

Recent advancements in AI-assisted tool path generation for CNC machining

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Abstract. The manufacturing industry is facing new challenges necessitating continuous development. In CNC machining, there are increasingly strict requirements for accuracy and surface quality, along with a growing demand for difficult-to-machine materials. These challenges can be addressed by implementing and advancing Industry 4.0 technologies. Digitalisation, digital twin technology, and the integration of artificial intelligence methods are essential to CNC machining to improve efficiency and quality. The strict requirements, the complexity of machining processes, and the need to balance often conflicting objectives, such as minimising machining costs while maximising sustainability, generally lead to complex multi-objective optimisation challenges. Addressing these issues demands intelligent computational methods. Although AI tools offer significant potential for optimising CNC tool path generation, their current application is still limited. This paper aims to provide an overview of this topic, focusing specifically on turning, drilling, and milling technologies, and reviewing results from recent years. Although this study cannot be exhaustive, it strives to give a comprehensive overview of the AI algorithms and their various applications in this field. These applications include optimising operational sequences and machining strategies, improving machining quality, enhancing productivity, increasing energy efficiency, avoiding collisions, and employing adaptive tool path shapes. The paper also reviews the challenges and future trends of AI applications in CNC technology. While the results achieved so far are already impressive, we can anticipate even more significant advancements in the near future, as extensive research is being conducted in this area.

Keywords: CNC Machining, Artificial Intelligence, Tool Path Optimisation, Productivity, Machining Quality, Energy Efficiency.

1 Introduction

The manufacturing industry faces emerging demands that can only be addressed through continuous development and transformation. In CNC machining, there are increasingly strict requirements for precision and surface quality, along with a growing demand for difficult-to-machine materials. The field of mass production is also evolving, with the philosophy of mass customisation gaining momentum. This approach emphasises the need for high-quality products in small batch sizes while maintaining high productivity and reduced lead times.

The challenges outlined can potentially be mitigated by implementing and further developing Industry 4.0 technologies. Digitalisation, digital twin technology, and the integration of artificial intelligence methods are essential in CNC machining to improve both efficiency and quality [1]. The digitalisation of manufacturing processes and the integration of sensors into machine tools have generated unprecedented amounts of data. This offers an opportunity to apply data-driven AI solutions to optimise the cutting process. Machine learning tools have led to the development of various solutions for predictive modelling of tool wear and tool life, cutting force, vibration, temperature, accuracy, surface roughness, energy consumption, etc. [2]. Currently, these tools are primarily used to optimise machining parameters, monitor operations for predictive maintenance, and schedule tool changes. Another significant category of AI tools used in manufacturing is related to operations research. The strict specifications, the complexity of machining processes, and the need to balance often conflicting objectives, such as minimising machining costs and maximising sustainability, create a complex multi-objective optimisation task. Solving these problems requires intelligent computational methods.

Traditionally, CNC tool path generation relies primarily on geometric principles and utilises only a few technological rules of thumb to improve machining efficiency. Therefore, the main goal is only to remove the allowance material while meeting the prescribed manufacturing tolerances. This is typically achieved through directional or contour-parallel machining strategies, even if it results in significant technological compromises [3]. Although AI tools have significant potential for optimal tool path planning, their current utilisation remains limited [4]. This is primarily due to two reasons: (1) these solutions often require excessive computing power, and (2) any errors are unacceptable because of safety-critical concerns. Kukreja and Pande [5] outlined the steps for tool path optimisation as follows: (1) generating the tool path, (2) performing simulations or machining, (3) measuring various parameters to assess the quality of the tool path, and (4) selecting the best tool path. This trial-and-error approach is difficult to avoid, and since the steps are computationally intensive, only advanced, intelligent algorithms can achieve usable results. Consequently, this area remains an active and challenging research field.

This paper aims to provide an overview of the modern CNC tool path generation solutions. Among the machining technologies, we focused only on turning, drilling, and milling, reviewing results from recent years. Given that some sub-areas have extensive literature in themselves, this study cannot be entirely exhaustive. There-

fore, this review aims to cover a broad spectrum of methods and applications, supported by illustrative examples. In the following, Section 2 discusses the optimisation objectives and the AI-based optimisation methods utilised for tool path generation. Section 3 covers the application areas of AI-driven tool path optimisation. Section 4 focuses on the challenges and future trends in this field. Finally, Section 5 provides a brief summary.

2 AI-based optimisation methods in tool path generation

Supporting tool path generation with AI tools can serve two primary purposes: automating the process planning or optimising the machining process. Regarding optimisation tasks, the objectives can vary widely, including maximising productivity, enhancing machining quality (such as accuracy and surface finish), promoting sustainability (through green machining and improving energy efficiency), minimising machining costs, reducing machining time, and preventing collisions.

In this paper, the term “artificial intelligence” is used in a broad sense to include not only data-driven learning approaches but also classical methods such as search, planning, and optimisation. In light of this, a wide variety of AI techniques can be considered when automating and optimising CNC tool path generation.

Determining the optimal sequence of operations in order to minimise idle times can be traced back to the classical graph search problem, often as an analogy to the travelling salesman problem (TSP) [6]. A typical example is finding the best drilling sequence for holes. If the number of points is relatively small, algorithms like depth- or breadth-first search [7, 8], greedy algorithm [9], A* or Dijkstra can be effectively employed [10]. However, when a large number of points need to be connected—such as when navigating discrete grid points on free-form surfaces with a milling cutter [11]—more advanced optimisation methods, such as evolutionary and other meta-heuristic algorithms [12, 13], may provide a solution.

Constraint Satisfaction Programming (CSP) is also used in tool path planning tasks. Typical examples are collision avoidance, primarily in five-axis milling and robotic machining [14], and determining the tool selection for a given machining feature [15].

During trajectory optimisation, local search techniques are often used to implement iterative improvement. In simple cases, gradient-based techniques like the hill-climbing algorithm [16] can be used effectively. However, due to the complexity of tool path planning tasks, the use of gradient-free methods is usually necessary. Consequently, techniques such as Simulated Annealing (SA) [17], various bio-inspired methods, e.g. Genetic Algorithm (GA) [18], Particle Swarm Optimisation (PSO) [19], Ant Colony Optimisation (ACO) [20], along with other population-based meta-heuristic algorithms [21], can lead to successful solutions. The largest group of AI-related applications in CNC tool path planning is the solution of multi-objective optimisation tasks, in which the aforementioned gradient-free, bio-inspired and metaheuristic methods are particularly effective [22]. Thus, these techniques are

essential for both the global trajectory optimisation and the automatic tool path generation.

Machine learning techniques, such as Support Vector Machines (SVM) [23], Artificial Neural Networks (ANN) [5, 24], Decision Trees (DT) [25], and regression analysis [26], are also widely used in tool path planning. By using data-driven machine learning-based predictive models, the effect of cutting parameters and tool path shape can be forecasted based on prior machining experiences, which paves the way for multi-objective optimisation, allowing the automatic selection of the most efficient machining strategies [5], and for adaptive control, including feed scheduling [27]. Machine learning-based surrogate modelling can enhance CNC tool path optimisation by effectively approximating complex process responses—such as cutting forces, chatter, machining error, surface quality, or energy consumption—allowing for rapid evaluation of alternative tool paths without requiring time-consuming physical or numerical simulations [26-28]. Additionally, reinforcement learning can also be employed to develop self-regulating models [24, 29-33].

Although with less importance, symbolic, knowledge-based methods, such as Expert Systems [34] and Fuzzy Logic [35], are also present in tool path optimisation. Their primary application field is determining the optimal machining strategy based on previous cases and predefined rules. Recently, the application of Large Language Models (LLMs) has rapidly developed, and now it has also started to be integrated into CNC technology [36]. Although only the monitoring of machine tools and interaction with CNC controls have been implemented so far, a notable example of this advancement is the concept called ChatCNC. This conversational machine monitoring framework incorporates large language models to facilitate natural language-driven interactions with real-time data from CNC machines. In their study, Jeon et al. [37] assessed the capabilities and limitations of three different models: GPT-4 from OpenAI, LLaMA 3-8B from Meta, and Mistral 7B from Mistral AI. They successfully achieved rapid adaptation of LLM application programming interfaces (APIs) through various prompting techniques.

After a brief overview of AI-based methods used for tool path generation and optimisation, the next section will present a collection of state-of-the-art results from recent implementations.

3 Application areas of AI-based tool path optimisation

The generation of CNC tool paths must comply with strict geometric requirements, including the complete removal of allowance material and the assurance of prescribed dimensional tolerances and surface roughness. Several technological criteria also need to be met, such as tool life, maximum cutting force, temperature, and vibrations. Consequently, tool path generation must rely on precise mathematical calculations. Traditionally, cutting path sections were determined solely on geometric principles, like direction- and contour-parallel strategies. The first use of AI-supported methods appeared in selecting the optimal machining operation sequence.

Automatic determination of the best machining strategy also represents a discrete choice. Section 4.1 reviews some recent results in these two areas. In addition to automatic tool path generation methods, AI-based tool path optimisation algorithms are also widespread. In the following, several related research results will be presented and classified according to the optimisation goal: Section 4.2 focuses on machining quality, Section 4.3 addresses machining productivity, and Section 4.4 concentrates on energy efficiency. Finally, separate subsections discuss AI-based methods developed for collision avoidance (Section 4.5) and adaptive tool path modification (Section 4.6).

Due to space limitations, the following overview cannot be exhaustive. However, we have attempted to cover a wide range of algorithm types and application areas by briefly presenting some recent studies.

3.1 Optimising the operation sequence and machining strategy

Optimising the sequence of operation elements for individual features has long been a research subject. A typical example of this is determining the optimal order of holes in drilling, but determining the machining sequence of independent geometric features leads to a similar problem. These tasks can be traced back to the Travelling Salesman Problem (TSP), where meta-heuristic methods such as genetic algorithms (GA) and particle swarm optimisation (PSO) are frequently used [20, 38].

Hu et al. [7] studied how the processing sequence of features of a part (PSFP) affects the energy used in tool changes and tool paths. A single-objective model is built to minimise machine energy consumption during feature transitions, including tool paths and tool changes. Modified depth-first search and genetic algorithm methods are then used to find the optimal PSFP with the lowest energy consumption of feature transitions. In the case study, the proposed method achieved a 28.6% reduction in energy consumption of feature transitions and a 27.9% reduction in transition time.

Most of the five-axis milling operations are not simultaneous, but only 3+2 axis indexed machining. Determining the indexing positions of rotary axes and determining the optimal sequence can also be interpreted as a search task. Hao et al. [6] derived this problem back to the classical travelling salesman problem (TSP) in the context of designing 3+2-axis tool paths for machining free-form surfaces with non-spherical tools. To do this, they first defined the set of possible subregions and tool orientations, then the corresponding three-axis tool path segments, and finally connected them into a continuous trajectory. In solving the TSP, they used a special partitioning algorithm to control the computation and memory requirements.

Choosing the best machining strategy is a discrete decision; however, evaluating the objective function can be very time-consuming, making traditional search methods less efficient. Historically, this task relied on the expertise of a technologist, but it can be enhanced and automated by incorporating expert systems and data-driven machine learning models.

Xu et al. [36] successfully applied large language models (LLMs) to automate manufacturing process planning using Knowledge Graphs (KG) derived from existing process plans. Their intelligent process planning method reduced computational time and manufacturing costs by nearly 50% in the case studies examined. However, this approach has not yet been extended to the hierarchical level of trajectory planning and optimisation, indicating potential opportunities for future research.

Kukreja and Pande [5] developed a machine learning based intelligent Strategy Prediction System (SPS). This system could assess three strategies for finishing free-form surfaces: adaptive planar, iso-scallop, and hybrid. The parameters considered were surface roughness, tool path length, and smoothness. Firstly, they analysed and labelled a large number of CAD models to create a dataset for supervised learning, then a Convolutional Neural Network (CNN) was designed and trained using this dataset to predict the best tool path strategy directly from the CAD model. During validation, the system achieved an impressive precision rate of 96.8% in predicting the optimal strategy out of the three tool path planning options.

Several industrial solutions are translating AI concepts into practical CNC applications. The solutions of “Manukai” [39, 40] use historical production data to accelerate programming and support human experience. The AI-powered estimating and CAM automation functions of “Toolpath” [41] use its proprietary Part Comprehension Engine to produce optimised machining strategies, operations, and tool paths while automating geometry selection and process planning. “CloudNC” [42] offers CAM Assist, which rapidly creates tool paths for up to 3+2-axis machining, estimates costs, and calculates feeds and speeds, enabling manufacturers to boost productivity and efficiency across global CAM platforms.

3.2 Improving machining quality

A general objective of tool path optimisation is to enhance machining quality, ensuring compliance with dimensional and shape accuracy as well as surface roughness requirements. This becomes particularly challenging when machining free-form surfaces with spherical or arbitrarily shaped tools.

Jin et al. [9] introduced a geometric decomposition strategy along with a multi-population-based meta-heuristic algorithm for optimising five-axis flank milling (Side Wall Axial Relief Feed - SWARF) tool path for finishing. The optimisation problem was quite extensive, making it prone to resource constraints if approached directly. To address this, the authors divided the surface into smaller subregions and performed tool path optimisation for each subregion separately using a multi-population harmony search algorithm. After optimising each subregion, they connected the optimal path segments to create a continuous final tool path. With this method, they were able to significantly reduce the machining error even with a short computing time. In this work, a greedy algorithm was employed to ensure quick results;

however, it occasionally fell short of achieving the global optimum. Thus, integrating more advanced optimisation algorithms could offer further improvement opportunities. To tackle the same problem, Chu et al. [12] employed a stochastic optimisation method known as the Electromagnetism-like Mechanism (EM) algorithm, which was enhanced by a simultaneous perturbation stochastic approximation (SPSA) technique. According to their research, this approach proved to be more effective than Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) for a specific five-axis milling task. In the presented case studies, improvements were achieved in computation time, geometric accuracy, and surface quality. Zekalmi et al. [19] introduced an innovative geometric error compensation method for five-axis CNC machine tools using the PSO algorithm. It post-processes tool paths based on the machine's inverse kinematic model, considering geometric errors and the impact of CAD/CAM software. The method solves a multi-objective optimisation problem to avoid tool-workpiece collisions while minimising deviation between the actual and CAM-designed paths. Zhao et al. [17] focused on improving the precision of turbine blade machining by reducing errors such as overcutting and undercutting during side milling. To do this, they used a smart hybrid algorithm that combines two methods—simulated annealing and particle swarm optimisation—to find the best tool path. The results showed that this combined algorithm works faster and more accurately than traditional methods.

Machine learning methods are increasingly being used in this area to reduce optimisation time. Jiang et al. [32] developed a method for modelling and compensating contour errors in CNC machining using deep learning and reinforcement learning. This approach achieved a reduction in contour errors by 60-85%, particularly in complex operational scenarios. Zhang et al. [28] developed a data-driven iterative pre-compensation method to address contouring errors in five-axis machine tools. Their approach involves using a trained Long Short-Term Memory Neural Network (LSTM-NN) to correct tracking errors predicted by an identified drive system model. Through this iterative process, they calculate a pre-compensation value. Before machining, the reference position command for each axis is adjusted using this optimal value. In the case studies examined, the contour errors during multiple machining passes were reduced by approximately 70%.

3.3 Improving the productivity

Besides enhancing machining quality, improving manufacturing productivity is another fundamental goal when optimising tool paths. A key aspect of this is minimising machining time while ensuring compliance with constraints on tool load and quality requirements. To reduce machining time for a given cutting operation, there are three main approaches: shortening the tool path length, improving the tool path's smoothness for high-speed traversal, and implementing intelligent feed rate scheduling.

Shortening the tool path length

One of the simplest ways to shorten the tool path is by minimising the linking movements, which has already been discussed in the paper when addressing the optimal sequence of operations. Shortening the length of cutting sections is significantly more complex, as it also requires careful control of the forces acting on the tool, as well as the quality of the machining.

In our previous work, we developed a mathematical model that describes the tool path in spline form, enabling the optimisation of the path. In some cases, the developed method increased the average material removal rate of trochoidal tool paths by up to 50% compared to the traditional cycloid strategy. This improvement was achieved by optimising the control points of spline curves, while ensuring that the maximum tool load was not exceeded. Both Bézier and B-spline curves were found to be effective in modelling the trajectory, while a stochastic hill-climbing [16] and a differential evolution algorithm [21] were implemented for optimisation.

To address the resource constraints related to trajectory optimisation, Zhang et al. [18] proposed a STEP-NC-supported edge-cloud collaborative manufacturing system called CAM as a Service (CaaS) with dynamic tool path generation and optimisation. The optimisation process was based on a non-dominated sorting genetic algorithm, which has been shown to reduce costs and improve efficiency by up to 70%.

Chichell et al. [22] developed a derivative-free stochastic algorithm using covariance matrix adaptation evolution strategy (CMA-ES) to optimise not only the tool orientation (rotation and tilt angles), but also the tool path shape (the contact point of the surface and the toroidal/flat end mill) simultaneously. The method was tested on complex free-form surfaces, such as turbine blades. This multi-objective optimisation framework effectively minimised machining time while keeping machining errors below a predefined threshold, and the tool positions and trajectories were free from both local and global collisions. Despite the promising results achieved with this approach, it still requires improvements in computational time. However, these challenges could potentially be addressed by accelerating the evaluation of the objective function or by employing the method to train neural networks.

Improving tool path smoothness

Simply shortening the path length is insufficient; it is also important that it has sufficient smoothness so that the tool does not need to slow down and accelerate again along corners. To solve this issue, Jiang et al. [26] used a deep learning based local smoothing algorithm called the Double-ResNet Local Smoothing (DRLS) algorithm. The First-Double-Local Smoothing (FDLS) algorithm optimised the positions of NURBS (Non-Uniform Rational B-Spline) control points, while the Second-Double-Local Smoothing (SDLS) algorithm optimised the NURBS weights to generate a smoother tool path. This approach enabled the cutting tool to traverse the tool path at a higher feed rate while assuring machining quality, geometric, drive condition, and contour error constraints.

Smoothing tool paths with pre-calculations to ensure high-speed traversal has been extensively studied; however, implementing these solutions in real-time poses challenges due to computational time constraints. Lu et al. [19] developed an intelligent neural network agent capable of determining servo commands directly based on the current tool path and operating state during each cycle using reinforcement learning. They referred to this neural network-based method for direct trajectory smoothing as Neural-Network Numerical Control (NNC), which can be easily applied to real-time CNC systems. Li et al. [24] developed a neural network-based method for direct toolpath smoothing of discontinuous G01 line segments in high-speed machining. Instead of pre-planned corner smoothing, an intelligent agent generated real-time servo commands using reinforcement learning. The approach improved cutting efficiency, ensured smooth motion, and can also be easily implemented in real-time CNC systems. Li et al. [43] developed a method to process and smooth the tool path from general G-code using an agent-based deep learning network technique. The model integrated several components, including Multi-layer Perceptron (MLP), convolutional neural network (CNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) models, along with a linear attention mechanism. Based on the identified degree of path roughness, they applied mean filtering, Bézier curve fitting, and the NACOA method for sharp corner recognition.

The optimisation of tool orientation in five-axis machining using ball nose cutters has been extensively researched. Due to the spherical geometry of the ball-end tool, the tool axis can be freely rotated around the contact point on the workpiece surface, enabling adjustment of both the tilt angle along the feed direction and the lead angle perpendicular to it. However, this additional opportunity also presents a challenge: the motion trajectories of the rotary axes must also be continuously smooth. In addition, the material removal process and the moving axes' motion functions are significantly influenced by the tool orientation, and therefore, their multi-objective optimisation is necessary. Lu et al. [44] approached the task as a classical search problem. They employed a greedy algorithm that added the neighbouring point with the slightest change in inclination at each step until reaching the endpoint. This method, through a two-level iteration process including rough and fine searches, effectively minimised the variation in the effective tool diameter and improved both the effective tool diameter and the tool path's smoothness, while preventing tool collisions.

Determining the tool's effective (or working) diameter is a computationally intensive operation in itself. To simplify this process, Mgherony and Miko [26] developed a geometric model to calculate effective diameters for nearly 3,000 tilt and lead angle combinations, and then trained a neural network with this data set. Then the neural network was able to immediately give an accurate estimate based on the input data without the need for complex geometric calculations. Their tests showed that using just two layers with 10 and 5 neurons, respectively, was sufficient to obtain better results compared to traditional regression models.

Intelligent feed rate scheduling

High-speed path traversing also requires proper feed rate scheduling. An important criterion for feed rate scheduling is that the movement components projected onto the axes must be continuously differentiable to several degrees. Additionally, it is essential to consider the kinematic and dynamic capabilities of the machine tool, as well as the tool load. Various algorithms are available to implement these requirements, typically involving extensive calculations. To intelligently predict tool load, in our previous work [27], we used a feed-forward fully-connected neural network, which significantly improved the accuracy of modelling the maximum force acting on the tool compared to traditional geometric methods. As a result, they achieved a 50% reduction in machining time for trochoidal milling, compared to scenarios without feed rate scheduling, by adjusting the feed according to the instantaneous cutter engagement angle.

Feed rate scheduling is particularly challenging for five-axis machine tools, as the relationship between the motion of the rotary axes and the spatial movements is extraordinarily complex and nonlinear. To address this issue, Ma et al. [45] developed an iterative control vector parametrisation method capable of keeping the velocity, acceleration, and jerk parameters within the specified limits using a bang-bang control principle. The technique is currently only capable of offline pre-scheduling, and in the future, its extension to real-time operation may be the next goal.

3.4 Improving the energy efficiency

The advancement of sustainability aspects is a general trend in CNC machining. One aspect of this is using environmentally friendly materials and technologies, but equally important is reducing energy consumption, which is significantly influenced by the tool path used during machining. To address sustainability in three-axis machining of free-form surfaces, Li et al. [46] developed a methodology for optimising tool paths in milling. Their approach aimed to enhance efficiency while reducing energy consumption and carbon emissions. The proposed solution calculates the cutter contact points and employs an adaptive genetic algorithm to optimise their sequence for machining free-form surfaces. Converting the multi-objective problem into a single-objective one using a weighted-sum approach facilitates efficient and accurate optimisation of tool paths.

Gao et al. [11] developed an algorithm for five-axis machining of free-form surfaces that can significantly increase energy efficiency by optimising the tool path. They created a Discrete Energy Consumption Path (DECP) model by discretising the cutting tool contact positions (CC points). Following this, they constructed an Energy Efficiency Solution Graph (EESG) by organising the nodes along with their weights and routes. This approach allowed them to transform the problem into a

shortest-path search issue within a directed graph. Then they used dynamic programming methods to determine the optimal tool path regarding minimum energy consumption.

Zhao et al. [13] developed an advanced multi-step optimisation method to reduce energy consumption during the five-axis finishing of free-form surfaces using ball end mill tools. In the first step, the surface to be machined was divided into subregions according to its curvature using a K-means clustering algorithm. Afterwards, a discrete grid was defined on the surfaces of each subregion using the Voronoi method. Finally, an adaptive dynamic genetic algorithm was employed to determine a meander-like tool path connecting the discrete grid points. The optimisation objective was to minimise the energy consumption function, while the constraints were the permissible ranges of cutting parameters and the requirements regarding the surface quality. Additionally, an intelligent method known as the adaptive simulated annealing algorithm was integrated into the selection operator of the genetic algorithm, which was able to speed up the calculation time.

Lu et al. [30] developed a hierarchical reinforcement learning algorithm to minimise the energy consumption of five-axis machining of thin walls, which can optimise cutting parameters and tool path together. After defining the models that describe energy consumption and the relationship between dynamic workpiece deformation and cutting parameters, the hierarchical reinforcement learning (HRL) algorithm with a Soft Actor Critic agent (SAC) decouples the model into two Markov Decision Processes operating at different timescales. The higher layer plans the cutting parameters for each machining pass on a macro timescale, while the lower layer, working at the micro timescale, performs multiple tool path expansions using the planned cutting parameters and provides feedback to the higher layer. The validation of this method demonstrated its effectiveness and accuracy in solving tool path planning while adhering to specified requirements. In the future, the next step could be to extend the algorithm to consider vibrations and the machine tool's kinematic and dynamic capabilities. In another study, Lu et al. [33] also aimed to make five-axis flank milling more energy-efficient, as it usually uses a lot of electricity when machining complex surfaces. To address this problem, the authors proposed a meta-reinforcement learning method for a tool path optimisation. A dynamic optimisation model was constructed for generating energy-efficient tool paths, which were described by multiple Markov Decision Processes (MDPs). Finally, meta-learning integrating with the Soft Actor-Critic (MSAC) framework was utilised to address the MDPs. In the case studies, a 40-70% reduction in energy consumption was achieved.

3.5 Collision avoidance

Avoiding collisions is a top priority when generating tool paths. A collision can cause damage not only to the tool and workpiece but also to the spindle and other machine components, which can result in significant repair costs. Additionally, we

must consider the indirect losses incurred while the damaged machine tool is out of production. Collision checking is relatively straightforward for up to three-axis machining, where only linear moving axes are involved. However, introducing rotary axes significantly increases the likelihood of collisions, making the task more complex. Consequently, collision checking is almost always included in five-axis path planning, as illustrated in the examples discussed above (refer to [19, 22, 44]).

Wu et al. [8] developed an algorithm for generating tool paths that prevent collisions between the tool and the workpiece during multi-axis machining. In the first stage, a repeated projection method was utilised to eliminate long-distance, non-intersecting collisions. The second stage focused on improving accuracy by constructing a hierarchical bounding box tree. Finally, a depth-first approach was used to solve the search tree. The experimental results demonstrated that the proposed method could meet the accuracy and real-time performance requirements.

In simulation-based collision detection systems, ensuring the accuracy of models is a critical concern. To address this uncertainty, Denkena et al. [47] developed a sensor-based image processing algorithm that integrates with a real-time collision detection system. Their approach utilises data from optical measurement technology in the actual machine environment, incorporates information from process planning, and conducts material removal simulations. If the simulation identifies a potential collision in advance, it can automatically send a machine stop command to the CNC control system using a process-parallel simulation.

3.6 Adaptive modification of the tool path shape

Adaptive control of the machining process is a key aspect of smart manufacturing, utilising sensor signals. One of the earliest solutions developed in this area focused on trajectory planning, specifically adaptive control of the feed rate based on tool load. However, research in this field is still ongoing. Recently, Jiang et al. [35] introduced a real-time solution using fuzzy control to manage the feed rate in relation to the main spindle's current consumption. They employed a self-adjusting method for quantifying factors to enhance the efficiency of their control approach in practical applications. In their case studies, the intelligent adaptive machining system demonstrated an average improvement in processing efficiency of 17% compared to conventional machining.

Besides feed rate control, adaptive control systems that increase the path tracking accuracy by locally adjusting the tool path are becoming increasingly important. Xiao et al. [48] introduced a Model Reference Adaptive Control (MRAC) system, which adds the estimated error to the reference trajectories to reduce contour errors, utilising a Model Predictive Control (MPC) algorithm. The transformation coefficients are updated in real-time according to a parameter adaptation law. This method has successfully reduced the tracking error to a minimal level. Dittrich et al. [23] developed a machine learning-based solution that utilises Support Vector Machine

(SVM) and Support Vector Regression (SVR) techniques to achieve similar objectives. The geometric errors in the machined shape were assessed by measuring it on the machine using a touch probe. Based on the collected data, they could model the expected geometric errors for different machining parameter sets. Then, this predicted deviation can be used to adjust the tool path, thereby reducing shape errors by shifting the tool's movement accordingly. A potential next step in automatic collision detection could be enabling the system to navigate these problematic sections by planning a new trajectory.

The issue of tool wear significantly complicates the constant assurance of production quality. Cutting tools gradually degrade until they reach the end of their usable tool life. Nowadays, many methods have been developed for automatic, sensor-based monitoring of tool conditions. Besides direct measurement of machining errors, intelligent solutions based on measuring and analysing acoustic emission [49], vibrations [50], cutting force [51], or spindle power [52] are noteworthy. These technologies enable better utilisation of tools, preventing premature replacements that are often made for safety reasons, thereby greatly enhancing productivity and cost-effectiveness. However, addressing the geometric errors caused by tool wear remains challenging. To address this issue, Zhang et al. [53] developed an intelligent tool compensation method for turning. Utilising PyTorch and various third-party libraries, they constructed and trained a deep learning model using labelled images of cutting tools. This model enabled accurate identification of wear regions and automatic classification of tool wear states. As a result, they were able to determine the tool wear value and successfully implement error compensation for the tool path. Advanced CNC control functions were also developed to employ machine learning techniques, compensating for thermal expansion by adjusting the tool path coordinates [54], as well as for retuning servo parameters, resulting in more accurate and faster path tracking [55].

4 Challenges and future trends

Most of the abovementioned methods can already be implemented in real industrial applications, although some have only been tested in experimental environments. In AI-supported tool path optimisation, computational requirements often present a bottleneck. Increasing computational power, such as through the development of quantum computers, could help address this issue. Furthermore, machine learning-based surrogate models may also provide a solution. However, their lack of explainability and transparency can be critical in many cases, particularly because CNC machining is considered a safety-sensitive area. This issue can be addressed by integrating physical laws and principles with statistical AI models, a key goal of today's machine learning research [56]. The flexibility and efficiency of data labelling also pose challenges in supervised learning systems, as there are few publicly available databases. Therefore, unsupervised or self-supervised learning is a potential future research area in AI for manufacturing [57]. In the future of CNC machining,

advancements in artificial intelligence are expected to drive several key trends, including the development of digital twins, improvements in image processing technologies, and wireless sensing technology [58]. Additionally, the potential for adaptive tool path modification is still largely untapped, representing another significant area for future development.

5 Conclusion

Nowadays, nearly every aspect of our lives is being transformed by advancements in artificial intelligence. This transformation is also evident in the field of CNC tool path generation, where AI-supported solutions are increasingly being implemented to enhance production efficiency and automate process planning.

This paper aimed to provide a comprehensive overview of the various applications of AI methods in this field, including optimising operational sequences and machining strategies, improving machining quality, enhancing productivity, increasing energy efficiency, avoiding collisions, and using adaptive tool path shapes. This paper discusses several AI methods that can be utilised to automate or optimise tool path generation. These include simple search algorithms, heuristic and local search techniques, evolutionary and other bio-inspired optimisation methods, constraint satisfaction programming, knowledge-based systems, machine learning models, and even large language models. Finally, the paper briefly reviewed the challenges and expected future trends of AI applications in CNC technology. Currently, the main challenges are primarily the high computational demand of tool path optimisation, the limited availability of labelled datasets, and the explainability difficulties of AI methodologies. These challenges indicate a future rise in sophisticated multi-objective optimisation techniques, unsupervised learning, and machine learning methods that integrate physical rules. Although the results achieved so far are already impressive, further improvements are expected as ongoing research continues to address computational and data challenges.

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