Enhancing Mechanical Design, Manufacturing, and Automation through AI-Based Computer Numerical Control (CNC) Optimization

Melhorando o projeto mecânico, a fabricação e a automatização através da otimização do controlo numérico computadorizado (CNC) baseado em IA

Mejora del diseño mecánico, la fabricación y la automatización mediante la optimización del control numérico computacional (CNC) basado en IA

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Abstract

The rapid advancements in Artificial Intelligence (AI) have provided new opportunities for optimizing Computer Numerical Control (CNC) technology, crucial for mechanical design, manufacturing, and automation. This study explores AI-driven optimization strategies in CNC systems to enhance machining efficiency, surface quality, tool life, and overall operational stability. The methodology integrates three AI technologies: reinforcement learning (RL) for tool path planning optimization, particle swarm optimization (PSO) for cutting parameter adjustment, and fuzzy logic for controlling abnormal situations. By using these techniques, the study aims to address inefficiencies in traditional methods and improve the adaptability and automation of CNC systems. A series of comparative experiments conducted on a DMG Mori DMU 50 five-axis CNC machining center demonstrate significant improvements in surface roughness, machining speed, tool wear rate, and energy consumption. The results highlight the potential of AI-based optimization in improving CNC machining performance, paving the way for more efficient, sustainable, and intelligent manufacturing processes. Future research should focus on further refining optimization algorithms for various materials and explore the integration of CNC technology with emerging technologies such as industrial internet and big data.

Keywords: CNC Technology, Optimization, Artificial Intelligence (AI), Reinforcement Learning (RL), Particle Swarm Optimization (PSO).

Resumo

Os rápidos avanços na Inteligência Artificial (IA) proporcionaram novas oportunidades para otimizar a tecnologia de controlo numérico computorizado (CNC), crucial para o projeto mecânico, fabrico e automação. Este estudo explora estratégias de otimização orientadas por IA em sistemas CNC para melhorar a eficiência da maquinação, a qualidade da superfície, a vida útil da ferramenta e a estabilidade operacional global. A metodologia integra três tecnologias de IA: aprendizagem por reforço (RL) para otimização do planeamento do percurso da ferramenta, otimização por enxame de partículas (PSO) para ajuste de parâmetros de corte e lógica difusa para controlo de situações anormais. Ao utilizar estas técnicas, o estudo visa abordar as ineficiências nos métodos tradicionais e melhorar a adaptabilidade e automatização dos sistemas CNC. Uma série de experiências comparativas realizadas num centro de maquinação CNC de cinco eixos DMG Mori DMU 50 demonstram melhorias significativas na rugosidade da superfície, velocidade de maquinação, taxa de desgaste da ferramenta e consumo de energia. Os resultados destacam o potencial da otimização baseada em IA para melhorar o desempenho da maquinação CNC, abrindo caminho para processos de fabrico mais eficientes, sustentáveis e inteligentes. A investigação futura deverá focar-se em refinar ainda mais os algoritmos de otimização para vários materiais e explorar a integração da tecnologia CNC com tecnologias emergentes, como a internet industrial e os big data.

Palavras- chave: Tecnologia CNC, Otimização, Inteligência Artificial (IA), Aprendizagem por Reforço (RL), Otimização por Enxame de Partículas (PSO).

Resumen

Los rápidos avances en Inteligencia Artificial (IA) han brindado nuevas oportunidades para optimizar la tecnología de Control Numérico Computacional (CNC), crucial para el diseño mecánico, la fabricación y la automatización. Este estudio explora estrategias de optimización basadas en IA en sistemas CNC para mejorar la eficiencia del mecanizado, la calidad superficial, la vida útil de la herramienta y la estabilidad operativa general. La metodología integra tres tecnologías de IA: aprendizaje por refuerzo (RL) para optimizar la planificación de la trayectoria de la herramienta, optimización por enjambre de partículas (PSO) para el ajuste de parámetros de corte y lógica difusa para controlar situaciones anormales. Mediante estas técnicas, el estudio busca abordar las ineficiencias de los métodos tradicionales y mejorar la adaptabilidad y la automatización de los sistemas CNC. Una serie de experimentos comparativos realizados en un centro de mecanizado CNC de cinco ejes DMG Mori DMU 50 demuestra mejoras significativas en la rugosidad superficial, la velocidad de mecanizado, el desgaste de la herramienta y el consumo de energía. Los resultados destacan el potencial de la optimización basada en IA para mejorar el rendimiento del mecanizado CNC, allanando el camino hacia procesos de fabricación más eficientes, sostenibles e inteligentes. Las futuras investigaciones deberían centrarse en el perfeccionamiento de los algoritmos de optimización para diversos materiales y en explorar la integración de la tecnología CNC con tecnologías emergentes como el internet industrial y el big data.

Palabras clave: Tecnología CNC, Optimización, Inteligencia Artificial (IA), Aprendizaje por Refuerzo (RL), Optimización por Enjambre de Partículas (PSO).

1. Introduction

The advent of Industry 4.0 has ushered in a transformative era for the manufacturing sector, marked by the rapid evolution of intelligent manufacturing technologies (Mohamed et al., 2024). Among these technologies, Computer Numerical Control (CNC) systems have played a pivotal role in enhancing the precision, efficiency, and flexibility of machining processes. As manufacturers face increasing pressure to meet high-quality standards while reducing costs and production times, optimizing CNC technology has become crucial (Li et al., 2024). However, traditional methods for CNC operation, though effective, often struggle with complex tasks, dynamic production environments, and the demands of modern manufacturing.

Recent advancements in Artificial Intelligence (AI) provide new opportunities to address these limitations. AI techniques, such as reinforcement learning (RL), particle swarm optimization (PSO), and fuzzy logic, offer powerful tools to optimize CNC operations (Mypati et al., 2023). By integrating these AI-driven solutions, CNC systems can adapt to a wide range of machining scenarios, improving not only operational efficiency but also surface quality, tool life, and energy consumption (Kasiviswanathan et al., 2024). This paper explores the integration of AI technologies in CNC systems, focusing on three key areas: tool path planning optimization using RL, cutting parameter adjustment via PSO, and abnormal situation control with fuzzy logic.

The primary objective of this study is to enhance the automation, stability, and precision of CNC systems in the realms of mechanical design, manufacturing, and automation. Through a series of experiments using state-of-the-art CNC equipment, we demonstrate the effectiveness of AI-driven optimization in improving machining outcomes. This research aims to contribute to the broader goal of creating smarter, more efficient manufacturing systems that can meet the demands of a rapidly evolving industrial landscape.

The paper is organized as follows: the next section reviews recent advancements in AI technologies for CNC optimization. This is followed by a detailed methodology that outlines the integration of RL, PSO, and fuzzy logic. Finally, the experimental results and discussions are presented, showcasing the impact of these optimizations on machining efficiency, surface quality, and overall system performance.

2. Literature Review

Recent developments in artificial intelligence (AI) have opened up new opportunities for enhancing CNC systems. The integration of AI technologies such as deep learning, machine vision, and intelligent decision support systems has the potential to significantly improve the flexibility, adaptability, and intelligence of CNC systems, enhancing both operational stability and automation capabilities to meet the increasing demands of industrial development.

2.1 Tool Path Planning Optimization

An essential aspect of improving CNC machining efficiency is tool path planning. Traditional tool path planning methods, such as the direct line method, contour offset method, and contour line method, often struggle with inefficiency and redundancy, especially when dealing with complex part shapes (Liang et al., 2021). To address these challenges, reinforcement learning (RL) has been introduced to optimize the tool path. RL models, such as the Markov Decision Process (MDP), incorporate key elements like tool position, workpiece shape, material type, and movement methods, including linear and circular interpolation (Nian et al., 2020). These models use Q-learning to iteratively update action-value functions and progressively find optimal tool paths, improving machining efficiency and quality.

2.2 Particle Swarm Cutting Parameter Adjustment

CNC cutting parameters—such as cutting speed, feed rate, and cutting depth—are crucial to machining efficiency and surface quality. However, traditional empirical methods for optimizing these parameters face limitations in dynamic and complex production environments (Soori et al., 2024). Particle Swarm Optimization (PSO), a global search algorithm, has emerged as an effective tool for optimizing CNC cutting parameters. PSO balances multiple objectives, such as minimizing surface roughness, cutting force, and maximizing material removal rate, by using a weighted aggregate objective function (Majeed et al., 2024; Osorio-Pinzon et al., 2020). The algorithm iteratively adjusts cutting parameters, optimizing them based on the fitness value of each solution. By simulating the foraging behavior of bird flocks, PSO accelerates convergence to optimal solutions, enhancing machining efficiency, surface quality, and tool longevity (Song et al., 2024; Khalid et al., 2023).

2.3 Fuzzy Logic for Abnormal Situation Control

Abnormal situations in CNC systems—such as vibration, thermal deformation, and degradation of machining accuracy—are often caused by fluctuations in spindle speed, cutting forces, and tool wear. Fuzzy logic control offers a solution to these issues by defining fuzzy rules and membership functions (Wong et al., 2020; Mohanraj et al., 2024). These fuzzy rules process and adjust input variables like spindle speed fluctuations and abnormal cutting forces, improving the stability and machining accuracy of CNC systems. The control system involves fuzzifying these variables and using a series of "IF-THEN" rules to make intelligent adjustments, enhancing system performance and accuracy (Passino et al., 1998; Isermann, 1998).

The optimization of CNC technology through artificial intelligence is crucial for improving machining quality, efficiency, and cost-effectiveness. With AI integration, CNC systems can address the increasing demands of industrial development, enhance automation capabilities, and promote sustainable growth in the manufacturing sector (Huang et al., 2021; Yao et al., 2024). Future research should focus on developing more precise optimization algorithms for different materials and exploring the fusion of CNC technology with emerging technologies such as industrial internet and big data, aiming to achieve smarter and more efficient machining processes.

3. Methodology

This study aims to optimize Computer Numerical Control (CNC) technology by integrating artificial intelligence (AI) methods such as reinforcement learning (RL), particle swarm optimization (PSO), and fuzzy logic for improving the efficiency, accuracy, and automation of CNC systems. The methodology is structured into three key areas: tool path planning optimization, cutting parameter adjustment, and abnormal situation control. Each optimization technique is chosen for its potential to enhance specific aspects of CNC machining, including surface quality, machining speed, tool longevity, and system stability.

3.1 Tool Path Planning Optimization using Reinforcement Learning (RL)

Tool path planning is a critical component of CNC machining, as it directly impacts machining efficiency and surface quality (Lasemi et al., 2010). Traditional geometric-based methods such as the direct line and contour offset methods often result in inefficiencies when dealing with complex geometries. To address these challenges, a reinforcement learning (RL) approach, specifically using the Markov Decision Process (MDP), is introduced.

The MDP is constructed with the following components:

- State Set (S): Contains information such as tool position, workpiece shape, and material type.

- Action Set (A): Defines movement methods like linear and circular interpolation. Reward Function (R): Evaluates actions based on machining time and quality.
- Transition Probability (P): Describes the likelihood of state transitions after an action.
- Discount Factor (γ): Balances immediate and long-term rewards.

A Q-learning algorithm is employed to iteratively update the action-value function, guiding the tool to choose optimal movements and achieve an efficient tool path. This iterative process helps reduce machining time and errors while improving the overall machining process.

3.2 Cutting Parameter Adjustment using Particle Swarm Optimization (PSO)

CNC cutting parameters, such as cutting speed, feed rate, and cutting depth, play a significant role in machining quality, efficiency, and tool longevity. Traditional optimization methods often fail to adapt to the complex dynamics of production environments (Bhateja et al., 2013; Ganeshkumar et al., 2022). To address this, Particle Swarm Optimization (PSO) is employed to optimize these parameters, considering multiple conflicting objectives.

The objectives of this optimization include:

- Minimizing surface roughness (R_a)
- Reducing cutting force (F)
- Maximizing material removal rate (M)

A weighted aggregate objective function is used to combine these multiple objectives into a single objective:

$$F_z = w_1 \cdot \frac{R_a}{R_{a_{\max}}} + w_2 \cdot \frac{F}{F_{\max}} + w_3 \cdot \frac{M}{M_{\max}}$$

Where w1, w2, w3 are weight coefficients that adjust the importance of each objective. PSO is applied to iteratively adjust the cutting parameters, simulating the behavior of bird flocks searching for optimal solutions. The algorithm is designed to converge quickly to optimal solutions, thus improving machining efficiency, surface quality, and tool life.

3.3 Abnormal Situation Control using Fuzzy Logic

CNC systems often encounter abnormal situations, such as vibration, thermal deformation, and degradation of machining accuracy, due to fluctuations in spindle speed, cutting forces, or tool wear (Wong et al., 2020; Mohanraj et al., 2024). To handle these challenges, fuzzy logic control is employed to intelligently adjust system parameters and maintain stability.

The process begins by fuzzifying input variables such as spindle speed and cutting force into membership functions. Fuzzy rules are then established in the form of "IF-THEN" statements to process these variables. For example, if the spindle speed is slightly abnormal and the cutting force is normal, a moderate adjustment is made. This fuzzy control system ensures that the CNC system adapts to abnormal situations, improving machining accuracy and system performance.

4. Comparative Experiments

To evaluate the effectiveness of the AI-based optimizations, a series of experiments were conducted using a DMG Mori DMU 50 five-axis CNC machining center equipped with the Siemens 840D sl CNC system. The experiments compared machining tasks before and after the optimization in terms of surface roughness, machining speed, tool wear rate, and energy consumption. The experimental results demonstrated significant improvements in these indicators, highlighting the potential of AI-based optimization in enhancing CNC machining performance.

5. Findings and Discussions

5.1Tool Path Planning Optimization

Tool path planning optimization is crucial for enhancing CNC machining efficiency, reducing machining time, improving surface quality, and extending tool life. The primary goal of this process is to minimize machining time, shorten tool travel paths, prevent machining interference, and reduce errors. Traditional tool path planning approaches are generally based on geometric algorithms, such as the direct line method, contour offset method, and contour line method. However, these methods often suffer from inefficiency and path redundancy when applied to complex part geometries. As a result, reinforcement learning techniques have been introduced to improve both the efficiency and accuracy of path planning.

A tool path planning model based on Markov Decision Process (MDP) is constructed. The MDP consists of five basic elements: the state set S, action set A, reward function R, transition probability P, and discount factor γ. Among these: the state set S includes key information such as tool position, workpiece shape, and material during the machining process; the action set A defines the tool movement methods, such as linear and circular interpolation; the reward function R evaluates the action's effectiveness based on criteria such as machining time and quality; the transition probability P describes the probability of state transitions after an action is performed; and the discount factor γ is used to balance short-term and long-term rewards.

On this basis, to optimize the tool path, Q-learning technology is used to iteratively update the action-value function, allowing the tool to choose the optimal action in different states. The specific optimization process is as follows:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[R(s,a) + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \quad (1)$$

In the formula: $Q(s,a)$ is the action-value function for taking action a in state s; α is the learning rate, where $0 < \alpha \leq 1$; $R(s,a)$ is the immediate reward obtained after executing action a from state s; and $\max_{a'} Q(s',a')$ is the maximum action-value function for all possible actions a' in the next state s'. Through this iterative process, the tool path planning can gradually approach the optimal or near-optimal path. By following these steps, the optimal or near-optimal tool path can be progressively found.

5.2 Particle Swarm Cutting Parameter Adjustment

CNC machine cutting parameters, including cutting speed, feed rate, and cutting depth, directly impact machining surface quality, tool life, and machining efficiency. However, due to the nonlinear and multi-objective optimization nature of the cutting process, traditional empirical or experimental methods often struggle to find the optimal parameter combination in complex and dynamic production environments. Particle Swarm Optimization (PSO) algorithm, with its global search capability and faster convergence speed, has become a powerful tool for optimizing CNC cutting parameters.

The optimization objectives of cutting parameters include minimizing surface roughness, minimizing cutting force, and maximizing material removal rate, among others. Since these objectives are often in conflict with each other, a weighted aggregate objective function method is used to transform the multi-objective optimization problem into a single-objective optimization problem. Let the optimization objectives include surface roughness Ra, cutting force F, and material removal rate M. The aggregate objective function F_z can be expressed as:

$$F_z = w_1 \frac{Ra}{Ra_{max}} + w_2 \frac{F}{F_{max}} - w_3 \frac{M}{M_{max}} \quad (2)$$

In the formula: w_1, w_2, and w_3 are the weight coefficients, representing the relative importance of each objective in the optimization; Ra_{max}, F_{max}, and M_{max} are the maximum values of the corresponding objectives. By adjusting the weight coefficients, a balance between different optimization objectives can be achieved.

Subsequently, the PSO algorithm is used to iteratively optimize F_z. This algorithm simulates the foraging behavior of bird flocks, gradually approaching the optimal solution through information sharing between individuals. Specifically, the PSO algorithm initializes a group of random particles in the solution space, where each particle represents a possible cutting parameter combination. The position of each particle indicates the specific value of the cutting parameters, and the velocity represents the direction and magnitude of parameter adjustment. The specific optimization process is as follows.

First, set the particle swarm size (number of particles), initial velocity, and position. The initial positions can be randomly distributed within the search space, and the velocities are set to zero or small values.

Second, calculate the fitness value of each particle under the current cutting parameters.

Third, update each particle's historical best value and the global best value based on the fitness values.

Fourth, adjust the velocity and position of each particle according to the velocity update formula and the position update formula. Let there be N particles in the swarm, with the current position of each particle denoted as $x_i(t)$, velocity as $V_i(t)$, best position as $p_i(t)$, and the global best position of the entire swarm as $g_i(t)$. The update formulas for the velocity $V_i\ (t+1)$ and position $x_i\ (t+1)$ of the particles at the next time step are as follows:

$$V_i\ (t+1) = w\ V_i\ (t)\ + c_1 r_1 [p_i(t) - x_i(t)]\ + c_2 r_2 [g_i(t) - x_i(t)] \tag{3}$$

$$x_i\ (t+1) = x_i\ (t)\ + V_i\ (t+1) \tag{4}$$

In the formula: w is the inertia weight, which controls the balance between the global and local search capabilities of the particle; c_1 and c_2 are learning factors, representing the particle's learning ability from its own historical best position and the global best position of the swarm, respectively; r_1 and r_2 are random numbers between 0 and 1.

Fifth, if the termination condition is met (such as reaching the maximum number of iterations or convergence threshold), the result is output and the process ends; otherwise, return to step two and continue with the next iteration. In each iteration, the particle swarm gradually converges to the global optimal solution, thus obtaining the optimal cutting parameters. By using the particle swarm algorithm to adjust and optimize CNC cutting parameters, the optimal cutting parameter combination can be quickly found under complex machining conditions, thereby improving machining efficiency, enhancing workpiece quality, and extending tool life.

5.3 Fuzzy Logic for Abnormal Situation Control

Abnormal situations in CNC systems typically include issues such as vibration, thermal deformation, and degradation of machining accuracy, caused by factors like uneven workpiece material, variations in cutting forces, and tool wear during the machining process. To effectively address these abnormalities, fuzzy logic control is employed. By defining fuzzy rules and membership functions, abnormal situations can be intelligently processed and adjusted, thereby improving the stability and machining accuracy of the CNC system.

The first step of fuzzy logic control is to fuzzify the potential abnormal situations that may occur in the CNC system. This involves converting input variables such as spindle speed fluctuations and abnormal cutting forces into membership functions $\mu(r)$ in a fuzzy set. The expression is as follows:

$$\mu(r) = \begin{cases} 1, & \text{if } r \leq r_{\min} \\ \frac{r_{\max}-r}{r_{\max}-r_{\min}}, & \text{if } r_{\min} < r < r_{\max} \\ 0, & \text{if } r \geq r_{\max} \end{cases}$$

In the expression: r represents the actual measured spindle speed; $r_{min}$and r_{max} are the predefined lower and upper limits of the spindle speed, respectively. This membership function defines the fuzzy membership of the spindle speed under different conditions, describing its sensitivity to abnormal situations.

The core of fuzzy logic control lies in the construction of a rule base, which consists of a series of fuzzy rules in the “IF-THEN” form to achieve effective control of the CNC system. Specifically, the fuzzy rule base is built to control abnormal situations in the CNC machining process. For example, IF the spindle speed is 'slightly abnormal', AND the cutting force is 'normal', THEN the adjustment amount is 'moderate adjustment'. Each rule in the rule base provides corresponding countermeasures for specific abnormal situations.

5. 4 Comparative Experiment

Experiment Environment

The primary experimental equipment selected is the DMG Mori DMU 50 five-axis CNC machining center, which is equipped with the Siemens 840D sl CNC system, known for its high precision and stability. The material used in the experiment is standard 45 steel, with dimensions of 200 mm × 200 mm × 100 mm. In the experiment, the workpiece is clamped using an FMB magnetic fixture to ensure clamping accuracy and efficiency. The experimental software environment includes Mastercam 2021 for Computer-Aided Design/Computer-Aided Manufacturing (CAD/CAM) design, as well as an artificial intelligence optimization algorithm developed based on the TensorFlow framework. To ensure consistency in experimental conditions and the accuracy of the results, the environment temperature is strictly controlled at 22°C ±2°C, with a relative humidity of 50% ±5%. Additionally, Keyence laser micrometers and Kistler three-dimensional force sensors are used to collect experimental data, ensuring the reliability and precision of the data.

Experimental Results

Three typical machining tasks—turning, milling, and drilling—were selected for the experiment to compare the machining effects of CNC technology before and after optimization in these tasks. The experimental indicators include part surface roughness, average machining speed, tool wear rate, and energy consumption. The experimental results are shown in Table 1.

Table 1
Experimental Results

Machining tasks	CNC technology	Surface roughness (μm)	Average machining speed (mm·min⁻¹)	Tool wear rate (%)	Energy consumption (kW·h)
Turning	Before optimization	1.6	87.61	0.075	8.77
	After optimization	1	95	0.031	6.31
Milling	Before optimization	1.63	89.75	0.085	9.34
	After optimization	1.01	95.34	0.035	6.53
Drilling	Before optimization	1.57	90.28	0.08	9.2
	After optimization	1.09	97.01	0.039	6.8

As shown in Table 1, the optimized CNC technology shows notable improvements in surface roughness for turning, milling, and drilling tasks, with an average reduction of 39%.

This reflects the critical role that the artificial intelligence optimization algorithm plays in enhancing machining accuracy and improving the surface quality of the parts. Additionally, the optimized CNC technology also leads to an increase in the average machining speed, with an average improvement of 7.8%, demonstrating that the optimization enhances machining efficiency and reduces processing time effectively. The tool wear rate is significantly reduced with the optimized technology, with a decrease of approximately 60%, indicating that the optimization algorithm helps to extend the lifespan of the tools. Moreover, energy consumption is reduced with the optimized CNC technology, highlighting that the algorithm not only improves machining efficiency but also contributes to energy conservation, with a decrease of about 20%.

6. Conclusion

The application of artificial intelligence technology to optimize CNC technology can effectively improve the machining quality, efficiency, and cost-effectiveness in mechanical design, manufacturing, and automation processes. This is of great significance for promoting technological progress and sustainable development in the machining industry. In the future, relevant personnel can further develop more precise optimization algorithms tailored to different material characteristics, while keeping pace with the development trend of intelligent manufacturing. They can also explore the integration of CNC technology with emerging technologies such as industrial internet and big data, in order to achieve more efficient and intelligent machining processes.

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