# 机器学习在板带冷轧工业的深度应用：机遇与挑战

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**摘　要：**板带冷轧是钢铁制造流程的关键环节，但长期以来面临着板形缺陷、厚度波动和轧机振动等问题，这些因素显著影响冷轧生产效率和产品质量。机器学习技术通过分析海量工艺数据，为实时预测和消除潜在缺陷提供解决方案。基于历史与实时数据，机器学习算法能够识别轧制力、辊缝、轧速等工艺参数与板形、厚度均匀性等质量指标间的复杂关联规律，实现工艺参数的动态优化，在保证产品一致性的同时有效降低废品率和停机时间。机器学习驱动的预测模型支持对轧制过程进行前瞻性调控，从源头上减少缺陷产生，提升整体效能。机器学习技术的应用不仅提高了冷轧过程的精度与可靠性，更带来显著的成本节约和产能提升。

**关键词：**机器学习；冷轧；板形缺陷；厚度波动；轧机振动

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听语音 聊科研 与作者互动

# Deep applications of machine learning in cold strip rolling industry: opportunities and challenges

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**Abstract:** The strip cold rolling process is a critical component of iron and steel manufacturing, yet it is often plagued by challenges such as flatness defects, thickness variations, and rolling mill vibrations, which can significantly impact productivity and product quality. Machine learning (ML) has emerged as a powerful tool to address these issues by analyzing vast amounts of process data to predict and mitigate potential defects in real-time. By leveraging historical and real-time data, ML algorithms can identify complex patterns and correlations between operational parameters（such as roll force, roll gap, and rolling speed）and key quality indicators like flatness and thickness uniformity. This enables the optim-

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ization of process parameters dynamically, ensuring consistent product quality while minimizing waste and downtime. Furthermore, ML-driven predictive models facilitate proactive adjustments to the rolling process, reducing the occurrence of defects and enhancing the overall efficiency. The integration of ML not only improves the precision and reliability of the cold rolling process but also leads to substantial cost savings and increased productivity.

**Key words:** Machine learning, cold rolling, flatness defects, thickness variations, rolling mill vibrations

## 0 引言

连续冷轧机组是生产高品质冷轧薄板的核心装备。尽管现代连轧机在过程控制系统方面已取得显著进步,但轧制力精度不足、板形欠佳、厚度波动等问题仍然存在,持续制约着成材率的提升。随着制造业数字化转型的深入推进,工艺数据与质量检测数据的无缝融合为机器学习与深度学习在质量保障中的应用开辟了广阔空间[1-5]。这种技术的协同效应赋予了生产系统先进的预测与决策能力,从根本上变革了现代生产体系中质量监控、控制与优化的范式。通过聚焦轧制力预测、弯辊力优化、厚度与板形控制、振动抑制等关键领域,机器学习技术正在推动金属加工数字化智能化的革命性突破,持续拓展精密制造与高效生产的边界[6]。在工业自动化与智能技术快速发展的背景下,将先进数据分析与机器学习深度融入冷轧流程,对于实现生产优化、质量提升与能效改善具有重大战略价值。机器学习技术的应用已实现实时工况监测与预测性维护,显著降低了停机时间与运营成本。

人工智能 AI 与传统制造流程无缝集成,凸显其在推动钢铁行业向高端化、智能化和绿色化发展的潜力。然而,目前针对冷连轧过程智能预测与优化的研究,仍缺乏对现有方法体系、技术挑战及未来发展方向的系统性梳理。笔者系统梳理了 2020 ~ 2025 年间冷连轧过程智能预测与优化领域的重要研究成果,首次从理论方法、技术实现和工业应用三个维度对金属加工领域人工智能解决方案的研究进展进行了全面评述。通过深入分析机器学习技术在冷轧工艺中的赋能效应,不仅揭示了当前面临的核心科学问题与技术瓶颈,更为行业数字化转型提供了一条具有可操作性的智能化发展路径。

## 1 冷轧产品质量提升面临的挑战

如图 1 所示,板形偏差与厚度波动是连轧过程中最主要的缺陷形态,这些缺陷不仅直接影响产品质量,更会导致断带、降速运行及设备损伤等严重后果[7]。确保厚度精度的一致性受到多重因素的制约,包括材料成分波动、来料初始厚度分布不均以及轧制工况变化等。这些变量会引入传统方法难以预测和控制的不确定性因素。

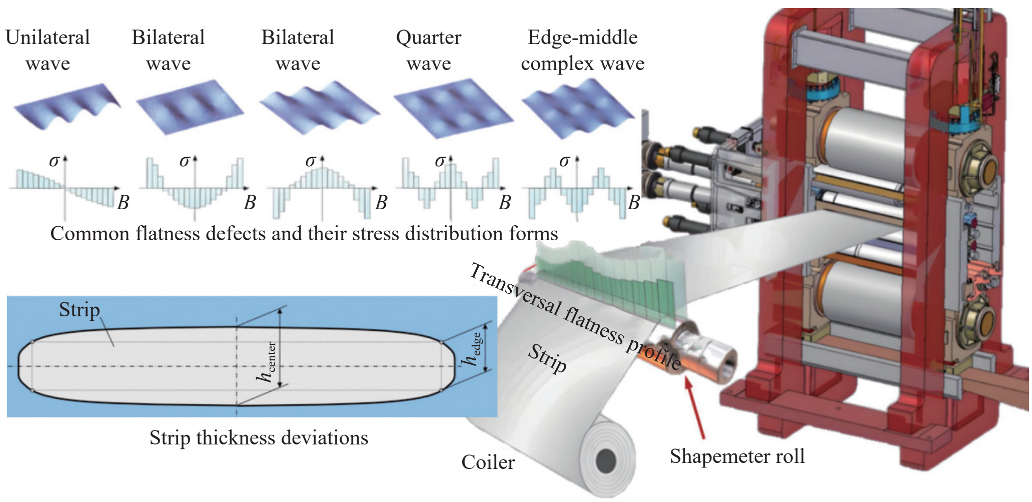



图 1 冷连轧带钢缺陷示意

Fig. 1 Schematic diagram of defects in tandem cold rolling

尽管数智化技术在冷连轧过程控制中展现出显著的应用潜力,但针对轧制系统多物理场耦合作用下的复杂波动特性,现有方法在精确建模与动态适应方面仍存在一些挑战。如连轧过程的高速特性

对 AI 系统提出了实时决策的严苛要求等。此外，连轧过程的高速特性对 AI 系统提出了实时决策的严苛要求，而现有技术体系在工业级部署中的成熟度仍有待提升。因此，开发能够适应复杂多变的轧制环境、具备高精度预测与控制能力的 AI 解决方案，成为冷轧数智化转型中的核心命题。这要求 AI 系统不仅要具备强大的数据处理和模型构建能力，还需深入融合领域知识，以实现对轧制过程的深度理解和精准调控。

## 2 冷轧制造流程中的机器学习

根据机器学习算法的方式和解决的任务类型，机器学习算法可以分为有监督学习、无监督学习和强化学习算法。监督学习[8-10] 是一种在标注数据上进行训练的机器学习方法。监督学习的目标是建立一个模型，该模型能够从输入数据中学习输入和输出之间的映射关系，从而在面对新数据时准确预测其标签。通过利用历史数据，监督学习算法能够识别模式和趋势，从而做出准确的预测。无监督学习[11-12] 以自动发现数据中的结构和模式。通过无监督学习，研究人员可以在不需要事先知道输出标签的情况下，了解数据的内在结构和分布。强化学习[13-15] 是一种机器学习方法，通过奖励机制引导模型做出决策，以最大化累积奖励。

监督学习适用于预测具有明确目标的属性，而无监督学习适用于探索数据中的隐藏结构。深度学习是机器学习领域中最前沿的研究方向[16-17]，涉及多层神经网络，这些层逐渐从原始输入数据中提取更高层次的特征，使系统能够做出准确的预测和决策。机器学习算法收集大量历史数据，从各种来源的大量数据中选择与目标任务相关的输入，并对其进行预处理(数据清洗和特征提取)，数据被分为训练集和测试集，训练集数据用于构建和训练模型，测试集数据用于测试和评估，经过验证的模型可用于对后续数据进行有效预测和智能决策。

## 3 冷连轧智能预测与优化研究现状

冷连轧生产条件的复杂性和部分参数的不可测性，提高传统模型预测精度和效率非常困难。在板带冷轧工业中，多变量强耦合非线性动力学问题导致厚度控制精度不佳，可通过数据驱动的动态模型替代传统 PID 控制；板形缺陷(如边浪、中浪)源于复杂应力场与材料各向异性演化，需采用人工智能进行缺陷生成与补偿；轧制力预测偏差大，则涉及热轧特征遗传和高应变率下的材料本构方程不确定性，需通过神经网络提升模型泛化能力。表 1 展示了各种机器学习技术在冷轧过程中应对不同挑战的应用，利用机器学习提高冷轧工艺质量方面取得的重大进展，通过解决轧制力预测、弯曲力预测、厚度预测、轮廓预测、平整度预测和振动预测等挑战，这些研究有助于推动机器学习在金属加工行业的深度应用。

**表 1 冷连轧智能预测与优化研究现状**

**Table 1 Research status of intelligent prediction and optimization in tandem cold rolling**

| Publications | Model application | ML method | Applicable mill | Data collection features | Training samples | Evaluation metric |
|---|---|---|---|---|---|---|
| SUN, et al. (2020) [18] | Flatness prediction and optimization | Kernel partial least square combined with artificial neural network (KPLS-ANN) | 5-stand universal crown mills (UCM) cold mills | Entrance thickness, exit thickness, width, strip thickness, rolling force, rolling force tilting, work roll bending force, intermediate roll bending force, roll gap tilting, intermediate roll shifting, rolling speed, strip tension, tension tilting, coil diameter, steel grade, rolling mode | 1 553 groups of samples | RMSE: 0.51, MAE: 0.34, MAPE: 0.09 |
| LU, et al. (2020) [19] | Rolling mill vibration prediction | XGBoost model | Five 6-high tandem cold rolling mills | Rolling speed, the cumulative rolling strip length of the work roll, strip deformation resistance, strip thickness at entry and exit point, total rolling force, back tension and front tension, work roll initial radius, work roll actual roughness, emulsion concentration, strip width, rraw thickness of hot strip, total reduction, roll vibration acceleration | 2 259 group of vibration data samples | $R^2$: 0.779, RMSE: 0.026 9, MAE: 0.018 9, MAPE: 9.7 |
| HU, et al. (2020) [20] | Roll gap prediction | Chaos-Embedded Fuzzy Particle Swarm Optimization Optimized Support Vector Machine (CF-PSO-SVM) | 1 450 mm 5-stand tandem cold rolling mills | Entry thickness, exit thickness, tension, rolling speed, rolling force, roll gap, etc.. | 7 000 groups of samples | $R^2$: 0.994 |

**表 1　续表 1**

| Publications and years | Model application | ML method | Applicable mill | Data collection sources and features | Training samples | Evaluation metric |
|---|---|---|---|---|---|---|
| SONG, et al. (2021) [21] | Bending Force prediction | Chaos-Embedded Fuzzy Particle Swarm Optimization Optimized Support Vector Machine (CF-PSO-SVM) | 1 700 mm 5-stand tandem cold rolling mills | The strip thickness before rolling, the strip thickness after rolling, the rolled strip width, the rolling speed, rolling force, shifting of intermediate roll , etc. | 16 000 group of industrial data samples | $R^2$: 0.993 |
| WANG, et al. (2021) [22] | Flatness prediction | Convolutional neural network (CNN) | Tandem cold rolling mills | The strip thickness before rolling, strip thickness after rolling, rolled strip width, rolling speed, forward slip, tension between stands, rolling force, shifting of intermediate roll, bending force of work roll, bending force of intermediate roll, flatness before rolling, flatness after final rolling | 23 000 groups of samples | $R^2$: 0.955 5 |
| CHEN, et al. (2022) [23] | Rolling Force Preset Model | Genetic Algorithm Optimized Backpropagation Neural Network (GA-BP) | 1 720 mm 5-stand universal crown mills (UCM) tandem cold rolling mills | Yield strength, strip width, entry thickness, exit thickness, exit speed, unit back tension, unit forward tension, working roll radius | 3 500 groups of samples | 98.76% |
| HUANG, et al. (2022) [24] | Thickness prediction | Radial basis function neural network based on variational Bayesian Gaussian mixture clustering algorithm (VBGM-RBF) | six-high High Crown (HC) mills | Rolling force, rolling speed, strip width, etc. selected as input parameters, and the strip thickness after finish rolling as output parameters | 16 000 groups of samples | $R^2$: 0.996 1, RMSE: 0.505 3 |
| CHEN, et al. (2022) [25] | Rolling force prediction | Genetic algorithm (GA)-feedback extreme learning machine (FELM) | 2030 mm 5-stand strip tandem cold rolling mills | Entry thickness, exit thickness, strip width, unit back tension, unit forward tension, rolling force, rolling speed, roll diameter, rolling length | 700 groups of samples | |
| CHEN, et al. (2022) [26] | Rolling force prediction | Mayfly algorithm (MA)-Support Vector Machine (SVM) | 1850 mm 5-stand strip tandem cold rolling mills | Entry thickness, exit thickness, strip width, unit back tension, unit forward tension, rolling force, rolling speed, roll diameter, rolling length, raw roughness of rolling mill | 800 groups of samples | $R^2$: 0.979 3, RMSE: 245.76 |
| YUAN, et al. (2022) [27] | Flatness prediction | BP-MOPSO, multi-objective particle swarm optimization algorithm (MOPSO) | 1 720 mm 5-stand 6-roller strip universal crown mills (UCM) | The strip thickness before rolling, strip thickness after rolling, rolled strip width, rolling speed, tension between stands, rolling force, intermediate roll shifting, work roll bending force, intermediate roll bending force, work roll wear, types of strip steel, fatness coefcient of the previous moment, entry crown, entry wedge | 5 000 groups of samples | $R^2$: 0.943 |
| DING, et al. (2022) [28] | Flatness prediction | CatBoost model | 1 450 mm 5-stand strip tandem cold rolling mills | The strip thickness before rolling, strip thickness after rolling, rolled strip width, rolling speed, tension between stands, rolling force, intermediate roll shifting, work roll bending force, intermediate roll bending force, work roll wear, types of strip steel, fatness coefcient of the previous moment | 1 225 groups of samples | $R^2$: 0.815, RMSE: 0.666, MAE: 0.436, MAPE: 12.257 |
| CHEN, et al. (2023) [29] | Flatness prediction | Attention-Long-short-term memory (LSTM) model | 1 360 mm 4 stand 6-high cold rolling mills | Entrance thickness, exit thickness, strip width, yield strength of steel grade, rolling speed, forward tension, backward tension, rolling force, work roll bending force, shifting value of intermediate roll, tilting value of work roll tilt, 23 flatness data points of shape meter measurement points | 68 382 groups of samples | $R^2$: 0.971, RMSE:1.209, MAE: 0.825, MSE: 1.145 4 |
| ZHAO, et al. (2023) [30] | Flatness prediction and optimization | artificial neural network algorithm optimized by an artificial bee colony algorithm (ABC-ANN) | 1 470 mm 5 stand 6-high cold rolling mills (UCM) | Steel grade, temperature at exit of finish rolling, temperature at entry of coiler, thickness at exit of finish rolling, crown of strip, wedge of strip, width of strip, entry thickness, exit thickness of SCR, bending force of work roll, bending force of intermediate roll, shifting value of intermediate roll, rolling speed, tension from entry to exit of SCR, roll gap tilting, roll size | 79 181 groups of samples | $R^2$: 0.929, RMSE:1.477, MAE:1.218 |

表 1　续表 2

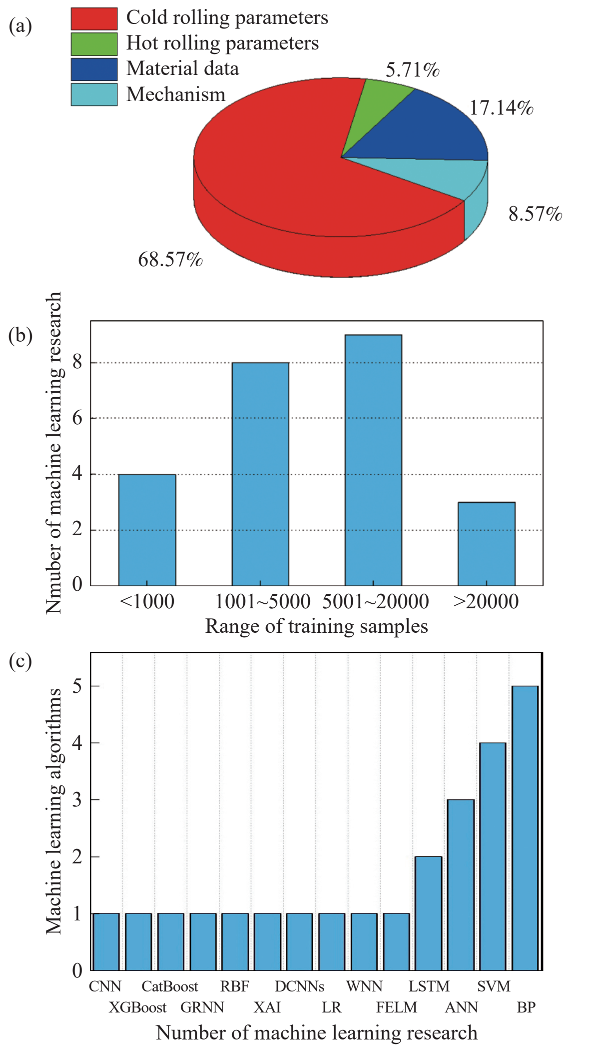
| Publications | Model application | ML method | Applicable mill | Data collection features | Training samples | Evaluation metric |
|---|---|---|---|---|---|---|
| ZHAO, et al. (2023) [31] | Deformation resistance prediction | Back propagation neural network optimized by the mind evolutionary algorithm (MEA-BP) | 1 420 mm 5-stand 6-high strip cold rolling mills | Entrance thickness, exit thickness, relative reduction rate, cumulative reduction rate, rolling speed, finish rolling temperature, coiling temperature, hot rolling finished thickness, deformation resistance analytical model | 1869 groups of hot and cold rolling samples | >95% |
| YAN, et al. (2023) [32] | Rolling force prediction | Improved Quantum Genetic Algorithm-Optimized Wavelet Neural Network (IQGA-WNN) ensemble learning | 1 450 mm 5- stand tandem cold rolling mills | Roll gap setting value, strip material, rolling speed, working roll diameter, working roll crown, entry thickness, exit thickness, intermediate roll crown, and intermediate roll diameter | 1 500 groups of samples | >93.75% |
| XIA, et al. (2023) [33] | Rolling force, power and slip | Artificial Neural Network (ANN) | 5 stand tandem cold rolling mills | Effective radius, friction coefficient, reduction, average rolling pressure, angular velocity and tension | 140 groups of samples | >94% |
| SONG, et al. (2023) [34] | Bending force prediction | Hybrid fruit fly optimization algorithm (FOA)-generalized regression neural network (GRNN) | 5 stand tandem cold rolling mills | Entrance thickness, exit thickness, rolled strip width, rolling force, shifting value of intermediate roll, target strip shape, actual strip shape | 2000 groups of samples | $R^2$: 0.97, |
| LI, et al. (2024) [35] | Thickness prediction | Differential Evolution Optimized Bidirectional Long Short-Term Memory Network (DE-BiLSTM) | 1 420 mm cold rolling mills | Steel grade, material parameters (e.g., hot-rolled finished thickness), and process parameters (e.g., coiling temperature) | | 98.3 % |
| HAN, et al. (2024) [36] | Profile prediction | PSO-BP algorithm | 5-stand universal crown mill with work roll shifting (UCMW) tandem cold rolling mills | Strip entry thickness, strip exit thickness, work roll diameter, strip width, strip deformation resistance, rolling force, front tension, back tension, friction coefficient, WRB, IMRB, WRS, IMRS | 85 groups of samples | |
| GAO, et al. (2024) [37] | Variable speed rolling force prediction | Long short-term memory (LSTM) network | 5- stand tandem cold rolling mills | Rolling length of work roll, raw thickness of hot strip, entry and exit thicknesses, rolling speed, entry and exit velocities, deformation resistance of strip, front and back tensions, actual position of roll gap, roll gap change rate, motor torque, power of internal plastic deformation, shear and tension, strip width, lubrication flow rate | 10 000 groups of samples | $R^2$: 0.993 5 |
| DING, et al. (2024) [38] | Flatness prediction | eXplainable Artificial Intelligence (XAI) | 5 stand universal crown mills (UCM) mills | Strip set thickness, strip width, rolling speed, rolling force, work roll bending force, intermediate roll bending force, roll tilting, intermediate roll shifting, tension, theoretical tension deviation, measured strip thickness, measured strip speed, coil diameter, square coefficient of the flatness target curve, quadratic Coefficient of the flatness target curve, manual adjusting, automatic adjusting , theoretical rolling force deviation | | $R^2$: 0.886 7, RMSE:0.912, MAE:0.573 7 |
| WANG, et al. (2024) [39] | Flatness prediction | Deep convolutional neural networks (DCNNs) | 1 450 mm 5-stand tandem cold rolling mills | Strip thickness, strip width, rolling speed, rolling force, work roll bending force, intermediate roll bending force, roll gap tilting value, intermediate roll shifting value, strip tension, tension difference, coil diameter, measured strip thickness, measured strip speed, coefficient of the square term of the flatness target curve, coefficient of the quadratic term of the flatness target curve, manual adjusting , automatic adjusting rolling force difference between OS and DS | 1 528 groups of samples | $R^2$: 0.863 8, RMSE:0.846 9, MAE: 0.274 |

**表 1　续表 3**

| Publications | Model application | ML method | Applicable mill | Data collection features | Training samples | Evaluation metric |
|---|---|---|---|---|---|---|
| YANG, et al. (2024) [40] | Flatness prediction | Elite Adaptive Lévy Flight Bat Algorithm-Optimized Logistic Regression (EALB-LR) ensemble model | 5-stand tandem cold rolling mills | Tension between stands, strip thickness, rolling speed between stands, rolling force between stands, actual roll gap length between stands, bending force of work roll, bending force of intermediate roll, speed after final rolling, tension after final rolling, rolling length, flatness after final rolling | 10 401 groups of samples | $R^2$: 0.958 4, MSE: 1.223 0, MAE: 0.479 7 |
| CHEN, et al. (2024) [41] | Vibration prediction | Multi-level network fusion | 5 th stand at a tandem cold rolling mill | Strip entrance speed, back tension, front tension, raw thickness of cold strip, strip entrance thickness, strip exit thickness, rolling speed, rolling force, roll gap value | 10 000 group of industrial online data samples | $R^2$: 0.925, RMSE: 0.001 1 |
| CHEN, et al. (2025) [42] | Thickness prediction | Radial basis function neural network (RBF) | 5-stand tandem cold rolling mills | Apply a random control signal sequence to the system in sequence based on the roll gap and speed, and record the output outlet thickness | 5 000 samples | |

增强线性回归的极限自动学习(EALB-LR)在板形预测方面表现出显著的准确性。通过合并不同的模型,研究人员使用来自 5 机架冷连轧机的 10 401 组样本,获得的 $R^2$ 值 0.958 4、均方误差 MSE 值 1.223 0 和平均绝对误差 MAE 值 0.479 7。表明集成方法在增强预测能力和减少误差方面的潜力[41]。在振动预测领域,采用多级网络融合技术对冷连轧机第五机架的数据进行分析。通过整合来自各种传感器的信息,研究人员使用 10 000 组工业在线数据样本获得 $R^2$ 值为 0.925 和均方根误差 RMSE 值为 0.001 1。说明利用综合数据集进行振动预测和缓解的重要性[42]。径向基函数(RBF)神经网络已被探索用于 5 机架冷连轧机的厚度预测。通过分析轧制间隙、速度和控制信号序列,证明使用 RBF 网络使用 5 000 组样本高精度预测出口厚度的可行性。不同机器学习和深度学习方法在应对冷连轧过程中的各种挑战方面的多功能性和有效性。图 2 进一步说明应用于冷连轧工艺的各种机器学习技术,包括输入特征、数据集大小、模型类型和应用领域的任务分布。如图 2(a)所示,智能预测中使用的冷轧参数比例为 68.57%,明显高于材料数据的 17.14%。学者们开始将热轧参数和机理特征纳入冷轧过程的系统建模中,综合分析机器学习在解决冷轧各个方面的多功能性,从预测机械性能到优化工艺参数。

如图 2(b)所示,智能冷连轧工艺的训练样本数量差异较大。从数百个样本到超过五万个样本不等,这反映了在实际工业应用中获取大量高质量数据的挑战。尽管深度学习模型通常受益于大规模数据集,但在某些情况下,由于资源限制或数据获取难度,只能使用相对较小的数据集进行训练。这种算法选择的多样性体现了学术界和工业界在探索最适合冷连轧工艺的机器学习解决方案方面的努力和创新。图 2(c)为应用的机器学习模型分布,不同机器学习模型的范围和方法的多样性,如 ANN、混合 FOA-GRNN、DE BiLSTM、PSO-BP、LSTM 网络、XAI、DCNN 和集成模型。




(a) 任务分布; (b) 数据集大小分布; (c) 算法统计分布

**图 2　机器学习算法在智能冷连轧过程中的统计分布**

**Fig. 2　The statistical distribution of ML techniques applied to the intelligent tandem cold rolling processes**

由于各种工艺参数和固有材料性能之间的复杂相互作用,冷轧中的板形控制尤其具有挑战性。通过结合先进的算法和丰富的样本数据集,研究人员能够开发出准确预测和控制板形的模型,提高产品质量并减少浪费。将机器学习技术集成到板形控制中,可以实时调整工艺参数,使制造商能够快速响应材料性能或工艺条件的变化,这种适应性在当今快节奏的制造环境中至关重要,因为产品需求和规格可能会频繁变化。除了板形控制,机器学习被应用于冷轧过程的其他方面,如振动预测和厚度预测。应用于冷连轧工艺的机器学习技术说明这些模型在应对各种质量改进挑战方面的多功能性和适应性。

## 4　机器学习赋能冷轧工业的机遇和局限性

在钢铁材料冷连轧领域,机器学习技术的应用研究主要聚焦于两大方向:一是明确技术适用的关键场景;二是揭示其潜在的挑战与局限。

### 4.1　智能冷轧面临的挑战

虽然机器学习方法在连轧冷轧工艺中展现出提升产品质量和推动技术创新的重要价值,但其应用仍面临显著制约。冷连轧过程中机器学习应用领域如图 3 所示,板形和轧制力的机器学习研究较多,而弯辊力、轧机振动、变形抗力等研究偏少。冷连轧的产品质量影响因素众多,各变量间非线性强耦合,造成控制困难。轧制力影响板带的板形平整度和厚度,精准的轧制力预测能够有效降低带材头尾切损。然而,在实际生产中,轧制过程往往要求毫秒级的响应速度,而复杂的机器学习模型可能难以满足这一实时性要求,需探索轻量级模型与高效算法的应用。

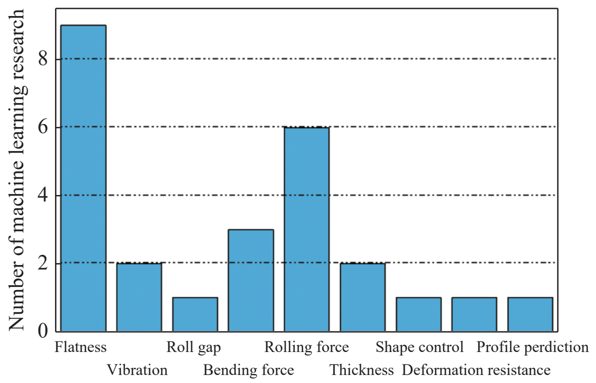



图 3　冷连轧过程中机器学习应用领域

**Fig. 3　Application fields of machine learning approaches in tandem cold rolling processes**

机器学习技术被广泛应用于增强冷轧工艺,每个应用领域都有独特的需求,需要量身定制的机器学习解决方案来实现最佳结果。尽管轧制过程产生海量数据,但数据存在噪声干扰、信息缺失及标注不足等问题,严重影响机器学习模型的精度与鲁棒性;轧制过程多变量耦合作用及非线性关系的复杂性为模型的开发与验证带来了挑战。为推动冷轧行业技术升级,未来研究应着力于以下战略方向:①应重点发展先进预测模型体系,借鉴变形抗力预测模型的成功经验[43],整合热轧历史数据、实时传感信号和材料特性等多源信息,通过融合动态材料行为与环境因素,实现轧制力参数的精准优化;②需构建跨工序数据平台[44],开发集成热轧、冷轧及后续工序的统一数据框架,通过实时数据共享与分析,提升板形特征预测等 AI 模型的准确性,特别是为非稳态工况提供解决方案。

### 4.2　未来智能冷轧的机遇

为解决传统冷轧理论模型的固有缺陷,提高轧制模型精度,需融合人工智能技术。这包括开发自适应控制算法,利用机器学习在速度过渡期间动态调整轧制参数,优化板形控制、厚度均匀性和实时减振。机器学习应用程序应通过优化能源消耗、减少材料浪费和提高资源效率来优先考虑可持续性,利用预测模型在保持高产品质量的同时最大限度地减少对环境的影响。最后,实施能够持续学习的机器学习系统将确保预测模型在生产条件演变时保持准确性和相关性,并结合反馈回路和自适应学习机制,随着时间的推移完善模型。如图 4 所示,应探索动态控制优化,以克服模型在非稳态条件下的局限性。

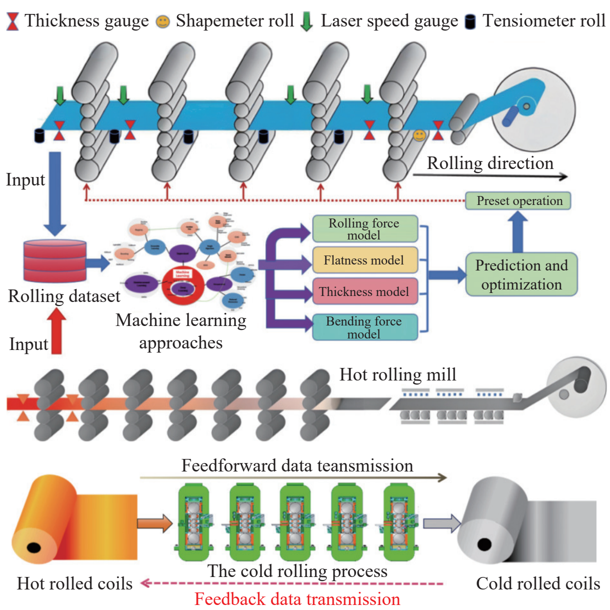



图 4　冷连轧过程中机器学习方法的机遇

**Fig. 4　Opportunities of machine learning approaches in tandem cold rolling processes**

确保机器学习模型的可靠性和可解释性，开发透明和可解释的机器学习模型，为决策过程提供帮助，并更好地理解和验证结果。通过结合可解释的机器学习技术来实现，例如（SHapley Additive exPlanations，SHAP）或（Local interpretable Model inoxic exPlanations，LIME），提供对单个特征的贡献说明。

机器学习方法为冷连轧工艺的智能化升级和产品质量提升提供了新的技术路径，但仍面临若干关键性挑战。冷轧制造过程具有显著的多尺度特征，其数据特性同时包含低频工艺参数和高频传感器信号，且正常样本与缺陷样本存在严重的类别不均衡问题。针对这一挑战，需要开发新型集成学习算法，并融合时间序列深度学习技术，以有效处理不均衡样本条件下的特征提取问题。受限于现有检测技术，部分关键工艺参数难以直接测量或测量精度不足，这严重制约了智能模型的性能上限。为此，可采用基于有限元仿真的数据增强方法，结合冷轧机理模型生成补充特征，从而提升模型的泛化能力和抗噪性能。更为重要的是，必须建立机器学习与传统机理模型的深度融合框架，通过将冶金学原理、塑性变形理论等工业知识嵌入智能模型，实现数据驱动与机理驱动的优势互补，最终构建具有强解释性和高可靠性的混合智能系统。这种融合创新不仅能提升模型在复杂工况下的适应能力，也将为冷连轧工艺的智能化转型提供更可靠的技术支撑。

## 5 结论与展望

1) 冷连轧过程的数据具有多尺度（低频工艺参数与高频传感器信号）和样本不均衡的特性，需开发集成时间序列深度学习与自适应采样的新型算法，以提升模型在复杂工况下的特征提取能力。

2) 针对关键参数测量受限的问题，通过有限元仿真和冷轧理论生成补充特征，结合数据降噪技术，增强模型的泛化性能与工业适用性。

3) 将机器学习与冷轧机理模型深度融合，构建“数据驱动+机理约束”的混合智能系统，实现工艺可解释性、动态适应性及复杂问题求解能力的协同提升，为冷轧工业智能化转型提供可靠技术支撑。

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