ARTIFICIAL INTELLIGENCE TOOLS & OPTIMIZATION TECHNIQUES

[1] Mohd Wadood, Computer science and Engineering, M.Tech Research Scholar, Maharishi University of Information Technology, Lucknow.

[2] Dr. R K Yadav , Associate Professor, Computer science and Engineering,Supervisor, Maharishi University of Information Technology, Lucknow

ABSTRACT: Advanced modeling and optimization strategies have turn out to be pivotal in driving wise production and allowing the digitalization brand new machining methods. the combination brand new artificial Intelligence (AI), especially system gaining knowledge statemodern and deep cutting-edge methods, has opened new avenues for enhancing operational performance, tool sturdiness, and product high-quality in machining operations. while severa research have focused on optimizing isolated process parameters consisting of tool wear, floor roughness, and dimensional accuracy, the complete development present day machining approaches necessitates multi-goal optimization techniques which are modern day unnoticed. This paper provides a detailed evaluation ultra-modern the modern-day in applying AI-driven optimization techniques to diverse machining operations, such as milling, turning, drilling, and grinding. it's far located that milling methods and deep contemporary strategies dominate current studies efforts, with surface roughness emerging because the most essential fine metric. The examine emphasizes the need today's a holistic optimization approach that simultaneously addresses multiple overall performance objectives across machining workflows. Key factors influencing the a hit utility trendy AI in general machining overall performance enhancement are identified and mentioned. The findings and methodologies presented are present day the wider research sports under the impact mission initiated by the CIRP, aiming to establish a sturdy framework for AI-assisted clever production.

Keywords: Artificial Intelligence (AI), Machine Learning, Deep Learning, Optimization Techniques, Intelligent Manufacturing, Multi-objective Optimization, Machining Processes, Milling, Surface Roughness, Tool Wear Prediction, Process Optimization, Digital Manufacturing, AI in Machining Operations.

1. Introduction

The exponential boom in computational strength, statistics garage capabilities, and facts transmission prices, coupled with the abundance of real-time records from sensors, net of factors (IoT) gadgets, and cyber-physical structures, has catalyzed the mixing of synthetic Intelligence (AI) in various software domains. AI has become an necessary generation in improving everyday existence applications, including navigation, healthcare, logistics, and conversation [1] [2].

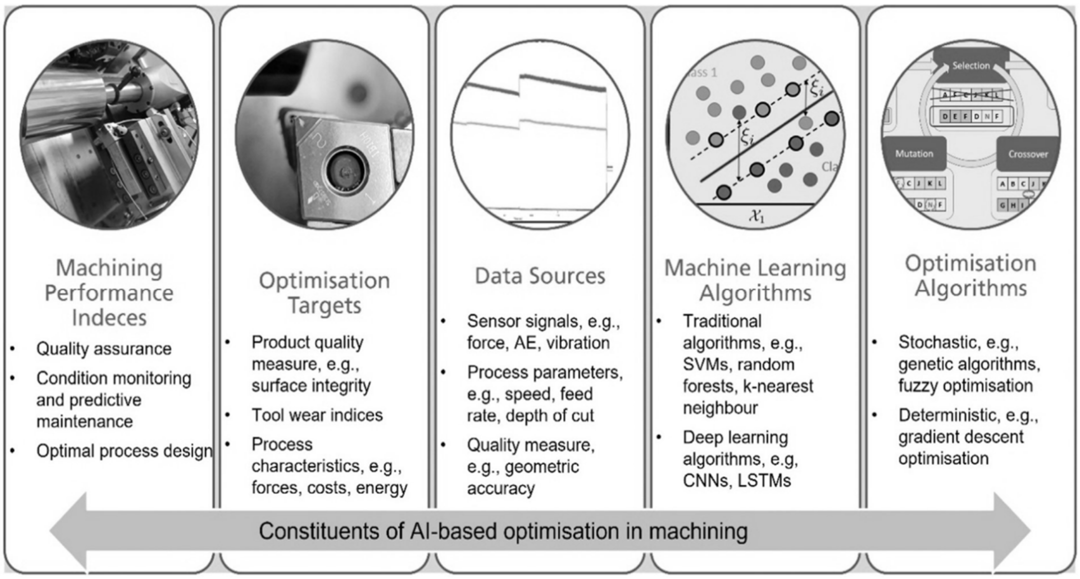

Figure:1- AI-based optimisation in machining involving performance index identification, predictive modelling, and intelligent optimisation for improved quality and efficiency [2] [3]

extra notably, AI is a cornerstone of industry four.0, riding the digitalization and automation of producing strategies. within the machining business enterprise, AI, device gaining knowledge of (ML), and optimization strategies have already started to redefine conventional manufacturing paradigms. Machining, being a vital secondary operation in manufacturing for producing useful surfaces with excessive precision, has benefited immensely from improvements in information and computational technologies. AI-pushed predictive fashions allow proactive tracking, actual-time manner regulation, and extra suitable useful resource optimization, making sure manufacturing with decreased operational prices [4] [5].

1.1 AI Technologies in Machining Operations

Regardless of the developing application of AI in machining, present day studies frequently isolates man or woman overall performance signs, which include surface roughness or tool wear, as singular optimization goals. but, machining is an inherently complex device inspired via the complex interactions amongst gadget gear, paintings substances, cutting parameters, and environmental situations. A comprehensive evaluation of total Machining overall performance (TMP) needs a multi-standards optimization technique encompassing surface finish, device wear quotes, dimensional accuracy, geometrical tolerances, reducing forces, strength consumption, chip morphology, and production fees [5] [6].

while traditional modelling strategies—analytical, empirical, numerical, and physics-based strategies—had been employed for technique characterization, the rapid improvements in AI have shifted the focus toward facts-pushed fashions. AI algorithms, such as fuzzy good judgment, synthetic Neural Networks (ANN), and Evolutionary Optimization Algorithms, have proven effective in managing the complex, non-linear relationships customary in machining approaches. the mixing of ML models allows adaptive method manage, enhances predictive accuracy, and fosters smart and sustainable production atmosphere [7]. latest literature reveals a full-size body of work specializing in AI-driven optimization in machining operations such as milling, turning, drilling, grinding, and laser machining. however, maximum research prioritize isolated objectives, missing a holistic approach that aligns more than one technique metrics toward normal process excellence. substantially, deep learning applications in device circumstance tracking and hybrid evolutionary algorithms for machining optimization underscore the transformative capability of AI-driven methodologies in production [8].

1.2 Optimization Techniques in Machining

Over the past decades, optimization algorithms have developed significantly, assisting within the enhancement of machining performance thru smart technique monitoring and parameter optimization. but, conventional performance evaluation techniques conflict with scalability because of the multitude of interdependent variables in machining systems. Fuzzy-set based mathematical models have been brought to address those challenges, but their effectiveness is often confined by way of the computational abilties of legacy systems. cutting-edge AI-based optimization frameworks, leveraging evolutionary algorithms, swarm intelligence, and deep reinforcement mastering, provide robust answers for addressing multi-objective optimization issues in machining. The convergence of AI with optimization has enabled adaptive, real-time selection-making, leading to good sized enhancements in machining performance, product satisfactory, and resource utilization. moreover, AI-powered hyperparameter tuning and self-optimizing systems gift new frontiers for advancing smart machining operations [9] [10].

1.3 Machine studying applications in Machining

Device getting to know has garnered massive interest inside the realm of manufacturing system optimization. cutting-edge studies incorporates a huge spectrum, from general surveys on ML packages in machining to focused case studies addressing device put on prediction, surface roughness estimation, and cutting pressure analysis. techniques including artificial Neural Networks (ANN), support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNN) have been hired to model complex method dynamics and enable records-driven predictive upkeep techniques. innovations in sensor fusion, fuzzy good judgment optimization, and real-time statistics acquisition have similarly stronger the efficacy of ML fashions [11]. no matter those improvements, the synergistic integration of ML strategies with optimization algorithms stays an underexplored region, with best a constrained variety of studies adopting a blended method for comprehensive machining performance enhancement. strategies like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), grey Relational analysis (GRA), and the Non-dominated Sorting Genetic set of rules II (NSGA-II) have proven promising outcomes whilst blended with ML fashions for achieving multi-objective optimization in machining contexts [12].

1.4 The Machining system

Machining remains a cornerstone of manufacturing, crucial for producing practical surfaces throughout vital industries which includes aerospace, car, electricity, and medical gadgets.

defined as a subtractive production process, machining involves chip elimination via interaction between a tool and a workpiece. This distinct mechanism

units machining other than additive production strategies. Machining operations are widely classified into traditional and non-traditional classes, differentiated by the source of strength used for fabric removal. conventional operations rely on mechanical interactions regarding relative movement among the tool and the paintings fabric, governed via the kinematics of the system [13]. these encompass slicing methods like turning, drilling, and milling, as well as abrasive processes which include grinding, lapping, and sprucing. slicing operations are characterised via geometrically defined slicing edges, whereas abrasive methods depend on statistically allotted reducing grains. Optimizing machining methods no longer handiest complements the first-rate of produced elements but also contributes to sustainable production through decreasing strength intake, emissions, and material waste. therefore, superior AI-pushed optimization strategies are imperative for attaining excessive-performance and f6ba901c5019ebe39975adc2eb223bef machining operations [14].

2 .Basics Of System Gaining Knowledge Of And Optimization

This phase introduces foundational concepts of gadget gaining knowledge of and optimization, emphasizing their applications in machining. ML algorithms often utilized in manufacturing method optimization.

2.1 Terminology and mastering Paradigms

AI, ML and Deep getting to know (DL) are frequently used interchangeably, even though they represent one-of-a-kind degrees of abstraction. AI refers to the broader field encompassing all technology that permit machines to mimic human intelligence. ML is a subset of AI targeted on algorithms that allow structures to research patterns from information. DL, a specialised branch of ML, involves multi-layered synthetic Neural Networks (ANNs) capable of autonomously getting to know hierarchical facts representations. An ML version is essentially a feature , mapping input times (features) to corresponding outputs (labels). relying on statistics availability and project objectives [15], ML responsibilities are labeled into supervised getting to know (with categorized data), unsupervised getting to know (with out classified facts), and reinforcement mastering (RL), where retailers examine via interactions with an surroundings to maximize cumulative rewards.

Supervised mastering encompasses regression (predicting continuous values) and class (assigning times to predefined categories). Unsupervised mastering entails clustering and dimensionality discount obligations, whilst RL specializes in sequential decision-making in dynamic environments. switch gaining knowledge of (TL) has won prominence as a approach to adapt models educated on one venture to associated domains with limited data [16].

SVM

It is strong supervised studying models used for class and regression. They perform via figuring out an optimum hyperplane that maximally separates records points of various classes. Kernel capabilities amplify SVMs to handle non-linear troubles with the aid of mapping inputs into higher-dimensional areas. versions like assist Vector Regression (SVR) and One-magnificence SVM for outlier detection develop their applicability [17].

Artificial Neural Networks (ANNs)

ANNs, inspired by using biological neurons, form the foundation of contemporary ML. along with interconnected neurons arranged in layers, ANNs technique enter alerts via weighted connections and non-linear activation functions. Feedforward Neural Networks, Convolutional Neural Networks (CNNs) for spatial records, and Recurrent Neural Networks (RNNs) for sequential facts are broadly used architectures. education involves backpropagation and gradient descent optimization. while ANNs excel at taking pictures complex statistics styles, their black-box nature poses demanding situations for model interpretability.

They recursively partition the enter space based totally on characteristic values, resulting in a tree shape wherein leaves represent elegance labels or anticipated values. Random Forests (RF) decorate DT overall performance through aggregating multiple timber the usage of bootstrap aggregation (bagging), enhancing generalization and reducing overfitting [18] [19] [20].

Regression evaluation

Regression analysis entails modeling the relationship among based and impartial variables. Linear Regression (LR), Polynomial Regression (PR), and Non-parametric methods like Gaussian method Regression (GPR) are common techniques. these fashions are drastically used for predicting machining outputs like surface roughness and slicing forces [21].

3 AI-Based Totally Performance Optimisation

This segment synthesises the insights drawn from the reviewed literature on AI packages in machining and emphasises the necessity of multi-goal optimisation (MOO) strategies to attain overall Machining overall performance (TMP) enhancement. no matter significant advancements in machine mastering (ML)-pushed predictions for isolated machining consequences, the complexity of machining tactics needs holistic optimisation techniques that concurrently consider more than one conflicting goals [22].

ML Predictions to process Optimisation

Achieving comprehensive optimisation in machining strategies mandates the simultaneous attention of numerous parameters and variables impacting TMP. This involves modelling a broad spectrum of technique-associated goals and integrating advanced MOO techniques to harmonise multiple performance standards. over the past decade, AI and ML applications in machining have broadly speaking accompanied 5 distinct methodologies:[23] [24]

Sequential ML-Optimisation Workflow: ML fashions are hired to establish the relationship among enter parameters and output responses, observed through optimisation algorithms that choose the maximum appropriate inputs to attain preferred results .

Direct records-based Optimisation: Utilisation of heuristic optimisation strategies (e.g., Genetic Algorithms, Particle Swarm Optimisation) to immediately compute top-quality process parameters through fitness features, bypassing express ML prediction degrees.

ML-pushed manner monitoring & indirect Optimisation: software of ML models for actual-time prediction and monitoring of process situations (e.g., device wear, reducing forces) without direct incorporation into remarks-based totally optimisation loops [25] [26].

Hyperparameter Tuning for ML model Optimisation: Employment of optimisation algorithms (e.g., Bayesian Optimisation, Grid search) to refine ML model configurations for superior predictive accuracy [27].

Optimisation for ML model training performance: Leveraging optimisation strategies (e.g., stochastic gradient descent, sequential minimum optimisation) to accelerate and stabilise ML version education processes [28] [29].

Table 1: AI Tools & Optimisation Techniques in Machining [30[[31] [32]

Process	AI Tools (ML Algorithms)	Optimisation Techniques	Key Inputs	Outputs/Monitored Variables	Year
Turning	ANN, SVM, RF, DT, KNN	GA, PSO, NSGA-II	Cutting speed, feed, depth of cut	Tool wear, AE, Forces	2021
Milling	CNN, RF, SVM, RNN, ANN	GA, NSGA-II, PSO	Cutting parameters	Cutting forces, Vibration, AE	2021
Grinding	Fuzzy Logic, SVM, RF, kNN	Grey Relational, GA, PSO	Cutting speed, tool properties	AE, Forces, Acceleration	2018
Drilling	ANN, SVM, RF, SDA	GA, SDA	Cutting speed, feed	Torque, Image Data	2020

The above Table provides an overview of recent applications of AI tools and optimisation techniques across various machining processes including turning, milling, grinding, and drilling. Machine Learning (ML) algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), Convolutional Neural Networks (CNN), and Fuzzy Logic models have been extensively used for predictive modelling in tool wear prediction and tool condition monitoring (TCM). These AI methods process input parameters like cutting speed, feed rate, depth of cut, tool geometry, and process signals (e.g., Acoustic Emission (AE), vibrations, spindle current, cutting forces) to predict critical machining outcomes [33] [34] [35].

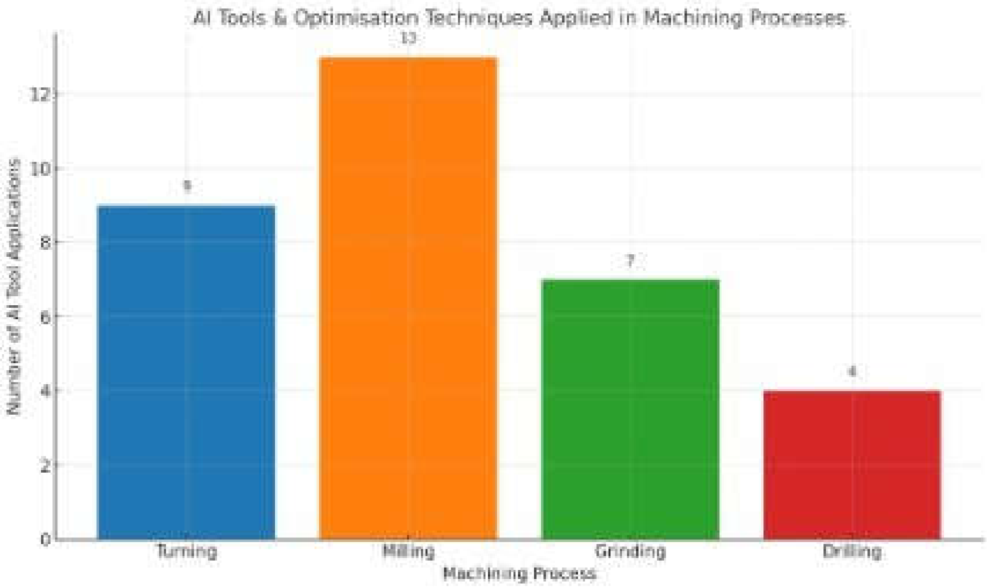

Figure:2- Applications of AI Tools & Optimisation Techniques Across Machining Processes

Optimisation techniques such as Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), and Non-dominated Sorting Genetic algorithm II (NSGA-II) are implemented to high-quality-song procedure parameters for enhancing floor end, decreasing device wear, and enhancing procedure efficiency. The table displays a growing fashion in integrating AI-driven fashions with heuristic optimisation strategies for actual-time process manipulate and adaptive production structures, permitting smart and sustainable machining.

4. Single Objective Vs Multi-Objective Optimisation In Machining

At the same time as unmarried-goal Optimisation (SOO) specializes in enhancing a singular overall performance criterion, such as floor roughness or device put on, it inherently neglects the interconnectedness of machining variables. This narrow optimisation scope regularly results in sub-foremost gadget-stage performance, as upgrades in one area would possibly inadvertently degrade some other. for example, an SOO approach aimed totally at maximising cloth elimination rate may additionally severely lessen tool life or surface finish satisfactory [36] [37]

Conversely, Multi-goal Optimisation (MOO) frameworks permit a simultaneous assessment of more than one targets, accounting for their synergistic and hostile relationships. MOO techniques for that reason produce a fixed of ideal trade-off solutions, known as the Pareto front, wherein no unmarried answer is superior throughout all taken into consideration targets [38].

The a success deployment of MOO in machining calls for:
strong ML fashions that can as it should be predict more than one machining outcomes (e.g., surface end, cutting forces, device put on) primarily based on varied procedure parameters. superior optimisation algorithms capable of managing high-dimensional, nonlinear, and conflicting objective features, which includes Non-ruled Sorting Genetic set of rules II (NSGA-II), Multi-goal Particle Swarm Optimisation (MOPSO), and Multi-objective Bayesian Optimisation. Adaptive remarks manage Loops to dynamically regulate manner parameters in actual-time primarily based on ML version predictions and optimisation outcomes.
several studies have efficaciously confirmed the software of ANNs, SVR, and RF fashions in predicting important machining results across exceptional processes. however, integrating these predictions into MOO frameworks remains an area with widespread scope for further research.

The literature indicates a predominance of single-goal modelling (SOO), with limited comprehensive research that adopt authentic multi-goal, MOO-pushed TMP optimisation frameworks [39] [40] [41].

To acquire complete-scale AI-primarily based TMP optimisation, future research need to cognizance on:

Growing hybrid AI frameworks that synergistically combine ML predictions with superior MOO algorithms. Leveraging actual-time sensor fusion and aspect computing for adaptive method manage. organising standardised information acquisition pipelines and open-get admission to machining datasets to foster generalisability and reproducibility of AI models. Investigating switch learning approaches to evolve ML fashions across varying machining contexts with minimal retraining [42] [43].

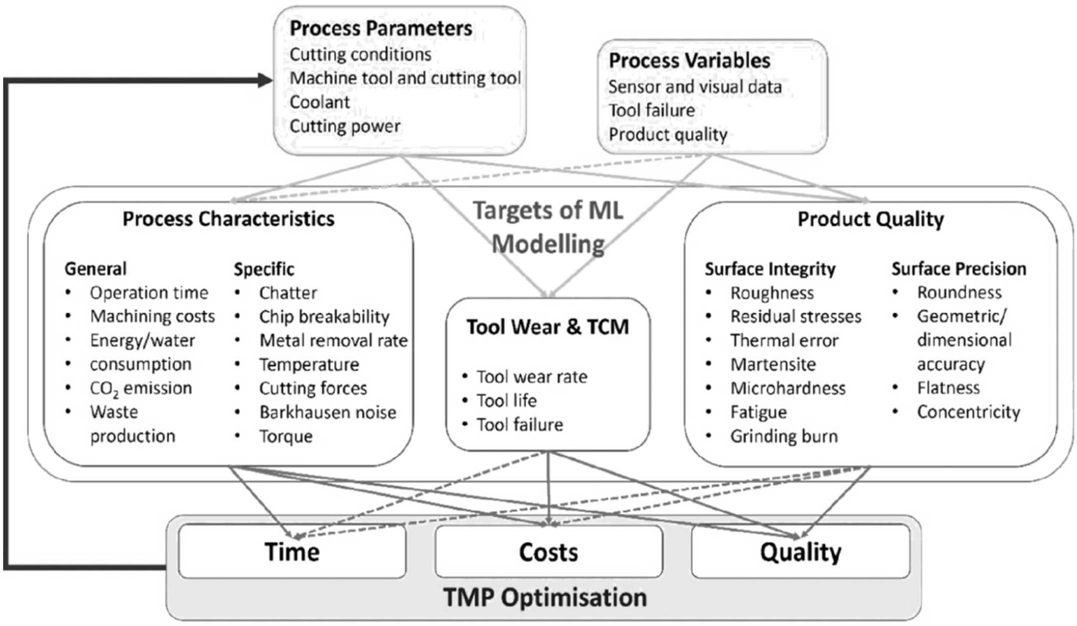

Figure 3: TMP optimization overview—Process parameters as ML inputs, model outputs as optimization targets, focusing on time, cost, and quality [44] [45] [46] [47]

4. Challenges And Success Factors In AI-Based Total Performance Optimisation

fixing MOO problems for machining operations is fraught with computational and practical challenges. Key issues include:

worldwide Optima seek Complexity: MOO often entails excessive-dimensional seek areas with a couple of neighborhood optima, making the identity of actual worldwide optima computationally luxurious [48] [49].

Convergence and Overfitting in ML models: in particular standard in deep studying models, massive datasets are required to avoid overfitting, while ensuring adequate generalisation [50] [51] [52]. A crucial enabler for sustainable and strong AI programs is transfer studying, which permits pre-trained fashions to evolve to new machining conditions or associated procedures with minimum retraining [53]. moreover, continuous getting to know strategies have to be carried out to combat concept glide—the degradation of version overall performance over the years because of adjustments in information distributions, device conditions, or environmental factors [54] [55].

Conclusion

The intersection of synthetic Intelligence (AI) equipment and optimisation techniques has profoundly revolutionised the sector of machining manner optimisation (MPO). Over recent years, a enormous frame of studies has underscored the role of machine getting to know (ML), Deep gaining knowledge of (DL), and information-pushed heuristics in modelling, predicting, and improving machining operations. those AI-enabled methodologies have enabled the ideal mapping of problematic relationships among process parameters, machine dynamics, device put on, and floor integrity, thereby offering a holistic perspective on overall Machining manner (TMP) overall performance.

AI equipment which includes synthetic Neural Networks (ANNs), assist Vector Machines

(SVMs), Random Forests (RF), Fuzzy Inference systems (FIS), and emerging Deep mastering architectures were widely adopted for supervised prediction responsibilities—together with regression and classification of machining traits. these gear provide powerful capabilities to version complicated, non-linear interactions among reducing parameters, sensor-derived manner indicators, and machining outputs like surface roughness, dimensional accuracy, and tool life. but, predictive modelling on my own does no longer inherently gain manner optimisation. therefore, the mixing of superior optimisation techniques is vital to translate AI-driven predictions into actionable manner enhancements. on this regard, evolutionary algorithms which include Genetic Algorithms (gasoline), Particle Swarm Optimisation (PSO),

Non-dominated Sorting Genetic set of rules II (NSGA-II), and Bayesian Optimisation (BO) have emerged as the dominant techniques. those techniques effectively take care of multi-goal optimisation (MOO) scenarios, balancing exchange-offs between competing objectives like satisfactory, productivity, fee-efficiency, and environmental effect.

Even as single-objective Optimisation (SOO) procedures had been hired for exceptional-tuning unique performance indicators, the developing complexity of machining environments necessitates a shift closer to Multi-goal Optimisation frameworks (MOO) which could concurrently address more than one, often conflicting, performance targets. MOO allows a comprehensive assessment of method first-class, cycle time, operational expenses, and sustainability metrics, main to Pareto-most advantageous solutions that cater to diverse industrial requirements. in spite of giant development, numerous demanding situations persist. those encompass version explainability, real-time manner comments integration, coping with large-scale, excessive-frequency datasets, and the deployment of AI-optimisation pipelines in stay production settings. moreover, the dearth of standardised statistics acquisition protocols, coupled with the need for strong sensor fusion strategies, poses hurdles for scalable . In end, the synergistic application of AI gear and advanced optimisation strategies offers a transformative opportunity for accomplishing shrewd, self sustaining, and sustainable machining procedures. by means of addressing cutting-edge challenges and leveraging rising AI improvements, the producing area can realize the imaginative and prescient of smart, self-optimising production systems, aligned with the ideas of enterprise five.zero and green manufacturing. Destiny studies will awareness on developing extra efficient and scalable optimization algorithms, integrating AI with quantum optimization techniques, and enhancing the transparency and explainability of optimization approaches.

References

1. Ghani JA, Choudhury IA, Hassan HH. Application of taguchi method in the optimization of end milling parameters. Journal of Materials Processing Technology 2004;145(1):84–92.

2. Ibrahim J, Husain A, Ghazali MI, Mohamed N. Predictive maintenance using machine learning for CNC machines: A systematic literature review. Journal of Manufacturing Systems 2022;62:228–48.

3. Sener B, Yildirim V. Multi-objective optimization in machining: A comprehensive review. Journal of Materials Research and Technology 2021;14:2717–35.

4. Joshi AM, Deshmukh AR. Surface roughness prediction and optimization in CNC turning using response surface methodology. Materials Today: Proceedings 2020;26:1445–50.

5. Hasan MF, Wahid KA. Machine learning and optimization techniques for machining processes: A state-of-the-art review. Journal of Manufacturing Systems 2023;67:34–57.

6. Wang J, Sun J, Zhu J, Li D. Application of particle swarm optimization algorithm in machining process parameter optimization. The International Journal of Advanced Manufacturing Technology 2020;109(1):229–42

7. Yan C, Xu Z, Yu X. Multi-objective optimization in manufacturing using NSGA-II: A case study on milling process. Materials Today: Proceedings 2021;47:6272–6.

8. Buj-Corral I, Vivancos-Calvet J. Sustainable machining strategies and environmental impact reduction: A systematic review. Journal of Cleaner Production 2021;294:126270.

9. Mandal D, Pal S, Majumder H. Tool wear prediction using hybrid machine learning model in CNC turning. Journal of Materials Research and Technology 2021;15:3504–15.

10. 10.Zhao Y, Lu Y, Wang Y, Li P. Recent advancements in multi-objective optimisation methods for sustainable machining. Journal of Cleaner Production 2022;351:131476.
11. Shahin M, Chen FF, Bouzary H, Krishnaiyer K. Integration of Lean practices and Industry 4.0 technologies: smart manufacturing for next-generation enterprises. The International Journal of Advanced Manufacturing Technology 2020;107: 2927–36.
12. Oztemel E, Gursev S. Literature review of Industry 4.0 and related technologies. Journal of Intelligent Manufacturing 2020;31:127–82.
13. Kim DH, Kim TJ, Wang X, Kim M, Quan YJ, Oh JW, Min SH, Kim H, Bhandari B, Yang I, Ahn SH. Smart machining process using machine learning: a review and perspective on machining industry. International Journal of Precision Engineering and Manufacturing-Greening Technology 2018;5:555–68.
14. Barbosa LFF, Nascimento A, Mathias MH, de Carvalho Jr JA. Machine learning methods applied to drilling rate of penetration prediction and optimization—a review. Journal of Petroleum Science and Engineering 2019;183:106332.
15. Correa M, Bielza C, Pamies-Teixeira J. Comparison of Bayesian networks and artificial neural networks for quality detection in a machining process. Expert Systems with Applications 2009;36(3):7270–9.
16. Eser A, Ayyıldız EA, Ayyıldız M, Kara F. Artificial intelligence-based surface roughness estimation modelling for milling of AA6061 alloy. Advances in Materials Science and Engineering 2021;2021:1–10.
17. Gu P, Zhu C, Tao Z, Yu Y. A grinding force prediction model for SiCp/Al composite based on single-abrasive-grain grinding. The International Journal of Advanced Manufacturing Technology 2020;109:1563–81.
18. Alajmi MS, Almeshal AM. Predicting the tool wear of a drilling process using novel machine learning XGBoost-SDA. Materials 2020;13(21):4952.
19. Chang WY, Wu SJ, Hsu JW. Investigated iterative convergences of neural network for prediction turning tool wear. The International Journal of Advanced Manufacturing Technology 2020;106:2939–48.
20. Wang X, Zhu B, Liu S, He Y, Shi D. Intelligent monitoring and fault diagnosis methods for key components in machine tools: A review. Chinese Journal of Aeronautics 2021;34(1):12-35.
21. Ramesh B, Padmanaban G, Sakthivel NR. Fault diagnosis of bearing using ensemble learning methods. Journal of Intelligent Manufacturing 2020;31:2137–49.

22. Liang S, Hecker RL, Landers RG. Machining process monitoring and control: The state-of-the-art. Journal of Manufacturing Science and Engineering 2004;126(2):297–310.
23. He D, Bechhoefer E, Qu Y. Use of Self-Organizing Map and Hidden Markov Model for Health Assessment in Machining Process. Mechanical Systems and Signal Processing 2016;64:781–95.
24. Dutta S, Chakraborty S, Ray P. Machine learning applications in machining: A review. Materials Today: Proceedings 2021;45(5):4997–5003.
25. Patel MJ, Jha RK. A hybrid machine learning approach for tool condition monitoring in CNC milling. Journal of Intelligent Manufacturing 2022;33(5):1419–33.
26. Deshpande KS, Deshmukh AR, Sonawane AA. Machine learning-based tool wear prediction models: a review and comparison. Advances in Manufacturing 2021;9:177–99.
27. Madireddy S, He Z, Madireddy S. A review of multi-objective optimization in machining using evolutionary algorithms. Journal of Manufacturing Processes 2021;63:348–66.
28. Ghorbani R, Younessi A, Hadad MJ. Data-driven models for process optimization in machining: A review. Journal of Manufacturing Systems 2022;63:142–58.
29. Shankar S, Mohanraj T, Rajasekar R. Prediction of machining performance using machine learning techniques: A review. Materials Today: Proceedings 2020;27:1513–8.
30. Sushil KS, Ramkumar J, Dhamangaonkar AC. Predictive modeling of surface roughness using machine learning techniques: a case study on end milling. Journal of the Brazilian Society of Mechanical Sciences and Engineering 2021;43:79.
31. Das SR, Kumar S, Mandal NC. Recent advances in machine learning applications in manufacturing: A review. Journal of Intelligent Manufacturing 2022;33:1365–86.
32. Chen Y, Gao R, Liu Y, Chen K. Data-driven methods for fault detection and diagnosis in manufacturing: A review. Journal of Manufacturing Systems 2020;56:636–53.
33. Yao Z, Li D, Zhao Y, Ma Z, Ding W. Tool condition monitoring in milling: A review. The International Journal of Advanced Manufacturing Technology 2020;109(1):33–55
34. Wang Y, Zhang Y, Liu X, Shen F, Wang K. A review of multi-objective optimization in machining processes. Journal of Manufacturing Processes 2021;65:237–58
35. Ma L, Li C, Chen G, Wang H. Tool wear prediction in turning using machine learning: A comprehensive review. Journal of Manufacturing Processes 2022;80:357–82

36. Rao TVV, Rao PV. Multi-objective optimization of machining parameters using genetic algorithms: A review. Materials Today: Proceedings 2020;33:4617–22.
37. Kadirgama K, Noor MM, Rahman MM, Rejab MR, Harun WM, Bakar RA, Mat Yamin AK. Fuzzy modeling for the prediction of surface roughness in end milling process. Journal of Materials Processing Technology 2009;201(1-3):731–5.

38. Davim JP, Conceição António C. Optimization of cutting conditions in machining of metal matrix composites using a genetic algorithm. Journal of Materials Processing Technology 2001;112(1):185–9.
39. Mohanraj T, Shankar S, Rajasekar R, Muralidhar M, Rajkumar S, Sakthivel NR. Tool condition monitoring techniques in milling process—a review. Journal of Materials Research and Technology 2020;9(1):1032–42.
40. Suykens JAK, Vandewalle J. Least squares support vector machine classifiers. Neural Processing Letters 1999;9(3):293–300.
41. Teti R, Jemielniak K, O'Donnell G, Dornfeld D. Advanced monitoring of machining operations. CIRP Annals 2010;59(2):717–39.
42. Weng D, Li H, Jin Y. A review on reinforcement learning for data-driven machining process optimization. Journal of Manufacturing Systems 2022;63:205-28.
43. Huang Y, Ren H, Liang SY. Tool wear monitoring using deep learning. Procedia Manufacturing 2018;26:980–90.
44. Kumar R, Singh R, Singh TP, Saini P, Singh AP. Recent advancements and challenges of sustainable machining: A comprehensive review. Materials Today: Proceedings 2021;46:1399–1407.
45. Fang X, Luo J, Tao D, Li Y, Han B. A review of data-driven fault diagnosis methods for rotating machinery. IEEE Access 2020;8:220700–22.
46. Zhang J, Zhu L, Ding H, Ding K. Machine Learning and Deep Learning Methods for Tool Condition Monitoring in Machining: A Review. Journal of Manufacturing Science and Engineering 2021;143(5):050801.
47. Madireddy S, He Z, Madireddy S. Hybrid AI-based model for machining parameter optimization in CNC turning. Procedia CIRP 2020;91:593–8.
48. Shankar S, Mohanraj T, Sakthivel NR. Intelligent approach for surface roughness prediction using least squares support vector machine in machining process. Measurement 2018;120:62–8.
49. Fu Y, Zhou Z, Zhang Y, Tang Y, Wang X. Data-driven fault diagnosis methods in mechanical systems: A review. Chinese Journal of Mechanical Engineering 2021;34(1):1–20.

50. Ozturk M, Kara F, Ayyıldız M, Ayyıldız EA. Surface roughness estimation in end milling using fuzzy logic. Strojniški vestnik-Journal of Mechanical Engineering 2019;65(5):267–74.
51. Namboodri T, Felhő C. AI for Quality Optimization in Turning: Short review. *MM Science Journal* 2025; Special Issue.
52. Lu X- L et al. DeepMachining: Online prediction of machining errors in lathe machines. *arXiv* 2024.
53. Hirsch E, Friedrich C. Data- driven tool wear prediction based on single-sensor approach. *arXiv* 2024.
54. Ren A et al. Cutting mechanics-based ML modeling to discover machining dynamics equations. *arXiv* 2025.
55. Liang Y. Typical applications and perspectives of ML in advanced precision machining. Review 2025.