Society of Production Engineering

ICPES 2025

40th INTERNATIONAL CONFERENCE ON PRODUCTION ENGINEERING - SERBIA 2025

DOI: 10.46793/ICPES25.259T

University of Nis Faculty of Mechanical Engineering

Nis, Serbia, 18 - 19th September 2025

RECENT ADVANCES IN ARTIFICIAL INTELIGENCE AND MACHINE LEARNING FOR PROCESS OPTIMIZATION IN TURNING

Aleksandar TRAJKOVIĆ[1]*, Miloš MADIĆ[2]

Orcid: 0009-0006-1390-8167; **Orcid:** 0000-0002-2310-2590;

[1]University of Niš, Faculty of Mechanical Engineering, Niš, Serbia

*Corresponding author: aleksandar.trajkovic@masfak.ni.ac.rs

Abstract: *The integration of artificial intelligence (AI) and machine learning (ML) into turning is transforming traditional manufacturing into a highly adaptive, data driven process. This review examines five key application areas, tool wear prediction, cutting force estimation, surface quality, energy consumption modeling and productivity optimization, highlighting the shift from static, empirical approaches to dynamic, hybrid frameworks that blend physics-based models with data driven algorithms. Advances in sensing technologies, digital twin platforms, and edge cloud integration now enable real time monitoring and multi objective optimization, enhancing both efficiency and sustainability. The analysis identifies multi modal data fusion, online adaptive learning, cross domain model transfer, and life cycle integrated decision making as emerging trends poised to drive the next generation of intelligent, sustainable, and self-optimizing turning systems.*

Keywords: *Turning, Artificial Intelligence, Machine Learning, Hybrid modeling, Predictive manufacturing*

1. INTRODUCTION

Turning is one of the oldest and most fundamental machining processes, traditionally employed to remove excess material from a rotating workpiece in the form of chips. Due to its versatility, ability to achieve high dimensional accuracy, and capability to produce a wide range of cylindrical geometries, turning has remained a cornerstone of modern manufacturing technologies. Its efficiency in the production of cylindrical components, combined with the potential to deliver superior surface quality under both conventional and advanced cooling/lubrication conditions, makes it a preferred method for achieving precise dimensional tolerances and functional surface integrity in high performance applications [1]. Industrial demand for components that can be most efficiently produced by turning, such as shafts, bushings, and precision cylindrical parts, has solidified its role as a primary metal cutting process in various sectors, including automotive, aerospace, and energy [2].

In a typical turning operation, the workpiece is held and rotated by the spindle while a single point cutting tool removes material by traversing parallel (Z axis) or perpendicular (X axis) to the axis of rotation [3]. Critical process parameters, such as cutting speed, feed rate, and depth of cut, directly influence machining efficiency, surface finish, tool wear, and overall productivity. These parameters must be carefully selected and optimized according to material properties, cutting tool characteristics, and required tolerances to achieve an effective balance between productivity and quality [4], [5]. Improper selection of these parameters can lead to excessive tool wear, poor surface integrity, and reduced material removal rate, ultimately increasing production costs.

Beyond its traditional role, turning has undergone continuous technological advancements, integrating high performance cutting tools, computer aided design and manufacturing (CAD/CAM) systems, and real time process monitoring. The introduction of coated carbide, cermet, and ceramic tools has extended cutting tool life while enabling higher cutting speeds and feeds, thereby improving overall process efficiency [6]. Additionally, the integration of advanced CNC control systems has enabled the implementation of adaptive control strategies, allowing for real time adjustment of cutting parameters in response to tool wear or varying workpiece conditions.

Artificial Intelligence (AI) refers to the ability of computer systems to perform tasks that typically require human cognitive functions, such as perception, reasoning, learning, and problem solving. It encompasses a wide range of subfields, including natural language processing, computer vision, and robotics, each aimed at enabling machines to make informed decisions and adapt to changing conditions. Machine Learning (ML), a subset of AI, focuses specifically on algorithms that learn patterns from data to improve their performance over time without explicit reprogramming [7]. These algorithms range from simple linear regression models to complex deep learning architectures capable of processing high dimensional datasets.

In the context of manufacturing, both AI and ML rely heavily on data collected from a wide variety of sources. Typical industrial data streams originate from sensors monitoring temperature, vibration, acoustic emission, cutting forces, and other process variables, as well as from control systems, computer aided manufacturing (CAM) platforms, and enterprise resource planning (ERP) databases[8]. The quality and structure of this data directly influences model accuracy, making preprocessing steps, such as noise reduction, normalization, and feature extraction, essential [9]. Properly processed data enables predictive analytics for tasks like process optimization, tool condition monitoring, and quality assurance, transforming raw measurements into actionable intelligence that supports autonomous and adaptive manufacturing systems.

The evolution of turning from a conventional metal cutting operation to an intelligent, data driven process reflects the broader transformation occurring in manufacturing under the influence of Industry 4.0 technologies. While fundamental knowledge of process kinematics, material behavior, and parameter optimization remains critical, the integration of AI and ML offers opportunities for enhancing precision, productivity, and adaptability. By leveraging multi source sensor data, advanced algorithms can accurately predict process outcomes, detect anomalies, and adapt control strategies in real time, thereby minimizing waste and maximizing efficiency [10]. This convergence of traditional machining expertise with computational intelligence establishes a foundation for developing robust, autonomous turning systems capable of meeting the growing demands for high quality, cost effective, and sustainable manufacturing. Against this backdrop, the present work aims to explore and advance AI and ML based approaches for turning process optimization.

2. APPLICATION OF AI AND ML IN TURNING MACHINING

2.1 Tool wear prediction

Tool wear prediction remains a central challenge in modern turning, directly affecting dimensional accuracy, surface integrity, tool life, and costs. In practical manufacturing environments, researchers are increasingly combining AI techniques with multi sensor monitoring systems to capture and anticipate wear progression as it unfolds on the shop floor. Such approaches often employ vibration, acoustic emission, spindle power, and cutting force signals, which are processed through advanced signal analysis methods and fed into machine learning models for accurate wear estimation [11]. By correlating sensor features with the actual wear state, researchers have demonstrated that AI driven methods can significantly outperform conventional threshold-based monitoring strategies in both prediction accuracy and adaptability to changing cutting conditions.

In addition to data driven models, hybrid approaches have been developed, combining physics-based wear models with AI algorithms to leverage the strengths of both domains [12]. These methods benefit from the interpretability of mechanistic models while gaining the flexibility of ML to adapt to complex and nonlinear wear patterns. Studies have shown that the fusion of physical insights with advanced regression or classification models enables a more robust prediction framework, particularly under variable machining parameters. Furthermore, the adoption of deep learning architectures, such as convolutional neural networks and recurrent neural networks, has enabled automatic feature extraction from raw signal data, reducing the reliance on manual feature engineering and improving generalization to unseen machining scenarios [13].

Another emerging direction is the utilization of cloud based and digital twin systems for tool wear prediction. By integrating sensor data into a virtual replica of the machining process, digital twins can continuously update the tool wear model based on real time inputs, thereby allowing adaptive process control [14]. This integration not only supports predictive maintenance but also enables optimization of cutting parameters to prolong tool life.

Some implementations have used streamlined neural architectures, such as pruned convolutional networks or compact gradient boosted ensembles, embedded directly into CNC controllers. These designs process sensor data locally, delivering wear state updates within milliseconds, and avoid the bandwidth load of constant cloud communication [15].

2.2 Cutting force

Cutting force prediction plays a decisive role in maintaining process stability and achieving consistent productivity. A growing body of work now explores hybrid AI models that merge physical process knowledge with adaptive learning strategies, enabling force estimation to remain accurate even under fluctuating machining conditions. One notable approach integrates mechanistic force models derived from cutting mechanics with data driven adjustment layers, producing hybrid systems that substantially improve prediction accuracy across variable machining regimes. This synergy supports robust predictions even when tool geometry, material properties, or machining conditions deviate from nominal parameters, providing flexibility without sacrificing interpretability [16].

Beyond hybrid frameworks, purely data driven methods have demonstrated exceptional adaptability and precision, particularly through deep learning. Multi-layer neural networks, including convolutional and recurrent architectures, have become especially adept at modeling the nonlinear, time dependent behavior of cutting forces. These models leverage large sensor datasets, captured from vibration, spindle load, acoustic emissions, or torque signals, to learn complex patterns that standard regression models struggle to detect. Their increasing accuracy and real time applicability mark them as critical tools for modern, intelligent machining systems [17].

Some studies have explored pairing live force measurements with virtual machining environments that update in real time. This approach allows the simulation to mirror the evolving cutting process, enabling immediate adjustments to feed rate or spindle speed when force spikes are predicted. This setup enables predictive control strategies such as adaptive feed rate optimization and proactive tool path adjustment, helping to minimize undesired force spikes and mitigate chatter. Cloud integration also offers scalable computational support and facilitates cross machine learning adaptations, ultimately helping to standardize performance across diverse setups [18].

At the same time, there’s growing interest in low latency, on edge inference solutions. Lightweight AI models, such as pruned neural networks or compact ensemble learners, are being optimized for real time deployment directly on CNC controllers. These solutions address the imperative for fast, reliable cutting force feedback without overloading communication channels or cloud infrastructure, paving the way for closed loop control even in resource constrained environments [19].

2.3 Surface quality prediction

Surface quality, commonly expressed through roughness parameters, remains a defining factor in part performance, influencing everything from assembly precision to service life. Increasingly, AI driven predictive models are being used to process real time sensor data, enabling proactive adjustments that keep surface finish within tight specification limits. By extracting features from spindle power, acoustic emissions, and vibration signals, these models can forecast surface roughness with noteworthy accuracy, enabling immediate on the fly adjustments to maintain desired finish standards [20].

Hybrid modeling approaches, integrating mechanistic surface generation models with machine learning corrections, have proven particularly robust. Mechanistic models capture the foundational physics of tool–workpiece interaction, while the data driven layer compensates for complex, real world non idealities such as tool vibration, material heterogeneity, and tool wear. This dual layer strategy enhances reliability across varied cutting conditions without sacrificing model interpretability [21].

Researchers have tested edge optimized predictors, including MobileNet style convolutional models and reduced tree ensembles, which can run on embedded controllers. This setup enables the control system to adjust spindle speed or feed rate almost instantly when the forecasted surface finish begins to drift. This enables real time roughness prediction and closed loop adjustment of feed rates or spindle speeds, all with minimal latency and without reliance on cloud back ends [22].

Certain research groups are experimenting with virtual process replicas that continuously incorporate live surface finish measurements. These replicas can forecast how surface quality will evolve if current parameters are maintained, helping engineers intervene before defects occur. By pairing live sensor streams with virtual replicas of the machining process, predictive roughness models can self-update continuously, adapting to tool wear progression, changes in material behavior, or shifts in ambient conditions. This enables not only predictive quality control but also long-term process optimization across tool life and across multiple machines [23].

Finally, a practical direction gaining traction is the use of transfer learning or few shot adaptations for surface quality models. Pretrained models, developed on datasets from one material or machine, can be swiftly adapted to new setups using minimal new data, significantly reducing the cost of model deployment in varied production environments [24].

2.4 Energy consumption prediction

In the drive toward sustainable manufacturing, predicting and optimizing energy consumption in CNC turning has gained strategic importance. Recent studies show that targeting specific cutting energy through parameter optimization can yield significant efficiency gains without sacrificing throughput or part quality. These approaches often involve fine tuning of machining parameters, such as cutting speed, feed rate, and depth of cut, using advanced optimization algorithms to minimize energy use without compromising productivity or quality [25].

Artificial intelligence techniques, particularly artificial neural networks (ANNs), have emerged as powerful tools for modeling and predicting energy consumption under varying cutting conditions. By leveraging multi sensor inputs and historical machining data, these models can capture the nonlinear relationships between process parameters and energy demand, enabling real time adjustments for optimal efficiency. Hybrid frameworks that combine ANN prediction with control and monitoring systems allow for dynamic recalibration of parameters during turning operations [26].

Sustainability focused studies further extend prediction models by incorporating specific cutting energy into multi objective optimization. This approach simultaneously targets energy efficiency, tool wear reduction, and overall process sustainability, particularly when using advanced techniques like minimum quantity lubrication (MQL). By integrating such lubrication strategies into predictive models, researchers have achieved significant reductions in energy usage alongside improvements in surface quality and tool life [27].

The inclusion of environmentally friendly lubricants, such as vegetable based MQL fluids, adds an ecological dimension to energy consumption optimization. In such cases, ANN based multi objective optimization frameworks can balance surface roughness, energy consumption, carbon emissions, and machining cost, providing a comprehensive decision-making tool for sustainable CNC turning [28].

Finally, recent advancements also highlight the role of material specific and process specific studies in energy consumption modeling. Tailored models that account for unique properties of workpiece materials, cutting tools, and machining setups can further enhance prediction accuracy, enabling a transition toward fully adaptive, sustainable, and energy aware manufacturing systems [29].

2.5 Productivity

Maximizing productivity in turning, whether measured as MRR, parts per hour, or effective throughput, remains a priority for competitive manufacturing. New AI driven modeling approaches are proving valuable in mapping the complex relationships between cutting parameters and real-world output, allowing for informed, high impact adjustments. By utilizing operational data streams, such as spindle power, feed rate, and machining cycles, these models can predict productivity with high fidelity, enabling proactive adjustments to maximize output without compromising quality [30].

Hybrid modeling approaches that combine mechanistic productivity estimators with data driven optimization layers show considerable promise. The mechanistic models provide baseline output estimates grounded in tool workpiece geometry and cutting mechanics, while machine learning corrections account for real world inefficiencies, like operator intervention, tool wear, or thermal deflection. This fosters a resilient productivity forecast that adapts to dynamic shop floor conditions [31].

Advanced optimization frameworks further elevate productivity prediction by integrating multi objective considerations. For example, productivity models are now designed to simultaneously balance output rate, energy consumption, and surface quality. These systems typically employ evolutionary algorithms, ANN based controllers, or reinforcement learning agents to discover optimal operating points that satisfy multiple production goals concurrently offering a comprehensive toolkit for sustainable, high efficiency machining [32].

Moreover, the rise of digital twin platforms and real time simulation has enhanced productivity modeling capabilities. By continuously integrating live sensor data into virtual replicas of the machining process, these systems can simulate “what if” scenarios in real time testing parameter shifts or tooling changes before committing them to actual production. This enables adaptive control strategies that autonomously enhance throughput while maintaining part quality and tool life [33].,

3. FUTURE DIRECTIONS

The evolution of AI and ML in turning will increasingly center on multi modal sensor fusion, combining acoustic, vibration, force, temperature, and vision data into unified process models. This integration will strengthen multi objective optimization, balancing quality, throughput, energy consumption, and tool life in real time. Online adaptive learning will replace static deployments, enabling continuous recalibration as tools wear, materials vary, and environmental conditions change. Transfer learning will reduce the cost and time of implementation across diverse machines and materials. On the sustainability front, integrating life cycle assessment (LCA) into optimization frameworks will make environmental impact a standard decision-making parameter. The convergence of digital twins with hybrid edge–cloud architectures will support distributed, predictive, and self-optimizing manufacturing networks, aligning with Industry 4.0 and paving the way toward Industry 5.0.

4. CONCLUSION

This review demonstrates that AI and ML based approaches, particularly hybrid models, are redefining predictive modeling in turning. Advances in tool wear, cutting force, and surface quality prediction are enabling real time control, while machining time models are closing the gap between CAM estimates and shop floor realities. Energy consumption modeling now integrates sustainability goals, and productivity optimization is evolving into a multi objective discipline. Collectively, these developments signal a transition toward intelligent, connected, and environmentally responsible machining systems, where adaptive algorithms, real time feedback, and digital twins converge to deliver high performance, resilient manufacturing in dynamic industrial environments.

ACKNOWLEDGEMENT

This research was financially supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia (Contract No. 451 03 137/2025 03/200109).

REFERENCES

[1] N. Jouini, J. A. Ghani, S. Yaqoob, and A. Z. Juri, Optimized Machining Parameters for High Speed Turning Process: A Comparative Study of Dry and Cryo+MQL Techniques, Processes, Vol. 13, No. 3, 2025, doi: 10.3390/pr13030739.

[2] W. Li, Advanced Manufacturing and Precision Machining, Applied Sciences, Vol. 14, No. 24, 2024, doi: 10.3390/app142411642.

[3] Z. Haitao, G. Jingfeng, T. Yongbo, Z. Shuixiang, and Y. Xiaoxi, An analysis of compensation for radial thermal errors of a turning center with a three axis feed system, Sci Rep, Vol. 15, No. 1, p. 23345, 2025, doi: 10.1038/s41598 025 05804 5.

[4] M. S. Surya, Optimization of machining parameters while turning AISI316 stainless steel using response surface methodology, Sci Rep, Vol. 14, No. 1, p. 30083, 2024, doi: 10.1038/s41598 024 78657 z.

[5] J. V Abellán Nebot, C. Vila Pastor, and H. R. Siller, A Review of the Factors Influencing Surface Roughness in Machining and Their Impact on

Sustainability, Sustainability, Vol. 16, No. 5, 2024, doi: 10.3390/su16051917.

[6] V. F. C. Sousa and F. J. G. Silva, Recent Advances in Turning Processes Using Coated Tools—A Comprehensive Review, Metals (Basel), Vol. 10, No. 2, 2020, doi: 10.3390/met10020170.

[7] R. X. Gao, J. Krüger, M. Merklein, H. C. Möhring, and J. Váncza, Artificial Intelligence in manufacturing: State of the art, perspectives, and future directions, CIRP Annals, Vol. 73, No. 2, pp. 723–749, 2024.

[8] S. J. Plathottam, A. Rzonca, R. Lakhnori, and C. O. Iloeje, A review of artificial intelligence applications in manufacturing operations, J Adv Manuf Process, Vol. 5, No. 3, p. e10159, 2023, doi: https://doi.org/10.1002/amp2.10159.

[9] A. Presciuttini, A. Cantini, F. Costa, and A. Portioli Staudacher, Machine learning applications on IoT data in manufacturing operations and their interpretability implications: A systematic literature review, J Manuf Syst, Vol. 74, pp. 477–486, 2024, doi: https://doi.org/10.1016/j.jmsy.2024.04.012.

[10] M. S. Ahmmed, S. P. Isanaka, and F. Liou, Promoting Synergies to Improve Manufacturing Efficiency in Industrial Material Processing: A Systematic Review of Industry 4.0 and AI, Machines, Vol. 12, No. 10, 2024, doi: 10.3390/machines12100681.

[11] Z. Che, C. Peng, J. Wang, R. Zhang, C. Wang, and X. Sun, KAN Based Tool Wear Modeling with Adaptive Complexity and Symbolic Interpretability in CNC Turning Processes, Applied Sciences, Vol. 15, No. 14, 2025, doi: 10.3390/app15148035.

[12] T. Namboodri and C. Felhő, AI FOR QUALITY OPTIMIZATION IN TURNING: A SHORT REVIEW., MM Science Journal, 2025.

[13] L. Colantonio, L. Equeter, P. Dehombreux, and F. Ducobu, Explainable AI for tool condition monitoring using Explainable Boosting Machine, Procedia CIRP, Vol. 133, pp. 138–143, 2025, doi: https://doi.org/10.1016/j.procir.2025.02.025.

[14] S. C. S and A. Ramesh, Digital twin enabled surface quality prediction and optimization in dry turning of Ti6Al4V using ANFIS and genetic algorithm, Journal of King Saud University – Engineering Sciences, Vol. 37, No. 5, p. 17, 2025, doi: 10.1007/s44444 025 00030 w.

[15] M. Kodrič, J. Korbar, M. Pogačar, and G. Čepon, Development of a resource efficient real time vibration based tool condition monitoring system using PVDF accelerometers, Measurement, Vol. 251, p. 117183, 2025, doi: https://doi.org/10.1016/j.measurement.2025.117183.

[16] A. Suárez, F. Veiga, X. Sandua, P. J. Rivero, L. N. L. de Lacalle, and A. Wretland, Machinability of Waspaloy: an investigation of cutting forces and tool wear in turning, The International Journal of Advanced Manufacturing Technology, Vol. 139, No. 5, pp. 3159–3172, 2025, doi: 10.1007/s00170 025 15983 0.

[17] M. Liu, H. Xie, W. Pan, S. Ding, and G. Li, Prediction of cutting force via machine learning: state of the art, challenges and potentials, J Intell Manuf, Vol. 36, No. 2, pp. 703–764, 2025, doi: 10.1007/s10845 023 02260 8.

[18] M. Mirzabagherian, S. Amini, and M. Bayat, Investigation of the effects of ultrasonic assisted face turning with CO2 cooling on cutting forces, residual stress, and surface quality, International Journal of Lightweight Materials and Manufacture, Vol. 8, No. 5, pp. 551–561, 2025, doi: https://doi.org/10.1016/j.ijlmm.2025.04.003.

[19] J. Stanojković, M. Madić, M. Trifunović, P. Janković, and D. Petković, A NOVEL APPROACH TO PREDICTING THE CUTTING FORCE IN TURNING USING DIMENSIONAL ANALYSIS, Facta Universitatis, Series: Mechanical Engineering, 2025.

[20] A. T. Abbas, N. Sharma, K. F. Alqosaibi, M. A. Abbas, R. C. Sharma, and A. Elkaseer, Investigation of Surface Quality and Productivity in Precision Hard Turning of AISI 4340 Steel Using Integrated Approach of ML

MOORA PSO, Processes, Vol. 13, No. 4, 2025, doi: 10.3390/pr13041156.

[21] T. Namboodri and C. Felhő, AI FOR QUALITY OPTIMIZATION IN TURNING: A SHORT REVIEW., MM Science Journal, 2025.

[22] T. Namboodri and C. Felhő, AI FOR QUALITY OPTIMIZATION IN TURNING: A SHORT REVIEW., MM Science Journal, 2025.

[23] J. H. Ko and C. Yin, A review of artificial intelligence application for machining surface quality prediction: from key factors to model development, J Intell Manuf, 2025, doi: 10.1007/s10845 025 02571 y.

[24] Y. Zhu, T. Österlind, A. Rashid, and A. Archenti, Data driven approaches for surface quality monitoring and prediction based on heterogeneous multi channel signal fusion in hard part machining, Eng Appl Artif Intell, Vol. 160, p. 111865, 2025, doi: https://doi.org/10.1016/j.engappai.2025.111865.

[25] K. Noor, M. A. Siddiqui, and A. I. Syed, Optimization of specific energy consumption in CNC turning of a hardened alloy steel roll at low cutting speeds, Journal of Engineering, Design and Technology, Vol. 23, No. 2, pp. 368–385, 2025.

[26] B. F. Abaza and V. Gheorghita, Artificial Neural Network Framework for Hybrid Control and Monitoring in Turning Operations, Applied Sciences, Vol. 15, No. 7, 2025, doi: 10.3390/app15073499.

[27] R. S. Revuru, K. T. Sanjay, B. Srinu, and P. V. Krishna, Evaluation of optimum process parameters based on specific cutting energy in turning for sustainability, The International Journal of Advanced Manufacturing Technology, Vol. 136, No. 10, pp. 4569–4579, 2025, doi: 10.1007/s00170 025 15068 y.

[28] T. Hakmi, H. Abderazek, Y. F. Yapan, A. Hamdi, and A. Uysal, Enhancing sustainability in CNC turning of POM C polymer using MQL with vegetable based lubricant: machine learning and metaheuristic optimization approaches, The International Journal of Advanced Manufacturing Technology, Vol. 139, No. 3, pp. 1661–1684, 2025, doi: 10.1007/s00170 025 15962 5.

[29] M. A. Khan, R. Ahmad, S. H. I. Jaffery, S. I. Butt, M. S. Khan, and D. Zahid, Sustainability analysis of tool wear, energy efficiency, surface quality, and energy during dry, MQL, and wet turning of Inconel 718, International Journal of Sustainable Energy, Vol. 44, No. 1, p. 2515447, Dec. 2025, doi: 10.1080/14786451.2025.2515447.

[30] A. T. Abbas, N. Sharma, K. F. Alqosaibi, M. A. Abbas, R. C. Sharma, and A. Elkaseer, Investigation of Surface Quality and Productivity in Precision Hard Turning of AISI 4340 Steel Using Integrated Approach of ML MOORA PSO, Processes, Vol. 13, No. 4, 2025, doi: 10.3390/pr13041156.

[31] A. Ginting, R. A. Sidabutar, F. D. Pranata, K. Syam, S. Situmorang, and T. Fikriawan, Productivity improvement in hard turning of AISI 4340 with response surface methodology and machine learning, International Journal of Machining and Machinability of Materials, Vol. 27, No. 1, pp. 85–103, Jan. 2025, doi: 10.1504/IJMMM.2025.145073.

[32] M. M. Nasr and S. Anwar, Developing an intelligent approach based on ANFIS and advanced NSGA III for improving the turning performance of additively manufactured γ TiAl alloy, The International Journal of Advanced Manufacturing Technology, Vol. 137, No. 7, pp. 3333–3358, 2025, doi: 10.1007/s00170 025 15366 5.

[33] K. Ramesha et al., ANN and machine learning based predictions of MRR in AWSJ machining of CFRP composites, Sci Rep, Vol. 15, No. 1, p. 14218, 2025.