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Evaluation of an Automated Online-Quality Assurance Framework for CNC-Machined Workpieces via Point Cloud Comparison Techniques

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***Abstract*— The increasing digitization of manufacturing systems demands new strategies for quality assurance during the operational phase of computer numerically control (CNC) machines. This paper presents a novel approach to online-quality assurance using operational-parallel real-time simulation and point cloud comparison techniques. During machining, a real-time simulation generates a virtual representation of the manufactured workpiece, reflecting the actual position values and process conditions. This simulated point cloud is then compared directly to the nominal CAD model to detect geometric deviations early in the production process. Unlike conventional approaches relying on post-process optical measurements, this method enables in-process evaluation without interrupting operations. It supports fast, non-invasive quality assessment and facilitates adaptive process control. The work presented in this study presents an evaluation of different point cloud comparison methods for an online-quality assurance framework.**

I. INTRODUCTION

The integration of digital twins and virtual manufacturing processes is becoming increasingly vital in the evolution of modern production systems, offering enhanced efficiency through their wide range of applications. In the domain of subtractive manufacturing, quality assurance remains a fundamental component. However, current quality control practices are predominantly carried out offline—either post-process or upon the completion of the final product. This time-delayed inspection often limits the ability to respond promptly to quality deviations.

Recent advancements point toward the adoption of real-time, in-parallel simulations that facilitate continuous monitoring of the manufacturing process. [1] These simulations enable virtual, online-quality assurance by replicating the behavior and outcomes of the production system in real-time. To support automation in this context, robust methods are required to assess the quality of virtually generated workpieces.

This work explores the potential for automated online-quality assurance during the manufacturing process through the use of point cloud comparison techniques. An architectural framework is first introduced to enable the automation of quality assurance tasks. Subsequently, various methods and processing steps are evaluated in terms of their performance and the accuracy of the comparison results. Finally, the implementation and experimental results are presented, highlighting the most effective algorithm identified in the preceding evaluation. First works in this topic are already presented in [2], [3]

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II. FUNDAMENTALS

A. Architecture of an operational-parallel real-time simulation

The use of simulation models for virtual manufacturing and testing is a well-established practice in engineering. Modern software tools support applications such as Virtual Commissioning (VC), where simulation models typically consist of a behavioral model, a visualization component, and process-specific models—for example, material removal in milling. Coupling these with a virtual control system enables early testing and optimization of control and motion sequences, known as Software-in-the-Loop (SiL). In Hardware-in-the-Loop (HiL) simulations, a real controller is connected via fieldbus for real-time interaction with the simulation.

Traditionally, such models are limited to the commissioning phase. However, the architecture proposed in [4], [5] extends HiL simulation for real-time operation, allowing continuous simulation and virtual workpiece generation throughout production. For the use case in this work a control architecture is chosen, where the simulation model from the VC is running on an edge-device (see Fig. 1). Over the fieldbus a real-time (RT) connection to the control system can be established. The online-quality assurance can be integrated on the edge device over a non real-time communication (NRT).

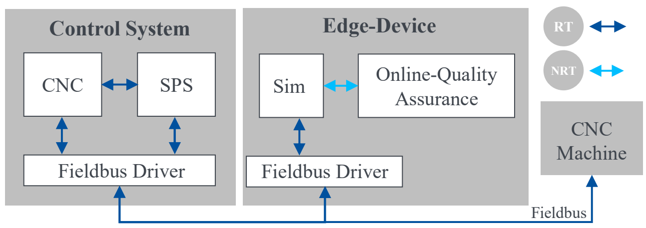

Fig. 1: Control architecture for an operational-parallel real-time simulation in an external simulation setup over fieldbus based on [4]

B. Offline-Quality Assurance of workpieces

To evaluate the quality of a feature of a workpiece manufactured by a CNC machine, specific boundary conditions must be defined. In this work, a feature is understood as a geometric characteristic of a workpiece that defines its function, such as through-holes, pockets, or grooves.

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To ensure interoperability with existing quality assurance systems, international standards are applied. The focus lies on form and positional tolerances, as specified in DIN EN ISO 1101 [6].

Form tolerances refer to deviations from an ideal geometry, while positional tolerances address deviations in location and orientation relative to a reference system. DIN EN ISO 8015 [7] sets the general conditions for such measurements: the workpiece is assumed to be a rigid, clean body measured at 20°C. Additional conditions (e.g., humidity) must be stated separately. Two key principles apply: the principle of geometrical elements, which defines features as bounded by natural limits (e.g., edges), and the principle of independence, which states that each feature is to be evaluated independently.

This work considers three common form tolerances as illustrated in Fig. 2:

- **Roundness:** deviation of a circular profile from a perfect circle, bounded by two concentric circles spaced by a tolerance t.
- **Straightness:** deviation of a line from an ideal straight line, with a tolerance zone of two parallel lines t apart.
- **Flatness:** deviation of a surface from a perfect plane, with a tolerance zone between two parallel planes spaced by t.

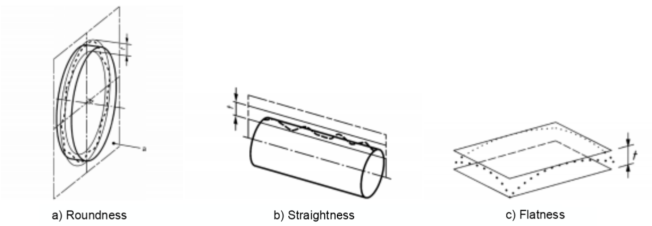


Fig. 2: Types of form tolerances/quality features [6]

To enable online-quality assurance, relevant quality features must be automatically extracted from the virtual representation of the workpiece. This work presents a system in which such features are computed in real-time during the manufacturing process, thereby facilitating in-process quality assurance. Additionally, the same setup can be applied to 3D-scanned representations of finished parts, allowing for automated post-process quality assessment as well.

III. Current Research

In the context of online-quality assurance, several approaches utilize simulation models driven by internal CNC control data to virtually replicate the manufacturing process in real time [1], [8], [9]. A common limitation in these works lies in the simulation model itself, which is often not designed for continuous operational use. The approach presented in this work introduces a complete pipeline—from VC to operation-parallel real-time simulation—enabling persistent use of the model throughout production. Moreover, the data interface to the control system is already fully integrated, eliminating the need for separate synchronization or buffering mechanisms during virtual workpiece generation.

Another emerging approach in current research involves the application of machine learning to NC data for predicting workpiece quality, thereby enabling in-process quality assurance [10]–[13]. A key challenge of this method lies in the requirement for substantial data generated during actual machining operations, which limits its applicability in early stages. Additionally, the computational overhead of inference and model evaluation often prevents real-time execution, making integration into fast control loops difficult.

All of these approaches lack the quality assurance during the process itself. The workpiece quality can only be accesses and calculated in a manual matter after the process. It helps to support the offline quality assurance, but faults during the process cant be accessed. Furthermore the quality assurance is still manually or digital supported, an automatic method is not researched.

In this work a concept and evaluation is presented for a fully automatic online-quality assurance framework using point cloud data of the virtual manufactured workpiece.

IV. Approach and Concept

This section presents the underlying concept of an online-quality assurance of manufactured workpieces based on point cloud data. First of all the derivation of a processing pipeline from these requirements is explained, along with the criteria used to evaluate each individual step of the pipeline.

Against this background, the concept of parallel in-process simulation, which enables online-quality assurance, gains importance. Using a VC model, material removal is simulated in both with "actual" data and a "target" data from the CNC control. Based on this data, virtual representations of the workpiece are continuously generated and compared on a feature based comparison with each other as well as with the engineered CAD model. This approach yields two main advantages: quality assurance can take place during process itself since the virtual workpiece can be accessed without being affected by chips or coolant; and the overall process is accelerated, as downstream compensation methods can be shortened or even omitted. Furthermore, resources are conserved, as defects can be detected and potentially corrected at an early stage.

This online-quality assurance framework imposes several requirements. Most critically, the system must be **fully automated** to minimize time and labor input. Additionally, it must operate with **low computational latency** to avoid impeding the actual process. The method must also be **generalizable and extensible** to other types of workpieces in order to ensure the necessary flexibility. Finally, the **accuracy** of the simulation and the virtual comparison must be sufficiently high to reliably detect deviations and defects.

To meet these requirements, a dedicated processing concept was developed, as illustrated in Fig. 3

The processing within the online-quality assurance framework begins after the completion of each relevant quality feature (see Fig. 2). Following the manufacturing step, both the target and actual virtual workpieces are exported from the system. Simulation tools typically provide the output in the

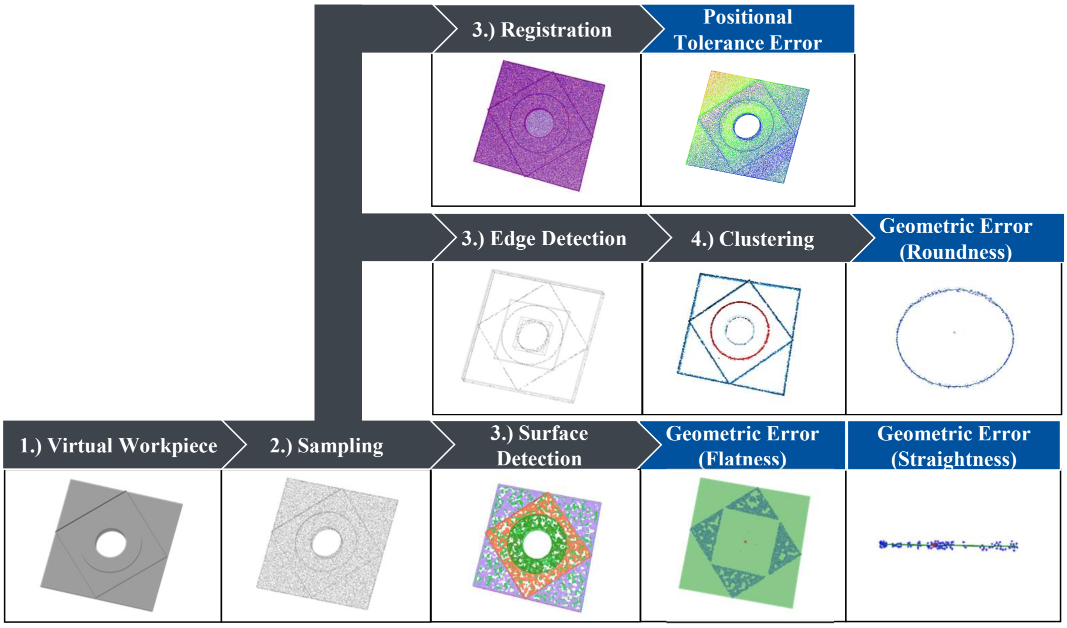


Fig. 3: Concept for an automatic online-quality assurance framework, with different pre-processing (grey) and quality calculations (blue) steps

form of mesh files, which lack semantic information about the manufactured features. Consequently, a pre-processing stage is required. This includes converting the mesh into a point cloud, applying edge or surface detection algorithms to identify form tolerances (e.g., roundness, flatness), and executing a registration procedure to evaluate positional deviations.

Point clouds are employed in this approach due to the absence of explicit feature data in raw mesh representations. Moreover, point cloud processing offers a well-established and extensively researched foundation for precise geometric comparison and tolerance evaluation.

V. Evaluation and Implementation

To validate the proposed concept, each step of the processing pipeline is implemented using various algorithmic approaches and evaluated against the criteria outlined in the preceding section. The implementation relies on standard open-source Python libraries (mainly CloudCompare [1] and Open3D [2]) to ensure reproducibility and compatibility.

A. Sampling

In mesh sampling, computation time and sampling quality are critical factors. Minimizing runtime is essential to allow frequent execution within an online-quality assurance framework. At the same time, high sampling quality—particularly uniform point distribution—significantly enhances the accuracy of subsequent processes such as edge and surface detection.

This study compares random sampling and Poisson-disk sampling methods as implemented in Open3D. Machine learning-based sampling techniques are not considered, as they primarily address the up-/downsampling of existing point clouds rather than mesh-to-point cloud conversion. Poisson-disk sampling offers superior spatial uniformity, which benefits downstream tasks such as edge detection. However, this quality comes at a significant computational cost. As shown in Table I, generating 10 000 points using Poisson-disk sampling is over 1000 times slower than random sampling; at 500 000 points, it is approximately 1600 times slower. While random sampling exhibits near-linear scalability, Poisson-disk sampling incurs a higher computational burden as the number of points increases.

TABLE I: Computation times for sampling a point cloud from a mesh (average of 5 trials)

Number of Points	Random Sampling	Poisson Disk Sampling
10 000	0.00198 s	2.11 s
50 000	0.00911 s	11.46 s
100 000	0.01834 s	24.83 s
500 000	0.08998 s	142.87 s

Open3D's random sampling was further compared to the implementation in CloudCompare, accessed via the CloudComPy Python wrapper. For a sampling size of 500 000 points, Open3D demonstrated a 38.2% faster runtime (1.239s) compared to CloudComPy.

Sampling quality was evaluated by comparing the sampled point clouds to their respective engineered meshes. Alignment between the point cloud and mesh was verified. Both random and Poisson-Disk sampling were analyzed at point counts of 10 000, 50 000, 100 000, and 500 000. Table II reports that the mean distance remain nearly constant across different point counts and sampling methods. This consis-

[1]https://www.danielgm.net/cc/
[2]https://www.open3d.org/

tency is expected, as sampling accuracy does not depend on the number of points; both methods are unbiased. This shows the validity of the method to use the point cloud sampling without changing the accuracy of the virtual workpiece.

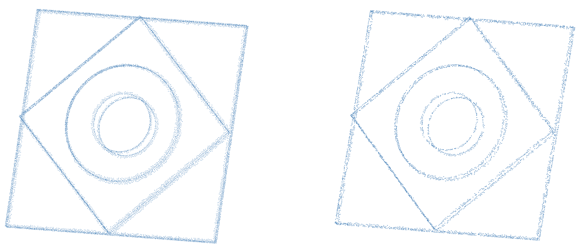
TABLE II: Comparison of point cloud sampling with its mesh file

Sampling Method	Number of Points	Mean Distance [mm]
Random	10 000	5.92491×10^{9}
	50 000	1.13355×10^{10}
	100 000	8.22981×10^{10}
	500 000	1.72210×10^{11}
Poisson Disk	10 000	8.38108×10^{10}
	50 000	1.18525×10^{9}
	100 000	4.63788×10^{10}
	500 000	-2.92183×10^{10}

B. Edge detection

A robust edge detection method is essential—one that reliably identifies edges in point clouds regardless of the underlying mesh quality. For the intended application, three key criteria must be met: (1) computation time, to support timely analysis; (2) a minimum point count of 25 000, ensuring adequate resolution for subsequent processing; and (3) edge detection accuracy, which is critical for effective quality assessment.

Edge detection was evaluated using CloudCompare's "Compute Curvature" method and a curvature-based approach in Open3D. The results indicate that Open3D produces sharper and less noisy edge representations, as illustrated in Fig. 4.



(a) CloudCompare (b) Open3D

Fig. 4: Comparison of edge detection from a point cloud sampled with 50k Poisson disks

This observation is supported both visually and quantitatively. As shown in Table III, distance measurements between the detected edge points and an ideal reference edge point cloud confirm the superiority of Open3D. Accuracy improves with increasing point density, and Open3D consistently achieves lower mean distances, indicating higher precision and reliability in edge detection.

Table IV also presents the runtime comparison between the two edge detection methods. As expected, runtime increases approximately linearly with the number of points. CloudCompare outperforms Open3D significantly, being over 100 times faster at 10 000 points and around 30 times faster at

TABLE III: Cloud-to-cloud distances from edge detection using CloudCompare and Open3D, compared to the ideal edge point cloud

	Mean Distance [mm]			
Points	CloudCompare		Open3D	
	Random	Poisson	Random	Poisson
10 000	0.521105	0.537439	0.987888	0.420024
50 000	0.291052	0.303204	0.172977	0.184779
100 000	0.212080	0.217285	0.123517	0.132662
500 000	0.113168	0.115409	0.059031	0.062034

500 000 points. CPU usage analysis reveals that Open3D operates on a single thread, while CloudCompare leverages multithreading, which accounts for its superior performance.

TABLE IV: Computation times for edge detection using CloudCompare vs. Open3D for different sampling methods and point counts (in seconds)

Points	CloudCompare		Open3D	
	Random	Poisson	Random	Poisson
10 000	0.0084	0.0117	0.9143	0.9285
50 000	0.0674	0.0872	4.5698	4.6204
100 000	0.1649	0.1784	9.2190	9.1420
500 000	1.6025	2.2975	46.5937	46.3822

C. Surface detection

To evaluate the form tolerance of a surface, it must first be geometrically isolated, necessitating a surface detection step. In point cloud data, this can be effectively achieved using the RANSAC algorithm. As illustrated in Fig. 5, each detected surface on the workpiece is visualized in a distinct color. Due to the stochastic nature of RANSAC and its reliance on random point sampling, incomplete or partially detected surfaces may occur, particularly in areas with sparse or noisy data.

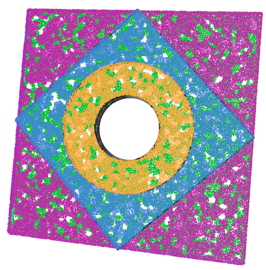


Fig. 5: Surface detection by using the RANSAC algorithm (each color one surface)

D. Clustering

Through parameter tuning, successful clustering of the workpiece was achieved, as shown in Fig. 6, where each color represents a distinct cluster. In this example, four clusters and several noise points were identified. The clustering was applied to a Poisson-disk–sampled point cloud containing 25 000 points, following the edge detection step. The total computation time was 0.01925 seconds. For the DBSCAN algorithm, the minimum number of points was set to 8, and the neighborhood radius (epsilon) to 0.0018. These parameters remain valid as long as the resolution and size of the point cloud remain unchanged. This clustering method enables the targeted isolation of circular features, which can subsequently be used for automated online-quality assurance.

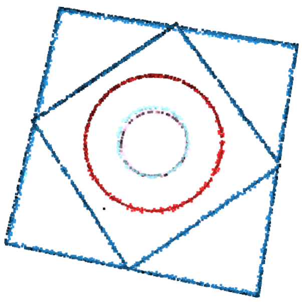


Fig. 6: Clustering of the different quality features

E. Positional tolerance

Positional tolerance can be both visualized and quantified within a online-quality assurance framework by comparing the actual workpiece to its engineered CAD model. This process begins with accurate registration of the two models. When both the nominal and actual geometries are represented as point clouds, point-to-point distance calculations can be used to assess deviations.

To optimize computational efficiency, the registration between the nominal and simulated point clouds is performed only once at the start of the simulation, as the relative position and size of the models remain constant throughout. Subsequent evaluations involve only the calculation and color mapping of point-wise distances, enabling rapid and intuitive visualization of positional deviations for quality assessment.

F. Form tolerance

This section focuses on the evaluation of form tolerances, specifically roundness, flatness, and straightness, within an online-quality assurance framework. To assess these tolerances, the relevant geometric feature (e.g., circle, plane, or line) must first be segmented. Once isolated, the feature is analyzed using Principal Component Analysis (PCA) to determine its principal axes and enable geometric characterization.

The PCA-based fitting approach is demonstrated using a circular feature (see Fig. 7). First, the centroid of the point cloud is computed and set as the local origin (marked by the red cross in the figure), ensuring analysis relative to the feature itself. PCA is then performed using scikit-learn, which calculates the covariance matrix followed by eigenvalue decomposition. The resulting eigenvectors define the directions of maximum, intermediate, and minimal variance. For circular and planar features, the first two eigenvectors span the local XY-plane, while the third represents the surface normal.

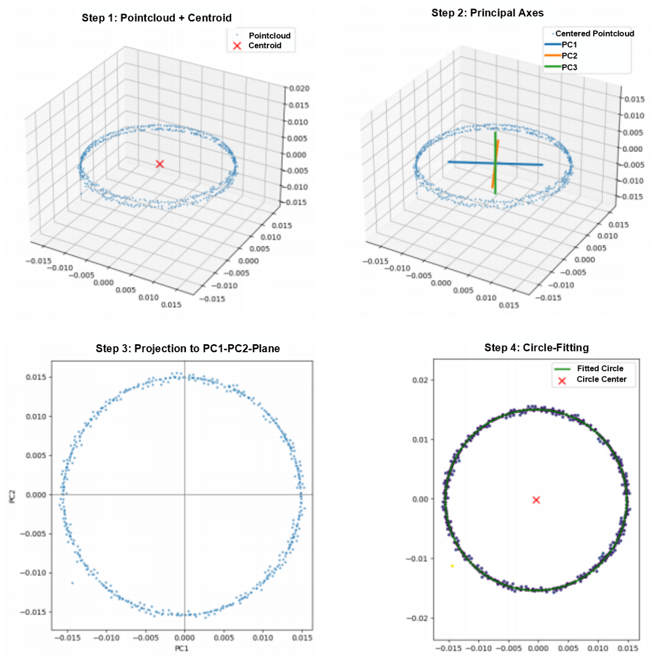


Fig. 7: PCA based fitting algorithm to fit a circle feature

In the third step, the point cloud is projected onto the XY-plane (first two principal components), reducing the problem to 2D. A least-squares circle fitting is then performed using the SciPy optimizer to determine the circle's center and radius. Key quality metrics include the mean and standard deviation of point-to-center distances (indicating circularity), the maximum distance (to detect outliers), and radius deviation (to identify anomalies).

For flatness evaluation, the same PCA procedure is used. A Gram-Schmidt orthogonalization ensures correct plane orientation, followed by projection to 2D. Unlike the circle, no fitting is required; quality is assessed by computing the arithmetic mean, standard deviation, and maximum of point-to-plane distances—referred to as average roughness.

In the case of straightness, PCA is again applied. The eigenvector with the largest eigenvalue defines the primary line direction. Quality metrics are derived from the alignment and distribution of points along this axis.

All evaluations were performed on a Poisson-Disk–sampled point cloud (25 000 points), extracted after edge detection. Total computation times for form tolerance evaluation, including PCA and fitting, were:

- Roundness: 0.01975 seconds
- Flatness: 0.01076 seconds
- Straightness: 0.00896 seconds

VI. Final Results

For the operational-parallel, real-time simulation, a 3-axis CNC machine model is used. Both the simulation and the online quality assurance framework run on an edge device to ensure low-latency processing and real-time integration. The simulation environment is implemented using ISG-virtuos, which establishes a real-time connection to the physical CNC control system via the fieldbus connection. Within the ISG-virtuos platform, a remote interface has been developed to dynamically export virtual workpieces after each machining feature.

The performance evaluation and runtime measurements of the entire pipeline are summarised in Table V. All computations were conducted on a Windows 11 system with an Intel Core i9-10900K CPU, 32 GB of RAM and an NVIDIA Quadro RTX 4000 GPU.

TABLE V: Average computation times of individual steps in the complete pipeline

Processing Step	**Computation Time in seconds**
Sampling	6.71361
Position Tolerance	0.07392
Edge Detection	2.26321
Clustering	0.01925
Surface Detection	0.08848
Form Tolerance: Circle	0.01975
Form Tolerance: Surface	0.01076
Form Tolerance: Line	0.00896

The results in Table V demonstrate that the most time-consuming step is the point cloud sampling, which dominates the overall computation time. In contrast, the subsequent stages—such as edge detection, clustering, surface segmentation, and form tolerance evaluation—require significantly less time, each executing well below one second. This highlights the feasibility of deploying the entire pipeline in an online-quality assurance context, particularly if the sampling stage can be optimized or preprocessed efficiently.

VII. Conclusion and Future Work

This work presents a fully automated online-quality assurance pipeline based on simulation-driven virtual manufacturing and point cloud analysis. Leveraging VC models in operational-parallel real-time simulations enables the system to continuously evaluate workpiece geometry during production. Key contributions include robust mesh sampling, edge and surface detection, clustering for feature isolation and PCA-based evaluation of form tolerances, specifically roundness, flatness and straightness. Furthermore, this work evaluates different methods in this domain by comparing calculation times for near real-time evaluations with accuracy. Experimental evaluation confirms the accuracy and efficiency of the proposed methods, demonstrating the viability of a point cloud–based framework for in-process and post-process quality control.

Future research will focus on evaluating the effectiveness of the proposed method and applying it to real-world manufacturing processes. Validation will be achieved by conducting a comparative analysis of the manufactured workpieces and state-of-the-art offline measurement techniques, in order to confirm the accuracy of the method. Furthermore, simulation models will be enhanced by integrating more precise behavioral models to enable the generation of virtual workpieces with greater accuracy. This will also facilitate the analysis of surface characteristics, such as roughness, within the virtual environment.

Acknowledgment

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