MM Science Journal | www.mmscience.eu
ISSN 1803-1269 [Print] | ISSN 1805-0476 [On-line]
Special Issue | CUTTING TOOLS 2024
1st International Conference on Cutting Tools
November 20-22, 2024, Trnava, Slovakia
DOI: 10.17973/MMSJ.2025_06_2025033

CUTTINGTOOLS2024-00013

AI FOR QUALITY OPTIMIZATION IN TURNING: A SHORT REVIEW

Tanuj Namboodri[1], Csaba Felhő[1*]
[1]University of Miskolc, Institute of Manufacturing Science, Miskolc, Hungary
*Corresponding author; csaba.felho@uni-miskolc.hu

Abstract

The advancement of Artificial Intelligence (AI) in manufacturing begins with the Fourth Industrial Revolution. AI allows manufacturing with efficiency optimization, product quality improvement, cost reduction, and ease of real-time predictive maintenance. The topic is clearly stated in the literature. However, it fails to note the turning operation and quality optimization. This review attempts to clarify the factors influencing the quality of the finished product, related challenges, and the integration of AI to address these issues. The article highlights several methods for developing AI models and their real-world implementation. The paper systematically assesses the available literature, categorizing process characteristics and AI techniques based on data sources and management methodologies. The key result demonstrates that artificial neural networks and regression analysis are widely used in machining and optimization procedures, with fuzzy logic proving advantageous. Data management and filtration are essential for a reliable AI model. This paper offers insights into pre-processing, algorithm choice, and optimization methodologies, guiding researchers in constructing successful AI models for quality optimization in turning operations.

Keywords:
Artificial Intelligence, Turning, Industry 5.0, Smart manufacturing

1 INTRODUCTION

The shift towards Industry 5.0 has already started through technological innovation and the adoption of Artificial Intelligence (AI) based models for predicting machined product quality in turning operations.

Traditional methods for predicting product quality usually depend on mathematical models or simulations, which can be time-consuming and less responsive to real-time changes in machining conditions. The introduction of AI has revolutionized this field, providing powerful tools for predicting various quality metrics such as surface roughness, tool wear, and dimensional accuracy.

Predicting machined product quality in turning operations is a critical aspect of modern manufacturing, aiming to ensure high-quality outputs while optimizing production efficiency. This review synthesizes recent advancements in AI-based predictive models for turning processes, highlighting the machining parameters and quality indicators that need to be considered to create an AI model for predicting the quality of the machined product for turning operations in real-time.

1.1 Paper Structure

Fig.1 represents the contents of this review paper. First, the paper discusses why turning is still necessary in changing industries from time to time. It clarifies whether the industry is moving towards 5.0 or has room for improvement in Industry 4.0. At the end, the paper discusses Industry 5.0.

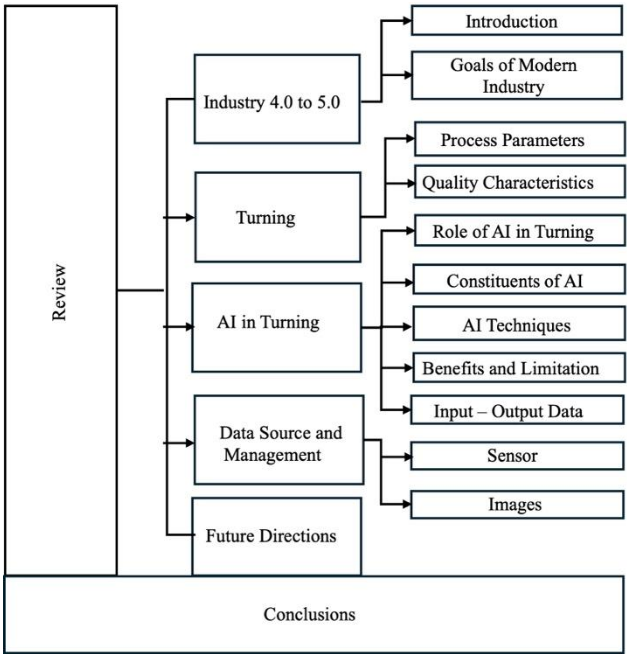

Fig. 1: Contents of Paper

The second part of the paper highlights the turning operation and the quality characteristics of the process parameters. In the third section, the paper highlights AI in turning, which will address the queries regarding the role of AI in the turning and the constituents of AI.

These AI techniques are used in the machining, benefits, and limitations of the AI, and the kind of Input-output data can be used to create AI for turning. The third part discusses the DATA sources, like sensors, types of sensors, and images, and how they can be analyzed. In the end, the future direction in this field is highlighted. This review paper covers the need for AI in turning operations. It is still a big part of the manufacturing industry. Turning operation creates mechanical parts by removing the unwanted material using the tool and orthogonal cutting [Astakhov 2011]. It is primarily used to make the shafts of the machine; however, it can be used to manufacture other mechanical parts used in the machine.

Being a widespread method, the process requires several complex characteristics or parameters that are part of the objective of this review, which is to structure the turning parameters for different modeling targets based on the literature review.

The final part consists of highlighting ML algorithms, mentioning optimization methods, identifying the challenges, and mentioning future research directions.

1.2 Transition of Industry

Industries experienced periodic shifts. First, the world faced the revolution of Industry 1.0, where the first industrial revolution began at the end of the 18th century and was represented by mechanical production plants based on water and steam power. After that, Industry 2.0 came into existence. The second industrial revolution started at the beginning of the 20th century with the symbol of mass labor production based on electrical energy, which brought mass production and mass development. The third industrial revolution began in the 1970s with automatic production based on electronics and internet technology. The fourth industrial revolution, namely Industry 4.0, is ongoing, and the characteristics of cyber-physical systems (CPS) production are based on heterogeneous data and knowledge integration, called Smart Manufacturing. It can be said that the industries are between Industry 4.0 and the transition towards Industry 5.0, which will be Human-machine interaction (Kumar et al. 2024).

1.3 Goals of Modern Industry

The modern manufacturing industry's goals are efficiency, sustainability, and technological advancement. These objectives are motivated by adjusting to a rapidly changing world market and using modern technology for competitive advantage.

Efficiency and Competitiveness – Modern manufacturing aims to enhance efficiency through effective management and leadership, enabling companies to adapt to changes and maintain competitiveness in a turbulent market [Lu 2017]. This includes adopting zero-defect manufacturing strategies to reduce costs, energy consumption, and waste while improving lead times and production planning [Trebuna et al. 2022].

Sustainability – There is a strong focus on sustainable development driven by global resource constraints and the need for long-term environmental responsibility. This involves optimizing resources and integrating sustainable practices into manufacturing processes [Machado et al. 2020].

Technological Integration – Integrating advanced techno logies such as the Internet of Things, cyber-physical systems, and big data is crucial for modern manufacturing. These technologies support the development of intelligent, sustainable production systems and facilitate the transition to Industry 4.0 [Sharman et al. 2004].

Innovation and Quality – Emphasizing innovation-driven manufacturing and quality over quantity is a key goal, as seen in initiatives like 'Made-in-China 2025,' which aims to enhance industrial capabilities and achieve green manufacturing [Xu et al. 2018]. Similarly, the Make-in-India initiative by India's government focuses on manufacturing innovation.

Flexibility and Adaptability – Modern manufacturing seeks to increase flexibility and adaptability by integrating lean and agile practices with Industry 4.0 technologies. This allows for rapid response to market changes and disruptions [Buer et al. 2018, Amjad et al. 2020].

2 THE TURNING PROCESS

Turning operations in the manufacturing industry involve removing unwanted material from a workpiece to achieve the desired shape and dimensions. This process is fundamental in machining and is typically performed on a lathe. It involves several machining parameters and machining conditions to develop the desired product. Fig. 2 represents the turning process in a CNC lathe.

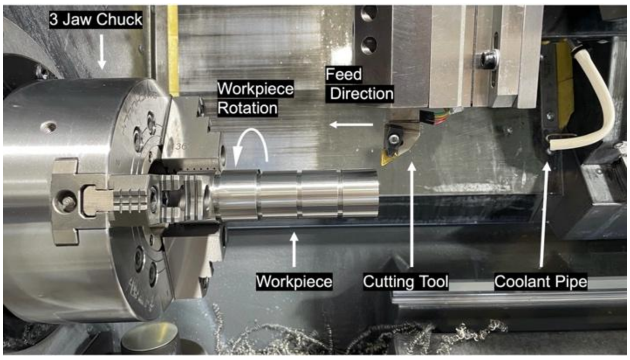

Fig. 2: Turning Operation

2.1 Evolution of Turning Operations

Turning operations have evolved from manual lathe machines requiring constant supervision to automated CNC machines, with advancements in optimization techniques and process parameters like spindle speed, cutting speed, depth of cut, and feed improving efficiency and outcomes. These machining parameters play an essential role in achieving good product quality.

Traditionally, turning operations relied heavily on manual control and basic automation. Optimization of machining parameters was often done through trial and error or basic analytical methods [Yusup et al. 2012].

The introduction of Industry 4.0 has significantly transformed the way operations are conducted. Modern techniques involve advanced optimization algorithms like genetic algorithms, differential evolution, and particle swarm optimization to enhance efficiency and precision [Yusup et al. 2012, Yildiz 2012]. The focus is on integrating digital technologies to enable intelligent manufacturing systems, which are interconnected and capable of real-time data processing [Alcácer and Cruz-Machado 2019, Mourtzis 2020].

The future of turning operations is leading towards complete automation and intelligent manufacturing systems. This includes developing models that allow rapid configuration and intelligent operation of manufacturing systems, catering to personalized product requirements and shorter product life cycles [Xie et al. 2022]. Simulation and digital twins will enhance manufacturing systems design and operation [Mourtzis 2020]. These projects need development in turning operations using AI models that improve the overall quality, and further look at sustainable production, which can reduce unwanted operational failures.

2.2 Requirements of Enhanced Turning Operation

One of the significant requirements for developing turning operations, including AI in the process, is quality optimization and efficiency. There is a strong emphasis on optimizing machining parameters to reduce costs, improve product quality, and reduce material waste. Techniques like differential evolution and genetic algorithms are employed to achieve these goals [Yusup et al. 2012, Yildiz 2012].

Modern turning operations require integration with digital platforms to enable smart manufacturing. This involves using sensors, real-time machining monitoring, and advanced information and communication technology for better interconnection and transparency in manufacturing processes [Alcácer and Cruz-Machado 2019].

The push towards automated and intelligent systems is crucial. This includes developing systems that can autonomously manage and optimize production processes, reducing the need for human intervention [Xie et al. 2022].

To integrate AI into turning operations, understanding the turning process and the factors involved in the turning process is necessary. In addition, those factors influence the quality characteristics of the turned workpiece.

2.3 Quality characteristics of the turned workpiece

The quality characteristics of turned workpieces are primarily determined by surface integrity, shape, hardness, and microstructure, which are influenced by factors such as cutting tool properties, tool material, and geometry. The other influencing factor is workpiece material. These materials are divided into various categories – steel, stainless steel, cast iron, non-ferrous material, superalloys, and challenging material. Manufacturers of these materials have defined the insert type and material.

Another factor is machining conditions, such as the environmental temperature and dry or wet machining. In addition to the cutting phenomenon, which depends on the environment, tool used, and workpiece material, the quality characteristics of the final product are also influenced.

Fig. 2 represents the fishbone diagram for factors influenci ng quality characteristics in turning. It is necessary to understand the influence of these factors to implement the effects of these parameters in developing an AI model. Also, it is essential to understand each factor's influence on the others.

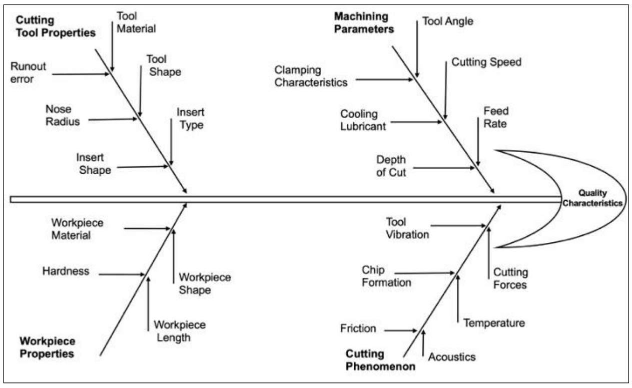

Fig. 3: Fishbone diagram for factors influencing quality characteristics in turning.

2.4 Process Parameters in Turning

Several process parameters significantly influence the machining outcomes, such as surface finish, material removal rate, and cutting forces. These parameters can be broadly categorized into cutting tool properties, machining parameters, workpiece properties, and cutting phenomena [Felhő et al. 2025].

Cutting Tool Properties

Many researchers have conducted experiments that keep cutting tool properties in the main frame and found that tool material, coating, and geometry influence the quality characteristics.

Table 1 represents the cutting tool properties and their influence on quality characteristics. The choice of tool material and whether it is coated or uncoated affects tool wear and cutting efficiency. Coated tools can enhance performance by reducing friction and wear [Salman et al. 2019]. This includes the tool nose radius and rake angle, influencing the cutting forces and surface finish. A larger nose radius can improve surface finish but may increase cutting forces [Salman et al. 2019a, Umamaheswarrao et al. 2021]. Some researchers have found that machining parameters are most influential in determining quality characteristics.

Machining Parameters

Machining parameters include cutting speed, feed rate, depth of cut, and, in some cases, spindle speed. This critical parameter affects the cutting force, surface finish, and tool life. Higher cutting speeds can improve surface finish but may increase tool wear [Salman et al. 2019]. The feed rate significantly impacts surface roughness and material removal rate. A higher feed rate can increase the material removal but may degrade the surface finish [Ho and Do, 2023]. The depth of the cut parameter substantially affects cutting forces and material removal rate. A greater depth of cut increases the cutting force and material removal rate [Petre and Găvruș, Ahmed et al. 2020]. The other influencing parameter that determines the quality of the final product is the workpiece properties

Workpiece Properties

Workpiece properties and getting the final product are challenging tasks in industries. The material of the workpiece, such as AISI 1040 steel or aluminum alloys, affects the choice of cutting parameters and tool material due to differences in hardness and machinability [Palanisamy et al. 2018]. The essential alloy elements in stainless steel, Cr and Ni, make it difficult to machine [Felhő and Namboodri 2024]. However, many researchers have examined the quality characteristics of Cr alloyed steel [Kundrak et al. 2021, Sztankovics 2024]. Some alloying elements like Sulphur (S) can make machinability easier, providing a better surface finish [Mujagić et al. 2021, Tanuj and Felhő 2024]. The initial surface condition of the workpiece can influence the final surface quality and the required machining parameters [Ho and Do, 2023]. The cutting phenomenon is another factor that affects the quality of the product.

Cutting Phenomenon

Cutting phenomena are parameters that proper precautions can control. They aren't parameters that machine operators or technicians can control. Cutting force is one of the factors

Tab. 1: *Information on the effect of cutting tool properties on quality characteristics.*

Reference	Cutting Tool Properties	Workpiece Material	Remark
[Yuan et al. 1996]	Diamond tool Sharpness, Cutting Edge radius	Aluminum alloy	Influences Surface roughness and microhardness.
[Palanisamy et al. 2018]	CVD-coated tool of TiN/Al2O3/TiCN/TiN	Incoloy 800H	The hardness of the tool was increased by cryogenic treatment.
[Salman et al. 2019a]	Coated and Uncoated	AISI 1035 alloy	Heat transfer during machining decreases Residual stress.
[Salman et al. 2019a]	Cutting tool with a smaller radius	AISI 1035 alloy	Reducing frictional heat generation.
[Umamaheswarrao et al. 2021]	Rake angle followed by nose radius	AISI 52100 Steel	A negative rake angle influences the cutting parameters.
[Nagwa Mejid Ibrahim Elsiti and Mohamed Handawi Saad Elmunafi 2023]	Coated carbide tool	AISI 420	Optimization of parameters.
[Brown and Schoop 2020]	Tool Properties, cutting edge, and Nose radius	Ti-6Al4V	Cutting-edge geometries with larger honing were found to reduce the roughness of the machined surface
[Xu et al. 2021]	Tool Rake Angles	Inconel 718	The increasing rake angles tend to decrease the cutting force.
[Wang 2018]	Tool structure, Tool material	Titanium and nickel	Geometrical characteristics, cutting-edge geometry, cutting tool shape, and coated or uncoated influences surface integrity.
[Molaiekiya et al. 2021]	Tool Material and Properties: SiAlON ceramic tools	IN718	The fresh ceramic tool produces a better surface finish than conventional coating.
[Dosbaeva et al. 2010]		Inconel 718	TiAlN PVD coating results in high tool life.
[Sivaiah et al. 2021]	Textured and untextured tool	AISI 304	Textured tools reduced the machining zone temperature, 'Vb', and 'Ra' remarkably over untextured tools, which indicates a steady cutting mechanism with textured tools.

Tab. 2: *Information on the effect of workpiece properties on quality characteristics.*

Reference	Workpiece Properties	Workpiece Material	Remark
[Aouici et al. 2012]	Workpiece Hardness	AISI H11 Steel	Workpiece hardness has a significant statistical influence on surface roughness.
[Barzani et al. 2015]	Bi- Element	Al–11.3Si–2Cu, Bi- and Sb	The bi-compound, which acts as a lubricant during turning, is more likely to be a reason to obtain the best surface roughness and the lowest main cutting force
[Dobrzynski and Mietka 2021]	Workpiece Rigidity	S355JR steel, AISI 304 stainless steel,	The properties of a workpiece material crucially affect the accuracy of execution. AISI 304 material is characterized by better machinability. The low rigidity of workpieces relative to the rigid parts of a machine tool hinders it. The cutting process is due to the generated vibrations.
[Li et al. 2024]	Workpiece Diameter	06Cr19Ni1	In turn, the workpiece diameter is an essential factor affecting cutting vibration, A rapid increase in surface roughness. Surface roughness is affected by the surface roughness to obtain better surface quality.
[Ho and Do 2023]	Workpiece Surface	N/A	Influences on finished product quality

Tab. 3: Information on the cutting phenomenon effect on quality characteristics.

Reference	Cutting Phenomenon	Workpiece Material	Remark
[Chen et al. 2017]	Cutting forces and Tool vibration	Ti6Al4V	Feed rate, cutting forces in the radial and tangential directions, and tool vibrations in three directions significantly correlate with the predicted value Ra based on the correlation analysis.
Thomas M.	Cutting Tool Vibration	N/A	Tool vibration analysis has revealed that two data types are correlated to the cutting parameters: the amplitude of vibration measured at the tool's natural frequency and the variation of this natural frequency.
[Hoang and Nguyen 2023]	Cutting forces and Tool vibration	SKH2 Steel	The feed rate's significant impact on cutting force and vibration is an essential factor that must be considered and controlled.
[Safi et al. 2022]	Cutting Tool Vibration	Cold-drawn medium carbon steel	Cutting tool acceleration has a significant effect on the surface roughness of the workpiece.
[Kong et al. 2016]	Cutting Tool Vibration	GCr15	Cutting speeds increased will first make the amount of vibration and surface roughness increase
[Kang et al. 2020]	Cutting Tool Vibration	AISI 316	At lower feed rates, the effect of vibration amplitude is not as significant as at the highest feed rate.

Tab. 4: Information on the effect of machining parameters on quality characteristics.

Reference	Machining Parameters	Workpiece Material	Remark
[Ahmed et al. 2020b]	DOC, feed, cutting speed	AISI 201	Influences on cutting forces
[Petre and Găvruș]	DOC, feed, cutting speed	AISI 1045	Forces in Turning
[Baskar et al. 2024]	DOC, feed, spindle speed	AL 6063 & AL 6068	MRR Investigation
[Palanisamy et al. 2018]	DOC, feed, cutting speed	Incoloy 800H	Surface roughness
[Salman et al. 2019b]	DOC, feed, environment	AISI 1035 alloy	Effect on surface residuals
[Hessainia et al. 2013]	DOC, feed	2CrMo4 steel [56 HRC] with Al2O3/Tic mixed ceramic.	Feed rate and the cutting speed have the highest influence on the evolution of machined surface roughness.

influenced by machining parameters and tool geometry. Optimizing these parameters can minimize cutting forces, enhancing tool life and surface quality [Nagwa Mejid Ibrahim Elsiti and Mohamed Handawi Saad Elmunafi 2023]. Analyzing cutting forces can be challenging as workpiece and tool material change according to consumer requirements, and having cutting forces data on every condition can be difficult. Similarly, tool vibration also impacts the quality of the finished product. Many researchers have studied tool vibration and found that tool vibration impacts the surface finish and sometimes leads to chatter marks [Jang et al. 1996, Afeen and Younis 2007, Hessainia et al. 2013a, Namboodri and Felhő 2024, Tanuj and Felhő 2024].

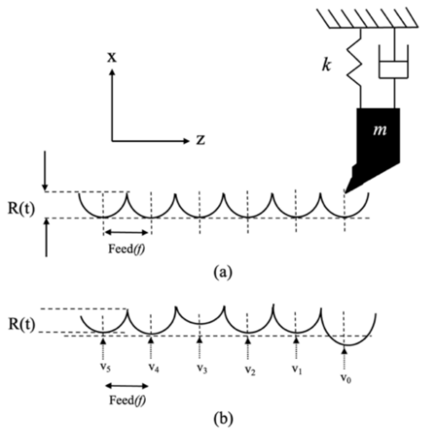

Fig. 4: Impact of vibration on surface roughness.

It can be noted that the turning process is a complex task, and analyzing all the parameters and their effects can be challenging to understand the parameters and their influence on the product quality. AI can offer a more effective solution.

3 AI IN TURNING

3.1 Role of AI in Turning Operations

AI can be more effective in turning operations within manufacturing by optimizing efficiency, precision, and decision-making processes.

AI integration into manufacturing is a key component of Industry 4.0, leading towards Industry 5.0, where it supports various aspects of production, from predictive maintenance to quality control and supply chain management. Fig. 5 describes the Role of AI in turning operations where adaptive control, predictive maintenance, and quality control can be the main tasks.

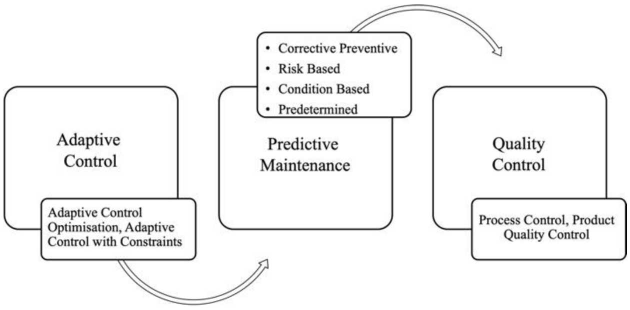

Fig. 5: Role of AI in Turning Operation.

Adaptive control uses AI-based optimization methods to modify machining parameters, including cutting speed, feed rate, and depth of cut, in real time.

This includes adaptive control optimization and adaptive control with constraints, assuring efficiency and reduced overall tool wear and providing better quality. Predictive maintenance uses AI models to assess machine performance data and forecast faults before occurrence, including corrective, preventive, risk-based, condition-based, predetermined maintenance, and tool change. This preventive approach reduces downtime and improves machine availability, providing AI-driven quality control. The AI will ensure a good surface finish, dimensional accuracy, and defect detection.

3.2 Constituents of AI for Turning

Developing an AI model for turning operations is like teaching a human to understand the machining process as the expert operator would. Every piece of data plays a role, and each element depends on the other to create a complete and accurate picture of how turning operations behave. It all starts with machining parameters like feed rate, depth of cut, cutting speed, and the type of machining. These fundamental settings determine how the process unfolds, directly impacting efficiency and product quality. At the same time, maintaining high-quality standards is crucial, so AI monitors surface integrity and material integrity to ensure the final product meets precision and durability requirements.

Fig. 6 represents the fundamental structure of the AI components for the turning operation quality optimization. AI can be structured using various parameters, quality targets, data collection, and setting parameters. The procedure involves training the model using gathered Input and output data, including the results, surface roughness parameters, and hardness variation. Different AI techniques need to be considered to develop a suitable model.

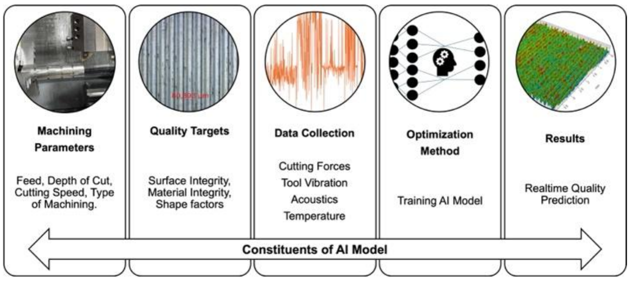

Fig. 6: Constituents of AI in Turning.

3.3 AI Techniques

To make smart decisions, AI needs data, and that's where real-time monitoring comes in. Sensors collect information on cutting forces, tool vibrations, acoustics, and temperature changes, giving AI a deeper understanding of how the machining process is performing. But collecting data alone isn't enough—AI must learn from it. By training on real machining scenarios, the model fine-tunes its ability to adjust parameters dynamically, optimizing efficiency while maintaining precision. The result is real-time quality prediction, allowing manufacturers to detect and correct potential issues before they impact production.

Because all these elements are interconnected, the AI model continuously improves by learning from every operation. The more data it gathers, the better it gets at predicting outcomes, fine-tuning processes, and ensuring a smoother, more reliable machining workflow. Ultimately, AI isn't just automating turning operations—it's making them more intelligent, efficient, and future-ready.

AI techniques can revolutionize operations by enhancing efficiency, reducing costs, and improving the overall machining performance. These techniques are machine learning (ML) algorithms, which work to create more intelligent machining systems.

Machine Learning algorithms are key in analyzing machining data, predicting outcomes, and automating decision-making processes. Popular ML methods include Artificial Neural Networks (ANN) [Petre and Găvruș, Hanief et al. 2017, Chen et al. 2017, Panetto et al. 2019], which help in predictive modeling and optimizing cutting parameters, and Support Vector Machines (SVM) [Ullrich et al. 2024], which assist in classifying machining conditions and detecting irregularities. Fig. 6 describes standard ML algorithms used to develop AI models. The common ML algorithms that are used are ANN and Regression analysis.

ANN – Artificial Neural Networks (ANNs) are computational models inspired by the human brain's structure and function. They consist of interconnected processing elements, or neurons, that work together to solve specific problems by learning from data. ANNs are composed of layers of neurons, each connected by weights. These weights are adjustable parameters optimized during learning to minimize prediction errors [Patel et al. 1AD, Agatonovic-Kustrin and Beresford 2000, Maind and Wankar 2014]. ANN learns by example, adjusting the synaptic weights between neurons based on input data. This process is akin to how biological systems learn, involving modifying synaptic connections [Wasukar 2014, Kalina et al. 2023]. Each neuron receives inputs, processes them through a transfer function, and produces an output. The transfer function introduces non-linearity, allowing the network to model complex relationships [Maind and Wankar 2014, Shehab et al. 2022]. The network's weights are adjusted during training to minimize the error between predicted and actual outputs. This is typically done using algorithms like backpropagation. ANNs are used for pattern recognition, data classification, and feature extraction. They are beneficial for handling non-linear data relationships and have applications in engineering and manufacturing [Lira et al. 202].

Regression Analysis - Regression analysis in machine learning is a method used to predict continuous output variables by establishing relationships between dependent and independent variables, utilizing various models such as linear, logistic, polynomial, and tree-based regressions, and is essential for data exploration and forecasting. Regression analysis in machine learning is a statistical method used to predict a continuous output variable based on one or more input variables. It is fundamental in understanding the relationships between variables and is widely used in engineering. Regression analysis aims to establish a relationship between dependent and independent variables, allowing for predictions of the dependent variable based on new data inputs [Moore 2001, Manikyala Rao et al. 2019, Kumar and Bhatnagar 2022].

There are several types of regression models, each suited for different data characteristics and analysis needs. Standard models include Linear Regression, which predicts the output as a linear combination of input features [Ansari and Nassif 2022, Qu 2024]. Polynomial regression extends linear regression by considering polynomial relationships between variables. Ridge and Lasso Regression are regularization techniques that prevent overfitting by adding penalties to the regression coefficients. Regression Trees use tree structures to model non-linear relationships and are known for their interpretability [Yang et al. 2017, Fernández-Delgado et al. 2019]. Regression models are trained using historical data to minimize the error between predicted and actual values. Techniques like mean squared error minimization are commonly used, although they may not always yield optimal results. Evaluation metrics such as mean absolute error (MAE) and R-squared are used to assess model performance [Liu et al. 2021, Ермаков and Леора 2022]. The other ML algorithms are SVM, HMM, and CNN.

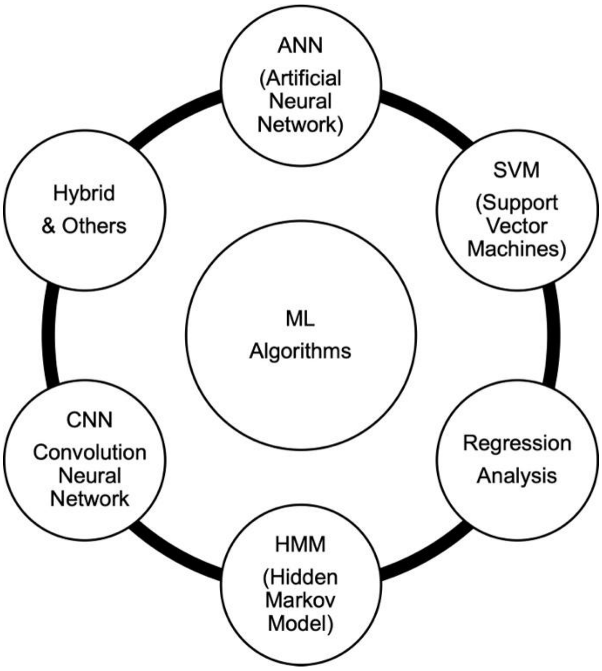

Fig. 7: ML algorithms.

Support Vector Machine (SVM) is a supervised machine learning algorithm for classification and regression tasks [Cervantes et al. 2020].

Hidden Markov Model (HMM) is a probabilistic model for modeling sequential data [Franzese and Iuliano 2025].

Convolutional Neural Network (CNN) is a deep learning algorithm for image recognition, object detection, and computer vision tasks. The human visual system inspires it and is widely used in AI applications [Jia et al. 2022]. ML algorithms are designed to learn patterns from data and make predictions. Optimization algorithms fine-tune ML models by minimizing or maximizing an objective function [Geranmayeh and Grass 2024].

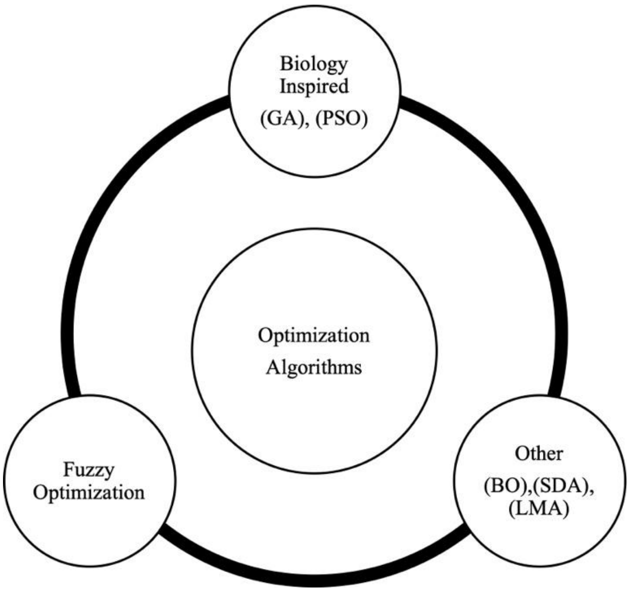

Fig. 8: Optimization Algorithms.

Optimization algorithms focus on fine-tuning machining parameters for optimal performance, such as Evolutionary Algorithms. Genetic Algorithms, Differential Evolution, and Teaching-Learning Optimization simulate natural selection to find the best machining conditions. Swarm Intelligence methods, including Particle Swarm Optimization (PSO) and Artificial Immune Systems (AIS), mimic the collective behavior found in nature to enhance machining efficiency. Fuzzy optimization helps manage uncertainties in cutting conditions, allowing for dynamic adaptation [Namboodri 2022]. Other specialized methods like Bayesian Optimization, Simulated Annealing, and Levenberg-Marquardt Algorithms are also used to refine AI models in machining [Rena et al. 2011, Kumar et al. 2015, Sivam et al. 2018, Sharma et al. 2019, Ahijith Kumar et al. 2024]. Combining ML with optimization algorithms allows AI-driven systems to offer real-time monitoring, adaptive control, and predictive decision-making. Integrating AI, IoT, and data-driven insights improves productivity, minimizes tool wear, and achieves superior machining results, transforming turning operations. Input and output data are required to develop these models as described.

3.4 Input and Output Data for AI

The AI models use input and output data to predict the outcomes using different input parameters. Tab. 5 describes the input and output variables used by several researchers. These input and output data can be different according to different modeling targets. In this paper, the main focus is on the Product quality. Fig. 9 describes the different modeling targets for the development of AI.

Different modeling targets require different Input and Output Data. For product quality, the key input parameters used are machining parameters - cutting speed, feed rate, and depth of cut, which are the most influential factors affecting machining performance [Sztankovics 2024a, c]. The other data, like cutting force tool vibration, can be used in real-time or after the collection to train the AI model. Some researchers have used temperature power to model the AI, which can help better understand the factors affecting the output.
The output parameters primarily focus on surface roughne ss (R_a, AA Surface Roughness), which is critical in determining the final product's quality [Maros et al. 2015, Sztankovics et al. 2024]. Other significant outputs include material removal rate (MRR) and shape factors like cylindricity, geometry, and tolerances. Microstructure formation can be studied during the turning operation [Felhő et al. 2023]. Some studies consider spindle speed and radial depth to capture various machining influences. Other studies mentioned tool and material characteristics, which were Inputs
may also include tool geometry, material properties, and coating types, such as AlTiSiN-coated carbide tools.

Environmental conditions factors like cooling systems (dry, MQL, flooding), while keeping the cutting fluid mixture ratio or solid-liquid lubricants in account. Optimizing these input parameters, manufacturers improve machined surface quality, extend tool life, reduce energy consumption, and enhance overall machining stability. This data can be useful in building an AI model as selecting the proper parameters allows for better control over the turning process, minimizing defects, and ensuring high precision in manufacturing. Some studies also analyze tool life, cutting temperature, chip morphology, and power consumption, providing insights into energy efficiency and tool performance. If the industrial requirement focuses on monitoring tool conditions, the input-output data for the AI model can be changed. The other two modeling targets mentioned in Fig. 9 are process characteristics and process condition prediction.

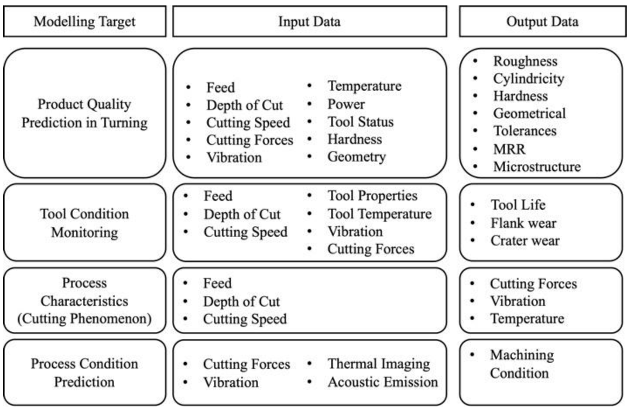

Fig. 9: Modelling Targets for AI in Turning.

These targets can allow AI to integrate adaptive control and predictive maintenance, as mentioned in subsection 3.1. AI models can bring numerous advantages and disadvantages, so it is essential to understand them.

3.5 Benefits and Limitations of AI

AI brings numerous benefits to turning operations, making them more efficient, sustainable, and cost-effective. One key advantage is tool wear prediction in stable turning processes [Mozaffar et al. 2022]. AI models can accurately predict when a tool will wear out, allowing for proactive maintenance and reducing downtime. AI also helps reduce undesirable effects such as vibrations or tool chatter, which can compromise product quality. By continuously analyzing real-time data, AI systems can adjust parameters to minimize these effects, leading to smoother and more precise machining. Another significant advantage is optimizing the machining process [Papadimitriou et al. 2024]. AI algorithms can adjust cutting parameters dynamically to achieve optimal performance, improving productivity and reducing the risk of tool damage or part defects. This is complemented by error compensation, where AI models correct machining errors automatically, ensuring the final product meets the required specifications. AI also contributes to energy saving by optimizing cutting speeds and feed rates, which minimizes energy consumption without sacrificing performance. Moreover, failure prevention is enhanced, as AI models can predict and prevent potential failures, allowing operators to take corrective actions before issues arise [Dwivedi et al. 2021]. Implementing AI leads to smart manufacturing, where systems are interconnected, self-learning, and capable of making real-time decisions. This enhances the overall efficiency and flexibility of the manufacturing process. As a result, good product quality is maintained consistently, with AI ensuring that machining operations stay within the ideal parameters. AI is crucial in sustainability by reducing waste, energy consumption, and material usage. By optimizing the machining process, AI helps minimize environmental impact and supports sustainable manufacturing practices [Colantonio et al. 2021].

Despite the numerous benefits, several challenges are associated with using AI in turning operations. One significant disadvantage is the high initial investment required to set up AI-driven systems, including the cost of hardware, software, and integration with existing machinery [Besigomwe et al. 2025]. AI systems also require highly experienced operators to effectively manage, monitor, and fine-tune the models [Kinkel et al. 2022]. These operators need advanced knowledge of AI techniques and machining processes, making it more challenging for companies with limited expertise. Consumption of materials and resources raises concerns about environmental sustainability in the short term [Xu et al. 2022]. Ethical issues can also arise, particularly regarding the use of AI in decision-making. There may be concerns about the transparency of AI models, accountability for mistakes, and potential job displacement due to automation in the industry [Zhang and Aslan 2021]. AI systems can also lead to over-reliance, where manufacturers become too dependent on the technology, ignoring the importance of human judgment and oversight. This reliance can pose a risk of failure, especially if the AI model encounters unforeseen issues or limitations in its design. Mathematical accuracy is critical in AI models, and even minor errors in the algorithms or data can lead to significant problems in machining outcomes [Alexander et al. 2024]. High error tolerance is essential, as even minor inaccuracies can affect the final product's quality and precision. In summary, while AI offers immense potential for improving turning operations, the challenges of high investment, skilled labor requirements, and potential ethical and environmental concerns should be carefully considered.

4 DATA SOURCE AND MANAGEMENT

Artificial Intelligence uses various data types, including structured and unstructured data such as images, text, point clouds, and sensor data. Fig. 10 represents the basic summary of data collected in the turning operation. These data are processed through machine learning, deep

Tab. 5: *Information on optimization method and Input, output parameters.*

Reference	Experiments Design	Optimization Method	Input Parameters	Output Parameters
[Nian et al]	Taguchi Method		Cutting Speed, Feed, Depth of Cut	Tool life, cutting force, and Surface Finish
[Tzeng et al. 2009]	Taguchi Method	Grey Relational Analysis	Cutting Speed, Feed, Depth of Cut, Cutting Fluid Mixture Ratio	Roughness Average, Roughness Maximum, and Roundness
[Kumar and Kumar]	TOPSIS		Cutting Speed, Feed, Depth of Cut, Nose Radius	MRR
[Abolghasem and Mancilla-Cubides 2022]	-	Artificial Neural Network, PSO	Cutting Speed, Feed, Depth of Cut, Nose Radius	AA Surface roughness, MRR
[Abhang and Hameedullah 2012]	-	Grey Relational Analysis, Factorial Design with eight center points.	Cutting Speed, Feed, Nose Radius, DOC, Concentration of Solid Liquid Lubricants	AA Surface roughness, Chip Thickness
[Duplak et al. 2023]	-	Statistical Model	Spindle Speed, Feed Rate, Radial Depth	Actual Chip Thickness, Chip Shape, Ra
[Sivam et al. 2018]	-	Fuzzy Logic	Cutting Speed, Feed, Depth of Cut	Surface Roughness and Cutting Force
[Kouahla et al. 2022]	Taguchi Method	RSM, GRA, ANOVA,	Nose Radius, Feed, Cutting Speed, Depth of Cut	AA Surface roughness, MRR, Tangential Vibration, Tangential Cutting Force, Power Consumption
[Savella et al. 2022]	-	Statistical Model	Spindle Speed and Feed	AA Surface roughness
[Kónya et al. 2024]	Taguchi Method	-	Cutting Speed, Feed	Cutting Forces, Cutting Temperature, Chip Morphology
[Siddique et al. 2023]	Taguchi Method	Statistical Model - ANOVA	Depth of cut, feed, and cutting speed	Tool wear, specific cutting energy, and surface roughness
[Safi et al. 2022]	Taguchi Method	GRA, MOORA, DEAR, WASPAS	Nose Radius, Feed, Cutting Speed, Depth of Cut	Ra, Fz, and Pc, and the maximization of MRR
[Nian et al.]	Taguchi Method		Cutting Speed, Feed, Depth of Cut	Tool life, cutting force, and Surface Finish
[Tzeng et al. 2009]	Taguchi Method	Grey Relational Analysis	Cutting Speed, Feed, Depth of Cut, Cutting Fluid Mixture Ratio	Roughness Average, Roughness Maximum, and Roundness

learning, and data fusion to enhance decision-making and improve applications across multiple domains. Sensor and image data are the primary data types used in machining. Real-time machining data, multisensory fusion data, and large-scale datasets containing machining parameters and tooling characteristics are crucial in AI-driven process optimization. These data sources enable AI to predict machining quality, enhance efficiency, and improve manufacturing performance. Effective data management in AI manufacturing is crucial for optimizing processes, enhancing productivity, and ensuring sustainable practices [Whang et al., 2023; Jiang et al., 2024]. To manage data from experiments, collecting, storing, and accessing it in real time can be challenging due to its volume. In manufacturing, a lot of data is collected from sensors and devices. It can be acceleration data, force measurement data, or thermal data. To manage data from various sources, there is a need to establish clear guidelines for

data management [Arinez et al. 2020; Rakholia et al. 2024; Dey et al. 2024].

Focus on data validation, cleaning, and integration to ensure high-quality data, essential for effective AI performance. Industry experts will be integrated to validate the data. In addition, the challenges are related to the high volume, variety, and frequency of data generated by sensors and digital manufacturing activities. Effective data management strategies are needed to harness this data for performance enhancement 10. Encourage collaboration between humans and AI systems, leveraging both automation and human expertise to optimize data management practices (Wang et al. 2019, Jamwal et al. 2022, Adeolu Adenekan et al. 2024).

4.1 Data Processing

Sensor data for force, vibration, and temperature can be monitored in real-time and afterward stored locally or sent to the cloud. The initial data processing stage is cleaning, which involves using filters (such as low-pass, high-pass, or Kalman filters) to reduce noise and improve signal quality [Kenda et al., Kaiser and Reed 1977]. An outlier identification method, including Z-score and interquartile range (IQR), can eliminate deviations [Anusha et al. 2019]. The interpolation method could address missing data points [Narang et al. 2013, Spatial Interpolation 2017].

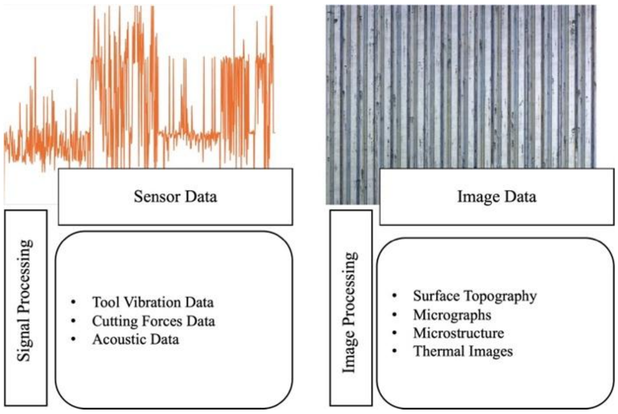

Fig. 10: Different Data and Processing.

The data is then normalized and scaled to ensure uniformity among sensor readings. Min-max scaling or Z-score normalization can be utilized to standardize values for improved comparison [Jain et al. 2018, Editors et al. 2024]. In addition to pre-processing, the data is analyzed using statistical methods, including mean, variance, skewness, and frequency-domain transformations such as the Fast Fourier Transform (FFT), which allow the identification of main vibration frequencies. Further feature extraction techniques like Wavelet Transform and Principal Component Analysis (PCA) may be employed to identify significant patterns [Sengupta and Kay 1995]. The processed data may then be Input into AI models for training and predictive analysis. Regression methods: Linear Regression is suitable for numerical predictions. The other models are mentioned in subsection 3.3.

Image data from microscopic analysis, surface topography, and thermal imaging can help AI to understand the outcome of turning operations. Techniques like image processing can be used to recognize the pattern and quality of the produced surface at any given parameter to understand images. The initial step involves capturing images of the object or surface to be analyzed. Pre-processing includes converting images to grayscale, noise reduction, and adjusting parameters like pixel fineness to prepare the image for further analysis [Corke 2017, Okamoto and Ura 2024]. Techniques such as contrast improvement and histogram processing are applied to enhance image quality, making it easier to identify features and defects. This step involves dividing the image into meaningful regions or segments, often using edge detection and thresholding techniques. Segmentation is crucial for isolating areas of interest, such as defects or specific workpiece features [Corke 2017, Kanavi 2021]. Extracting relevant features from the segmented image is essential for analysis. Identifying surface textures, tool wear, or surface tearing. [Rajakumar et al. 2023, Parfenov and Parfenov 2024, Ercetin et al. 2024]. The extracted features are analyzed using algorithms and machine learning models to make decisions or predictions. This can involve comparing features to a database of known defects or using AI to predict maintenance needs [Russ 2006, Burger and Burge 2008, Yapp and See 2008]. The final step involves using the analysis results to inform quality control processes. This can include automatic adjustments in CNC programming or feedback for predictive maintenance, ultimately improving manufacturing precision and reducing errors [Parfenov and Parfenov 2024, Ercetin et al. 2024].

5 FUTURE DIRECTION

AI-based Sustainable Machining - AI-driven predictive modeling for power consumption is crucial for optimizing energy use in machining, aligning with sustainability goals. Future work should develop more sophisticated models to predict and manage energy consumption effectively [Soori et al. 2023, Singh et al. 2024]. *Integration of IoT for Real-time Monitoring* - Future research should explore the integration of AI with other advanced technologies like the Internet of Things (IoT), digital twins, and sensor monitoring to enhance real-time adaptability and predictive maintenance in machining operations [Rajesh et al. 2022, Murzin 2024 *Multi-Objective Optimization* – There is a need for developing multi-objective optimization approaches that consider various aspects of machining processes, such as tool wear, product quality, and energy consumption, to improve overall performance [Aggogeri et al. 2021, Ullrich et al. 2024]. *Interdisciplinary Collaboration* - Addressing the technical and economic complexities of integrating AI into existing manufacturing environments will require multidisciplinary collaboration. This includes combining expertise from computer science, engineering, and materials science [Gao et al. 2024].

6 SUMMARY

Artificial intelligence will completely transform the machining process in Industry 5.0 by enabling continuous product quality monitoring and avoiding unwanted manufacturing failures. Modern manufacturing requires efficiency, sustainability, and improved product quality. The turning process evolved from manual lathes to CNC, with the most recent development being its integration with AI. The future of the turning process depends on integrating AI into production, and integrating AI requires knowledge of process parameters and their impact on quality. Shape, surface roughness parameters, and hardness can characterize quality features. An in-depth understanding of machining parameters, tools, and cutting phenomena is essential for predicting these quality indicators. Artificial intelligence offers a suitable resolution for analyzing complex behaviors and giving precise outcomes. Creating AI models for turning requires machine learning techniques such as Artificial Neural Networks (ANN) and regression models for predictive analysis and decision-making. Different input and output properties are essential for developing a model.

It uses structured and unstructured data, including sensor and image data, for real-time monitoring and optimization. Data processing involves filtering sensor noise, statistical analysis, and feature extraction for AI model training. Future AI advancements in machining will focus on sustainable practices, IoT integration, and multi-objective optimization. Industries can get advantages from AI-driven predictions of tool wear, reduced defects such as chatter and vibration, and improved product quality and precision in machining. Additionally, AI can help reduce energy consumption, contributing to a more sustainable environment.

7 FUNDING

Project no. 2020-1.2.3- EUREKA-2022-00025 has been implemented with support from the Ministry of Culture and Innovation of Hungary from the National Research, Development, and Innovation Fund, financed under the 2020-1.2.3-EUREKA funding scheme.

NATIONAL RESEARCH, DEVELOPMENT AND INNOVATION OFFICE HUNGARY

PROJECT FINANCED FROM THE NRDI FUND

8 REFERENCES

Abhang LB, Hameedullah M (2012) Determination of optimum parameters for multi-performance characteristics in turning by using grey relational analysis. *International Journal of Advanced Manufacturing Technology* 63(1–4):13–24.

Abolghasem S, Mancilla-Cubides N (2022) Optimization of machining parameters for product quality and productivity in the turning process of aluminum. *Ingenieria y Universidad* 26.

Adeolu Adenekan O, Okina Solomon N, Simpa P, Chinenye Obasi S, Author C (2024) Enhancing manufacturing productivity: A review of AI-Driven supply chain management optimization and ERP systems integration. *International Journal of Management & Entrepreneurship Research* 6(5):1607–1624.

Afeen Y, Younis K (2007) The Effect of Cutting Tool Vibration on Surface Roughness of Workpiece in Dry Turning Operation. *Engineering and Technology Journal* 25(7):879–889.

Agatonovic-Kustrin S, Beresford R (2000) Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *J Pharm Biomed Anal* 22(5):717–727.

Aggogeri F, Pellegrini N, Tagliani FL (2021) Recent Advances on Machine Learning Applications in Machining Processes. *Applied Sciences 2021, Vol. 11, Page 8764* 11(18):8764.

Ahijith Kumar P V., Patnaik L, Bharati K, Venkatesh VSS, Kumar S (2024) Investigating tool wear rate and surface quality of hardened tool steel: a fuzzy-MARCOS analysis and response surface methodology study. *International Journal on Interactive Design and Manufacturing* 18(6):4137–4158.

Ahmed T, Mollick N, Mahmud S, Ahmad T (2020a) Analysis of Effects of Machining Parameters on Cutting Force Components in Turning AISI 201 Stainless Steel Using Cemented Carbide Cutting Tool Insert. *Mater Today Proc* (Elsevier Ltd), 832–837.

Ahmed T, Mollick N, Mahmud S, Ahmad T (2020b) Analysis of Effects of Machining Parameters on Cutting Force Components in Turning AISI 201 Stainless Steel Using Cemented Carbide Cutting Tool Insert. *Mater Today Proc* (Elsevier Ltd), 832–837.

Alcacer V, Cruz-Machado V (2019) Scanning the Industry 4.0: A Literature Review on Technologies for Manufacturing Systems. *Engineering Science and Technology, an International Journal* 22(3):899–919. (June 1).

Alexander Z, Chau DH, Saldana C (2024) An Interrogative Survey of Explainable AI in Manufacturing. *IEEE Trans Industr Inform* 20(5):7069–7081.

Amjad MS, Rafique MZ, Hussain S, Khan MA (2020) A new vision of LARG Manufacturing — A trail towards Industry 4.0. *CIRP J Manuf Sci Technol* 31:377–393.

Anon (2017) Spatial Interpolation. *Encyclopedia of GIS*:2032–2032.

Anon Application of ANN in predicting ACC of SCFST column - ScienceDirect. Retrieved (March 31, 2025),

Ansari S, Nassif AB (2022) A Comprehensive Study of Regression Analysis and the Existing Techniques. *2022 Advances in Science and Engineering Technology International Conferences, ASET 2022*.

Anusha PV, Anuradha C, Chandra Murty PSR, Kiran CS (2019) Detecting outliers in high dimensional data sets using Z-score methodology. *International Journal of Innovative Technology and Exploring Engineering* 9(1):48–53.

Aouici H, Yallese MA, Chaoui K, Mabrouki T, Rigal JF (2012) Analysis of surface roughness and cutting force components in hard turning with CBN tool: Prediction model and cutting conditions optimization. *Measurement (Lond)* 45(3):344–353.

Arinez JF, Chang Q, Gao RX, Xu C, Zhang J (2020) Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook. *Journal of Manufacturing Science and Engineering, Transactions of the ASME* 142(11).

Astakhov VP (2011) Turning. *Modern Machining Technology*:1–78.

Barzani MM, Sarhan AAD, Farahany S, Ramesh S, Maher I (2015) Investigating the machinability of Al-Si-Cu cast alloy containing bismuth and antimony using coated carbide insert. *Measurement (Lond)* 62:170–178.

Baskar N, Nurul Islam MA, Rosario AS (2024) Investigation of Machining Parameters for Turning Process. *Copyright@ REST Publisher 32 REST Journal on Advances in Mechanical Engineering* 3(1):32–36.

Besigomwe K, Global O, Corresponding U (2025) Closed-Loop Manufacturing with AI-Enabled Digital Twin Systems. *Cognizance Journal of Multidisciplinary Studies* 5(1):18–38.

Brown I, Schoop J (2020) The effect of cutting edge geometry, nose radius and feed on surface integrity in finish turning of Ti-6Al4V. *Procedia CIRP* (Elsevier B.V.), 142–147.

Buer SV, Strandhagen JO, Chan FTS (2018) The link between industry 4.0 and lean manufacturing : Mapping current research and establishing a research agenda. *Int J Prod Res* 56(8):2924–2940.

Burger W, Burge MJ (2008) Digital Image Processing : An Algorithmic Introduction Using Java, First Edition. *Texts in Computer Science* :1–564.

Cervantes J, Garcia-Lamont F, Rodríguez-Mazahua L, Lopez A (2020) A comprehensive survey on support vector machine classification: Applications, challenges and trends. *Neurocomputing* 408:189–215.

Chen Y, Sun R, Gao Y, Leopold J (2017) A nested-ANN prediction model for surface roughness considering the effects of cutting forces and tool vibrations. *Measurement (Lond)* 98:25–34.

Colantonio L, Equeter L, Dehombreux P, Ducobu F (2021) A Systematic Literature Review of Cutting Tool Wear Monitoring in Turning by Using Artificial Intelligence Techniques. *Machines 2021, Vol. 9, Page 351* 9(12):351.

Corke P (2017) Images and Image Processing. *Springer Tracts in Advanced Robotics* 118:359–411.

Dey PK, Chowdhury S, Abadie A, Vann Yaroson E, Sarkar S (2024) Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small- and medium-sized enterprises. *Int J Prod Res* 62(15):5417–5456.

Dobrzynski M, Mietka K (2021) Surface texture after turning for various workpiece rigidities. *Machines* 9(1):1–10. (January 1).

Dosbaeva GK, Veldhuis SC, Elfizy A, Fox-Rabinovich G, Wagg T (2010) Microscopic observations on the origin of defects during machining of direct aged (DA) inconel 718 superalloy. *J Mater Eng Perform* 19(8):1193–1198.

Duplak J, Duplakova D, Zajac J (2023) Research on Roughness and Microhardness of C45 Material Using High-Speed Machining. *Applied Sciences (Switzerland)* 13(13).

Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, Crick T, Duan Y, et al. (2021) Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int J Inf Manage* 57:101994.

Editors A, Stepinski T, Marinos V, Gavin K, Kovačevi MS, Bači M, Abbaszadeh Shahri A, Shan C, Larsson S, Johansson F (2024) Normalizing Large Scale Sensor-Based MWD Data: An Automated Method toward A Unified Database. *Sensors 2024, Vol. 24, Page 1209* 24(4):1209.

Ercetin A, Der O, Akkoyun F, Gowdru Chandrashekarappa MP, Şener R, Çalışan M, Olgun N, Chate G, Bharath KN (2024) Review of Image Processing Methods for Surface and Tool Condition Assessments in Machining. *Journal of Manufacturing and Materials Processing 2024, Vol. 8, Page 244* 8(6):244.

Felhő C, Namboodri T (2024) Statistical Analysis of Cutting Force and Vibration in Turning X5CrNi18-10 Steel. *Applied Sciences* 15(1):54.

Felhő C, Namboodri T, Sisodia RPS (2025) Taguchi's L18 Design of Experiments for Investigating the Effects of Cutting Parameters on Surface Integrity in X5CrNi18-10 Turning. *Designs (Basel)* 9(3):59.

Felhő C, Sztankovics I, Maros Z, Kun-Bodnár K (2023) FEM Simulation of the Flange Turning in the Production of Aluminium Aerosol Cans.

Fernández-Delgado M, Sirsat MS, Cernadas E, Alawadi S, Barro S, Febrero-Bande M (2019) An extensive experimental survey of regression methods. *Neural Networks* 111:11–34.

Franzese M, Iuliano A (2025) Hidden Markov Models (HMM). *Encyclopedia of Bioinformatics and Computational Biology*:324–335.

Gao RX, Krüger J, Merklein M, Möhring HC, Váncza J (2024) Artificial Intelligence in manufacturing: State of the art, perspectives, and future directions. *CIRP Annals* 73(2):723–749.

Geranmayeh P, Grass E (2024) Comparison of Optimization Techniques and Machine Learning Methods for Optimized Beamforming in Wireless Networks. *Proceedings of the IEEE-APS Topical Conference on Antennas and Propagation in Wireless Communications, APWC* (2024):66–70.

Hanief M, Wani MF, Charoo MS (2017) Modeling and prediction of cutting forces during the turning of red brass (C23000) using ANN and regression analysis. *Engineering Science and Technology, an International Journal* 20(3):1220–1226.

Hessainia Z, Belbah A, Yallese MA, Mabrouki T, Rigal JF (2013a) On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations. *Measurement (Lond)* 46(5):1671–1681.

Hessainia Z, Belbah A, Yallese MA, Mabrouki T, Rigal JF (2013b) On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations. *Measurement (Lond)* 46(5):1671–1681.

Ho NTQ, Do TT (2023) Effects of Workpiece Surface and Cutting Parameters on the Finished Surface Quality in Turning Based on Finite Element Method. *Journal of Technical Education Science* (78B):18–25.

Hoang L, Nguyen LT (2023) Analysing the impact of cutting force and vibration on surface roughness in external cylindrical grinding of SKH2 steel. *Journal of Machine Engineering* 23(3):130–140.

Jain S, Shukla S, Wadhvani R (2018) Dynamic selection of normalization techniques using data complexity measures. *Expert Syst Appl* 106:252–262.

Jamwal A, Agrawal R, Sharma M (2022) Deep learning for manufacturing sustainability: Models, applications in Industry 4.0 and implications. *International Journal of Information Management Data Insights* 2(2):100107.

Jang DY, Choi YG, Kim HG, Hsiao A (1996) Study of the correlation between surface roughness and cutting vibrations to develop an on-line roughness measuring technique in hard turning. *Int J Mach Tools Manuf* 36(4):453–464.

Jia S, Liao J, Xu M, Li Y, Zhu J, Sun W, Jia X, Li Q (2022) 3-D Gabor Convolutional Neural Network for Hyperspectral Image Classification. *IEEE Transactions on Geoscience and Remote Sensing* 60.

Jiang Xu, Jiang Xiaoxian, Sun W, Fan W (2024) How Do Manufacturing Firms Manage Artificial Intelligence to Drive Iterative Product Innovation? *IEEE Trans Eng Manag* 71:6090–6102.

Kaiser JF, Reed WA (1977) Data smoothing using low-pass digital filters. *Review of Scientific Instruments* 48(11):1447–1457.

Kalina KA, Linden L, Brummund J, Kästner M (2023) FE ANN : an efficient data-driven multiscale approach based on physics-constrained neural networks and automated data mining. *Comput Mech* 71(5):827–851.

Kanavi V (2021) Analysis of Image Processing and Its Challenges. *International Journal for Research in Applied Science & Engineering Technology (IJRASET)* 9:2321–9653.

Kang WT, Derani MN, Ratnam MM (2020) Effect of Vibration on Surface Roughness in Finish Turning: Simulation Study. *International Journal of Simulation Modelling* 19(4):595–606.

Kenda K, Skrbec J, Skrjanc M Usage of the Kalman filter for data cleaning of sensor data.

Kinkel S, Baumgartner M, Cherubini E (2022) Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies. *Technovation* 110:102375.

Kong L, Chen G, Wang L, Wang D, Chen W, Zhang T (2016) Research on vibration and surface roughness in hard cutting process of hardened stee. *Key Eng Mater* 693:878–883.

Kónya G, Takács J, Miskolczi I, Kovács ZF (2024) Investigation of the effects of machining parameters on cutting conditions during orthogonal turning of austenite stainless steel. *Production Engineering Archives* 30(1):86–93.

Kouahla I, Yallese MA, Belhadi S, Safi K, Nouioua M (2022) Tool vibration, surface roughness, cutting power, and productivity assessment using RSM and GRA approach during machining of Inconel 718 with PVD-coated carbide tool. *International Journal of Advanced Manufacturing Technology* 122(3–4):1835–1856.

Kumar Ashwani, Bansal P, Kumar Abhishek, Gupta AK, Choudhari A (2024) Digital Manufacturing Artificial Intelligence in Industry 5.0. *Artificial Intelligence and Communication Techniques in Industry 5.0*:1–25.

Kumar N, Kumar K *Investigation on effects of various process parameters in turning operation*

Kumar S, Bhatnagar V (2022) *A Review of Regression Models in Machine Learning*

Kumar S, Gupta M, Satsangi PS (2015) Multiple-response optimization of cutting forces in turning of UD-GFRP composite using Distance-Based Pareto Genetic Algorithm approach. *Engineering Science and Technology, an International Journal* 18(4):680–695.

Kundrak J, Sztankovics I, Molnar V (2021) Accuracy and topography analysis of hard machined surfaces. *http://journalmt.com/doi/10.21062/mft.2021.057.html* 21(4):512–519.

Li C, Zhao G, Ji D, Zhang G, Liu L, Zeng F, Zhao Z (2024) Influence of Tool Wear and Workpiece Diameter on Surface Quality and Prediction of Surface Roughness in Turning. *Metals (Basel)* 14(11).

Lira JOB, Riella HG, Padoin N, Soares C (2022) Computational fluid dynamics (CFD), artificial neural network (ANN) and genetic algorithm (GA) as a hybrid method for the analysis and optimization of micro-photocatalytic reactors: NOx abatement as a case study. *Chemical Engineering Journal* 431:133771.

Liu J, Zhu C, Long Z, Liu Y (2021) Tensor Regression. *Foundations and Trends® in Machine Learning* 14(4):379–565.

Lu Y (2017) Industry 4.0: A survey on technologies, applications and open research issues. *J Ind Inf Integr* 6:1–10. (June 1).

Machado CG, Winroth MP, Ribeiro da Silva EHD (2020) Sustainable manufacturing in Industry 4.0: an emerging research agenda. *Int J Prod Res* 58(5):1462–1484.

Maind SB, Wankar P (2014) Research Paper on Basic of Artificial Neural Network. *International Journal on Recent and Innovation Trends in Computing and Communication* 2(1):96–100.

Manikyala Rao V, Uma Pavan Kumar K, Priyanka B (2019) Statistical methods in the usage of correlation and regression of the machine learning models. *International Journal of Recent Technology and Engineering* 8(2 Special Issue 11):2489–2491.

Maros Z, Felhő C, Vass Z, Maros MB (2015) Application of 2D-3D Surface Geometrical Features in Tribological Analysis of Ceramics and Ceramic Layers. *Materials Science Forum* 812:435–440.

Molaiekiya F, Aliakbari Khoei A, Aramesh M, Veldhuis SC (2021) Machined surface integrity of inconel 718 in high-speed dry milling using SiAlON ceramic tools. *International Journal of Advanced Manufacturing Technology* 112(7–8):1941–1950.

Moore T (2001) Regression Analysis by Example. *Technometrics* 43(2):236–236.

Mourtzis D (2020) Simulation in the design and operation of manufacturing systems: state of the art and new trends. *Int J Prod Res* 58(7):1927–1949.

Mozaffar M, Liao S, Xie X, Saha S, Park C, Cao J, Liu WK, Gan Z (2022) Mechanistic artificial intelligence (mechanistic-AI) for modeling, design, and control of advanced manufacturing processes: Current state and perspectives. *J Mater Process Technol* 302:117485.

Mujagić D, Imamović A, Hadazalić M (2021) Properties of austenite stainless steel microalloyed with tellurium and zirconium. *Journal of Sustainable Technologies and Materials* 1(1):20–29.

Murzin SP (2024) Artificial Intelligence-Driven Innovations in Laser Processing of Metallic Materials. *Metals 2024, Vol. 14, Page 1458* 14(12):1458.

Nagwa Mejid Ibrahim Elsiti, Mohamed Handawi Saad Elmunafi (2023) Optimization of machining parameters for turning process by using grey relational analysis. *World Journal of Advanced Research and Reviews* 17(1):756–761.

Namboodri T (2023) Prediction of surface roughness using AI. (2023) : 81-84.

Namboodri T, Felhő C (2024) Correlation Analysis Between Components of Force and Vibration in Turning Of 11SMn30 Steel. *Cutting & Tools in Technological System* (101):39–50.

Narang SK, Gadde A, Ortega A (2013) Signal processing techniques for interpolation in graph structured data. *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*:5445–5449.

Nian CY, Yang WH, Tarng YS *Optimization of turning operations with multiple performance characteristics*

Okamoto T, Ura S (2024) Verifying the Accuracy of 3D-Printed Objects Using an Image Processing System. *Journal of Manufacturing and Materials Processing 2024, Vol. 8, Page 94* 8(3):94.

Palanisamy A, Selvaraj T, Sivasankaran S (2018) Optimization of Turning Parameters of Machining Incoloy 800H Superalloy Using Cryogenically Treated Multilayer CVD-Coated Tool. *Arab J Sci Eng* 43(9):4977–4990.

Panetto H, Iung B, Ivanov D, Weichhart G, Wang X (2019) Challenges for the cyber-physical manufacturing enterprises of the future. *Annu Rev Control* 47:200–213. (January 1).

Papadimitriou I, Gialampoukidis I, Vrochidis S, Kompatsiaris I (2024) AI methods in materials design, discovery and manufacturing: A review. *Comput Mater Sci* 235:112793.

Parfenov A, Parfenov D (2024) Creating an Image Recognition Model to Optimize Technological Processes. *2024 IEEE International Multi-Conference on Engineering, Computer and Information Sciences (SIBIRCON)*:421–424.

Patel MB, Patel JN, Bhilota UM, Patel MB, Patel JN, Bhilota UM (1AD) Comprehensive Modelling of ANN. *https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-7998-4042-8.ch002*:18–29.

Petre IM, Găvruș C *ANNALS of Faculty Engineering Hunedoara-International journal of engineering Tome XIX*

[2021] | Fascicule 2 [May] Experimental research regarding the influence of cutting parameters on cutting force in turning operation

Qu K (2024) Research on linear regression algorithm. *MATEC Web of Conferences* 395:01046.

Rajakumar PS, Geetha S, Ananthan T V. (2023) Fundamentals of Image Processing. *Fundamentals of Image Processing*.

Rajesh AS, Prabhu Swamy MS, Krishnasamy S (2022) Smart Manufacturing through Machine Learning: A Review, Perspective, and Future Directions to the Machining Industry. *Journal of Engineering* 2022(1):9735862.

Rakholia R, Suárez-Cetrulo AL, Singh M, Carbajo RS (2024) Advancing Manufacturing Through Artificial Intelligence: Current Landscape, Perspectives, Best Practices, Challenges and Future Direction. *IEEE Access*.

Rena Q, Balazinskia M, Barona L, Jemielniakb K (2011) TSK fuzzy modeling for tool wear condition in turning processes: An experimental study. *Eng Appl Artif Intell* 24(2):260–265.

Russ JC (2006) The Image Processing Handbook, Fifth Edition. *The Image Processing Handbook, Fifth Edition*:1–819.

Safi K, Yallese MA, Belhadi S, Mabrouki T, laouissi A (2022) Tool wear, 3D surface topography, and comparative analysis of GRA, MOORA, DEAR, and WASPAS optimization techniques in turning of cold work tool steel. *International Journal of Advanced Manufacturing Technology* 121(1–2):701–721.

Salman K h., Elsheikh AH, Ashham M, Ali MKA, Rashad M, Haiou Z (2019b) Effect of cutting parameters on surface residual stresses in dry turning of AISI 1035 alloy. *Journal of the Brazilian Society of Mechanical Sciences and Engineering* 41(8).

Savella FB, Pereira VWS, Shiki SB, Ventura CEH, Antonialli AIS (2022) Analysis of the effect of part geometry and cutting parameters over tool vibration and surface integrity on hard turning. *International Journal of Advanced Manufacturing Technology* 122(9–10):4065–4077.

Sengupta SK, Kay SM (1995) Fundamentals of Statistical Signal Processing: Estimation Theory. *Technometrics* 37(4):465.

Sharma V, Kumar P, Misra JP (2019) Cutting force predictive modelling of hard turning operation using fuzzy logic. *Mater Today Proc* (Elsevier Ltd), 740–744.

Sharman ARC, Hughes JI, Ridgway K (2004) Workpiece surface integrity and tool life issues when turning inconel 718TM nickel-based superalloy. *Machining Science and Technology* 8(3):399–414.

Shehab M, Abualigah L, Omari M, Shambour MKY, Alshinwan M, Abuaddous HY, Khasawneh AM (2022) Artificial neural networks for engineering applications: a review. *Artificial Neural Networks for Renewable Energy Systems and Real-World Applications*:189–206.

Siddique MZ, Faraz MI, Butt SI, Khan R, Petru J, Jaffery SHI, Khan MA, Tahir AM (2023) Parametric Analysis of Tool Wear, Surface Roughness and Energy Consumption during Turning of Inconel 718 under Dry, Wet and MQL Conditions. *Machines* 11(11).

Singh Shweta, Singh Satendra, Pawar R, Kulhar KS (2024) Artificial Intelligence Approaches for Predictive Power Consumption Modeling in Machining-Short Review. *E3S Web of Conferences* 540:06015.

Sivaiah P, Revantha Kumar M, Bala Subramanyam S, Prasad KLV (2021) A comparative study on different textured and untextured tools performance in turning process. *Materials and Manufacturing Processes* 36(8):926–935.

Sivam SPSS, Rajendrakumar S, Rajasekaran A, Karuppiah S (2018) Prediction Model of Setting Input Parameters for Turning Operation TI-6AL-4V by Fuzzy Rule based modeling. *IEEE International Conference on Power, Control, Signals and Instrumentation Engineering, ICPCSI 2017*:1343–1349.

Soori M, Arezoo B, Dastres R (2023) Machine learning and artificial intelligence in CNC machine tools, A review. *Sustainable Manufacturing and Service Economics* 2:100009.

Sztankovics I (2024a) A study of the micro-geometric errors of tangentially turned surfaces using the design of experiments method. *Materials Research Proceedings* 46:106–113.

Sztankovics I (2024b) The Analytical and Experimental Analysis of the Machined Surface Roughness in High-Feed Tangential Turning. *Eng 2024, Vol. 5, Pages 1768-1784* 5(3):1768–1784.

Sztankovics I, Felhő C, Kun-Bodnar K, Maros Z (2024) Shape Accuracy Improvement of the Flange Turning Process in Aluminum Aerosol Can Production. *Eng 2024, Vol. 5, Pages 3381-3396* 5(4):3381–3396.

Tanuj N, Felhő C (2024) Investigating the impact of vibration characteristics on the surface roughness using MPU6050 sensor at turning of 11SMn30 steel. *Multidiszciplináris Tudományok* 14(4):287–300.

Trebuna P, Pekarcikova M, Dic M (2022) Comparing Modern Manufacturing Tools and Their Effect on Zero-Defect Manufacturing Strategies. *Applied Sciences (Switzerland)* 12(22).

Tzeng CJ, Lin YH, Yang YK, Jeng MC (2009) Optimization of turning operations with multiple performance characteristics using the Taguchi method and Grey relational analysis. *J Mater Process Technol* 209(6):2753–2759. (March 19).

Ullrich K, von Elling M, Gutzeit K, Dix M, Weigold M, Aurich JC, Wertheim R, Jawahir IS, Ghadbeigi H (2024) AI-based optimisation of total machining performance: A review. *CIRP J Manuf Sci Technol* 50:40–54.

Umamaheswarrao P, Rangaraju D, Suman KNS, Ravisankar B (2021) Application of TOPSIS for multi response optimization of Process Parameters in dry hard turning of AISI 52100 steel. *INCAS Bulletin* 13(1):211–224.

Wang B (2018) The Future of Manufacturing: A New Perspective. *Engineering* 4(5):722–728. (October 1).

Wang D, Weisz JD, Muller M, Ram P, Geyer W, Dugan C, Tausczik Y, Samulowitz H, Gray A (2019) Human-AI Collaboration in Data Science. *Proc ACM Hum Comput Interact* 3(CSCW).

Wasukar AR (2014) Artificial Neural Network-An Important Asset for Future Computing. *International journal for research in emerging science and technology* (1).

Whang SE, Roh Y, Song H, Lee JG (2023) Data collection and quality challenges in deep learning: a data-centric AI perspective. *VLDB Journal* 32(4):791–813.

Xie S, Zhang W, Xue F, Li D, Liu Y, Fleischer J, Ehrmann C (2022) Industry 4.0-Oriented Turnkey Project: Rapid Configuration and Intelligent Operation of Manufacturing Systems. *Machines* 10(11).

Xu D, Ding L, Liu Y, Zhou J, Liao Z (2021) Investigation of the influence of tool rake angles on machining of inconel 718. *Journal of Manufacturing and Materials Processing* 5(3).

Xu J, Kovatsch M, Mattern D, Mazza F, Harasic M, Paschke A, Lucia S (2022) A Review on AI for Smart Manufacturing: Deep Learning Challenges and Solutions. *Applied Sciences 2022, Vol. 12, Page 8239* 12(16):8239.

Xu L Da, Xu EL, Li L (2018) Industry 4.0: State of the art and future trends. *Int J Prod Res* 56(8):2941–2962.

Yang L, Liu S, Tsoka S, Papageorgiou LG (2017) A regression tree approach using mathematical programming. *Expert Syst Appl* 78:347–357.

Yapp CHW, See AK Bin (2008) Teaching image processing: A two-step process. *Computer Applications in Engineering Education* 16(3):211–222.

Yildiz AR (2012) A comparative study of population-based optimization algorithms for turning operations. *Inf Sci (N Y)* 210:81–88.

Yuan ZJ, Zhou M, Dong S (1996) Effect of diamond tool sharpness on minimum cutting thickness and cutting surface integrity in ultraprecision machining. *J Mater Process Technol* 62(4):327–330.

Yusup N, Zain AM, Hashim SZM (2012) Evolutionary techniques in optimizing machining parameters: Review and recent applications (2007-2011). *Expert Syst Appl* 39(10):9909–9927. (August).

Zhang K, Aslan AB (2021) AI technologies for education: Recent research & future directions. *Computers and Education: Artificial Intelligence* 2:100025.

Ермаков СМ, Леора СН (2022) О выборе базисных функций регрессии и машинном обучении. *Вестник Санкт-Петербургского университета. Математика. Механика. Астрономия* 9(1):11–22.