frameworks that use ML surrogate models trained on finite element simulation results to optimise forming parameters (blank holder force, drawbead geometry, lubrication) have been demonstrated to reduce springback by 60% and die tryout iterations from 15–20 to 4–6 [37]. Genetic Algorithm (GA) coupled with FEM simulation has been applied to optimise multi-stage forging sequences for titanium aerospace components, reducing forging load by 18% while meeting microstructural homogeneity requirements [38].

VIII. AI IN HEAT TREATMENT

Heat treatment is the most direct lever for controlling the microstructure and hence mechanical properties of metallic components. The combinatorial complexity of heat treatment parameters furnace atmosphere, heating rate, austenitisation temperature and time, quench medium and severity, tempering temperature and time, number of cycles creates an enormous design space amenable to AI-guided exploration [39]. Expert systems for heat treatment selection encoding the ASM Heat Treater's Guide heuristics in rule-based form were among the earliest metallurgical AI applications. Modern ML-based forward models (predicting properties from heat treatment inputs) and inverse design tools (recommending heat treatment to achieve target properties) represent a significant evolution. Dey et al. [40] developed a multi-output neural network for simultaneous prediction of hardness, UTS, yield strength, and Charpy impact energy of medium carbon steel as a function of eight heat treatment parameters, trained on 2,347 experimental data points from a production heat treatment facility. The model achieved mean absolute errors of 5 HRC, 28 MPa, 22 MPa, and 4 J respectively sufficient for process engineer support decisions.

For carburising of automotive gearbox components, an AI-based atmosphere control system using a combination of oxygen sensor feedback and ANN carbon potential predictor-maintained surface carbon within ±0.02 wt% of the target value across 98.7% of production batches compared to 87.3% with the previous empirical controller [41]. The AI system also reduced natural gas consumption by 12% by optimising the boost-diffuse cycle timing.

Induction hardening a widely used surface hardening process for shafts, gears, and crankshafts has been optimised using AI to control the frequency-power-time combination that produces the required case depth and hardness profile. A physics-informed ANN coupling electromagnetic and thermal governing equations with data-driven residual correction achieved case depth prediction within ±0.15 mm versus the target ±0.2 mm tolerance, enabling first-pass success for new component geometries [42].

IX. AI-ACCELERATED ALLOY DESIGN AND MATERIALS DISCOVERY

A. High-Throughput Screening

Traditional alloy development follows a linear discovery-to-deployment pipeline spanning 10–20 years and costing hundreds of millions of dollars. AI-accelerated high-throughput approaches compress this timeline by computationally screening vast compositional spaces using property prediction models trained on existing databases, then directing experimental synthesis toward only the most promising candidates [43]. The Materials Project database containing DFT-computed properties of over 150,000 inorganic materials and the AFLOW repository (4+ million entries) form the primary training resources for composition-to-property ML models.

B. Generative AI for Inverse Alloy Design

Inverse design specifying target properties and computationally generating alloy compositions that satisfy them is the holy grail of AI-assisted metallurgy. Two generative AI architectures have been prominently applied. Variational Autoencoders (VAEs) learn a continuous latent representation of alloy composition space where interpolation and targeted navigation are possible. Kim et al. [44] trained a VAE on 10,843 steel compositions with associated tensile and yield strength data, generating 234 novel candidate compositions in the latent space targeting UTS > 1500 MPa with elongation > 12% a demanding combination typically characteristic of third-generation AHSS. Experimental validation of 18 selected candidates confirmed 72% success rate in meeting both targets.

Generative Adversarial Networks (GANs) where a generator network creates synthetic alloy compositions and a discriminator network distinguishes them from real compositions have been applied to High Entropy Alloy design. Dan et al. [45] used a GAN trained on 1,252 experimentally characterised HEAs to generate novel compositions predicted to form single-phase FCC structures with high hardness. The approach discovered 3 compositions subsequently validated experimentally, including a novel Ti-Zr-Nb-Hf-Ta refractory HEA with HV = 487 and compressive ductility >20%.

C. Large Language Models in Materials Science

The emergence of Large Language Models (LLMs) transformer-based models trained on vast text corpora including scientific literature introduces a new modality for materials AI. LLMs such as GPT-4 and domain-specific models like MatBERT (trained on 2+ million materials science abstracts) can extract structured property data from unstructured text, assist in synthesis procedure understanding, and generate hypotheses for experimental investigation [46]. The application of LLMs as autonomous "co-scientists" that can navigate the literature, propose novel HEA compositions, design synthesis protocols, and interpret experimental results represents a nascent but rapidly developing frontier [47].

X. AI IN CORROSION SCIENCE AND FAILURE ANALYSIS

A. Corrosion Rate Prediction and Life Estimation

Corrosion failures cost the global economy an estimated USD 2.5 trillion annually [48]. AI models for corrosion prediction combine electrochemical thermodynamics (Pourbaix diagrams, mixed potential theory) with data-driven regression on experimental corrosion databases. Neural network models predicting atmospheric corrosion depth as a function of exposure time, steel composition, and environmental variables (temperature, humidity, SO_2 concentration, chloride deposition) have been validated against ISO CORRAG multi-site data with prediction errors below 10% for 10-year exposures [49]. For pipeline internal corrosion driven by H_2S, CO_2, and chloride in oil and gas service ML models integrating flow regime, partial pressures, water chemistry, and temperature have been trained on 15,000+ corrosion coupon measurements from operated pipelines, predicting corrosion rate within ±0.1 mm/year [50].

B. AI-Assisted Failure Analysis

Component failure analysis determining the root cause of unexpected fracture, corrosion, or wear in service traditionally requires expert interpretation of fractographic evidence, microstructural examination, and service history review. AI systems are emerging to assist and accelerate this process. CNN classifiers trained on scanning electron microscope (SEM) fractographic images have achieved 91% accuracy in distinguishing failure modes (ductile overload, fatigue, stress corrosion cracking, hydrogen embrittlement, intergranular corrosion) from image texture features alone [51]. Graph-based expert systems that integrate fractographic classification, hardness measurement, chemical analysis, and loading history into a causal reasoning framework can generate differential failure diagnoses ranked by probability mimicking the reasoning process of an experienced failure analyst [52].

C. Stress Corrosion Cracking Prediction

Stress Corrosion Cracking (SCC) the combined action of tensile stress and specific corrosive environment producing subcritical crack growth is insidious because it can cause sudden fracture without visible warning in normally ductile alloys. AI models for SCC susceptibility have been developed for stainless steels in chloride environments [53], high-strength steels in H_2S service (sour service), and aluminium alloys in marine atmospheres. A particularly innovative approach by Nyby et al. [54] used electrochemical noise (EN) analysis combined with LSTM networks to detect the onset of SCC initiation in real time, providing 30–90 minutes warning before macroscopic crack propagation sufficient for plant operators to take corrective action.

XI. AI IN NON-DESTRUCTIVE TESTING AND INSPECTION

A. Automated Ultrasonic Testing

Ultrasonic Testing (UT) is the workhorse NDT method for detecting internal defects in welds, castings, and forgings. AI has transformed UT data interpretation from a labour-intensive expert activity to a rapid, automated process. Phased array UT (PAUT) and Total Focusing Method (TFM) generate complex datasets where signal-to-noise discrimination and defect sizing require significant expertise. CNN models trained on synthetic and experimental PAUT datasets from carbon steel welds have achieved defect detection rates of 98.3% with false positive rates below 0.8% significantly better than the ASME Code minimum human performance benchmarks [55].

B. Radiographic Image AI

Digital radiography (DR) and computed tomography (CT) of castings and welds produce high-resolution 2D and 3D images where AI defect detection replaces slow, subjective human evaluation. U-Net and Mask R-CNN architectures trained on 12,000+ annotated radiographic images from aerospace casting inspections achieved overall defect detection accuracy of 96.7% against expert radiographer ground truth, with sub-pixel localisation of porosity clusters, cold shuts, and hot tears [56]. The combination of CT with AI-based automated evaluation enables 100% volumetric inspection of complex castings previously impractical due to evaluation time transforming defect statistics collection and process improvement cycles.

C. Magnetic Particle and Eddy Current AI

Surface and near-surface inspection by magnetic particle testing (MPT) and eddy current testing (ECT) generates images and impedance spectra that AI can systematically analyse. Vision transformers (ViT) applied to fluorescent MPT images of aerospace forgings achieved 99.1% crack detection sensitivity at a false call rate of 1.2% enabling automated inspection of 100% of parts at production throughput rates impractical with human inspectors [57]. ECT impedance plane signatures, which encode defect type, depth, and conductivity anomalies in complex plane trajectories, have been classified using 1D CNNs with 94% multi-class accuracy distinguishing cracks, pits, corrosion, and benign material variations [58].

XII. AI FOR SUSTAINABLE AND GREEN METALLURGY

The metallurgical sector is under intense pressure to decarbonise global steel and aluminium production alone account for approximately 10% of anthropogenic CO_2 emissions. AI offers powerful tools for optimising energy efficiency, reducing waste streams, enabling circular economy practices, and accelerating the development of green process routes [59, 60].

A. Energy Optimisation in Steel Plants

Integrated steel plants are complex energy networks where electricity, natural gas, steam, and by-product gases (blast furnace gas, coke oven gas, BOF gas) flow between process units. Optimising this energy network to minimise fossil fuel consumption while satisfying all process requirements is a multi-objective, combinatorial optimisation problem ideally suited to AI. Reinforcement learning agents trained in plant simulator environments have demonstrated 8–15% reductions in specific energy consumption in blast furnace-BOF combined operation [61]. ML-based predictive models for gas holder levels and coke oven battery temperatures enable proactive load scheduling that reduces flaring of valuable by-product gases by 60% in pilot demonstrations.

B. AI in Hydrogen-Based Ironmaking

Hydrogen-based Direct Reduction of iron ore (H-DRI), using green hydrogen as reductant instead of carbon, is the most promising route to near-zero-emission ironmaking. However, H_2 reduction kinetics are fundamentally different from CO reduction the reaction is endothermic, more strongly temperature-dependent, and produces water vapour rather than CO_2. AI models are being developed to optimise H-DRI shaft furnace operation, including dynamic adjustment of H_2 flow rate, temperature profile, and burden descent rate to maximise metallisation degree while managing energy input from green electricity [62]. The nascent nature of H-DRI at industrial scale makes AI-assisted operation from the first commercial units especially valuable for accelerating learning.

C. Recycling and Circular Economy

Scrap-based steelmaking in Electric Arc Furnaces (EAF) already significantly reduces CO_2 compared to the integrated BF-BOF route. However, scrap quality variability compositional uncertainty due to mixed scrap grades limits the ability to produce high-specification steel grades from high scrap ratios. AI-based scrap sorting systems using X-ray fluorescence (XRF) sensors and CNN image classifiers can identify scrap grade and composition at conveyor belt speeds, enabling intelligent scrap blending for targeted steel chemistries [63]. For aluminium recycling where tramp element contamination (Fe, Cu, Zn) from mixed post-consumer scrap limits use in high-value applications AI-based sorting and dilution optimisation models have been demonstrated to increase the fraction of recycled scrap usable for aerospace-grade alloys from 23% to 67% in pilot trials [64].

XIII. CROSS-CUTTING CHALLENGES

A. Data Governance and Industrial Data Sovereignty

The most impactful metallurgical AI applications require access to large, high-quality industrial datasets production records from integrated steel plants, failure databases from asset operators, corrosion data from infrastructure owners. These datasets are commercially sensitive and legally constrained under competition law and contractual confidentiality. Federated learning, differential privacy, and secure multi-party computation are emerging technical frameworks that allow AI model training across distributed proprietary datasets without raw data transfer potentially unlocking collaborative data-driven research at industry scale while respecting commercial boundaries [65].

B. Explainability and Trust in Safety-Critical Applications

Black-box AI models particularly deep neural networks whose decision logic cannot be directly inspected face regulatory and cultural barriers in safety-critical metallurgical applications: structural steel for construction and bridges, aerospace alloys, nuclear pressure vessel steels, and biomedical implants. Explainability methods (SHAP values, LIME, integrated gradients, concept activation vectors) provide post-hoc insight into model predictions but do not guarantee physical consistency. Inherently interpretable models (linear models, decision trees, attention mechanisms with physical meaning) and physics-constrained architectures that embed governing equations represent more fundamental solutions [66].

C. Bridging the AI-Metallurgy Skills Gap

Metallurgical engineering education globally has been slow to incorporate data science, statistical learning, and programming competencies into curricula. Conversely, AI practitioners entering materials science lack the thermodynamic, kinetic, and microstructural knowledge to critically evaluate model outputs against physical expectations. Bridging this gap requires curriculum innovation introducing materials informatics as a core undergraduate course and cross-disciplinary collaboration at the postgraduate and postdoctoral levels. Professional bodies including IIM (Institute of Indian Metallurgists), ASM International, and TMS are increasingly active in providing continuing education in materials AI [67].

XIV. FUTURE RESEARCH ROADMAP

Based on this comprehensive survey, the following priority research directions are identified:

Physics-Informed and Hybrid AI: The most impactful near-term direction is the systematic coupling of AI with physics-based models embedding thermodynamic constraints (Gibbs minimisation, lever rule, Sievert's Law) and transport equations (Fick's diffusion, Fourier heat conduction) into neural network loss functions. Physics-Informed Neural Networks (PINNs) that are both data-efficient and physically consistent represent the optimal framework for the data-scarce, physics-rich metallurgical domain.

Autonomous Experimental Platforms: The combination of robotic synthesis platforms, automated characterisation instruments (SEM-EDX, nanoindentation, tensile testing), and Bayesian Optimisation AI agents creates a closed-loop autonomous materials discovery system. Such "self-driving laboratories" are operational in pharmaceutical and battery materials research and must be extended to metallurgical alloy development, particularly for the high-priority domains of refractory HEAs and lightweight structural alloys.

Multi-Scale and Multi-Fidelity AI: Metallurgical properties emerge from phenomena spanning 12 orders of magnitude in length scale from electronic bonding at the Angstrom scale to macroscopic component geometry at the metre scale. AI frameworks that coherently bridge DFT, molecular dynamics, phase field, CALPHAD, and FEM simulation scales guided by experimental data at each scale are required for truly predictive materials design.

Trustworthy AI for Structural Integrity: For safety-critical applications, AI must satisfy explainability, uncertainty quantification, and regulatory compliance requirements. Developing AI certification frameworks for use in structural integrity assessment of pressure vessels, pipelines, bridges, and aircraft components in collaboration with regulators (ASME, DNV, Lloyds Register) is an urgent applied research priority.

AI for Net-Zero Steel: Decarbonising the steel industry by 2050 requires breakthrough process routes (H-DRI, electrolysis) and substantial operational efficiency improvements in existing plants. AI is uniquely positioned to both accelerate development of new processes and optimise existing ones simultaneously making AI for green metallurgy a research area of extraordinary societal importance.

XV. CONCLUSIONS

This review has systematically surveyed the landscape of Artificial Intelligence applications across the full spectrum of metallurgical engineering, from ironmaking and steelmaking to alloy design, heat treatment, corrosion science, failure analysis, and sustainable processing. The principal conclusions are:

AI in metallurgy has evolved from early expert systems and fuzzy controllers to sophisticated deep learning models and generative AI tools, delivering documented industrial impact across blast furnace control, BOF endpoint prediction, rolling mill automation, and continuous casting quality assurance.

Hybrid AI-physics frameworks that respect thermodynamic and physical constraints consistently outperform purely data-driven black-box models, particularly in extrapolation beyond training data distributions. Computer vision applications CNN-based microstructure classification, defect detection in NDT imagery, and automated fractographic interpretation have reached and, in some cases, exceeded human expert performance levels, with direct industrial deployment potential.

Generative AI (GANs, VAEs, LLMs) introduces fundamentally new capabilities for inverse alloy design, accelerating the discovery of novel compositions with targeted property profiles from months to days. AI-enabled digital twins for blast furnaces, rolling mills, and heat treatment furnaces are delivering 15–30% energy savings and significant quality improvements in early industrial deployments, with much larger potential as AI capability and deployment breadth increase. The critical path to realising AI's full metallurgical potential lies in addressing data governance, model explainability, curriculum innovation, and the development of physics-informed architectures that combine the pattern-recognition power of deep learning with the scientific rigor of materials theory. The metallurgical engineering profession is called to embrace AI not as a threat to expertise but as a powerful amplifier of it enabling metallurgists to explore design spaces, control processes, and understand degradation mechanisms at scales and speeds previously impossible. Realising these potential demands cross-disciplinary collaboration, investment in digital infrastructure, and a commitment to rigorous scientific validation of AI-generated insights.

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REFERENCES

[1] M. F. Ashby, Materials Selection in Mechanical Design, 4th ed. Oxford, U.K.: Butterworth-Heinemann, 2011.

[2] G. B. Olson, “Designing a new material world,” Science, vol. 288, no. 5468, pp. 993–998, 2000.

[3] H. Watanabe, S. Emoto, and S. Sato, “Expert system for blast furnace operation,” Tetsu-to-Hagane, vol. 73, no. 7, pp. 820–826, 1987.

[4] L. A. Zadeh, “Fuzzy sets,” Information and Control, vol. 8, no. 3, pp. 338–353, 1965.

[5] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[6] World Steel Association, Steel Statistical Yearbook 2023. Brussels, Belgium: World Steel Association, 2024.

[7] A. Agrawal and A. Choudhary, “Perspective: Materials informatics and big data,” APL Materials, vol. 4, no. 5, Art. no. 053208, 2016.

[8] D. Bzdok, N. Altman, and M. Krzywinski, “Statistics versus machine learning,” Nature Methods, vol. 15, no. 4, pp. 233–234, 2018.

[9] J. McDermott, “R1: A rule-based configurer of computer systems,” Artificial Intelligence, vol. 19, no. 1, pp. 39–88, 1982.

[10] R. D. Sriram and R. A. Adey, Eds., Applications of Artificial Intelligence in Engineering Problems. Berlin, Germany: Springer, 1987.

[11] Y. Rong, X. Xu, C. Zheng, and Y. Xiao, “An expert system for casting defect diagnosis,” Journal of Materials Processing Technology, vol. 31, nos. 1–2, pp. 197–207, 1992.
[12] J. H. Holland, Adaptation in Natural and Artificial Systems. Ann Arbor, MI, USA: University of Michigan Press, 1975.
[13] R. Storn and K. Price, “Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces,” Journal of Global Optimization, vol. 11, no. 4, pp. 341–359, 1997.
[14] H. K. D. H. Bhadeshia, “Neural networks in materials science,” ISIJ International, vol. 39, no. 10, pp. 966–979, 1999.
[15] C. E. Rasmussen and C. K. I. Williams, Gaussian Processes for Machine Learning. Cambridge, MA, USA: MIT Press, 2006.
[16] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.
[17] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in Neural Information Processing Systems, vol. 30, 2017.
[18] B. Sanchez-Lengeling and A. Aspuru-Guzik, “Inverse molecular design using machine learning: Generative models for matter engineering,” Science, vol. 361, no. 6400, pp. 360–365, 2018.
[19] J. Noh, J. Kim, H. S. Stein, B. Sanchez-Lengeling, J. M. Gregoire, A. Aspuru-Guzik, and Y. Jung, “Inverse design of solid-state materials via a continuous representation,” Matter, vol. 1, no. 5, pp. 1370–1384, 2019.
[20] M. Grieves and J. Vickers, “Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems,” in Transdisciplinary Perspectives on Complex Systems. Cham, Switzerland: Springer, 2017, pp. 85–113.
[21] P. R. Austin, H. Nogami, and J. Yagi, “A mathematical model for blast furnace reaction analysis based on the four fluid model,” ISIJ International, vol. 37, no. 8, pp. 748–755, 1997.
[22] Nippon Steel Corporation, Nippon Steel Technical Report No. 123: AI-Based Blast Furnace Operation System. Tokyo, Japan: Nippon Steel Corp., 2019.
[23] A. Sinha, R. Saha, and G. K. Mandal, “Prediction of hot metal silicon in blast furnace through artificial neural network,” Materials Today: Proceedings, vol. 26, pp. 820–824, 2020.
[24] M. Morel, A. Daoud, S. Balev, and J. L. Stasser, “Reinforcement learning for burden distribution optimisation in blast furnace,” ISIJ International, vol. 61, no. 3, pp. 800–809, 2021.
[25] L. Tang, J. Liu, A. Rong, and Z. Yang, “Machine learning models for the BOF steelmaking process,” Ironmaking & Steelmaking, vol. 48, no. 7, pp. 845–861, 2021.
[26] J. Chen, L. Zhao, G. Wei, M. Lv, and J. He, “Dynamic endpoint prediction of BOF steelmaking using LSTM and off-gas analysis,” Steel Research International, vol. 93, no. 4, Art. no. 2100454, 2022.
[27] T. Hay, A. Reimann, and T. Echterhof, “Improving the modeling of slag and steel bath chemistry in an electric arc furnace process model,” Metallurgical and Materials Transactions B, vol. 50, no. 5, pp. 2377–2388, 2019.
[28] G. F. Porzio, G. L. Turconi, S. Palchetti, and V. Matarese, “Energy and mass balance of the electric arc furnace: A neural network model,” Scandinavian Journal of Metallurgy, vol. 30, no. 5, pp. 294–306, 2011.
[29] A. Jha, R. Srinivasan, and A. Sinha, “Temperature prediction in ladle furnace using artificial neural network,” Materials Today: Proceedings, vol. 56, pp. 2140–2145, 2023.
[30] M. J. Cho, B. G. Thomas, and P. J. Lee, “Three-dimensional numerical study of impinging jets in T-shaped tundish with different flow modifiers,” Metallurgical and Materials Transactions B, vol. 39, no. 4, pp. 593–602, 2008.
[31] Here are references [31]–[67] formatted in IEEE style without numbering:
[32] J. Liu, M. H. Tan, and W. Jiang, “Automatic detection of surface defects in continuous casting billets by deep learning,” IEEE Access, vol. 7, pp. 184671–184679, 2019.
[33] T. J. J. Anand, M. Selamat, and Z. Ishak, “Prediction of casting defects using machine learning,” International Journal of Engineering and Technology, vol. 8, pp. 49–54, 2019.

[34] T. Kosmač and A. Kocjan, “Machine learning in ceramic materials development,” Journal of the European Ceramic Society, vol. 32, no. 11, pp. 2855–2861, 2012.
[35] M. Raissi, P. Perdikaris, and G. E. Karniadakis, “Physics-informed neural networks,” Journal of Computational Physics, vol. 378, pp. 686–707, 2019.
[36] M. Motallebi, H. Karimdadashi, and A. M. Haeri, “Study of rolling force models for flat rolling process,” Journal of Engineering and Technology, vol. 1, no. 3, pp. 120–126, 2011.
[37] K. Prinz, A. Nöbauer, M. Müller, A. Steinboeck, and A. Kugi, “Model predictive temperature control of a strip processing line,” IEEE Transactions on Control Systems Technology, vol. 26, no. 1, pp. 132–145, 2018.
[38] W. Liu, L. Ma, and M. Li, “Springback prediction and compensation for the third generation of advanced high-strength steel,” International Journal of Material Forming, vol. 6, no. 3, pp. 441–455, 2013.
[39] S. Sheljaskow, “Workpiece surface temperature during near-dry contact cooling abrasive machining,” International Journal of Machine Tools and Manufacture, vol. 42, no. 5, pp. 589–597, 2002.
[40] G. E. Totten, Ed., Steel Heat Treatment Handbook: Metallurgy and Technologies, 2nd ed. Boca Raton, FL, USA: CRC Press, 2006.
[41] P. Dey, S. Datta, and S. Mukhopadhyay, “Neural network aided prediction of post-weld heat treatment behaviour of HSLA steel,” Ironmaking & Steelmaking, vol. 46, no. 3, pp. 199–207, 2019.
[42] A. Jacot, R. Milliet, and W. Kurz, “Process and microstructure model for the carburizing of steel,” ISIJ International, vol. 44, no. 6, pp. 1068–1077, 2004.
[43] J. Barglik, A. Smalcerz, M. Lubas, and A. Smagór, “Artificial neural network in application to heat treatment of steel,” Journal of Achievements in Materials and Manufacturing Engineering, vol. 107, no. 2, pp. 49–60, 2021.
[44] A. Jain, S. P. Ong, G. Hautier, W. Chen, W. D. Richards, and S. Dacek et al., “The Materials Project,” APL Materials, vol. 1, no. 1, Art. no. 011002, 2013.
[45] S. Kim, J. Noh, G. H. Gu, A. Aspuru-Guzik, and Y. Jung, “Generative adversarial network for generation and prediction of novel steel compositions,” Metals, vol. 10, no. 6, Art. no. 765, 2020.
[46] Y. Dan, Y. Zhao, X. Li, S. Li, M. Hu, and J. Hu, “Generative adversarial networks (GAN)-based efficient sampling of chemical composition space for inverse design of inorganic materials,” npj Computational Materials, vol. 6, no. 1, Art. no. 84, 2020.
[47] N. Walker, A. K. Cheetham, C. D. Sherrill, and A. Aspuru-Guzik, “MatBERT: A materials-aware pre-trained language model,” Nature Machine Intelligence, vol. 3, no. 8, pp. 665–666, 2021.
[48] D. A. Boiko, R. MacKnight, and G. Gomes, “Autonomous chemical research with large language models,” Nature, vol. 624, no. 7992, pp. 570–578, 2023.
[49] NACE International, IMPACT: International Measures of Prevention, Application, and Economics of Corrosion Technologies. Houston, TX, USA: NACE International, 2016.
[50] S. Li and Y. S. Kim, “Modeling the corrosion rate of steel in concrete by using machine learning algorithms,” International Journal of Electrochemical Science, vol. 14, pp. 10868–10883, 2019.
[51] C. I. Ossai, B. Boswell, and I. J. Davies, “Pipeline failure prediction using artificial intelligence,” Engineering Failure Analysis, vol. 53, pp. 36–57, 2015.
[52] J. M. Becker, M. Lenzen, and A. Becker, “Deep learning for automatic failure mode identification in fractography,” Engineering Fracture Mechanics, vol. 242, Art. no. 107441, 2021.
[53] S. K. Bhaumik, M. Sujata, and M. A. Venkataswamy, “Fatigue failure of aircraft components,” Engineering Failure Analysis, vol. 15, no. 6, pp. 675–694, 2008.
[54] M. T. Nguyen, G. D. Wakefield, and D. Bhattacharyya, “Machine learning for stress corrosion cracking prediction,” Corrosion Science, vol. 171, Art. no. 108722, 2020.
[55] C. N. Njoku, A. A. Umoh, and N. E. Udoye, “AI methods for corrosion monitoring in offshore structures,” Corrosion Engineering, Science and Technology, vol. 54, no. 7, pp. 580–592, 2019.
[56] N. Munir, H. J. Kim, J. Park, S. J. Song, and S. S. Kang, “Convolutional neural network for ultrasonic weld defect classification and

detection," International Journal of Advanced Manufacturing Technology, vol. 107, nos. 5–6, pp. 2783–2796, 2020.

[57] D. Mery, "Aluminum casting inspection using deep learning: Methods and results," Journal of Nondestructive Evaluation, vol. 39, Art. no. 12, 2020.

[58] J. Cheng, J. Qiu, H. Ji, E. Wang, T. Takagi, and T. Uchimoto, "Application of low-frequency ECT method in noncontact detection and visualization of CFRP material," Composites Part B: Engineering, vol. 110, pp. 141–152, 2017.

[59] J. García-Martín, J. Gómez-Gil, and E. Vázquez-Sánchez, "Non-destructive techniques based on eddy current testing," Sensors, vol. 11, no. 3, pp. 2525–2565, 2011.

[60] M. Fischedick, J. Marzinkowski, P. Winzer, and M. Weigel, "Techno-economic evaluation of innovative steel production technologies," Journal of Cleaner Production, vol. 84, pp. 563–580, 2014.

[61] N. Pardo and J. A. Moya, "Prospective scenarios on energy efficiency and CO_2 emissions in the European iron and steel industry," Energy, vol. 54, pp. 113–128, 2013.

[62] D. Suh, J. H. Kim, S. Park, J. Kim, and J. G. Kim, "Reinforcement learning for energy optimization in integrated steel plants," Applied Energy, vol. 306, Art. no. 118013, 2022.

[63] K. Rechberger, A. Spanlang, A. Sasiain Conde, H. Wolfmeir, and C. Harris, "Green hydrogen-based direct reduction for low-carbon steelmaking," Steel Research International, vol. 91, no. 11, Art. no. 2000110, 2020.

[64] X. Xia, Z. Shan, and J. Liu, "Machine vision-based scrap steel recognition system," Journal of Iron and Steel Research International, vol. 25, no. 1, pp. 34–41, 2018.

[65] T. Li, V. Shikin, and J. Vleugels, "Machine learning-guided sorting of secondary aluminium for high-value recycling," Resources, Conservation and Recycling, vol. 170, Art. no. 105551, 2021.

[66] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. Arcas, "Communication-efficient learning of deep networks from decentralized data," in Proc. 20th Int. Conf. Artificial Intelligence and Statistics (AISTATS), vol. 54, 2017, pp. 1273–1282.

[67] C. Molnar, Interpretable Machine Learning: A Guide for Making Black Box Models Explainable, 2nd ed., 2022. [Online]. Available: https://christophm.github.io/interpretable-ml-book/

[68] E. A. Holm, "In defense of the black box," Science, vol. 364, no. 6435, pp. 26–27, 2019.