• 金属材料领域：机器学习在设计–制造–深加工中的应用机遇与挑战
Field of Metal Materials: Application Opportunities and Challenges of Machine Learning in Design–Manufacturing–Deep Processing •

特邀专栏

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机器学习在炼钢工业的深度应用：机遇与挑战

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摘　要：随着人工智能的快速发展，机器学习算法在炼钢工业中的应用成为研究热点。本文系统探讨智能模型在短流程炼钢过程复杂工业场景的深度应用挑战与机遇，重点分析其在电炉、精炼和连铸等核心环节的应用现状。结合钢铁流程的典型场景，阐述机器学习在工艺优化、异常诊断与自主决策等方面的思考。针对炼钢环境下的实时性、可靠性需求，提出机器学习在智能制造体系中的研究方向，包括多模态感知、因果推理与数字孪生等前沿技术。最后，探讨机器学习在短流程炼钢工业深度应用面临的挑战、潜在的解决方案和未来应用展望。

关键词：机器学习；短流程炼钢；质量预测；自主决策；基础模型

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Deep Applications of Machine Learning in the Steelmaking Industry: Opportunities and Challenges

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Abstract: With the rapid development of artificial intelligence, the application of machine learning algorithms in the steelmaking industry has become a research hotspot. This paper systematically explores the challenges and opportunities of intelligent models in complex industrial scenarios of short-process steelmaking, with a focus on analysing their current applications in key stages such as electric arc furnaces, refining, and continuous casting. An examination of typical scenarios in the steelmaking process elaborates on the role of machine learning in process optimization, anomaly detection, and autonomous decision-making. In response to the real-time and reliability demands of the steelmaking environment, this study proposes research directions for machine learning within intelligent manufacturing systems, including cutting-edge technologies such as multimodal sensing, causal reasoning, and digital twins. Finally, this study explores the challenges, potential solutions, and future application prospects of machine learning in deep integration with the short-process steelmaking industry.

Key words: machine learning; short-process steelmaking; quality prediction; autonomous decision; foundation models

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短流程炼钢是钢铁行业绿色低碳转型发展的必然趋势，短流程电弧炉炼钢的主要原料是废钢，能源介质是绿电(清洁电力)，利用电能融化废钢和直接还原铁得到液态钢液，避免高炉长流程炼钢过程的煤炭消耗，实现钢铁流程降低二氧化碳排放的效果。短流程炼钢是多相、高温和多场耦合的黑箱过程，存在众多质量影响因素。炼钢过程优化控制与参数预测主要依靠经验和专家二级系统，非稳态工况下的模型适应性较差，很难实现窄窗口的钢液成分和温度控制。

钢铁流程工业特有的连续化生产特性、多物理场耦合机制以及强实时性要求，使得基础模型在工艺优化、故障诊断等核心环节面临数据异构性、知识可解释性差、系统可靠性不足等问题。机器学习算法能够深度挖掘钢铁生产数据价值，实现多模态感知信息的高效解析与因果推理。通过构建融合冶金领域知识的流程工业基础模型，形成包含物理机理约束的机器学习技术框架。重点攻克多源数据动态融合、跨工序协同优化等关键技术瓶颈，支撑智能炼钢系统决策[1-4]。利用冶金机理和机器学习等方法探索智能制造体系的实现路径。研究成果将为短流程炼钢工业的智能化升级提供理论支撑与方法指导。传统的短流程炼钢需要向智能连铸转型，基于短流程炼钢过程中的大量数据和机器学习算法，以探索有价值的信息或逻辑关系。建立具有决策能力和预断功能，以实现连铸机的高效生产和智能控制[5]。本文系统梳理 2020 至 2025 年间短流程炼钢过程智能预测与优化领域的重要研究成果，对机器学习在短流程炼钢生产中的应用现状进展进行系统评述，重点介绍协同优化复杂性、数据集特征和实际应用中面临的挑战，为钢铁企业提供短流程炼钢数智化转型的研发思路和主攻方向。

1 短流程炼钢深度应用的场景特点

短流程炼钢过程如图 1 所示，短流程炼钢(以电炉为核心)的深度应用场景具有原料灵活、低碳集约、柔性生产特征，电炉以废钢(80%~100%)为主料，适配直接还原铁(direct reduced iron, DRI)，吨钢 CO_2 排放可低至长流程的 1/3。耦合薄带连铸、近终形轧制形成工序紧凑流程，降低能耗 15%~20%，特别适合高端特钢小批量定制生产。

短流程炼钢的质量控制难点在于原料波动与工艺协同性挑战，废钢成分复杂导致残留元素积累，影响钢液纯净度，高端钢种的硫磷及夹杂物控制困难。冶炼周期短、过程温度与成分波动大，合金收得率不稳。短流程缺乏铁液预处理工序，脱硫脱磷高度依赖精炼，连铸工序因钢水洁净度波动易引发皮下气泡、夹杂或偏析缺陷，需优化保护浇注与电磁搅拌。紧凑的“电炉–精炼–连铸”工序衔接要求极高协同性，否则易出现温降失控或成分超标。未来突破方向需融合人工智能技术，预测关键指标、AI 智能动态调控及数据挖掘等新技术，实现产品质量稳定化提升。

2 机器学习在短流程炼钢中的应用现状

2.1 电炉冶炼制造过程中的机器学习应用

在电炉冶炼制造过程中，机器学习通过集成先进的传感器和数据分析技术，能够预报炉内温度、成分变化及冶炼状态，实现对冶炼过程的精准控制。这不仅有助于优化合金添加策略，提高合金收得率，还能有效应对原料波动带来的挑战。此外，机器学习算法还能预测并调整冶炼参数，确保冶炼周期的稳定性，减少过程温度与成分的波动。通过这些智能化手段，短流程炼钢的电炉冶炼环节得以显著提升效率与产品质量，国内外研究学者近几年提出基于机器学习的电炉冶炼智能模型，如表 1 所示[6-16]。

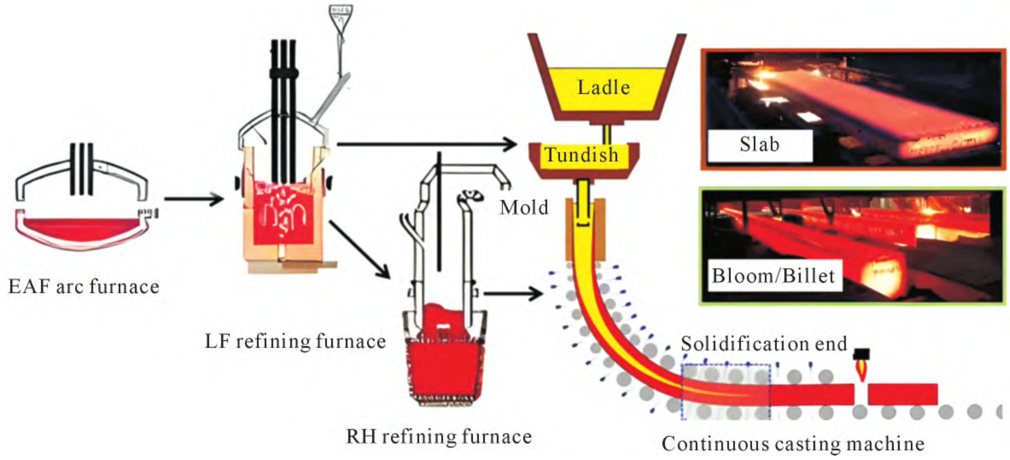

图 1 短流程炼钢工序示意图
Fig.1 Schematic diagram of short-term steelmaking

表1 国内外电炉冶炼工序的人工智能应用现状

Tab.1 Current status of artificial intelligence applications in electric furnace steelmaking processes at home and abroad

Publications	Data collection features	Model application	ML method	Training samples	Evaluation metric
Rezvani et al. (2022)[6]	Process data (ladle argon pressure, argon flow rate, stopper position) with timestamps	Foam slag property prediction	Evolutionary wavelet neural network	4033 training samples, 449 validation samples, 499 test samples	99%
Yang et al. (2022)[7]	13 factors affecting EAF endpoint carbon (scrap weight, hot metal weight, [C], [Si], [Mn], [P], [S], temperature, etc.)	Endpoint carbon prediction	Artificial neural network	1200 heats (800 training samples, 200 test samples, 200 validation samples)	96.67%
Vinayaka et al. (2021)[8]	Time-series current and voltage data	EAF voltage prediction	Modified backpropagation neural network	3 zones (15 samples each), 11 training samples, 4 test samples	-
Godoy-Rojas et al. (2022)[9]	49 process variables (electrode current, voltage, arc power, chemical composition, etc.) 16 thermocouples	Furnace wall temperature prediction	Attention-based deep recurrent neural network	177312 samples (90% training, 10% test)	-
Tomažič et al. (2022)[10]	EAF process parameters (scrap weight, melting time, heating delays, temperature, O_2 and C inputs, etc.)	Energy consumption prediction	Takagi-Sugeno Fuzzy Modeling	577 samples (404 training, 173 test)	-
Zou et al. (2022)[11]	Process data (scrap and hot metal weight, [C], [Si], [Mn], [P], temperature, power, O_2 and lime consumption)	Endpoint phosphorus prediction	Backpropagation neural network	580 datasets (400 training, 180 test)	87.78%(±0.004%), 75.56%(±0.003%)
Yildiz et al. (2022)[12]	Electrode control data (position, active and reactive power, current, hydraulic pressure, etc.)	Electrode control	Artificial neural network	80% training, 20% test	98%
Panoiu et al. (2024)[13]	Power quality metrics (active and reactive power, harmonic distortion)	Energy quality analysis	Hybrid CNN-LSTM-GRU	400 samples (85% training, 15% test)	94%
Niyayesh et al. (2024)[14]	Process inputs (scrap gas, O_2, DRI, slag, carbon injection, arc power, pressure, CO_2, Fe, N_2, CO levels, etc.)	Steel carbon content, oxide composition, and temperature prediction	Artificial neural network	42 000 samples	-
Zhuo et al. (2024)[15]	DRI quantity, flux addition, temperature, tapping time, natural gas, O_2, slag, carbon inputs	EAF energy efficiency analysis	XGBoost	699 samples	-
Azzaz et al. (2025)[16]	Process data (scrap weight, [C], [Mn], [Cr], [S], O_2 volume, lime addition, energy, temperature, etc.)	Endpoint phosphorus prediction	Artificial neural network	1 700 samples (1 005 after cleaning; 80% training, 20% test)	100%

机器学习技术被广泛应用于预测和优化各种关键参数,如泡沫渣性能、终点碳含量、电炉电压、炉墙温度、电能消耗、终点磷含量、电极控制、电能质量、钢液的成分和温度等。不同的方法,如进化小波神经网络(evolutionary wavelet neural network, EWNN)、人工神经网络 (artificial neural network, ANN)、改进的反向传播神经网络(backpropagation neural network, BP)、注意力机制结合深度递归神经网络(attention-based deep recurrent neural network, RNN)、Takagi-Sugeno 模糊建模以及 XGBoost 等,被应用于处理和分析从电炉冶炼过程中收集的大量工艺数据。EWNN 通过将小波变换与进化神经网络相结合,可有效分析钢铁生产中的时序数据,通过小波分解同时捕捉瞬态和长期模式,动态适应工艺波动并规避局部最优,满足实时监测需求。电炉冶炼过程具有多变量耦合、强非线性和工况多变的特点,但高质量生产数据获取成本高,数据增强策略能够比避免小样本机器学习的过拟合风险。Niyayesh 等[14]在钢液参数预测研究中,针对工业数据中的噪声问题采用滑动窗口均值滤波结合专家经验剔除异常值,对缺失数据则根据缺失比例分别采用时间序列线性插值和随机森林回归估计。在特征处理阶段,对连续变量实施基于四分位数的 RobustScaler 标准化,对类别变量进行 One-Hot 编码有效支撑电弧炉炼钢终点参数的神经网络预测。

电炉工序是一个物理化学耦合的复杂冶金过

程，加入经验、半经验模型和基础冶金机理方程能够增加输入数据的样本特征，提高机器学习模型的泛化性和预测准确性，但冶炼过程中的化学反应、传热传质等机理的参数很难量化，会增加机器学习模型构建的成本。因此，不断探索如何有效结合机理模型和机器学习模型，以实现更精确的控制和预测。通过数据挖掘技术，从大量的工艺数据中提取有用的信息，利用这些信息来优化机器学习模型的参数。PCA-CBR(principal component analysis-case-based reasoning)和 CBR-HTC(improved case-based reasoning with heat transfer calculation)方法在小样本集工况下展现出了卓越的适应性，它们能够有效地从有限的数据中提取关键特征并进行案例推理，这对于处理某些特定场景下的数据稀缺问题尤为关键。而深度神经网络(deep neural network, DNN)则以其强大的机理融合能力脱颖而出，能够通过多层网络结构自动学习数据中的复杂关系，并将这些关系与炼钢过程中的物理、化学机理相结合，从而提供更精确的预测和优化结果。

2.2 精炼制造过程中的机器学习应用

国内外学者在精炼制造过程中应用了多种机器学习模型和算法，针对不同的工艺数据和任务进行了建模和预测。这些研究涵盖了 LF(钢包精炼炉)和 RH(真空循环脱气)等精炼工序，预测目标包括钢液温度、通电时间、合金收得率等关键参数，如表 2 所示[17-27]。

机器学习模型在精炼制造过程中能够预测和优化多种关键参数，从而提高精炼效率和产品质量。机器学习技术还用于优化精炼过程中的能耗、脱渣温度和出钢温度等参数，进一步降低生产成本和提高生产效率。表明机器学习模型在精炼制造过程中具有较高的预测能力和应用价值。不同研究之间的预测精度存在差异，这可能与数据质量、模型选择、参数设置等因素有关。因此，在实际应用中，需要根据具体场景和数据特点选择合适的机器学习模型和算法，并进行充分的模型调优和验证，以提高预测精度和可靠性。机器学习模型在精炼制造过程中的应用还面临着一些挑战，如数据稀疏性、模型可解释性、实时性要求等。未来研究可以进一步探索更加高效、准确的机器学习算法和模型，以及针对精炼制造过程特点的定制化解决方案，以推动机器学习在短流程炼钢工业中的深度应用和发展。

2.3 连铸制造过程中的机器学习应用

机器学习方法广泛应用在连铸过程，主要包括分类和回归两个任务，具体应用场景包括漏钢、铸坯内裂纹、铸坯表面裂纹和结晶器异常液面波动等预报和过程参数寻优，如表 3[28-46]和 4[47-53]所示。研究者们利用结晶器热电偶温度数据、工艺参数及其他相关连铸工艺参数，构建了深度神经网络(如长短期记忆网络等)并将其应用于时序数据处理，以此捕捉连铸过程中的复杂动态特征，进而提升预报准确性与工况适应性。

漏钢预报对于保障生产安全和减少经济损失至关重要。通过机器学习模型，可实时分析连铸过程中的温度、应力、振动等关键参数，准确预测漏钢风险，并提前采取干预措施，有效避免漏钢事故的发生。铸坯内裂纹和表面裂纹的预报也是连铸过程中的重要环节。这些裂纹不仅影响产品的质量，还可能导致生产中断。机器学习模型通过分析裂纹形成的相关因素，可实现对裂纹的精确预报，从而指导生产参数的调整，减少裂纹的产生。

图 2 为机器学习在智能连铸过程中的应用领域统计分布，机器学习方法已被广泛应用于智能漏钢预报，比例占 57.69%。板坯纵裂纹和水口堵塞预报的研究相对较多，分别占比 19.23%和 11.54%，但内裂纹和结晶器液位的预报研究较少。机器学习用于优化连铸过程中的参数设置，以提升铸坯质量和生产效率。通过对大量历史数据的分析，研究者们能够识别出影响铸坯质量的关键因素，并利用这些因素构建预测模型，为实时调整工艺参数提供指导。

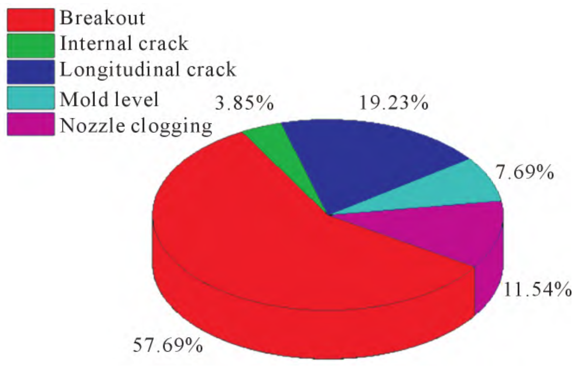

图 2 机器学习在智能连铸过程中的应用领域统计分布
Fig.2 Statistical distribution of application areas of machine learning in the intelligent continuous casting process

机器学习方法不仅减少了试错成本，还显著提高生产线的稳定性和可控性。在连铸制造过程中，机器学习模型的准确性和鲁棒性至关重要。因此，研究者们不断探索新的算法和技术，以提高模型的预测性能和泛化能力。同时，数据的质量和完整性也是影响模型效果的关键因素。为确保模型的准确性和可靠性，必须加强对数据的采集、清洗和预处理工作。通过深入挖掘数据中的潜在信息，结合先进的算

表2 国内外精炼工序的人工智能应用现状

Tab.2 Current status of artificial intelligence applications in refining processes at home and abroad

Publications	Data collection features	Model application	ML method	Training samples	Evaluation metric
Gu et al. (2020)[17]	Process data (11 factors: RH start temperature, scrap quality, oxygen blowing volume, ladle thermal status (waiting time, lifespan), refining cycle, slag thickness, molten steel quality, RH vessel temperature, vacuum refining time)	RH endpoint molten steel temperature prediction	Principal component analysis-case-based reasoning	1928 datasets (1628 case library, 300 test)	69.67%(±5 ℃), 83.67%(±7 ℃), 97%(±10 ℃)
Yuan et al. (2021)[18]	Process data (start time, scrap weight, power supply, ladle lifespan, casting time, emptying time, total processing time, slag layer thickness, molten steel weight, alloy addition, argon flow rate, endpoint temperature)	LF molten steel temperature prediction	Improved case-based reasoning with heat transfer calculation	1 898 datasets (1 598 training, 300 test)	57.33%(±3 ℃), 81%(±5 ℃), 93%(±7 ℃), 98%(±10℃)
Xin et al. (2022)[19]	Process data (alloy addition, slag-forming materials, ladle turnover cycle, molten steel weight, initial temperature, refining time, heating time, argon consumption)	LF molten steel temperature prediction	Expert control and deep neural network	2 000 samples (1 500 training, 500 test)	91.4%(±3 ℃), 99.4%(±5 ℃)
Shao et al. (2020)[20]	Process data (7 variables: molten steel weight, initial temperature, alloy addition, slag-forming materials, slag layer thickness, ladle usage count, soft blowing time)	LF power-on time prediction	Hybrid power consumption mechanism-deep neural network (PCM-DNN)	2 500 samples (2 000 training, 500 test)	93.0%(±3 ℃), 96.9%(±5 ℃)
Xin et al. (2022)[21]	Process data (gas flow rate, liquid depth, slag layer thickness)	LF mixing time (MT) and slag eye area (SEA) prediction	Response surface methodology	20 experimental datasets	96.0%(MT), 97.1%(EA)
Heo et al. (2022)[22]	Process data (operation time, molten steel weight, initial carbon content, carbon addition, vacuum chamber pressure, circulation flow rate, CO and CO_2 concentration, top-blown oxygen flow)	RH real-time carbon content prediction	Artificial neural network	626 datasets (70% training, 30% test)	-
Xin et al. (2023)[23]	Process data (ladle turnover time, molten steel weight, initial temperature, refining time, heating time, argon consumption, additive dosage)	LF molten steel temperature prediction	Isolation forest, zero-phase component analysis whitening-deep neural network (IF-ZCA-DNN)	9 764 heats (8 264 training, 1 500 test)	77.9%(±3 ℃), 92.3%(±5 ℃), 99.6%(±10 ℃)
Xin et al. (2022)[24]	Process data (molten steel weight, initial/endpoint temperature, refining/heating time, argon consumption, fluorite/lime weight, initial, [C], [Mn], [S], [P], [Si], [Als] content, ferrosilicon content)	LF alloy yield prediction	Principal component analysis-deep neural network (PCA-DNN)	1 549 heats (1 149 training, 400 test)	Si yield rate：54.0%(±1%), 93.8%(±3%), 98.8%(±5%)
Xin et al. (2024)[25]	Process data (6 variables: heating time, ladle turnover time, argon consumption, refining time, molten steel weight, initial temperature)	LF molten steel temperature prediction	LightGBM and grey wolf optimizer (GWO-LGBM)	8 962 datasets (80% training, 20% test)	89.35%(±5 ℃)
Wang et al. (2025)[26]	Process data (ladle preheating temperature, molten steel weight, returned slag volume, alloy and slag addition, initial temperature, refining time)	LF endpoint temperature prediction	Particle swarm optimization-long short-term memory (PSO-LSTM)	2 368 samples (1 646 after cleaning; 80% training, 20% test)	43.16%(±3 ℃), 71.12%(±5 ℃), 88.15%(±8 ℃), 94.83%(±10 ℃)
Jiang et al. (2024)[27]	Process data (initial temperature, [O], [C], [Si], [Mn], [Al] content, decarburization time)	LF oxygen absorption rate prediction	Backpropagation neural network	330 heats (280 training, 50 test)	-

表 3 国内外连铸工序的人工智能分类应用现状

Tab.3 Current status of classified AI applications in continuous casting processes at home and abroad

Publications	Data collection features	Model application	ML method	Training samples	Evaluation metric
Duan et al. (2020)[28]	Mold thermocouple temperatures (120 thermocouples installed on wide and narrow faces)	Breakout risk classification	Hierarchical clustering and dynamic time warping (DTW)	30 breakout cases, 50 false alarms	100%
Duan et al. (2020)[29]	Mold thermocouple temperatures (120 thermocouples)	Breakout risk classification	DTW-DBSCAN	20 normal, 30 false alarms, 30 breakout cases	-
Duan et al. (2020)[30]	Mold thermocouple time-series data	Breakout risk classification	k-means and DTW	50 normal, 20 breakout, 50 false alarms	100%
Tian et al. (2020)[31]	Process parameters, mold thermocouple data	Breakout risk classification	Support vector machine (SVM)	37 breakout cases, 58 false alarms	100%
Duan et al. (2020)[32]	Mold thermocouple data (19×3 wide face, 1×3 narrow face)	Breakout risk classification	k-means clustering	40 breakout cases, 50 normal/false alarms	100%
Zou et al. (2021)[33]	Casting and cooling parameters, EMS data, chemistry	Internal crack classification	PCA and deep neural network	1600 samples	92.2%
Duan et al. (2021)[34]	Mold thermocouple data (19×3 wide face, 1×3 narrow face)	Longitudinal crack classification	PCA-SVM	50 crack cases, 50 normal	96%
Duan et al. (2021)[35]	Mold thermocouple data (19×3 wide face, 1×3 narrow face)	Longitudinal crack classification	DTW-KNN	50 crack cases, 50 normal	99%
Zhang et al. (2022)[36]	Mold thermocouple time-series data	Longitudinal crack classification	Random forest and k-means (RF-kMeans)	31 normal, 31 crack cases	-
Wang et al. (2022)[37]	Thermocouple data (19×3 wide face, 1×3 narrow face), casting speed, geometric/motion features	Breakout risk classification	Auxiliary classifier WGAN-GP (ACWGAN-GP)	40 breakout, 40 false alarms	98%
Sala et al. (2023)[38]	Mold thermocouple, casting process and chemistry data	Longitudinal crack classification	FCN-CNN-SE	5600 samples	-
Liu et al. (2024)[39]	Mold thermocouple data (19×3 wide face, 1×3 narrow face)	Longitudinal crack classification	PSO-XGBoost	30 crack cases, 90 normal	95.8%
Wang et al. (2023)[40]	Thermocouple data (19×3 wide face, 2×3 narrow face), casting speed	Breakout risk classification	Genetic algorithm-BP neural network (GA-BP)	560 samples (280 normal, 280 breakout)	97.56%
Shi et al. (2020)[41]	Mold thermocouple time-series data	Breakout risk classification	Tabu search-genetic algorithm (TS-GA)	-	-
Yu et al. (2024)[42]	Mold thermocouple time-series data	Breakout risk classification	One-vs-rest decision tree	80 normal, 80 breakout cases	98. 39%
Zhang et al. (2024)[43]	Mold thermocouple time-series data	Breakout risk classification	Firefly algorithm-BP neural network (LFFA-BP)	80 normal, 80 breakout cases	99.23%
Liu et al. (2024)[44]	Thermocouple data (7×3 wide face, 1×3 narrow face)	Breakout risk classification	XGBoost	43 breakout, 128 false alarms	99.5%
Liu et al. (2024)[45]	Thermocouple data (7×3 wide face, 1×3 narrow face)	Breakout risk classification	Stacked multi-classifier	43 breakout cases	98.3%
Diniz et al. (2024)[46]	SEN opening, mold level, casting speed, tundish drainage time	SEN clogging detection	ConvLSTM#7	-	97.8%

法和模型，有望实现更加精准、高效的连铸生产。由于机器学习应用中模型适应性不足、数据质量不高，导致在实际应用中面临预测精度受限、模型稳定性差等挑战。需要开发更先进的机器学习算法和模型，不仅要具备更高的准确性和鲁棒性，还能更好地适应不同的生产环境和工艺条件。针对数据质量不高的问题，探索更为有效的数据采集、清洗和预处理方法，确保输入到模型中的数据准确、完整且可靠。

表4 国内外连铸工序的人工智能回归应用现状

Tab.4 Current status of regression–based continuous casting processes at home and abroad

Publications	Data collection features	Model application	ML method	Training samples	Evaluation metric
Ansari et al. (2022)[47]	Casting speed, mold level, mold thermocouple temperatures, mold taper	Breakout risk regression	Backpropagation neural network (ANN-BP)	100 breakout cases, 405 normal samples	100%
Wang et al. (2022)[48]	Process data (ladle argon pressure, argon flow rate, stopper position) with timestamps	Nozzle clogging regression	Long short-term memory network (LSTM)	70% training set	ULC and LC:100%, MC:71%,Ca:67%
Shi et al. (2020)[49]	Tundish temperature, mold thermocouple data (10×6 wide face, 2×6 narrow face), casting speed, mold level/taper, slab cross-section, mold lifespan/water flow	Breakout risk regression	Whale optimization algorithm-twin support vector regression (LWOA-TSVR)	2000 datasets	98.2%
Xu et al. (2023)[50]	Process parameters (tundish mass, stopper position, pulling force, mold oscillation)	Mold level regression	Whale optimization algorithm-backpropagation neural network (WOA-BP)	8 000 samples (90% training, 10% test)	91%
Wu et al. (2023)[51]	Slab width, slab thickness, target level curve, time-series data	Mold level regression	Soft actor-critic reinforcement learning (SAC)	Real-time sensor data	89.5%
Kirmse et al. (2023)[52]	Time-series mold signals (thermocouples, level), steel chemistry/grade	Breakout risk regression	LSTM	-	-
Kuthe et al. (2024)[53]	Process data (casting speed, stopper position, temperature)	Nozzle castability regression	Adaptive neuro-fuzzy inference system (ANFIS) and LSTM	150 samples (120 training, 30 validation)	-

3 机器学习模型面临的挑战和应用

3.1 协同优化面临的挑战

炼钢制造过程涉及热力学、化学反应动力学、流体力学等复杂物理化学机制，整个过程表现出高度的非线性特征与参数间的相互依存性。因此，难以通过简单数学模型或经验公式准确刻画各过程参数间的相互作用规律，现有机理模型也难以实现对其的精确建模。炼钢过程具有动态特性，在保持连续和不间断操作的同时，原料和反应条件会频繁变化。随着反应过程的动态发展，需要模型来促进实时和精确的控制，使得自主精确控制具有挑战性。炼钢流程有许多生产环节，每个环节之间存在复杂的相关性。不同操作中的参数和反应过程相互影响，实现整个过程的协同优化需要同时考虑多个阶段之间的相互依赖性，以及整体生产效率的最大化，这给协同优化带来了困难。

炼钢过程中数据的质量和完整性也是一个重要挑战。由于高温、粉尘和腐蚀性环境，传感器可能遭受损坏或数据失真，导致数据不完整或不准确。这种数据质量问题会影响机器学习模型的训练效果和预测准确性。在协同优化过程中，需要综合考虑这些因素，开发能够适应复杂环境和高度不确定性的机器学习模型。高温腐蚀(热电偶寿命缩短)、电磁干扰(信号信噪比降低)等恶劣工况导致传感器失效率高，这样因素导致传统模型预测波动增大，需嵌入质量守恒方程的PINN模型和基于工况自适应的XG-Boost-DNN集成。未来需重点突破抗干扰传感技术和在线自适应学习算法，优先部署自诊断智能传感器和数字孪生校准系统。

3.2 智能模型在炼钢流程的深度应用展望

通过引入先进的传感器技术和数据预处理方法，可以提高数据的质量和完整性，从而为机器学习模型提供更加可靠的数据支持。结合深度学习等先进技术，智能模型将能够更好地适应炼钢过程中的不确定性和复杂性。通过对大量历史数据的分析和学习，模型将能够识别出潜在的规律和趋势，为操作人员提供更加精准的决策支持。智能模型还有望实现与炼钢设备的无缝集成，实现实时监控和自动调节。这将进一步提高生产效率，降低能耗和成本，为钢铁行业的可持续发展贡献力量。随着技术的不断进步和应用场景的不断拓展，智能模型在炼钢流程中的应用前景将更加广阔。

构建面向钢铁冶炼领域的大模型垂直应用产业基础模型，深入开展新一代基础理论创新与核心技术攻关。包括机制能力认知、知识问答、模拟和生成、

过程控制、优化和决策和科学机理发现。基础大模型的应用，将不仅仅局限于现有的炼钢流程优化，而是能够深入到炼钢的每一个细节，从原料的选择到最终产品的质量控制，实现全方位的智能化管理。通过与炼钢专家的紧密合作，基础大模型将能够不断学习和进化，将人类的经验和智慧融入模型之中，形成人机协同的新模式。多模态感知、因果推理和数字孪生等前沿技术在工业制造领域正加速融合应用。在感知层面，通过融合视觉、听觉等多模态数据实现设备状态立体监测和跨模态特征动态分配，因果推理技术能够显著降低能耗物耗。数字孪生技术实现关键参数的实时同步，加强物理机理与数据驱动的深度融合。未来研究应重点关注多模态缺失补偿算法、可解释领域因果模型，以及多尺度孪生架构等方向，这些突破将推动钢铁智能制造向自主决策阶段发展。这种新模式将极大地提升炼钢行业的智能化水平，推动短流程炼钢技术向更高层次智能化发展。

4 结论及展望

(1)先进的传感器和数据预处理方法可改善数据质量，深度学习能帮助模型从历史数据中挖掘规律，提供更精准的决策支持。未来，应探索基础大模型在炼钢全流程的垂直深度应用，实现从原料选择到质量控制的智能化全生命周期生产，结合专家经验形成人机协同模式，推动行业智能化升级。

(2)多模态感知、因果推理和数字孪生等技术提升机器学习模型的适应能力，多环节协同优化要求模型兼顾实时性与全局目标，优化工艺、诊断异常并辅助决策。智能模型与炼钢设备深度集成，实现实时监控与自动调节，提高能效、降低成本。

(3)探索不均衡样本量的优化智能算法，耦合低频数据特征和高频特征数据源，集成工业机理与机器学习模型实现智能短流程炼钢场景。机器学习将助力短流程炼钢向更高效、绿色、智能的方向发展，为钢铁行业数智化转型提供重要支撑。

参考文献：

[1] ZONG N F, JING T, GEBELIN J C. Machine learning techniques for the comprehensive analysis of the continuous casting processes: Slab defects[J]. Ironmaking & Steelmaking, 2025, 52: 1-20.

[2] FLORIANO B R O, VARGAS A N, ISHIHARA J Y, FERREIRA H C. Neural-network-based model predictive control for consensus of nonlinear systems[J]. Engineering Applications of Artificial Intelligence, 2022, 116: 105327.

[3] 宗男夫，刘宏亮，李爽，刘佳韵，杨军，石凤丽，GHALATI M K，董洪标. 机器学习在高效连铸制造中的应用现状及展望[J]. 鞍钢技术，2024(6): 23-33, 49.
ZONG N F, LIU H L, LI S, LIU J Y, YANG J, SHI F L, GHALATI M K, DONG H B. Application status and prospects of machine learning in high-efficiency continuous casting manufacturing [J]. Angang Technology, 2024(6): 23-33, 49.

[4] 宗男夫，费鹏，刘鸿智，荆涛. 轴承钢中夹杂物调控的冶金技术现状及智能化展望[J]. 铸造技术，2024, 45(6): 514-522.
ZONG N F, FEI P, LIU H Z, JING T. Current status and intelligent prospects of metallurgical techniques for the control of inclusions in bearing steels[J]. Foundry Technology, 2025, 45(6): 514-522.

[5] TAKAMI K M, MAHMOUDI J, DAHLQUIST E, LINDENMO M. Multivariable data analysis of a cold rolling control system to minimise defects[J]. The International Journal of Advanced Manufacturing Technology, 2011, 54: 553-565.

[6] REZVANI H, KHODADADI H. Designing evolutionary wavelet neural network for estimating foaming slag quality in electric arc furnace using power quality indices [J]. CSEE Journal of Power and Energy Systems, 2022, 8(4): 1165-1174.

[7] YANG L Z, LI B, GUO Y F, WANG S, XUE B T, HU S Y. Influence factor analysis and prediction model of end-point carbon content based on artificial neural network in electric arc furnace steelmaking process[J]. Coatings, 2022, 12(10): 1508.

[8] VINAYAKA K U , PUTTASWAMY P S. Prediction of arc voltage of electric arc furnace based on improved back propagation neural network[J]. SN Computer Science, 2021, 2: 167.

[9] GODOY-ROJAS D F, LEON-MEDINA J X, LEON-MEDINA B, VARGAS W, ROMERO J, PEDRAZA C, POZO F, TIBADUIZA D A. Attention-based deep recurrent neural network to forecast the temperature behavior of an electric arc furnace side-wall[J]. Sensors, 2022, 22(4): 1418.

[10] TOMAŽIČ S, ANDONOVSKI G, ŠKRJANC I, LOGAR V. Data-driven modelling and optimization of energy consumption in EAF[J]. Metals, 2022, 12(5): 816.

[11] ZOU Y C, YANG L Z, LI B, YAN Z F, LI Z H, WANG S, GUO Y F. Prediction model of end-point phosphorus content in EAF steelmaking based on BP neural network with periodical data optimization[J]. Metals, 2022, 12(9): 1519.

[12] YILDIZ E, ÖZDEMIR E. The use of artificial neural networks in the control of electric arc furnaces[J]. International Journal of 3D Printing Technologies and Digital Industry, 2022, 6(3): 578-591.

[13] PANOIU M, PANOIU C. Hybrid deep neural network approaches for power quality analysis in electric arc furnaces[J]. Mathematics, 2024, 12(19): 3071.

[14] NIYAYESH M, UYGUN Y. Predicting endpoint parameters of electric arc furnace-based steelmaking using artificial neural network[J]. The International Journal of Advanced Manufacturing Technology, 2024, 138: 155-167.

[15] ZHUO Q T, AL-HARBI M N, PISTORIUS C P. Feature engineering to embed process knowledge: Analyzing the energy efficiency of electric arc furnace steelmaking[J]. Metals, 2024, 15(1): 13.

[16] AZZAZ R, JAHAZI M, KAHOU S E, MOOSAVI-KHOONSARI E. Prediction of final phosphorus content of steel in a scrap-based electric arc furnace using artificial neural networks[J]. Metals, 2025, 15(1): 62.

[17] GU M, XU A, HE D, WANG H, FENG K. Prediction model of

end-point molten steel temperature in RH refining based on PCA-CBR [M]//PENG Z W, HWANG J, DOWNEY J P, GREGUREK D, ZHAO B J, YÜCEL O, KESKINKILIC E, JIANG T, WHITE J F, MAHMOUD M M. 11th International Symposium on High-Temperature Metallurgical Processing. The Minerals, Metals & Materials Series. Cham: Springer, 2020: 741-755.
[18] YUAN F, XU A J, GU M Q. Development of an improved CBR model for predicting steel temperature in ladle furnace refining[J]. International Journal of Minerals, Metallurgy and Materials, 2021, 28: 1321-1331.
[19] XIN Z C, ZHANG J S, ZHENG J, JIN Y, LIU Q. A hybrid modeling method based on expert control and deep neural network for temperature prediction of molten steel in LF[J]. ISIJ International, 2022, 62(3): 532-541.
[20] SHAO X, LIU Q, ZHOU T, LI S S. A hybrid model for power-on time prediction in LF based on deep neural network and metallurgical mechanism[A]. 2022 15th International Symposium on Computational Intelligence and Design (ISCID)[C]. Hangzhou: IEEE, 2020. 82-85.
[21] XIN Z C, SUN J K, ZHANG J S, HE B C, ZHANG J G, LIU Q. Multiobjective collaborative optimization of argon bottom blowing in a ladle furnace using response surface methodology[J]. Mathematics, 2022, 10(15): 2610.
[22] HEO J, KIM T W, JUNG S J, HAN S. Real-time prediction model of carbon content in RH process[J]. Applied Sciences, 2022, 12 (21): 10753.
[23] XIN Z C, ZHANG J S, ZHANG J G, ZHENG J, JIN Y, LIU Q. Predicting temperature of molten steel in LF-refining process using IF-ZCA-DNN model[J]. Metallurgical and Materials Transactions B, 2023, 54: 1181-1194.
[24] XIN Z C, ZHANG J S, JIN Y, ZHENG J, LIU Q. Predicting the alloying element yield in a ladle furnace using principal component analysis and deep neural network[J]. International Journal of Minerals, Metallurgy and Materials, 2022, 30: 335-344.
[25] XIN Z C, ZHANG J S, PENG K X, ZHANG J G, ZHANG C H, WU J, ZHANG B, LIU Q. Explainable machine learning model for predicting molten steel temperature in the LF refining process[J]. International Journal of Minerals, Metallurgy and Materials, 2024, 31(12): 2657-2669.
[26] WANG H, WANG M, LIU Q, YANG Z Y, XING L D. Prediction of ladle furnace refining endpoint temperature based on particle swarm optimization algorithm and long short-term memory neural network[J]. JOM, 2025, 77: 282-293.
[27] JIANG L H, WANG M, ZHAO J Q, YAO C, XING L D, AI X G. Coordinated control of decarbonization efficiency and oxygen absorption rate in Ruhrstahl-Heraeus degasser based on mechanism model and BP neural network[J]. Journal of Iron and Steel Research International, 2024, 32: 606-618.
[28] **段海洋,王旭东,姚曼. 基于密度聚类和动态时间弯曲的结晶器黏结漏钢预报方法的开发**[J]. **工程科学学报**,2020, 42(3): 348-357.
DUAN H Y, WANG X D, YAO M. Development of prediction method for mold sticking breakout based on density-based spatial clustering of applications with noise and dynamic time warping[J]. Chinese Journal of Engineering, 2020, 42(3): 348-357.
[29] **段海洋,王旭东,姚曼. 基于温度时序特征层次聚类的连铸黏结漏钢预报方法开发**[J]. **机械工程学报**,2020, 56(8): 250-256.
DUAN H Y, WANG X D, YAO M. Development of sticking breakout prediction method based on hierarchical clustering of temperature timing characteristics in continuous casting[J]. Chinese Journal of Mechanical Engineering, 2020, 56(8): 250-256.
[30] DUAN H Y, WANG X D, BAI Y, YAO M, LIU Y, GUO Q T. Modeling of breakout prediction approach integrating feature dimension reduction with K-means clustering for slab continuous casting [J]. The International Journal of Advanced Manufacturing Technology, 2020, 109: 2707-2718.
[31] TIAN Y P, LIU Y. Intelligent breakout prediction method based on support vector machine[J]. Journal of Physics: Conference Series, 2020, 1653: 012052.
[32] DUAN H Y, WANG X D, BAI Y, YAO M, GUO Q T. Application of k-means clustering for temperature timing characteristics in breakout prediction during continuous casting[J]. The International Journal of Advanced Manufacturing Technology, 2020, 106: 4777-4787.
[33] ZOU L L, ZHANG J S, HAN Y S, ZENG F Z, LI Q H, LIU Q. Internal crack prediction of continuous casting billet based on principal component analysis and deep neural network[J]. Metals, 2021, 11(12): 1976.
[34] DUAN H Y, WEI J J, QI L, WANG X D, LIU Y, YAO M. Longitudinal crack detection approach based on principal component analysis and support vector machine for slab continuous casting [J]. Steel Research International, 2021, 92(10): 2100168.
[35] **段海洋,王旭东,姚曼. 基于动态时间弯曲和 k 近邻分类预测铸坯纵裂纹**[J]. **连铸**,2021(4): 66-71, 77.
DUAN H Y, WANG X D, YAO M. Predicting longitudinal crack of slab based on dynamic time warping and k-Nearest Neighbor[J]. Continuous Casting, 2021(4): 66-71, 77.
[36] **张赫,段海洋,王旭东,姚曼. 基于随机森林和聚类的连铸坯纵裂纹预报方法**[J]. **连铸**,2022(6): 21-28, 44.
ZHANG H, DUAN H Y, WANG X D, YAO M. Longitudinal crack prediction method of continuous cast slab based on random forest and clustering[J]. Continuous Casting. 2022(6): 21-28, 44.
[37] WANG Y Y, WANG X D, YAO M. Integrated model of ACW-GAN-GP and computer vision for breakout prediction in continuous casting[J]. Metallurgical and Materials Transactions B, 2022, 53: 2873.
[38] SALA D A, VAN YPEREN-DE DEYNE A, MANNENS E, JALALVAND A. Hybrid-input FCN-CNN-SE for industrial applications: Classification of longitudinal cracks during continuous casting[J]. Metals, 2023,13(10): 1699.
[39] LIU Y, JIANG L, SHI J, LIU J B, LI G H, WANG Z F, ZHANG Z. Recognition of longitudinal cracks on slab surfaces based on particle swarm optimization and eXtreme gradient boosting model[J]. Processes, 2024, 12(6): 1087.
[40] **王荣荣,王敏,王仲亮,邢立东,艾新港,包燕平. 连铸黏结漏钢发生机理及预报模型**[J]. **中国冶金**,2023, 33(11): 138-150.
WANG R R, WANG M, WANG Z L, XING L D, AI X G, BAO Y P. Mechanism and forecast model of sticker breakout in continu-

ous casting[J]. China Metallurgy. 2023, 33(11): 138-150.

[41] SHI C Y, GUO S Y, CHEN J, ZHONG R X, WANG B S, SUN P, MA Z C. Breakout prediction based on twin support vector machine of improved whale optimization algorithm [J]. ISIJ International, 2020, 63(5): 880-888.

[42] **余浩辰,张本国,吴恒,张瑞忠. 基于一类对余类法的遗传算法优化决策树漏钢预报模型研究**[J]. **特殊钢**, 2024, 45(2): 112-117.
YU H C, ZHANG B G, WU H, ZHANG R Z. Research on a steel leakage prediction model based on one vs rest genetic algorithm optimization decision tree[J]. Special Steel, 2024, 45(2): 112-117.

[43] ZHANG B G, MA B B, SHENG W B, ZHANG K J, WU D, ZHANG R Z. Research on LFFA-BP neural network model in breakout prediction[J]. Metallurgical Research & Technology, 2024, 121(3): 307.

[44] LIU Y, MA Z X, WANG X D, GAO Y L, YAO M, XU Z Q, YU M. Analysis and prediction of sticker breakout based on XGBoost forward iterative model [J]. ISIJ International, 2024, 64(8): 1272-1278.

[45] LIU Y, MA Z X, WANG X D, YAO M. Sticker breakout recognition based on temperature characteristics and stacking multi-classifier model[J]. Ironmaking & Steelmaking, 2024, 50(7): 678-686.

[46] DINIZ A P M, CIARELLII P M, SALLES E O T, COCO K F. Use of deep neural networks for clogging detection in the submerged entry nozzle of the continuous casting[J]. Expert Systems with Applications, 2024, 238: 121963.

[47] ANSARI M O, GHOSE J, CHATTOPADHYAYA S, GHOSH D, SHARMA S, SHARMA P, KUMAR A, LI C H, SINGH R, ELDIN S M. An intelligent logic-based mold breakout prediction system algorithm for the continuous casting process of steel: A novel study[J]. Micromachines 2022, 13(12): 2148.

[48] WANG R B, LI H, GUERRA F, CATHCART C, CHATTOPADHYAY K. Predicting quantitative indices for SEN clogging in continuous casting using long short-term memory time-series model [J]. ISIJ Interational, 2022, 62(11): 2311-2318.

[49] SHI C Y, GUO S Y, CHEN J, ZHONG R X, WANG B S, SUN P, MA Z C. Breakout prediction based on twin support vector machine of improved whale optimization algorithm[J]. ISIJ International, 2020, 63(5): 880-888.

[50] **徐猛,刘娟娟,雷洪,李强,张秀香. 基于鲸鱼算法优化** BP **神经网络的结晶器液面波动的预测**[J]. **冶金自动化**, 2023, 47(2): 66-72.
XU M, LIU J J, LEI H, LI Q, ZHANG X X. Prediction of mold level fluctuation based on BP neural network optimized by whale optimization algorithm[J]. Metallurgical Industry Automation, 2023, 47(2): 66-72.

[51] WU X J, KANG H J, YUAN S, JIANG W Z, GAO Q, MI J Z. Anomaly detection of liquid level in mold during continuous casting by using forecasting and error generation[J]. Applied Science, 2023, 13(13): 7457.

[52] KIRMSE C, MURTHY R, MOHATA P, MANATKAR R. Real-time breakout prediction of LFC indicated breakouts[A]. METEC 6th ESTAD 2023[C]. Düsseldorf: VDEh, 2023. 1-8.

[53] KUTHE S, OÑA I A, GLASER B. Adaptive neuro-fuzzy inference system-long short-term memory hybrid model to forecast castability of Al-killed steel prior to continuous casting[J]. Steel Research International, 2024, 96(8): 2400220.

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