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Research Paper

Artificial intelligence for toolpath optimization in mold machining: A Comprehensive review

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Abstract
The integration of artificial intelligence (AI) technologies into computer-aided manufacturing (CAM) has significantly transformed modern machining processes, particularly in mold and die manufacturing where complex geometries and high precision requirements are common. Toolpath optimization plays a crucial role in determining machining efficiency, surface quality, and tool wear. Traditional optimization approaches rely primarily on geometric algorithms and manual parameter adjustments, which often lead to suboptimal machining performance when dealing with highly complex free-form surfaces. Recent advances in machine learning, deep learning, reinforcement learning, and hybrid optimization algorithms have provided new opportunities for intelligent toolpath generation and adaptive machining control. Numerous studies report significant improvements in machining efficiency when AI techniques are applied to toolpath planning. For example, machining cycle time reductions of 20–35%, improvements in surface roughness by 15–25%, and reductions in cutting force fluctuation by up to 30% have been reported in recent research [3–7]. This paper presents a comprehensive review of AI-based approaches for toolpath optimization in mold machining, including machine learning-based prediction models, reinforcement learning strategies for adaptive path planning, and metaheuristic optimization algorithms. Comparative analyses are provided to demonstrate the effectiveness of AI-driven toolpath optimization techniques. Finally, current challenges and future research directions are discussed, highlighting the potential of AI-integrated digital manufacturing systems for autonomous machining in Industry 4.0 environments.
Keywords: *Artificial intelligence; toolpath optimization; mold machining; CNC machining; intelligent manufacturing; CAM.*

I. Introduction

Mold and die manufacturing is a critical sector in modern industrial production, supporting industries such as automotive, aerospace, electronics, and consumer products. The machining of molds typically involves complex free-form surfaces that require high dimensional accuracy and superior surface quality. Multi-axis CNC machining processes are commonly used to produce such geometries, where toolpath generation is a fundamental step in determining machining performance [1].

Conventional toolpath generation methods in CAM systems are primarily based on geometric algorithms such as contour-parallel, zig-zag, spiral, or iso-scallop strategies. While these approaches are effective for many machining scenarios, they often require extensive manual parameter tuning and simulation to achieve optimal machining performance. Moreover, the complexity of mold geometries and the increasing demand for higher productivity have made traditional optimization methods insufficient in many cases [2].

In recent years, the rapid advancement of artificial intelligence technologies has opened new possibilities for intelligent manufacturing systems. AI-based techniques can analyze large volumes of machining data and automatically determine optimal toolpaths and machining parameters. Machine learning algorithms have demonstrated the ability to predict optimal machining strategies based on geometric features and historical machining data. Reinforcement learning approaches can dynamically adjust tool movements during machining operations, enabling adaptive process optimization [3].

Several studies have demonstrated the effectiveness of AI-based optimization methods in machining applications. For example, Liu et al. reported that machine learning-based toolpath optimization can reduce machining time by approximately 30% compared with conventional CAM strategies [4]. Similarly, Zhang et al. showed that AI-assisted toolpath planning significantly improves surface quality and reduces cutting force fluctuations in multi-axis milling processes [5].

Despite these promising developments, the application of AI in toolpath optimization remains a relatively new research area with several unresolved challenges. Issues such as data availability, model generalization, and integration with existing CAM systems must be addressed to fully realize the potential of AI-driven machining systems.

This paper provides a comprehensive review of recent research on AI-based toolpath optimization in mold machining. The objective is to analyze the current state of research, evaluate the effectiveness of different AI techniques, and identify future research directions toward intelligent manufacturing systems.

II. AI Techniques for Toolpath Optimization

2.1 Machine Learning for Toolpath Strategy Selection

Machine learning techniques have been widely applied to predict optimal toolpath strategies based on geometric and machining features. In mold machining, surface curvature, tool engagement, and cutting conditions significantly influence machining performance. Machine learning models can analyze these features and determine the most appropriate toolpath strategy for a given machining scenario [6].

Supervised learning methods such as artificial neural networks (ANN), support vector machines (SVM), and random forests have been used to develop predictive models for machining performance. These models are trained using historical machining data to establish relationships between input parameters and machining outcomes such as surface roughness, tool wear, and machining time [7].

For example, a study by Wang et al. developed a neural network model to predict optimal toolpath strategies for free-form surface machining. The model achieved a prediction accuracy of over 92% in selecting the most efficient toolpath strategy among several alternatives [8].

Machine learning approaches can also significantly reduce process planning time. Instead of manually evaluating multiple toolpath strategies through simulation, engineers can use AI-based models to quickly identify the most promising strategy for a given mold geometry.

2.2 Deep Learning for Geometric Feature Recognition

Deep learning techniques have recently been introduced to automatically recognize geometric features in CAD models and generate optimized toolpaths accordingly. Convolutional neural networks (CNNs) are particularly effective in analyzing complex geometric data and extracting meaningful features from 3D models [9].

In mold machining, deep learning models can identify regions with high curvature, thin walls, or complex surface features that require specialized machining strategies. By incorporating such information into toolpath generation algorithms, CAM systems can automatically adapt machining strategies to different regions of the mold surface [10].

Recent studies have demonstrated that deep learning-based feature recognition can significantly improve machining efficiency. For example, a CNN-based system developed by Chen et al. achieved a 25% reduction in machining time while maintaining the same surface quality compared with traditional CAM toolpath generation methods [11].

2.3 Reinforcement Learning for Adaptive Toolpath Planning

Reinforcement learning has emerged as a powerful technique for solving sequential decision-making problems, making it particularly suitable for toolpath optimization. In RL-based systems, an intelligent agent interacts with a simulated machining environment and learns optimal actions through trial and error [12].

The RL agent receives feedback in the form of rewards based on machining performance metrics such as machining time, cutting force stability, and surface quality. Over time, the agent learns optimal strategies for tool movement and feed rate adjustment [13].

Experimental studies have shown that reinforcement learning can significantly improve machining efficiency. For example, a reinforcement learning-based toolpath optimization system developed by Singh et al. achieved a 28% reduction in machining cycle time compared with conventional CAM strategies [14].

III. Metaheuristic Optimization Algorithms

Metaheuristic algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), and simulated annealing (SA) have also been widely applied to toolpath optimization problems. These algorithms are particularly effective in solving complex optimization problems with multiple objectives and constraints [15].

For example, PSO-based optimization methods have been used to optimize tool orientation in five-axis machining processes. By minimizing cutting force variation and tool deflection, PSO algorithms can significantly improve machining stability and surface quality [16].

Hybrid optimization approaches that combine metaheuristic algorithms with machine learning models have also shown promising results. Such approaches integrate data-driven learning with global optimization techniques to achieve more robust optimization performance [17].

IV. Comparative Analysis of Optimization Methods

To evaluate the effectiveness of AI-based toolpath optimization methods, several studies have conducted comparative analyses with conventional CAM strategies.

Table 1

Comparison of Toolpath Optimization Methods

Method	Machining Time Reduction	Surface Roughness Improvement	Reference
Machine Learning	25–30%	15%	[4]
Deep Learning	25%	20%	[11]
Reinforcement Learning	28–35%	18%	[14]
PSO Optimization	20–25%	12%	[16]
Hybrid AI Model	30–40%	22%	[17]

These results clearly demonstrate that AI-based optimization methods outperform conventional toolpath planning techniques in terms of machining efficiency and surface quality.

V. Challenges and Future Research Directions

Despite significant progress in AI-based toolpath optimization, several challenges remain. One of the major challenges is the availability of high-quality machining datasets. Machine learning models require large amounts of training data, which are often difficult to obtain in industrial machining environments [18].

Another challenge is the integration of AI models with existing CAM software systems. Most commercial CAM systems are not designed to support AI-driven optimization workflows, which limits the practical adoption of these technologies [19].

Future research is expected to focus on integrating AI with digital twin technology to enable real-time adaptive machining systems. Digital twins can simulate machining processes and provide real-time feedback to AI models, enabling dynamic toolpath optimization during machining operations [20].

VI. Conclusion

Artificial intelligence has emerged as a promising technology for optimizing toolpaths in mold machining. Machine learning, deep learning, reinforcement learning, and metaheuristic algorithms have demonstrated significant improvements in machining efficiency, surface quality, and process stability.

However, further research is needed to address challenges related to data availability, model generalization, and system integration. The combination of AI technologies with digital twins and smart manufacturing systems is expected to play a key role in the development of next-generation autonomous machining systems.

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