The Use of Artificial Intelligence Techniques to Improve Production Quality in Machining Processes

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Introduction

Overview of Industrial Revolutions and Their Impact on Manufacturing

Industrial revolutions have been among the most significant transformation processes in human history. Beginning in the 18th century with the first industrial revolution driven by steam power and mechanization, it marked the initial transition from manual labor to machine use in production processes. Subsequently, the second industrial revolution, characterized by the advent of electric power and mass production techniques, dramatically increased production speed and scale. The third industrial revolution introduced digitalization and automation, bringing greater flexibility to manufacturing (Vogel and Hess, 2016).

The Fourth Industrial Revolution (Industry 4.0) is currently revolutionizing manufacturing processes through the incorporation of cyber-physical systems, the Internet of Things (IoT), artificial intelligence (AI), and big data analytics. These advancements contribute to improved efficiency, flexibility, and product quality, while simultaneously lowering costs and fostering sustainability in production systems (Thoben et al., 2017).

All stages of the industrial revolutions have profoundly impacted precision and quality-dependent manufacturing processes, such as machining. The transition from traditional methods to intelligent manufacturing systems has become critical for gaining a competitive edge and meeting customer expectations (Guo et al., 2018).

The Role of Advanced Technologies in Enhancing Production Quality

Advanced technologies play a crucial role in enhancing quality in production processes. Precision manufacturing techniques and advanced control systems optimize the dimensional accuracy and surface quality of products while minimizing errors. In particular, big data analytics enables proactive management of processes by identifying potential issues on production lines in advance (Guvenc, 2022).

Artificial intelligence (AI) is one of the most significant technologies developed to improve production quality. For example, machine learning algorithms analyze sensor data to enhance product quality and minimize machine downtime (Cakir, 2022). Robotic automation systems, on the other hand, accelerate production processes, helping to achieve more consistent and higher-quality products (Gilchrist, 2016).

Modern production processes face numerous challenges, including high competition, diversity in customer demands, and sustainability requirements (Li et al., 2017). Key challenges include:

- **Production Efficiency**: Competing with traditional methods has become increasingly difficult. Shorter production cycles and high-quality demands necessitate continuous improvement of production processes.
- **Resource Management**: Rising raw material and energy costs drive businesses toward more sustainable production methods.
- **Technology Adaptation**: Transitioning to Industry 4.0 technologies poses financial and operational challenges, particularly for small and medium-sized enterprises (SMEs).
- **Workforce Shortages**: High-tech requirements demand a more skilled and equipped workforce, complicating the recruitment and training of qualified personnel.
- **Environmental Impact**: Sustainability goals encourage the adoption of innovative production methods to reduce the carbon footprint.

These challenges necessitate the integration of innovative technologies and AI-powered solutions. Manufacturers must overcome these barriers to establish more sustainable, flexible, and efficient processes (Li et al., 2015).

Additionally, technologies such as virtual reality (VR) and augmented reality (AR) are being employed in production design and process planning, offering new methods to reduce errors and enhance quality. The combined use of these technologies significantly raises quality standards, particularly in complex and detail-oriented processes like machining.

Importance of Machining Processes in Modern Manufacturing

Machining is an indispensable part of modern manufacturing technologies. In industries where factors such as precision, surface quality, and material properties are critical, machining methods offer high accuracy. Sectors requiring advanced technologies, such as automotive, aerospace, defense, and medical devices, heavily rely on machining processes. Machining methods provide flexibility to work on materials like metal, plastic, and composites. These methods include milling, turning, grinding, and drilling. Each process must be optimized to meet the dimensions, surface characteristics, and functional requirements of the product (Guvenc, 2022; Bilgic, 2019).

In addition to traditional approaches, the integration of AI-supported systems into machining processes in modern production offers significant potential for preventing manufacturing defects, increasing production speed, and improving final product quality. In this context, the role of technology in machining processes is becoming increasingly critical for the continuous development and competitiveness of the industry (Hoe et al., 2018; Guvenc, 2023).

Industrial Developments and Their Influence on Manufacturing Efficiency

The transition from the Third Industrial Revolution to the Fourth Industrial Revolution has created a radical transformation in manufacturing processes. While Industry 3.0 marked the beginning of digitalization, it also witnessed the widespread adoption of automation, programmable logic controllers (PLCs) and computer-operated machines. During this era, manufacturing processes became faster, more reliable, and more repeatable (Gilchrist, 2016).

Industry 4.0, however, goes beyond this digital foundation by leveraging cyber-physical systems and the Internet of Things (IoT) to make manufacturing processes smarter and more interconnected. Machines can now communicate with one another and make decisions based on real-time data. This transition has enabled manufacturing processes to become more efficient and flexible (Kim et al., 2018).

For instance, digital twin technology creates a simulation of the production line, allowing for the identification of potential errors and the optimization of processes. Furthermore, big data analytics and AI-based systems enhance manufacturing efficiency while continuously learning and adapting to improve quality (Khuntia, 2019).

This transition has also impacted the workforce. Manufacturing processes now require less human intervention but demand higher levels of technical expertise and knowledge. Consequently, the effects of Industry 4.0 extend beyond manufacturing processes to reshape workforce training and management strategies (Thoben, 2017).

Smart manufacturing encompasses the most significant trends shaping the future of production processes. By transcending traditional automation, it integrates artificial intelligence, robotics, IoT, and big data analytics, leading to a complete transformation of manufacturing systems (Thoben, 2017; Guvenc, 2022). The key trends include:

- **Robotic Automation**: The shift from traditional production lines to robot-assisted flexible systems ensures speed and precision in manufacturing. For instance, collaborative robots (cobots) operate in conjunction with human workers, augmenting overall productivity and improving operational efficiency.
- **Cyber-Physical Systems**: Full integration of manufacturing machines with the digital world enables real-time monitoring and optimization of processes.
- **Big Data and Analytics**: The acquisition and examination of manufacturing data facilitate predictive and proactive management of production processes. For example, predictive maintenance algorithms can identify potential machine malfunctions prior to their occurrence, enabling timely interventions.
- **Sustainability-Oriented Technologies**: Practices such as using recyclable materials, reducing energy consumption, and minimizing waste are integral components of smart manufacturing.
- **Artificial Intelligence and Machine Learning**: Applications of AI in quality control, process optimization, and decision-support systems are becoming increasingly prevalent.

These trends make manufacturing processes more flexible, efficient, and sustainable. Additionally, they provide businesses with a competitive advantage by enabling the delivery of high-quality products that meet customer expectations (Teti et al., 2010).

Factors Influencing Product Quality in Machining Processes

Material Properties and Their Effects on Machining

Material properties are among the most critical factors determining product quality in machining processes. Characteristics such as hardness, strength, ductility, and thermal conductivity of the workpiece material directly influence both machining parameters and the resulting surface quality (Teti et al., 2010).

- **Hardness**: Harder materials can accelerate tool wear and increase surface roughness. In such cases, selecting the appropriate cutting tool and fine-tuning machining parameters are crucial.

- **Strength**: High-strength materials require more power and energy during machining, which can impose additional loads on machine performance and potentially affect machining accuracy.
- **Ductility**: Ductile materials may hinder chip breaking during machining, leading to reduced surface quality. Chip breaker designs or specialized cooling fluids can be employed to address this issue.
- **Thermal Properties**: The thermal conductivity of a material impacts its ability to dissipate heat during machining. Materials with low thermal conductivity may cause overheating in the cutting zone, which can compromise dimensional accuracy.

Understanding material properties and making informed material selections are essential for producing high-quality products. Employing machining methods tailored to the material's characteristics is necessary to optimize surface roughness and dimensional accuracy (Zhang et al., 2015).

Machine Tool Parameters: Spindle Speed, Feed Rate, and Depth of Cut

The parameters of machine tools are crucial in influencing both the performance and the quality of products in machining processes. It is vital to optimize factors such as spindle speed, feed rate, and depth of cut to enhance the efficiency and effectiveness of cutting operations:

- **Spindle Speed**: Influences surface roughness and machining time. Higher speeds can improve surface smoothness but may accelerate tool wear.
- **Feed Rate**: Determines the material's movement speed across the machine. Higher feed rates can reduce production time but may increase surface roughness and cutting forces.
- **Depth of Cut**: Defines the amount of material removed in a single pass. Greater depths of cut can shorten machining time but may increase tool load, reducing tool life.

An optimal combination of these parameters enhances product quality while minimizing production costs. Experimental studies or AI-assisted modeling methods are often used to determine the best parameter settings (Guvenc, 2022; Abouelattta, 2001).

Environmental and Operational Factors: Temperature, Lubrication, and Tool Wear

Environmental and operational factors significantly influence the efficiency of machining processes and product quality:

- **Temperature**: Heat generated during cutting has a profound effect on machining quality. High temperatures can cause thermal expansion of the material, leading to dimensional inaccuracies. Additionally, thermal damage may occur to the cutting tool.
- **Cooling and Lubrication**: Coolants control temperature in the cutting zone, reduce friction, and facilitate chip removal. However, improperly selected or insufficiently applied coolants can lead to undesirable surface roughness.
- **Tool Wear**: Tool wear is inevitable over the tool's lifespan. A worn tool degrades surface quality and requires higher cutting forces. Monitoring and timely replacement of worn tools are vital for ensuring process continuity.

Effectively managing these factors is a critical step toward achieving consistent production of high-quality products (Upase and Ambhore, 2020).

Integration of Artificial Intelligence in Machining Processes

Applications of Artificial Intelligence in Machining

AI has a variety of applications in machining processes, offering significant potential to enhance production quality, optimize process efficiency, and reduce costs:

- **Predictive Maintenance**: AI-based predictive models analyze data from machine sensors to detect equipment failures in advance. This reduces unplanned downtimes and extends machine lifespan.

- **Process Optimization**: AI algorithms are employed to optimize key machining parameters, including spindle speed, feed rate, and depth of cut, thereby facilitating the efficient production of high-quality products within reduced time intervals.

- **Quality Control**: Image processing and deep learning algorithms assess surface quality and dimensional accuracy of products. These systems can detect defects that are too small for the human eye to perceive.

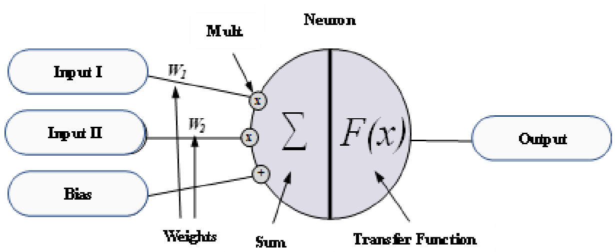
- **Chip Formation and Management**: In machining processes, controlling the shape and size of chips influences machining stability. AI analyzes chip formation mechanisms and develops optimal chip-breaking strategies (Kim, 2018).

Types of AI Used in Machining: ANN, ANFIS, and Metaheuristic Algorithms (A Practical Approach)

Various artificial intelligence methods are applied in machining processes to perform prediction and optimization tasks across different stages of production:

- **Artificial Neural Networks (ANNs)**: ANNs modeled after the human nervous system, are composed of interconnected units referred to as artificial neurons. Similar to biological neurons, artificial neurons evaluate incoming information and transmit it to other neurons or output units. As illustrated in Figure 2, ANNs are widely used to model complex process relationships and perform data analytics. A schematic representation of the artificial neuron model is shown in Figure 3.15. If formalized, Equation 1 can be derived to describe this system (Jain and Mao, 1996).

Figure 1
The Structure of Artificial Neuron (Güvenç, 2022)



$$y(k) = F(\textstyle\sum_{i=0}^{m} \quad x_i . w_i + b) y(k) = F(\textstyle\sum_{i=0}^{m} \quad x_i . w_i + b) \tag{1}$$

In the equation:

- ***xi*** represents the input value at time *k*, ranging from 0 to m.

- ***wi*** denotes the weight value at time *k*, ranging from 0 to m.
- ***b*** is the bias term.
- ***F*** is the transfer function.
- ***y(k)*** is the output value at time *k.*

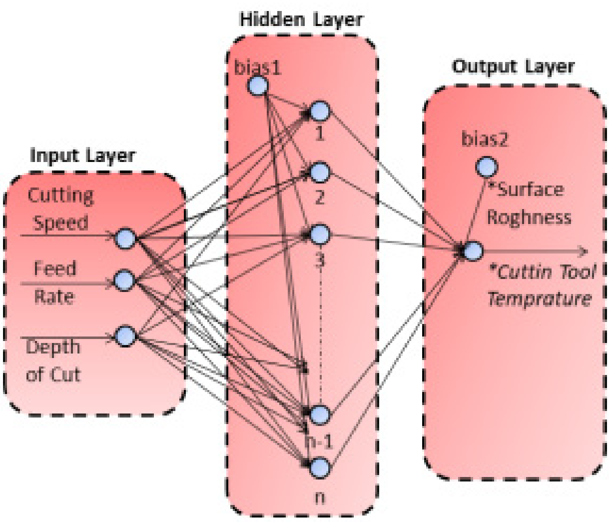
ANNs have extensive applications in machining processes. ANNs are highly effective for modeling datasets with complex and nonlinear relationships. Key applications of ANN in machining processes include:

- **Prediction of Surface Roughness**: Surface roughness during machining is influenced by factors such as spindle speed, feed rate, and depth of cut. ANN models learn the complex relationships between these parameters to predict surface quality (Bilgic, 2019).
- **Process Optimization**: ANN is employed to determine optimal machining parameters in production processes. For instance, it can predict parameters that maximize quality while minimizing production costs.
- **Monitoring Tool Wear**: Tool wear affects product quality and machining time. ANN-based systems analyze sensor data to predict tool wear in advance and determine optimal replacement times (Upase and Ambhore, 2020).

In a study conducted by Güvenç (2022), ANN was used to predict surface roughness and tool-tip temperature during the turning of S235JR alloy material. An image captured during the study is provided in Figure 2.

Figure 2
Image taken during turning (Güvenç, 2022)

Figure 3
Structure of ANN Model (Bilgic, 2019)



The results obtained from the Artificial Neural Network (ANN) model were compared with those derived from the Multiple Linear Regression Model (MLRM). The schematic representation of the ANN model is illustrated in Figure 3. In this model, cutting speed, feed rate, and depth of cut were provided as inputs to predict surface roughness and tool-tip temperature (Güvenç, 2022).

Table 1 presents the performance criteria for training, testing, and overall data for both the MLRM and ANN models. As shown in the table, the coefficient of determination (*R*) for tool-tip temperature evaluations was approximately 92% for the ANN, while it was only 76% for the MLRM. Similarly, for surface roughness predictions, the *R* value of the ANN model was 93%, whereas it remained at 43% for the MLRM (Güvenç, 2022).

Table 1

The performance results of ANN (Güvenç 2022, Bilgic, 2019)

Tool Temperature						
	Train		**Test**		**All Data**	
	ANN	MLRM	ANN	MLRM	ANN	MLRM
MSE	1,0611	1,1994	0,0186	4,2618	0,8006	2,3400
MAE	0,5219	1,0008	0,0847	1,8641	0,4126	1,2166
RMSE	1,0301	1,3036	0,1374	2,0664	0,8947	1,5297
R	0,8889	0,8100	0,9986	0,8228	0,9189	0,7555
Surface Roughness						
	Train		**Test**		**All Data**	
	ANN	ÇLRM	ANN	ÇLRM	ANN	ÇLRM
MSE	0,1484	0,7693	0,0529	1,8960	0,1245	1,0510
MAE	0,2566	0,7059	0,1863	1,2388	0,2390	0,8391
RMSE	0,3852	0,8771	0,2300	1,3770	0,3528	1,0252
R	0,9228	0,5941	0,9825	0,0001	0,9320	0,4276

To better visualize the model performances, the surface roughness and tool-tip temperature predictions are depicted as graphs in Figures 4 and 5, respectively. Based on these figures, as well as evaluations of metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and *R*, ANN—a widely used artificial intelligence technique demonstrates significantly higher accuracy than the traditional MLRM (Guvenc, 2022).

Figure 4

Model Achievement Results for Surface Roughness (Güvenç, 2022)

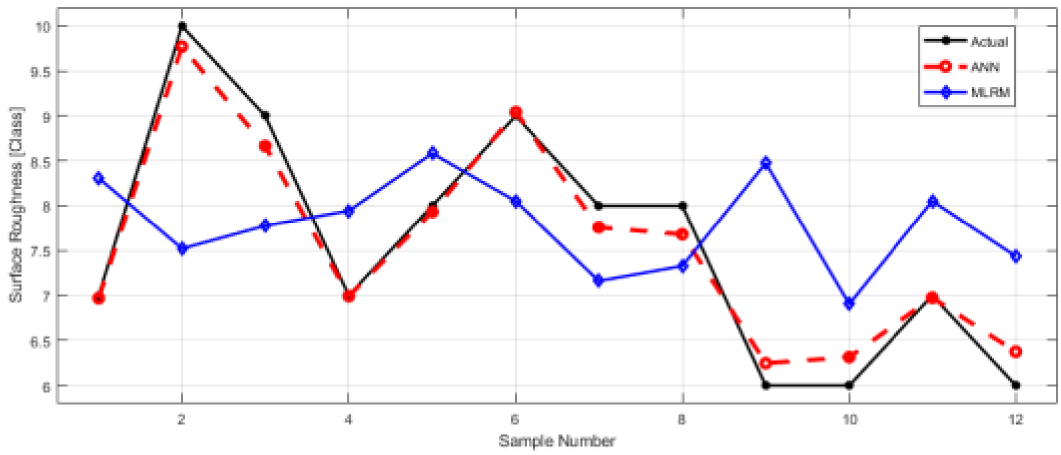
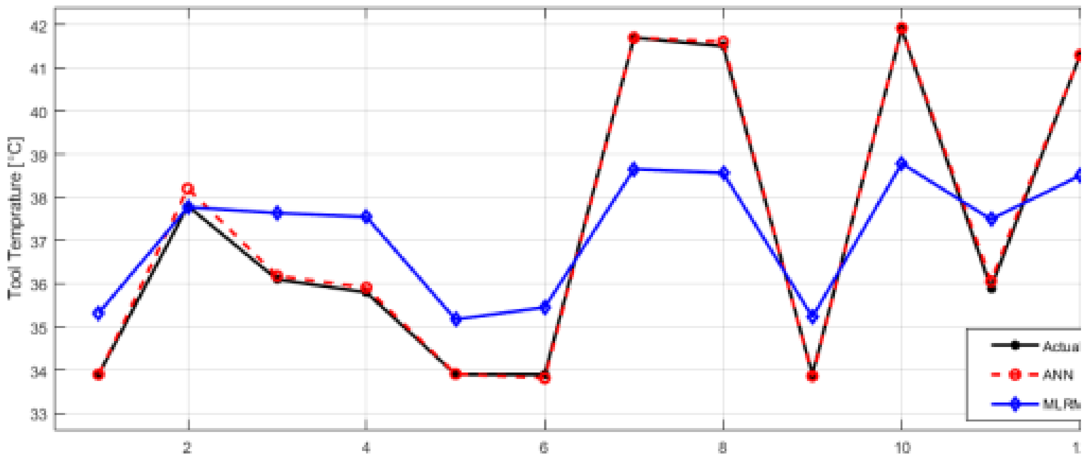


Figure 5.

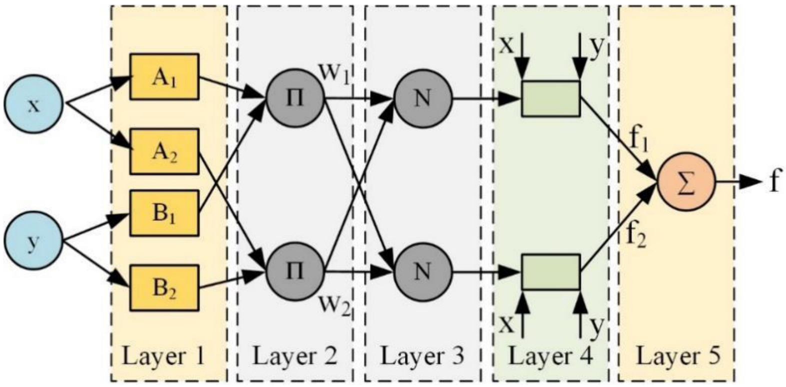
Model Achievement Results for Tool Temperature (Güvenç, 2022)



As evident from the aforementioned study, ANN serves as a powerful tool for making production processes more efficient and consistent.

- **Adaptive Neuro-Fuzzy Inference System (ANFIS)**: ANFIS integrates the capabilities of fuzzy logic and artificial neural networks, leveraging the advantages of both methodologies in a synergistic framework (Siddhpura and Paurobally, 2012). It is highly effective for analyzing and optimizing complex relationships between parameters in machining processes (Guvenc, 2022). ANFIS operates through five key stages. Bunlar sırasıyla **Input Fuzzification** (Layer 1), **Fuzzy Operators** (Layer 2), **Application Method** (Layer 3), **Aggregation of All Outputs** (Layer 4) ve **Defuzzification** (Layer 5) (Jang, 1991). The basic structure of ANFIS is illustrated in Figure 6.

Figure 6
Basic ANFIS structure with two inputs and one output (Güvenç, 2022)

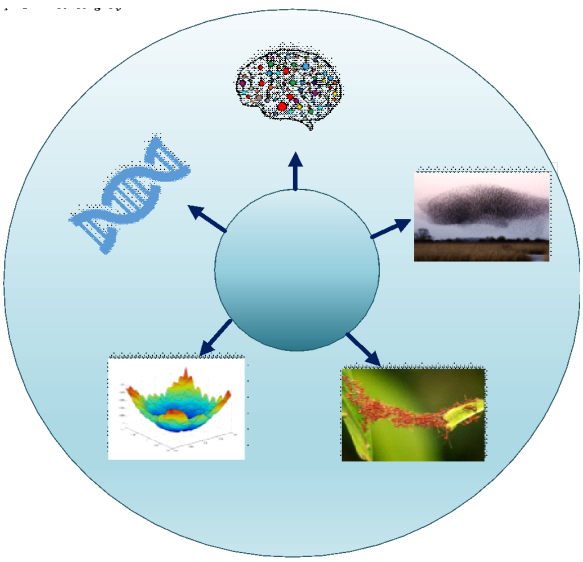


- **Metaheuristic Algorithms**:

Optimization involves finding the best solution among various alternatives to solve a problem. Metaheuristic algorithms have been developed through the effective application of different heuristic methods. Numerous well-established and frequently used metaheuristic algorithms exist in the literature, including Genetic Algorithms (GA), Ant Colony Optimization (ACO), Differential Evolution (DE), Artificial Bee Colony Algorithm (ABC), and Teaching-Learning-Based Optimization (TLBO). Many applications utilize metaheuristic algorithms in combination with methods like ANFIS (Güvenç, 2022).

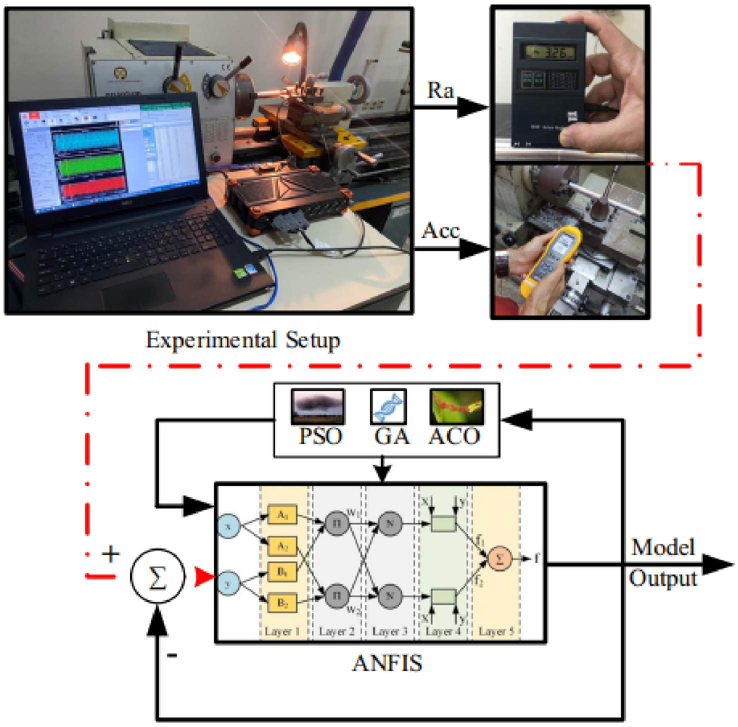
In a study conducted by Güvenç (2022), tool vibrations and surface roughness during the turning of AA6013 alloy were predicted using ANFIS optimized with metaheuristic algorithms. The optimization process incorporated three different metaheuristic algorithms. One of these is an Ant Colony Optimization (ACO), modeled on how ants find the shortest path to a food source (Paul et al., 2015). The other one is these a Genetic Algorithm (GA), Based on Darwin's theory of evolution (Akdagli et al., 2006). The last one is a Particle Swarm Optimization (PSO), Inspired by the social behavior of bird flocks (Wahid et al., 2019). The schematic representation of this study is presented in Figure 7.

Figure 7
Schematic view of study



The experimental setup and block diagram used in the study are illustrated in Figure 8. For the turning process, different values of cutting depth, feed rate, and rotational speed were selected from the system. Using these varied parameters, data for surface roughness (Ra) and tool vibration (Acc) were collected (Güvenç, 2022).

Figure 8
Experimental setup and block scheme of study (Guvenc, 2022)



The results obtained from the study are summarized in Table 2. According to the findings:

- For **Acc prediction**, the Multiple Linear Regression Model (MLRM), with an RRR value of 0.726, was identified as the least effective model among the proposed approaches. On the other hand, the **GA-ANFIS model**, achieving an RRR value of 0.946, was found to be the most effective model for Acc prediction.
- In the context of Ra prediction, the **ACO-ANFIS** model demonstrated the lowest efficacy among the proposed methodologies, achieving an RRR value of 0.810. Conversely, the PSO-ANFIS model emerged as the most proficient approach, attaining an RRR value of 0.916.

The GA-ANFIS and PSO-ANFIS models exhibited superior performance relative to conventional approaches, highlighting their potential as robust and reliable predictive tools for analogous applications (Güvenç, 2022).

Table 2
Comparison of Forecast Models

		MSE		MAE		R	
		Train	**Test**	**Train**	**Test**	**Train**	**Test**
Acc	**ÇLRM**	0.068847	0.083466	0.217571	0.241197	0.725249	0.726901
	ACO	0.066702	0.078225	0.217374	0.23551	0.720807	0.761294
	GA	0.030968	0.025861	0.15536	0.146241	0.892455	0.946903
	PSO	0.031444	0.049664	0.139707	0.162712	0.883234	0.88679

Ra	ÇLRM	0.044783	0.049864	0.174726	0.193745	0.755374	0.8244
	ACO	0.042983	0.053632	0.167134	0.196744	0.758745	0.810425
	GA	0.025824	0.034109	0.123148	0.144264	0.876478	0.911402
	PSO	0.020494	0.031704	0.109358	0.13957	0.894505	0.916647

Challenges and Opportunities in Implementing Artificial Intelligence Techniques

While predictive and optimization analytics using artificial intelligence methods offer great opportunities, they can also bring some challenges (Sivarajah et. al., 2017). These include:

Challenges:

- **Data Quality:** The integrity and reliability of the data employed in the analysis are of paramount importance, as inaccuracies or omissions in the dataset may lead to erroneous predictive outcomes.
- **Infrastructure Requirements:** Predictive analytics requires high-performance computers and sensor infrastructure.
- **Operator Training:** Operators must have adequate training to understand and utilize these technologies effectively.

Opportunities:

- **Faster Decision Making:** Predictive analytics accelerates decision-making during processes, thus increasing production speed.
- **Cost Reduction:** Preventing process errors and enabling scheduled maintenance helps reduce operational costs.
- **Competitive Advantage:** Predictive analytics allows companies to respond more quickly to market demands.

Future Directions and Research Opportunities

The continuous evolution of machining technologies presents new opportunities for research and the application of cutting-edge techniques to improve production quality and efficiency. Emerging technologies, particularly those related to Artificial Intelligence (AI) and Digital Twins, are transforming the optimization of machining processes. AI is rapidly advancing, offering innovative solutions for enhancing machining processes. New AI techniques, especially deep learning (DL) and advanced machine learning (ML) algorithms, are expected to play a key role in improving process efficiency and product quality in machining. These techniques enable more precise optimization of machining parameters, predictive maintenance, and real-time process adjustments.

The integration of autonomous process control and dynamic parameter adjustment through AI algorithms will enhance the adaptability and efficiency of machining systems. Furthermore, computer vision and natural language processing (NLP) technologies are increasingly being incorporated to streamline the analysis of machining data, enabling faster anomaly detection and decision-making. Research into these emerging AI techniques holds the potential to enhance production flexibility, reduce energy consumption, and improve surface quality, positioning AI as a central technology for the future of machining (Khuntia, 2019; Kim, 2018).

Conclusion

The quality and efficiency improvements in machining processes are undergoing a significant transformation with the integration of Artificial Intelligence (AI) and other advanced technologies. This section summarizes the key findings of the study, explores their implications for both industry and academia, and outlines the future path for AI-driven machining.

This study has examined the application of AI techniques for improving quality and efficiency in machining processes. The key findings are as belows:

- **AI** offer substantial potential in optimizing machining parameters and improving production processes. Specifically, deep learning and advanced machine learning algorithms are shown to yield effective results in process optimization, predictive maintenance, and real-time process adjustments.

- **Digital Twins** and **Simulation technologies** create virtual models of physical machining processes, enabling real-time monitoring and optimization. These technologies provide valuable insights into potential inefficiencies, tool wear, and deviations before they impact production, enhancing process reliability.

- **Metaheuristic Algorithms** and **Multi-Objective Optimization** methods allow for the simultaneous optimization of multiple conflicting objectives. These methods provide solutions in more complex and broader parameter spaces compared to traditional optimization techniques, offering better adaptability and efficiency in machining operations.

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