AI-Driven Intelligent Grinding Automation for Precision Motorcycle Camshaft Manufacturing

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Keywords：AI-driven automation, Intelligent grinding system, Taguchi optimization, Real-time monitoring and control, Precision camshaft manufacturing.

ABSTRACT

Precision and efficiency are essential in modern manufacturing, yet motorcycle camshaft production still faces labor shortages and inconsistent manual machining challenges. In this study, an AI-driven intelligent grinding automation system was developed to enhance machining accuracy and productivity. The system integrated real-time monitoring, data acquisition, and adaptive parameter control to replace manual adjustments. Key machining parameters were optimized using the Taguchi method and polynomial regression modeling, while a simulated machining environment with image recognition enabled real-time prediction and correction. Experimental results showed a 95% qualification rate at a surface roughness below 2.4 μm, a 38% reduction in processing time, and an increase in daily output from 128 to 235 units. These findings demonstrate that the proposed system provides a scalable and efficient approach to precision camshaft manufacturing and represents a significant advancement toward intelligent, data-driven production in the Industry 4.0 era.

INTRODUCTION

With the rapid development of the global manufacturing industry, many factories face persistent challenges such as labor shortages, low production efficiency, and increasing precision requirements. The emergence of Industry 4.0 has accelerated the adoption of smart factories that integrate cyber–physical systems, automation, and data-driven intelligence to achieve sustainable competitiveness (Ahuett-Garza & Kurfess, 2018; Gorecky et al., 2014; Wang et al., 2016). Previous studies have emphasized the critical role of human–machine interaction, enabling technologies, and intelligent control systems such as PLC- and SCADA-based architectures to enhance manufacturing autonomy and efficiency (Kermani et al., 2021; Kiangala & Wang, 2019; Morsi & El-Din, 2014).

As a key international hub for motorcycle manufacturing, Taiwan recorded more than 23.3 million registered motorcycles in 2023, averaging 99.7 units per 100 people. However, traditional manual machining methods have struggled to meet rising market demand due to inherent limitations in precision, consistency, and process stability. Fig. 1 (a)-(b) compares conventional manual machining with the proposed automated grinding system. The manual process relies heavily on operator experience, often resulting in variability in surface quality. In contrast, the proposed computerized grinding system integrates real-time sensor feedback, process data acquisition, and AI-assisted decision-making, enabling machining parameters to be dynamically adjusted according to actual processing conditions. This approach ensures consistent machining accuracy and productivity while embodying the core Industry 4.0 principles of real-time monitoring and intelligent control.

Materials' mechanical and tribological behaviors in precision surface finishing directly affect grinding performance and durability. Recent studies have demonstrated that incorporating nanoadditives (Shi et al., 2020), optimizing semiconductor processing conditions (Shi et al., 2005), and reinforcing polymer and cellulose-based materials (Rahmadiawan et al., 2024; Shi et al., 2024) can significantly enhance mechanical strength, surface integrity, and functional stability. As demonstrated in roll-to-roll film manufacturing, optical measurement and stress quantification have also proven effective for continuous-process quality assurance (Shi et al., 2025). These findings underscore the need for intelligent, data-driven control to maintain microstructural precision and minimize process defects. To address these challenges, this study proposes an automated grinding system that integrates real-time monitoring, data acquisition, and self-adjusting capabilities to enhance production efficiency and machining

Paper Received November 2025. Revised December January 2026. Accepted January, 2026. Author for Correspondence: Shih-Chen Shi.

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accuracy. The system optimizes camshaft machining parameters using the Taguchi method (Patel et al., 2021) and polynomial regression analysis (Ajona et al., 2022; Kumar et al., 2019; Maulud & Abdulazeez, 2020). A virtual simulation environment utilizing image recognition (Cheung et al., 2011; Lu et al., 2019) and machine-vision-based monitoring (Bu & Guo, 2022; Deng et al., 2021; Songwen et al., 2019; You et al., 2022) dynamically adjusts parameters and predicts machining outcomes. By dividing the machining surface into specific zones and applying optimized parameter combinations, the system effectively compensates for surface irregularities, ensuring high-quality output and improved repeatability.

Overall, this research aims to enhance production efficiency, reduce human error and material waste, and meet the demands of high-precision, large-scale manufacturing. Future applications may extend to other industrial sectors, advancing the realization of intelligent and adaptive manufacturing systems.

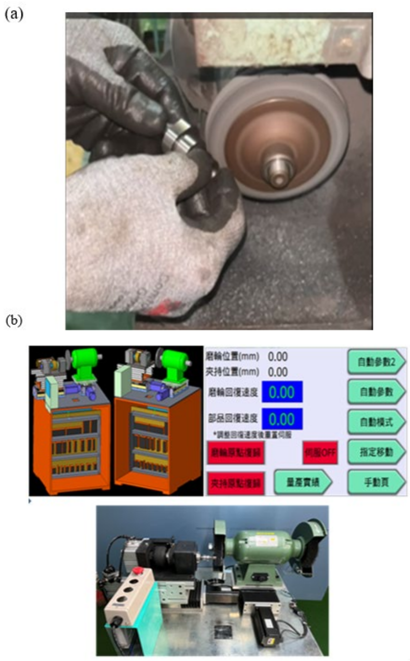

Fig. 1 (a) Schematic of manual machining (b) Schematic of automated machining system

MATERIALS AND METHODS

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Experimental Setup

To address labor shortages and precision requirements, we developed a fully automated machining system that integrates programmable logic controllers, sensors, and actuators for precise machining control. Camshafts were used as test workpieces and mounted on the system for brush-based grinding. Surface roughness was measured using a probe to ensure consistency. The Taguchi method was employed in the initial phase, optimizing key parameters, as shown in

Table. 1 L_9 Taguchi experiment parameter

Brush Speed, rpm (rpm)	Workpiece Speed (rpm)	Brush Grit (#)	Processing Time (s)
1000	5	120	30
1500	10	240	45
2000	15	360	60

The system includes a brush motor with adjustable speed, ensuring control over rotational speed. Sensors monitor the machining process, and real-time data is recorded for analysis.

Simulation Environment

The proposed intelligent machining system was developed and validated within a comprehensive simulation environment designed to emulate real-world production conditions. The environment integrates three major components: image recognition, machining simulation, and production line implementation.

Fig. 2 illustrates the image recognition workflow developed in this study to standardize surface evaluation and defect detection of camshafts. The process begins with image binarization (Step 1), where the original image is converted into a high-contrast binary image to enhance contour visibility and suppress background noise. Next, reference alignment is performed using the Hough Circle Transform (Step 2) to accurately identify the camshaft center and geometric position. Finally, contour-based qualification evaluation is conducted (Step 3), in which the extracted contour is overlaid with a reference template and quantitatively assessed against predefined tolerance thresholds to determine pass or fail results.

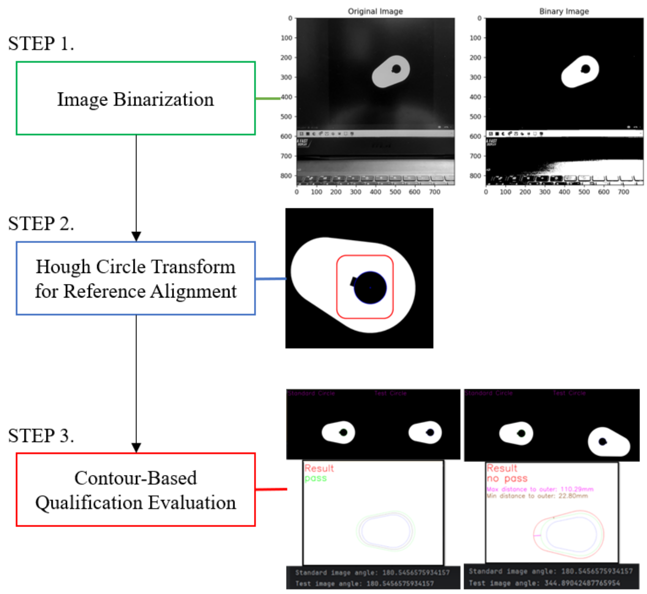

Fig. 2 Workflow of the image recognition and

qualification evaluation process.

dynamic machining simulation module was implemented to replicate actual machining behavior. Randomized surface profiles were generated to simulate machining variations, and a segmented optimization method was used to calculate deviations from ideal surface height. Guided by historical machining data, the system adaptively adjusted processing parameters to ensure optimal material removal and stable surface roughness. Post-processing analysis further established correlations between machining parameters and resulting surface quality trends.

Finally, the system was deployed in a factory production line for continuous operation testing. The automated setup integrated optimized machining parameters in real time, continuously recording operational data such as machining stability, response time, and data processing efficiency. A built-in data acquisition module monitored surface variations and provided immediate feedback for dynamic adjustments, thereby maintaining high machining precision and process reliability under actual manufacturing conditions.

RESULTS AND DISCUSSIONS

Experimental Parameter Optimization

The Taguchi method effectively determined the optimal machining parameters with a minimal number of experimental trials (Table. 2). After identifying the key parameter combination, a polynomial regression analysis was performed to further refine and validate the optimization results.

The findings reveal that the parameter configuration (ω_1 = 1500 rpm, ω_2 = 5 rpm, ε_1 = #240, t_1 = 60 s) achieves an optimal balance between machining efficiency and surface quality. Although the Taguchi method provides a robust framework for global optimization, its capability for fine-tuning individual parameters remains relatively limited.

Polynomial Regression for Precision Tuning

Polynomial regression was employed to analyze the relationship between specific parameters, such as brush rotation speed (ω_1), and surface roughness while maintaining other factors constant. As shown in Fig. 3, results indicate that when ω_1 is within the 1200-1300 rpm range, surface roughness stabilizes near its optimal state with a consistent improvement trend. The findings underscore polynomial regression as an effective tool for precise parameter tuning, complementing the broader optimization capabilities of the Taguchi method.

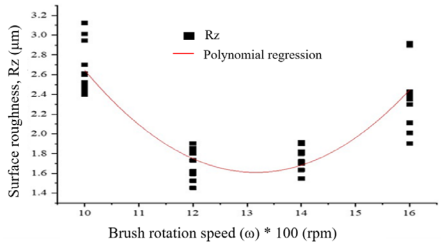

Fig. 3 Results of the polynomial regression

Automated Surface Recognition and Defect Detection

The image recognition model utilized reference standard surface images, binarization processing, and Hough transform techniques to detect surface deviations and machining defects. As illustrated in Fig. 4 and Fig. 5, the system accurately extracted outer contours and key feature points, enabling precise machining corrections. The Canny edge detection algorithm ensured high feature clarity while minimizing background noise and false detections. Experimental validation demonstrated an overall recognition accuracy of 95%, with robust performance in high-contrast and well-defined images.

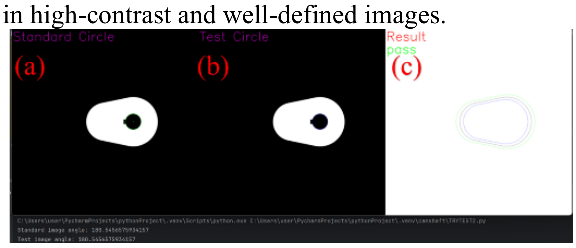

Fig. 4 Qualified workpiece illustration: (a) Standard design drawing, (b) Captured image, (c) Overlapping comparison results.

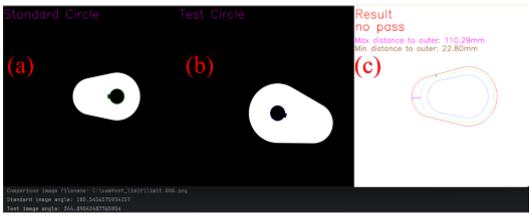

Fig. 5 Non-conforming workpiece illustration: (a) Standard design drawing, (b) Captured image, (c) Overlapping comparison results.

Comparison of Adaptive and Fixed-Speed Machining

The machining simulation system segmented the workpiece surface into distinct machining zones, allowing a direct comparison between adaptive speed control (Fig. 6 (a)) and fixed-speed processing (Fig. 6(b)). The chart illustrates the machining process through various curves and annotations. The blue curve (Original Surface Profile) represents the pre-machining surface profile, simulating height variations across different angles. After processing, the black dashed curve (Processed Surface Profile) depicts the modified surface, showing height

Table. 2 Results of the L_9 Taguchi experiment

No.	Brush Speed, rpm (rpm)	Workpiece Speed (rpm)	Brush Grit (#)	Processing Time (s)	Rz (μm)
1	1000	120	5	60	2.399
2	1000	240	10	45	2.608
3	1000	320	15	30	2.905
4	1500	120	10	30	1.831
5	1500	240	15	60	1.599
6	1500	320	5	45	1.698
7	2000	120	15	45	2.526
8	2000	240	5	30	2.201
9	2000	320	10	60	2.401

variations in each segment following material removal. The green dashed horizontal line (Minimum Point) is the reference baseline for surface specifications. In contrast, the red dashed boundaries (Lower Bound and Upper Bound) define the acceptable machining tolerance range, ensuring material removal remains within the specified limits. To facilitate zone differentiation, orange vertical dashed lines mark every 30-degree interval, segmenting the machining regions. Each 30-degree segment is annotated with its height difference relative to the minimum point, helping identify machining requirements for different zones. The orange RPM curve, displayed on the right axis, illustrates the adaptive speed settings, with each segment representing the RPM values applied to specific regions, providing a clear visualization of speed adjustments. At the top of the chart, "Total Removal" and "Total Loss Rate" indicate the cumulative material removal and overall loss rate across 12 machining zones, demonstrating the efficiency and precision of the adaptive machining strategy. The results highlight significant differences in machining efficiency and surface quality.

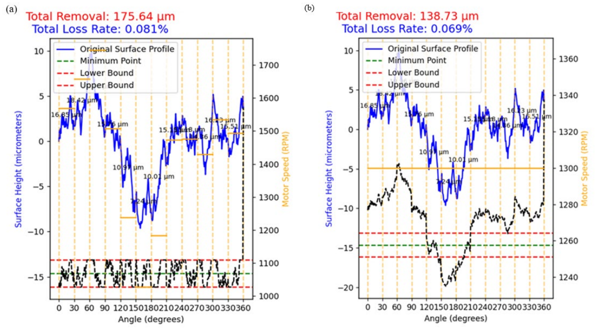

Fig. 6 (a) Adaptive machining: original surface and predicted surface illustration, (b) Fixed-speed machining: original surface and predicted surface illustration.

Adaptive Speed Control and Fixed-Speed Processing

Traditional Fixed-Speed Processing methods lack adaptability to surface inconsistencies, resulting in limited effectiveness in roughness improvement—particularly in regions with high surface variation. This approach operates at a constant brush rotation speed, making it difficult to achieve uniform material removal or maintain consistent surface quality.

In contrast, the proposed Adaptive Speed Control dynamically adjusts the brush RPM based on real-time surface variations. By leveraging real-time feedback, the system maintains surface roughness variation within ±3 μm, ensuring high machining precision. The adaptive mechanism reduces total machining time by approximately 15%, improving efficiency without compromising quality.

Furthermore, the adaptive machining system incorporates self-learning and optimization capabilities. It analyzes accumulated processing data to refine future parameter settings, identifying a nonlinear relationship between machining efficiency and brush rotation speed. Through iterative learning, the system continuously optimizes processing parameters, achieving more uniform material removal and stable surface quality. Experimental results validate the feasibility of intelligent parameter optimization and real-time adaptive machining, demonstrating significant advancements in production efficiency, machining precision, and defect reduction.

Production Implementation Results

The deployment of the automated machining system in a factory setting demonstrated significant improvements in production efficiency, product quality, and process stability. Initially, the product qualification rate was approximately 70%, but after implementing optimized machining parameters, it increased to 95%, significantly reducing defect rates and rework costs. Production output also saw a substantial boost, rising from 125–130 units per day to 235–240 units, reflecting a 20–25% improvement in capacity. Additionally, the dynamic machining strategy effectively reduced processing time per workpiece by 38%, cutting the original machining time from 210 seconds to 130 seconds, thereby enhancing operational efficiency.

Beyond production improvements, the upgraded system integrated real-time data monitoring, enabling automated fault detection, emergency shutdown, and alert notifications, significantly reducing reliance on manual intervention. Previously, the system lacked standardized data feedback, but with computerized data acquisition, machining processes became more precise and responsive to variations in surface conditions. As illustrated in Fig. 7 (a)-(b), pre-machining camshaft surfaces exhibited significant roughness variations and visible waviness defects, whereas post-machining surfaces showed remarkably improved uniformity and defect elimination. These findings validate the effectiveness of the automated machining system in enhancing production efficiency, machining precision, and product consistency, offering a scalable and reliable solution for industrial applications.

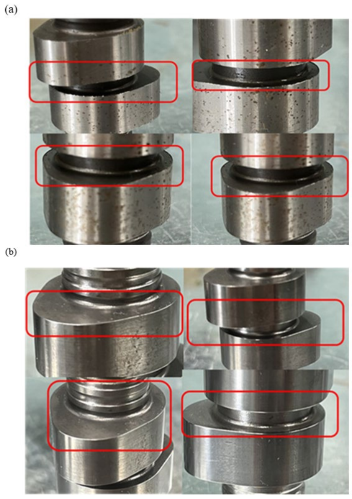

Fig. 7 (a) Camshaft surface before machining (b) Camshaft surface after machining.

CONCLUSION

This study hypothesized that integrating automation, intelligent control, and real-time monitoring would enhance the stability, precision, and productivity of camshaft machining. Experimental results supported this hypothesis, demonstrating a 95% qualification rate at a surface roughness of ≤2.4 μm, a 38% reduction in processing time, and an increase in daily output from 128 to 235 units. The simulated machining environment further validated the system's stability and self-correction capabilities, effectively reducing material waste and compensating for variations in machining conditions. These findings confirm that predictive modeling and parameter optimization significantly improve machining performance and process reliability.

From a practical perspective, the proposed system offers clear industrial value by reducing reliance on skilled manual labor, standardizing machining quality, and enabling stable mass production under real factory conditions. Its modular architecture, data-driven control strategy, and adaptive parameter adjustment make the system readily scalable and transferable to other precision-machined components, such as shafts, gears, and rotational mechanical parts. Overall, the developed automated grinding system provides a high-efficiency and scalable solution aligned with Industry 4.0 principles. Future research will extend this framework to higher-precision machining tasks and more complex geometries, further advancing the realization of fully adaptive and intelligent manufacturing systems.

ACKNOWLEDGMENT

This work was supported by the National Science and Technology Council (NSTC), Taiwan, under Grant Nos. 113-2221-E-006-087-MY2, 113-2221-E-006-112-MY2, and 114-2221-E-006-090. The authors also acknowledge the Core Facility Center of National Cheng Kung University (NCKU), Taiwan, for providing access to EM000600, funded by NSTC project 114-2740-M-006-001. Additional support from the Higher Education Sprout Project, Ministry of Education, Taiwan, through the Headquarters of University Advancement at NCKU, is gratefully acknowledged.

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