
AI Driven Adaptive Control in CNC Machining

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Abstract

The rapid evolution of Computer Numerical Control (CNC) machining has demanded smarter and more efficient control systems. Conventional CNC systems, while reliable, often fail to optimally adjust to dynamic changes in cutting conditions, leading to reduced productivity and tool wear. Adaptive control systems driven by Artificial Intelligence (AI) have emerged as a solution, enabling real-time monitoring, parameter optimization, and fault prediction. This review paper explores AI-driven adaptive control (AI-AC) in CNC machining, highlighting its methodologies, benefits, challenges, and future potential. Key AI techniques such as neural networks, fuzzy logic, and reinforcement learning are examined for their role in enhancing machining efficiency and product quality. The paper also discusses integration challenges, implementation strategies, and comparative analyses of AI-based adaptive control systems versus conventional control methods.

Keywords: *AI, CNC machining, adaptive control, neural networks, fuzzy logic, reinforcement learning, tool wear, process optimization*

INTRODUCTION

Computer Numerical Control (CNC) machining has become a cornerstone of modern manufacturing, providing high-precision, repeatable, and automated machining capabilities. Despite these advantages, traditional CNC systems operate on pre-programmed commands and are often unable to respond dynamically to variations in workpiece material, tool wear, cutting speed, or load fluctuations. Such rigidity may result in suboptimal machining efficiency,

increased tool wear, surface defects, and energy wastage.

Adaptive control systems were introduced to overcome these limitations by adjusting process parameters in real-time based on sensor feedback. The incorporation of Artificial Intelligence (AI) into adaptive control systems has further revolutionized CNC machining. AI algorithms can analyze large volumes of machining data, detect patterns, predict outcomes, and optimize parameters autonomously, paving the way for smarter manufacturing systems.

The objective of this paper is to provide a comprehensive review of AI-driven adaptive control in CNC machining, emphasizing its methodologies, applications, challenges, and research trends.

CNC MACHINING AND CONVENTIONAL CONTROL SYSTEMS

Computer Numerical Control (CNC) machining is a widely used manufacturing technology that enables high-precision production by automating the movement of machine tools based on pre-programmed sequences. CNC machines operate by interpreting coded instructions (G-code or M-code), which control the motion of the tool along multiple axes and regulate auxiliary functions such as coolant flow or spindle speed. Common operations performed using CNC machining include **milling, turning, drilling, and grinding**, which are essential in industries ranging from automotive and aerospace to electronics and medical device manufacturing.

Conventional CNC control systems typically rely on **predefined, fixed parameters** such as spindle speed, feed rate, and depth of cut. These parameters are programmed based on prior knowledge of the material, tool, and desired output. The machine uses **closed-loop feedback systems** to maintain the accuracy of tool position, velocity, and torque. Sensors measure position and movement errors, which are corrected by the controller to ensure that the tool follows the programmed path precisely.

However, while conventional CNC systems maintain geometric precision, they **lack real-time adaptability** to variations in the machining environment. Factors such as workpiece material inhomogeneity, tool wear, temperature fluctuations, or unexpected loads can affect the cutting process, but conventional systems do not adjust process parameters in response. This can lead to suboptimal machining outcomes, such as increased tool wear, higher scrap rates, or uneven

surface finish.

1. Limitations of Conventional Control

Conventional CNC control systems have several inherent limitations when operating in dynamic machining conditions:

A. Fixed Feed Rate and Spindle Speed:

Most traditional CNC systems operate at constant feed rates and spindle speeds set in the program. While these values may be optimal under ideal conditions, real-world variations in material hardness, tool sharpness, or temperature can lead to inefficient cutting. For example, cutting a harder-than-expected section of material with a fixed feed rate may cause excessive tool wear or surface roughness, while softer sections may reduce productivity due to unnecessarily slow cutting.

B. Delayed Detection of Tool Wear or Breakage:

In conventional CNC systems, tool wear or breakage is often detected visually by the operator or through periodic inspection. This reactive approach can result in **unexpected tool failure during operation**, leading to machine downtime, damaged workpieces, and increased production costs.

C. Higher Likelihood of Surface Defects:

Variations in material properties, tool sharpness, or environmental conditions can cause surface irregularities, chatter marks, or dimensional inaccuracies. Conventional control systems cannot compensate for these variations in real-time, so operators may need to slow the process, use conservative cutting parameters, or perform additional post-processing to meet quality standards.

D. Inefficient Energy Usage and Potential Machine Overloads:

Without real-time adaptation, machines may consume more energy than necessary. For instance, running at a higher spindle speed than required for a particular material section wastes power. Similarly, unexpected load variations may cause motor overloading or thermal stress, which can shorten the machine's lifespan or reduce overall efficiency.

Example Scenario:

Consider a CNC milling operation on a batch of aluminum alloy parts. Due to slight differences in alloy hardness between batches, the conventional CNC machine operating at a fixed feed and spindle speed may experience localized vibration in harder areas, producing rough surfaces, while wasting time in softer areas where higher speeds could have been safely used. Adaptive control driven by AI could dynamically adjust these parameters, reducing vibration, improving surface finish, and optimizing cycle time.

In summary, conventional CNC systems are reliable for precise geometric control but **lack intelligence** to respond to real-time machining variations. These limitations highlight the need for **adaptive control systems**, which can monitor and adjust process parameters dynamically to optimize tool life, surface quality, and overall productivity.

ADAPTIVE CONTROL IN CNC MACHINING

Adaptive control represents a significant advancement over conventional CNC control by allowing the machine to **dynamically adjust its operating parameters in real-time**. Unlike traditional systems that rely solely on pre-programmed feed rates, spindle speeds, and depth of cut, adaptive control systems continuously monitor the machining process through sensors and respond to variations in cutting conditions. These variations may include changes in **workpiece material hardness, tool wear, cutting force fluctuations, vibration, and thermal effects**.

The goal of adaptive control is to **maintain optimal machining performance**, ensuring high surface quality, dimensional accuracy, and tool longevity while maximizing productivity. By automatically adjusting parameters such as **feed rate, spindle speed, cutting depth, and tool path**, adaptive control systems reduce reliance on human intervention and improve process robustness.

Key Components of an Adaptive Control System:

1. **Sensors:** Measure cutting forces, vibration, temperature, and acoustic emission.
2. **Process Monitoring Unit:** Collects and analyzes real-time sensor data.
3. **Control Algorithm:** Determines necessary adjustments to machining parameters.
4. **Actuators:** Implement the calculated adjustments on the machine.
5. **Feedback Loop:** Ensures continuous system performance improvement.

Adaptive control is particularly beneficial in industries where **high-value components** are manufactured from materials with **non-uniform properties**, such as aerospace alloys, composites, or medical-grade titanium.

TYPES OF ADAPTIVE CONTROL

Adaptive control methods are generally classified based on how they monitor the process and adjust system parameters. The most common types include:

1. Model Reference Adaptive Control (MRAC)

Principle:

MRAC uses a **reference model** that represents the desired or ideal system behavior. The adaptive controller compares the actual machine performance with the reference model and adjusts control parameters to minimize the difference.

Example:

In a milling operation, the reference model may define ideal spindle speed and feed rate for a specific surface finish. If sensors detect increased vibration due to tool wear, MRAC modifies the feed rate and spindle speed to maintain the target surface quality.

Advantages:

- Ensures system performance closely follows desired specifications.
- Effective for systems with predictable dynamics and known reference behavior.

Limitations:

- Requires accurate modeling of desired performance.
- Performance may degrade if the actual process significantly deviates from the reference model.

2. Self-Tuning Regulators (STR)

Principle:

STRs automatically **estimate process parameters** such as stiffness, damping, and cutting forces in real-time. Controller gains are then updated dynamically based on these estimates to optimize machining performance.

Example:

During a turning operation on a steel workpiece, STR continuously measures cutting force. If the cutting force rises due to increased material hardness, the system adjusts the feed rate or spindle speed to prevent excessive tool wear or vibration.

Advantages:

- Does not require a predefined reference model.
- Can adapt to gradual changes in machine or tool characteristics.

Limitations:

- Complex estimation algorithms are needed.
- Slow convergence may occur in rapidly changing conditions.

3. Gain Scheduling

Principle:

Gain scheduling uses **predefined sets of control gains** corresponding to different operating conditions. The controller switches or interpolates between these gains based on measured process variables.

Example:

A CNC milling machine may have one set of controller gains for soft aluminum and another for hard steel. Sensors detect the material type or cutting load, and the system selects the appropriate gain schedule.

Advantages:

- Simple implementation for systems with identifiable operating regimes.
- Improves performance in known variable conditions.

Limitations:

- Less effective for unknown or highly nonlinear variations.
- Requires comprehensive prior knowledge of process conditions.

AI TECHNIQUES FOR ADAPTIVE CNC CONTROL

Adaptive control in CNC machining can be significantly enhanced using Artificial Intelligence (AI) techniques. Unlike conventional adaptive systems that rely on fixed mathematical models

or predefined rules, AI methods enable **pattern recognition, prediction, and autonomous decision-making**. These systems can learn from historical and real-time data to optimize machining parameters, predict tool wear, improve surface quality, and prevent machine faults. The most widely used AI techniques for adaptive CNC control are **Artificial Neural Networks (ANNs), Fuzzy Logic, and Reinforcement Learning (RL)**. Each technique offers unique capabilities for handling uncertainties, nonlinearities, and dynamic variations in machining processes.

1. Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of the human brain. They consist of interconnected neurons organized in layers—**input, hidden, and output layers**—which collectively learn patterns from input data and generate predictions or decisions. ANNs are particularly effective in CNC machining because **cutting processes are highly nonlinear**, and traditional mathematical models often fail to capture the complexity.

Applications in CNC Machining:

- **Tool Wear Prediction:** ANNs can predict tool wear based on input parameters like cutting force, vibration, spindle speed, and temperature. This allows the machine to proactively adjust feed rates or initiate tool replacement, reducing unexpected downtime.
- **Surface Roughness Estimation:** By learning the relationship between machining parameters and surface finish, ANNs can dynamically adjust cutting speed and feed to maintain consistent quality.
- **Cutting Force Prediction:** ANNs can forecast cutting forces under varying conditions, allowing adaptive adjustment of spindle speed and feed rate to minimize vibration and improve dimensional accuracy.

Example Application:

Consider a milling operation on a titanium alloy, where the cutting force varies unpredictably due to material heterogeneity. An ANN trained on historical cutting force data can **predict force spikes**, and the CNC controller adjusts feed rate and spindle speed in real-time. This

reduces chatter, prevents tool overloading, and improves surface finish.

Advantages of ANN-Based Adaptive Control:

- Can model highly nonlinear and complex relationships.
- Capable of learning from historical and real-time data.
- Improves predictive maintenance and process optimization.

Limitations:

- Requires large datasets for accurate training.
- Computationally intensive, especially for deep networks.
- Model performance may degrade for conditions outside the training data range.

2. Fuzzy Logic

Fuzzy logic is an AI technique that enables reasoning under **uncertainty or imprecise conditions**, making it suitable for machining operations where exact models are difficult to derive. Instead of binary true/false logic, fuzzy systems work with **linguistic variables** (e.g., “high,” “medium,” “low”) and membership functions to represent gradual transitions.

Applications in CNC Machining:

- **Adaptive Feed and Speed Adjustment:** Fuzzy controllers can adjust spindle speed and feed rate based on real-time measurements of cutting forces, vibration, or acoustic emissions. For example, if vibration is “high,” the system reduces feed rate to stabilize machining.
- **Tool Condition Monitoring:** Fuzzy systems can interpret sensor signals to classify tool wear as “acceptable,” “moderate,” or “severe,” enabling real-time corrective actions.
- **Surface Quality Control:** Linguistic rules can map input parameters to output adjustments, maintaining desired surface roughness without requiring an exact mathematical model.

Working Principle:

1. **Fuzzification:** Convert sensor inputs into fuzzy linguistic variables.

2. **Rule Evaluation:** Apply “IF-THEN” rules derived from expert knowledge (e.g., “IF vibration is high AND cutting force is medium, THEN reduce feed rate”).
3. **Defuzzification:** Convert the fuzzy output into actionable numeric commands for the CNC machine.

Advantages of Fuzzy Logic:

- Handles uncertainties and nonlinearities efficiently.
- Requires less data compared to ANNs.
- Easier to implement when expert knowledge is available.

Limitations:

- Performance depends on quality and completeness of the rule base.
- May be less effective in highly dynamic or unknown conditions.

Example Application:

In a turning operation of a steel shaft, the cutting forces fluctuate due to minor hardness variations along the workpiece. A fuzzy logic controller evaluates vibration and force signals, categorizes them as “medium” or “high,” and adjusts feed rate and spindle speed accordingly. This reduces chatter and maintains a smooth surface finish without the need for an explicit physical model.

Table 1: Comparison of AI Techniques in Adaptive Control

AI Technique	Strengths	Limitations	Applications
ANN	Learns complex nonlinear patterns, predictive capability	Requires large dataset, computationally intensive	Tool wear prediction, force modeling
Fuzzy Logic	Handles uncertainty, intuitive design	Limited adaptability without expert rules	Real-time feed/spindle adjustments
Reinforcement Learning	Learns optimal strategies from trial and error	Slow convergence, requires simulation	Process parameter optimization, adaptive scheduling

REINFORCEMENT LEARNING (RL)

Reinforcement Learning (RL) is a branch of Artificial Intelligence that enables machines to **learn optimal strategies through trial-and-error interactions** with the environment. Unlike supervised learning, where models are trained on pre-labeled datasets, RL systems **discover optimal actions by receiving feedback in the form of rewards or penalties**. In CNC machining, this approach allows machines to autonomously adapt to dynamic cutting conditions, varying material properties, and tool wear without requiring explicit mathematical models.

1. Working Principle in CNC Machining

The RL framework for CNC adaptive control typically involves the following components:

- A. **Agent:** The CNC machine or the adaptive controller making decisions.
- B. **Environment:** The machining process including the workpiece, cutting tool, and machine dynamics.
- C. **Action:** Adjustments to machining parameters such as **feed rate, spindle speed, depth of cut, or tool path**.
- D. **State:** Current process conditions, represented by sensor measurements such as cutting force, vibration, temperature, and acoustic emissions.
- E. **Reward:** Feedback based on performance metrics. Positive rewards are given for actions that improve **surface quality, reduce tool wear, minimize cycle time**, or optimize energy efficiency; penalties are given for undesirable outcomes like chatter, excessive tool wear, or dimensional errors.

Workflow Example:

1. The RL agent observes the current state (e.g., cutting force = high, vibration = medium).
2. It selects an action (e.g., reduce feed rate by 10%, increase spindle speed slightly).
3. The machine executes the action, and the resulting process output is measured.
4. A reward is calculated based on predefined objectives (e.g., reward = +10 for reduced vibration and improved surface finish).
5. The RL agent updates its policy to increase the likelihood of taking successful actions in similar states in the future.

Over repeated iterations, the RL algorithm **learns an optimal policy**, i.e., the best set of actions for different machining conditions, without requiring explicit programming of every possible scenario.

2. Applications in CNC Machining

RL has shown promising results in several adaptive control applications:

1. Process Parameter Optimization:

RL can simultaneously optimize feed rate, spindle speed, and depth of cut for different materials, ensuring maximum material removal rate while maintaining tool life and surface quality.

2. Tool Wear Management:

By learning the relationship between cutting conditions and tool degradation, RL can proactively adjust parameters to extend tool life and reduce downtime.

3. Vibration and Chatter Suppression:

RL agents can detect conditions leading to chatter and dynamically modify cutting parameters to stabilize the machining process.

4. Energy-Efficient Machining:

RL can optimize machining parameters to reduce power consumption without compromising productivity or product quality.

AI-DRIVEN ADAPTIVE CONTROL SYSTEM ARCHITECTURE

The architecture of an AI-driven adaptive control (AI-AC) system in CNC machining integrates **sensors, data acquisition, intelligent decision-making algorithms, actuators, and feedback loops** to create a dynamic, self-optimizing machining environment. Unlike conventional CNC control, which operates with fixed parameters, AI-AC systems **continuously sense, analyze, and adjust machining parameters in real-time**, ensuring optimal tool performance, high surface quality, and reduced machine downtime.

The following subsections describe each component in detail and illustrate how they interact to form a fully adaptive CNC control system.

1. Sensors

Sensors form the foundation of an AI-AC system by providing **real-time measurements of the machining environment**. Commonly used sensors in CNC machining include:

- **Force Sensors:** Measure cutting forces along different axes to detect overload, excessive tool stress, or material hardness variations.
- **Vibration Sensors (Accelerometers):** Monitor spindle and tool vibrations to prevent chatter, resonance, and surface defects.
- **Temperature Sensors:** Track the heat generated at the tool-workpiece interface, which affects tool life and surface finish.
- **Acoustic Emission (AE) Sensors:** Detect high-frequency signals generated by micro-fractures or tool wear, enabling early warning of tool damage.

Example: During a high-speed milling operation, force and vibration sensors detect sudden spikes in cutting load caused by hard inclusions in the workpiece. These signals are immediately fed to the AI controller to adjust spindle speed and feed rate, preventing tool breakage.

2. Data Acquisition and Preprocessing

The raw sensor signals are collected by a **Data Acquisition System (DAQ)**, which serves as the interface between sensors and the AI controller. Data preprocessing is critical for accurate AI decision-making and may include:

- **Noise Filtering:** Removing electrical or environmental noise using digital filters.
- **Normalization:** Scaling measurements to a consistent range for AI algorithms.
- **Feature Extraction:** Identifying relevant parameters, such as RMS vibration, peak cutting force, or acoustic emission frequency components.

Example: In a turning operation, the DAQ system converts analog vibration signals into digital data, calculates root-mean-square (RMS) values, and forwards them to the ANN controller for tool wear prediction.

3. AI Controller

The **AI controller** is the decision-making core of the system. It uses advanced AI algorithms such as **Artificial Neural Networks (ANNs), Fuzzy Logic, or Reinforcement Learning**

(**RL**) to analyze incoming data and determine optimal machining adjustments.

- **ANNs:** Predict tool wear, cutting forces, and surface roughness based on historical and real-time data.
- **Fuzzy Logic:** Implements human-like reasoning to adjust feed rates, spindle speeds, or cutting depth under uncertain conditions.
- **RL:** Learns optimal control policies through continuous interaction with the machining process, optimizing multiple objectives such as cycle time, tool life, and surface finish.

Example: The AI controller may detect increasing vibration levels during milling. A fuzzy logic module interprets the signal as “high” and commands the spindle to slow down, while the ANN predicts the remaining tool life, and RL adjusts the feed rate to optimize productivity.

4. Actuators

Actuators are responsible for executing the control actions calculated by the AI controller. They directly influence **key machining parameters** in real-time:

- **Feed Drive Actuators:** Modify tool movement along the X, Y, or Z axes.
- **Spindle Drive Actuators:** Adjust spindle speed to optimize cutting conditions.
- **Tool Positioning Actuators:** Fine-tune tool orientation or depth of cut.
- **Coolant or Lubrication Systems:** In some advanced setups, coolant flow may be adjusted dynamically to prevent overheating.

Example: If the AI controller detects a sudden increase in cutting force, the feed drive actuator reduces feed rate while the spindle actuator adjusts rotation speed to maintain smooth cutting, avoiding tool damage and ensuring consistent surface finish.

5. Feedback Loop

The feedback loop is a critical component that enables **continuous learning and adaptation**. After each adjustment, sensors re-measure the process conditions, and the AI controller evaluates the effects of its actions. This loop allows the system to:

- **Refine AI Models:** Update ANN weights or RL policies based on real outcomes.
- **Correct Deviations:** Immediately respond to unexpected disturbances such as material inconsistencies or tool degradation.

- **Improve Accuracy:** Over time, the system becomes more precise in predicting optimal machining parameters.

Example: After the AI controller adjusts feed rate and spindle speed, vibration sensors measure the new system response. If vibration persists, further adjustments are made, and the RL algorithm updates its policy for similar future situations.

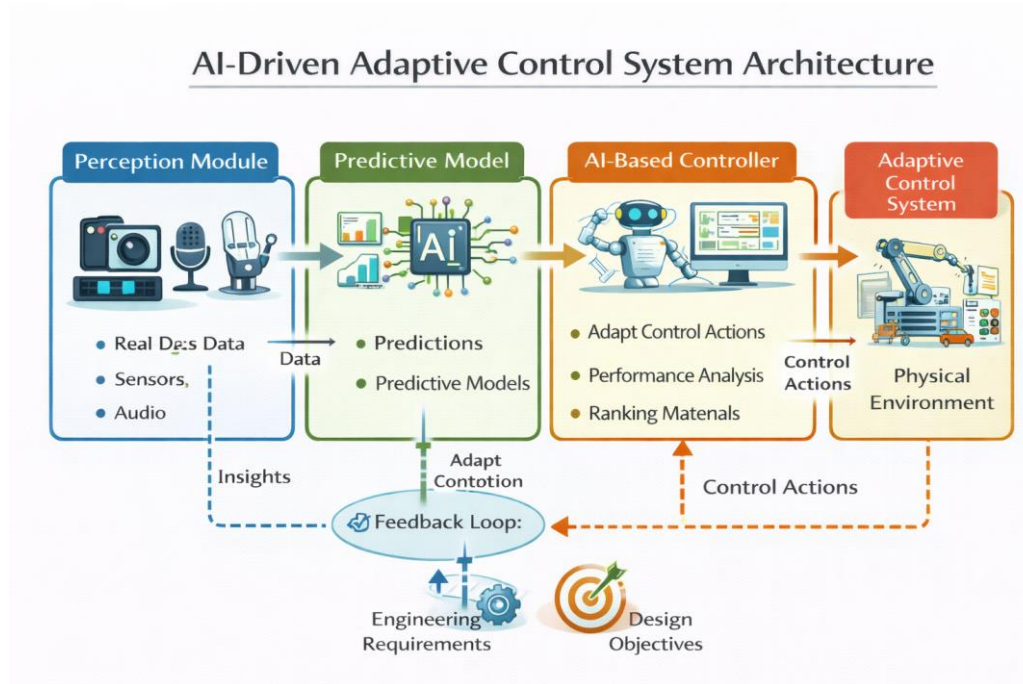


Figure 1: AI-Driven Adaptive Control System Architecture

APPLICATIONS OF AI-DRIVEN ADAPTIVE CONTROL

1. Tool Wear Monitoring and Prediction

AI algorithms predict tool wear by analyzing vibration, acoustic emission, and cutting force data. Predictive adjustments extend tool life and reduce unexpected downtime.

2. Surface Quality Improvement

Adaptive control optimizes spindle speed and feed rates to maintain consistent surface roughness, especially in complex geometries.

3. Process Optimization

AI-AC systems dynamically modify parameters for high material removal rates while minimizing tool wear, energy consumption, and thermal effects.

4. Fault Detection and Prevention

AI algorithms detect anomalies like chatter, overload, and tool breakage early, preventing damage to the machine and workpiece.

CHALLENGES IN AI-DRIVEN ADAPTIVE CNC SYSTEMS

Despite significant advantages, AI-AC implementation faces several challenges:

1. **Data Requirements:** AI models require large datasets covering diverse machining conditions for accurate predictions.
2. **Computational Cost:** Real-time processing demands high-performance hardware and efficient algorithms.
3. **Integration Complexity:** Retrofitting AI systems into existing CNC machines can be challenging.
4. **Uncertainty in Learning:** RL systems may converge slowly or behave unpredictably under extreme conditions.
5. **Cost Considerations:** Implementation may require significant investment in sensors, computing, and software.

CASE STUDIES

1. Neural Network-Based Tool Wear Control

A study by Singh et al. (2022) used ANN to predict tool wear in milling of stainless steel. The system adjusted feed and speed, reducing tool wear by 25% and improving surface finish by 15%.

2. Fuzzy Logic in Turning Operations

Kumar and Mehta (2021) implemented fuzzy logic control in a CNC turning machine. Real-time adjustments in spindle speed reduced vibration and chatter, improving dimensional accuracy.

3. Reinforcement Learning for Milling

Patel et al. (2023) applied RL for optimizing milling operations. The system learned optimal spindle speed and feed rate, achieving 10% faster cycle time without compromising surface quality.

FUTURE TRENDS

AI-driven adaptive control is expected to evolve in the following areas:

1. **Digital Twins Integration:** Virtual replicas of machines can simulate AI control strategies before real-world implementation.
2. **Edge AI Deployment:** On-machine AI processing reduces latency and dependency on cloud computing.
3. **Multi-Objective Optimization:** Simultaneous optimization of tool life, surface quality, and energy consumption.
4. **Collaborative Manufacturing:** AI-AC in networked CNC machines for smart factory operations.

CONCLUSION

AI-driven adaptive control represents a significant advancement in CNC machining, bridging the gap between rigid conventional control and real-time process optimization. By incorporating AI techniques like neural networks, fuzzy logic, and reinforcement learning, CNC systems can predict tool wear, optimize process parameters, improve surface quality, and enhance overall productivity. While challenges such as data requirements, computational costs, and integration remain, ongoing research and emerging technologies like edge AI and digital twins are poised to make AI-AC standard in modern machining environments. This review underscores the potential of AI to transform CNC machining into a truly intelligent and adaptive manufacturing process.

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