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Structural Optimization Simulation of Bearing Polishing Machine and Intelligent Optimization System Design for Polishing Process Parameters

Wei-Tao Jia[1,2], Juan-Hong Jing[1], Xiang-Yun Yi[1],
Rui-Da He[1], Yu-Lan Huai[1], and Tao Zhang[1*]

[1] Hebei Institute of Mechanical and Electrical Technology,
Xingtai City 054000, Hebei Province, China

jwtyjj0101@126.com, juanhong678@163.com, xiangyun7987@163.com,
ruida8908@163.co, 15131935857@163.com, sqxyyx@126.com

[2] Xingtai Intelligent Technology Innovation Center for Calibration Equipment,
Xingtai City 054000, Hebei Province, China

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Abstract. This paper proposes a general solution to improve the process of bearing polishing, a key operation in precision machining. The paper is centered on the combination of structural optimization through the use of advanced simulation tools and process parameter adjustment through the use of intelligent optimization. The study emphasizes the importance of machine setup and operating conditions for improving bearing quality and manufacturing efficiency. The study delves into how simulation techniques can be used to optimize the design of the structural components of the machine for maximum performance, accuracy, and durability. Furthermore, the article investigates how machine learning algorithms can be used to dynamically adjust polishing parameters to achieve optimal results in real time. By combining two leading-edge technologies, smart process control and structural optimization, the platform has the potential to significantly improve process performance, reduce cost of production, and ensure consistency of the final product. Combined strategy is the foundation of developing next-generation automation and intelligent manufacturing platforms that will transform precision machining technology.

Keywords: bearing polishing, structural optimization, intelligent system, process parameters, machine design, precision machining

1 Introduction

Mechanical structure optimization and its intersection with polishing process optimization and smart optimization techniques is an evolving area of research aimed at improving the efficiency, stability and precision of manufacturing processes. Progress in the field over recent years has involved many various routes, ranging from experimental studies to the application of artificial intelligence (AI) for optimizing mechanical structures and process parameters for various applications, including precision material polishing and mechanical dynamics optimization.

Srivastava and Pandey [1] gave an example of experimental method application and process optimization in polishing silicon wafers. Their work discussed the effect of ultrasonic vibration on the material removal rate (MRR) during polishing using a double-disk chemically assisted magnetorheological polishing system. Through response surface methodology (RSM) and genetic algorithms, they identified the important process factors that are most influential and have maximum impact on MRR, such as polishing speed, abrasives concentration, and especially ultrasonic power. It highlights how to optimize the process parameters, not just to enhance the efficiency but to tailor the machining process to the specific needs of the material.

In another similar study, Pal et al. [2] studied experimentally optical glass polishing, material removal, and surface roughness. Optical glass has its application in precision optics. As a result, surface finish demands in optical glass are extremely high. Using a Taguchi L9 orthogonal array in experimental design, they revealed the strong effect of abrasive slurry concentration on material removal rate and surface roughness, indicating the need for proper optimization of polishing parameters for the desired results in optical applications.

* Corresponding Author

Xu et al. [3] experimented with methods of optimizing machine structure by researching the structure and manufacturing potential of ion beam (IBF) machines used in the production of sub-nanometer optical surfaces. Their research focused on optimizing the fast response platform of the machine in order to improve its dynamical performance, demonstrating how structural adjustments can significantly improve the precision and performance of expert machining equipment.

As Rasool Mokhtari Homami [4] have explained, artificial intelligence in optimizing machining processes has emerged as a revolutionary approach. Their systematic review offers an overview of the application of artificial intelligence technology to intelligent machining processes like machining parameter optimization and tool state and chatter management. This indicates the growing relevance of AI-based methods in improving machining process sustainability and intelligence and provides some valuable lessons on future trends for machine and process optimization.

Overall, the papers demonstrate the intricacy of machine structure and polishing process optimization. From the fine-tuning of polishing parameters for delicate materials to the mechanical structure optimization of high-precision operations, and the increasing role of artificial intelligence in revolutionizing machining processes, the field is characterized by a relentless pursuit for excellence. Blending smart optimization techniques with traditional methodologies offers a promising path to achieving unprecedented accuracy and effectiveness in production processes, ushering in a new era of flexible, efficient, and increasingly smart mechanical design and operation. An important direction will be to implement hybrid optimization approaches, like utilizing deep reinforcement learning with on-line sensor feedback for adaptive process control. Interdisciplinary collaboration with mechanical design, artificial intelligence (AI) modeling, and industrial systems engineering will be key to develop systems that are capable of adapting in dynamic settings with mixed materials. Furthermore, future work could consider digital twin technology for on-line simulation and predictive maintenance, which not only improves performance, but also contributes to system reliability and lifetime management. This work will assist in overcoming the barriers to reconciling simulation with real performance and allow smart manufacture systems to exhibit greater autonomy and resilience.

This paper presents a comprehensive methodology combining structural and intelligent optimization for bearing polishing machines. Structural optimization is achieved through Finite Element Analysis (FEA) and topology optimization to enhance machine stiffness and reduce vibration, improving stability and precision. An intelligent optimization system is developed using machine learning algorithms (SVM, DNN) and genetic algorithms (GA) to dynamically adjust polishing parameters in real-time, based on continuous feedback. This integrated approach ensures optimal performance by minimizing polishing time while maximizing surface finish quality, laying a solid foundation for intelligent and efficient precision manufacturing.

2 Bearing Polishing Machine Design

This section primarily introduces the overall structure of the polishing machine, as well as the simulation-based optimization of its joint structures and components. Structural optimization is employed to enhance the overall performance of the polishing machine. The general layout is shown in Fig. 1.

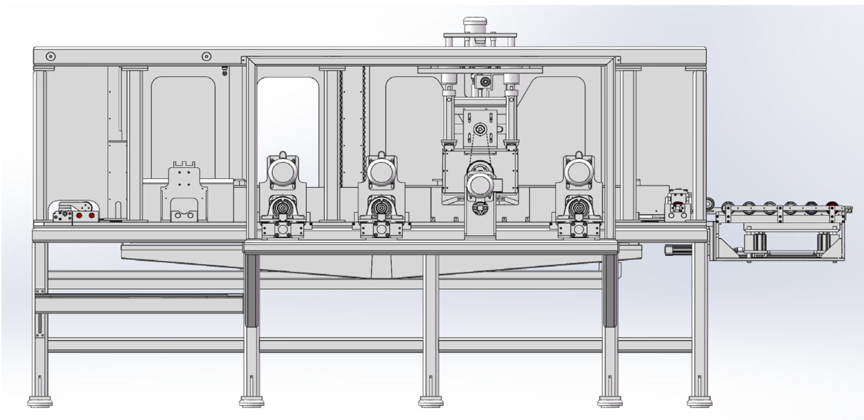

Fig. 1. Overall structure of the polishing machine

2.1 Structural Optimization Simulation for Bearing Polishing Machines

Structural optimization of bearing polishing machine is one important factor in making the machine efficient to run and last long, especially under dynamic loads during the polishing process [5]. Structural optimization typically is done in a computational method, and among the most typical methods used, the Finite Element Analysis (FEA) leads the pack [6].

The joint component in the polishing machine structure is the polishing disk surface. The polishing structure is shown in Fig. 2.

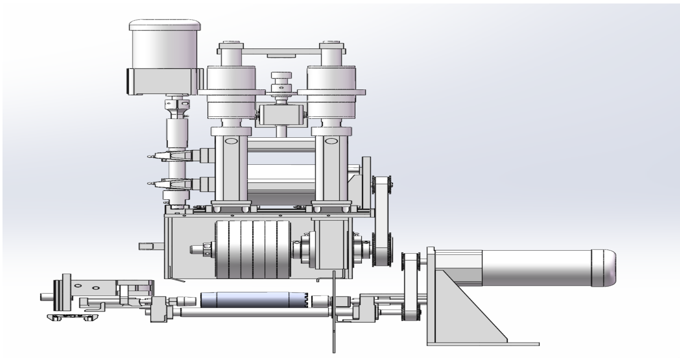

Fig. 2. Structure of the polishing disk surface

Mathematically, the reaction of a loaded structure by external forces can be described by the following general equation of structural dynamics:

$$[M]\{u\}+[C]\{u\}+[K]\{u\}=\{F(t)\} \tag{1}$$

Where $[M]$ is the mass matrix, $[C]$ is the damping matrix, $[K]$ is the stiffness matrix, $\{u\}$ is the displacement vector, $\{u\}$ is the velocity vector, $F(t)$ is the time-dependent external force vector. The objective in optimization is to minimize the displacement $\{u\}$, as this represents the deformation that could potentially affect the precision of the polishing process. In addition to dynamic considerations, the optimization also takes into account the material properties, such as Young's modulus (E) and Poisson's ratio (v), which define the elasticity and deformation behavior of materials. The stiffness matrix $[K]$ can be derived from the material properties and geometry as follows:

$$[K]=\int [B]^T [D][B]dv \tag{2}$$

Where $[B]$ is the strain-displacement matrix, $[D]$ is the material property matrix (for elastic materials, this is typically a function of E and v), v is the volume of the element being analyzed. By adjusting the design through methods such as topology optimization, the goal is to minimize the compliance (inverse of stiffness) while satisfying various design constraints, including maximum stress limits and displacement limits. The optimization problem can be formulated as:

$$\begin{aligned} &\min \int \frac{1}{2} u^T [K(p)] u d\Omega \\ &Subject \quad to: \\ &\sigma_{\max}(\rho) \le \sigma_{limit} \\ &u_{\max}(\rho) \le u_{limit} \end{aligned} \tag{3}$$

Where ρ is the material density distribution in the design domain, u is the displacement field, $[K(p)]$ is the stiffness matrix depending on the material distribution ρ, $\sigma_{\max}$ and $u_{\max}$ are the maximum stress and displacement constraints, respectively [7]. The optimization process aims to reduce the material usage while ensuring that the machine components meet the structural integrity requirements. By solving this problem using numerical methods, one can determine the optimal material distribution for each component of the machine.

The polishing process mechanism is shown in Fig. 3.

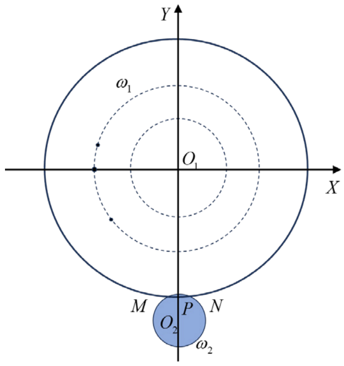

Fig. 3. Polishing process mechanism

The material removal rate (MRR) at point P on the polishing disk surface is related to the position of point P. It continuously changes over time. Therefore, the MRR at point P is a function of its relative distance from the polishing disk center and time, expressed as:

$$MRR = k_{pv} = f(l,t) \tag{4}$$

When point P is located at different radial positions, the entry point M and exit point N of the dressing tool will also vary. The direction $\overline{MN}$ changes accordingly. If the dressing tool rotates around the center O_1 of the polishing disk with angular velocity ω_1, then the time T taken to pass through point P is related to angle $\angle MO_1N$:

$$T = \frac{\angle MO_1N}{\omega_1} \tag{5}$$

The angle $\angle MO_1N$ can be obtained using the law of cosines:

$$\angle MO_1N = 2cos^{-1}\left(\frac{l^2+e^2-r^2}{2le}\right) \tag{6}$$

At any moment during the dressing process, the rotation angle swept by the dressing disk center O_2 is:

$$\alpha = \omega_1 t, t \in [0,T] \tag{7}$$

From this, it follows that:

$$\angle PO_1O_2 = \frac{1}{2}\angle MO_1N - \alpha \tag{8}$$

$$PO_2 = \sqrt{r^2+e^2-2recos\angle PO_1O_2} \tag{9}$$

$$\angle O_1PO_2 = cos^{-1}(\frac{l^2 + PO_2^2 - e^2}{2l \cdot PO_2}) \tag{10}$$

Where e is the distance between the dressing tool and the center of the polishing disc.

The linear velocity of the dressing tool center O_2 relative to the polishing disk center O_1 is $\overrightarrow{v_1}$. The linear velocity of the abrasive at point P relative to the dressing center O_2 is $\overrightarrow{v_2}$. Therefore, the velocity of point P relative to O_1 is:

$$\vec{v} = \overrightarrow{v_1} + \overrightarrow{v_2} \tag{11}$$

Sensitivity represents how responsive an objective function is to changes in its parameters. This helps identify which variables significantly impact the objective function, allowing for targeted process control or optimization to achieve desired goals.

The sensitivity of the objective function $f(x)$ reflects the rate of change $f(x)$ with respect to its variable $x = (x_1, x_2, \dots, x_j, \dots, x_n)$. If $f(x)$ is differentiable, its first-order sensitivity S in a continuous system is defined as:

$$S(x_i) = \frac{\partial f(x)}{\partial x_i} \tag{12}$$

Based on regression experiments of abrasive belt polishing, the empirical model for surface roughness can be expressed as follows:

$$R_a = f(\omega, P, a_p, v_f, P) = c_0 \omega^{c_1} P^{c_2} a_p^{\ c_3} v_f^{\ c_4} P^{c_5} \tag{13}$$

The empirical model for predicting surface roughness R_a in abrasive belt polishing is based on sensitivity analysis of process parameters. It expresses R_a as a function of six key variables: abrasive belt rotation speed ω(r/min), polishing pressure P(N), compression amount a_p(mm), feed speed v_f(mm/min), and abrasive grain size P, along with a constant coefficient c_0.

This study expands sensitivity analysis and interval optimization of process parameters based on the empirical model in Equation 13. According to the concept of sensitivity, Equation 13 is used as the objective function, and the process parameters are treated as variables. A sensitivity model is established to quantify how changes in individual process parameters affect surface roughness. The absolute sensitivity and relative sensitivity of surface roughness to process parameters are numerically expressed to reflect how strongly surface roughness responds to a given parameter change. The expression is shown in Equation 14:

$$\begin{aligned}
S_{R_a}^{\omega} &= \frac{\partial f(\overline{\omega}, \overline{P}, \overline{a_p}, \overline{v_f}, \overline{P})}{\partial \omega} \\
S_{R_a}^{p} &= \frac{\partial f(\overline{\omega}, \overline{P}, \overline{a_p}, \overline{v_f}, \overline{P})}{\partial p} \\
S_{R_a}^{a_p} &= \frac{\partial f(\overline{\omega}, \overline{P}, \overline{a_p}, \overline{v_f}, \overline{P})}{\partial a_p} \\
S_{R_a}^{v_f} &= \frac{\partial f(\overline{\omega}, \overline{P}, \overline{a_p}, \overline{v_f}, \overline{P})}{\partial v_f} \\
S_{R_a}^{P} &= \frac{\partial f(\overline{\omega}, \overline{P}, \overline{a_p}, \overline{v_f}, \overline{P})}{\partial P}
\end{aligned} \tag{14}$$

Equation 14 defines the sensitivity of process parameters, reflecting the rate of change in surface roughness induced by unit variations of a given parameter within a certain range. The graphical slope of the corresponding curve visually represents this sensitivity. Therefore, the optimal range for each parameter can be selected based on its sensitivity to ensure the desired surface roughness is achieved.

2.2 Design of Intelligent Optimization System

The intelligent optimization platform in Table 1 for the polishing process applies ML algorithms to learn and adjust process parameters like polishing speed, pressure, and abrasive grade dynamically. The system employs a data-driven approach where historical process data, variables like material types, machine setups, and process outcomes, is used to train the algorithm to predict optimum setup for specific types of bearings and operating conditions. With the use of real-time feedback and multi-parameter optimization techniques, such as genetic algorithms (GA), the system is able to constantly enhance the polishing process to minimize the polishing time and provide a stable and desired surface finish.

Table 1. Intelligent polishing optimization system

Component	Description
Machine learning algorithms	Utilizes algorithms like SVM and DNN to learn from historical and real-time data for predictive optimization.
Multi-parameter optimization	Employs genetic algorithms (GA) to optimize combinations of polishing parameters for best performance.
Real-time feedback	Monitors key metrics such as vibration, polishing rate, and surface roughness to inform adjustments.
Adaptive control strategies	Uses feedback from the environment to adaptively control process settings in real-time.
Optimization problem formulation	Defines variables X and objective function $f(X)$ based on surface roughness and polishing time within a feasible space S.
Fitness function	$f(X) = \alpha$ * Surface Roughness + β * Polishing Time
GA evolution process	GA operations include selection, crossover, and mutation to find optimal parameters over generations.
Model-based Predictive Control (MPC)	MPC uses a predictive model to minimize the error between desired and actual output across a prediction horizon.

The backbone of the intelligent optimization system is based on the integration of multi-parameter optimization algorithms. The most frequently applied algorithms to this end are the GA, a heuristic search algorithm with an analogy in the process of natural selection. The GA generates an evolving population of candidate solutions (parameter sets) over generations toward the optimum possible combination of process parameters. In this optimization framework, the fitness function $f(X)$ can be defined as a combination of factors like surface roughness $R_a(x)$ and polishing time $t_{polish}(x)$:

$$f\left(X\right)=\left(X\right)+R_a\left(x\right)+\beta\cdot t_{polish}\left(x\right) \tag{15}$$

Where α and β are weighting factors to balance the trade-off between surface quality and process efficiency (polishing time), $R_a(x)$ is the surface roughness, a key performance indicator for the quality of the polished surface, $t_{polish}(x)$ is the time taken to complete the polishing process for a given set of parameters. The GA algorithm iterates over selection, crossover, and mutation to evolve the population of solutions [8]. After each generation, the system chooses the most promising parameter sets based on their fitness, recombines them to hunt for new promising solutions, and randomly introduces variations to avoid local minima. The iteration continues until convergence is reached, where the optimal polishing parameters are found. Furthermore, real-time feedback from the machine, i.e., vibration levels and surface roughness measurements, is continuously fed back into the system. The feedback signals are processed using dynamic data-driven algorithms to predict and update the optimal settings. A model-based predictive control (MPC) approach can be employed to dynamically regulate the polishing parameters in real-time based on the continuous feedback.

In addition to these algorithms, the intelligent optimization system also seeks the help of advanced technologies such as real-time feedback systems and adaptive control strategies to improve polishing performance. Through continuous monitoring of the machining environment, the system is able to adjust process parameters based on real-time information such as vibration levels and surface roughness measurements. This feedback system enables the system to make extremely precise adjustments in real time, thereby improving surface finish and reducing polishing time.

In addition, with the help of real-time sensor feedback integrated into the machine, the process is monitored through key performance parameters such as vibration rate, polishing rate, and surface roughness during polishing. All of this is used to adaptively correct process parameters through dynamic data-driven algorithms such as support vector machines (SVM) or deep neural networks (DNN). These models always predict the optimal conditions, allowing the system to adjust parameters in real time and maintain a high level of performance.

This intelligent optimization system thus enables adaptive and real-time process improvement of polishing, enhancing the precision and efficacy of the process, which advantageously aids the construction of intelligent manufacturing systems. Incorporation of real-time feedback mechanisms makes it possible for the system to dynamically adjust and optimize the process parameters, leading to more uniform and high-quality polished surfaces [9].

3 Experiment Design

The objective of this experiment is to simulate the structural and process optimization of a polishing machine using the finite element analysis and genetic algorithm methods described in Section 3. The goal is to enhance the machine's stability, precision, and efficiency during the polishing process. This study focuses primarily on the optimization of the polishing disk structure and polishing parameters to achieve the shortest possible polishing time and the highest surface finish quality. This simulation-based approach ensures mechanical integrity and appropriate refinement of process parameters to meet the high demands of precision manufacturing applications, particularly where surface quality and dimensional accuracy are critical performance indicators.

The overall design of the optimization system is illustrated in Fig. 4.

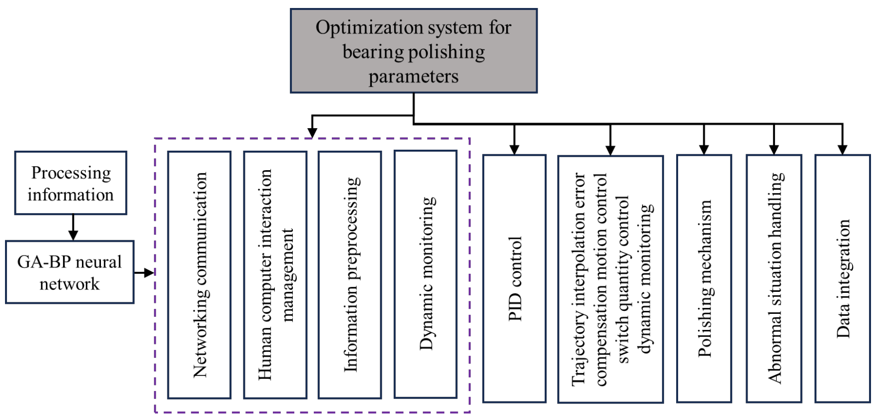

Fig. 4. Overall design of the optimization system for the polishing disk structure

The optimization idea of parameter optimization algorithm is to use the BP neural network with significant self-adaptation, self-learning and generalization capabilities, which can effectively explore the complex nonlinear relationship between data and is highly sensitive to the initial weights and thresholds. The BP neural network is easy to fall into the local minimum rather than the global minimum. The genetic algorithm achieves global optimization through efficient adjustment and search mechanisms, and finds a set of global optimal solutions as the initial parameters of the BP neural network. Compared with the traditional random initialization method, this method significantly reduces the randomness of the initial weights and thresholds.

The optimization steps are as follows:

1) The network topology and related parameters need to be determined.

2) Encode the weights and thresholds of the network to generate the initial population.

3) Design the fitness function according to the network error, calculate the fitness value of each individual, and select individuals with excellent performance.

4) By setting the appropriate crossover rate and mutation rate, perform crossover and mutation operations to further optimize the population.

5) Train the BP neural network to achieve the expected performance level. The optimization process is shown in Fig. 5.

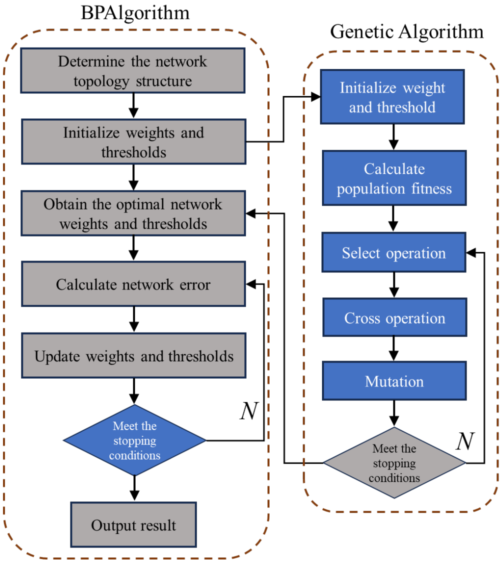

Fig. 5. Optimization process of the parameter optimization algorithm

This study aims to perform a comprehensive simulation-based optimization of the polishing machine's structural components and polishing process parameters, with the ultimate goal of improving the machine's stability, accuracy, and efficiency. The optimization focuses on enhancing the stiffness and vibration resistance of key components such as the base, spindle, and support structure to ensure overall mechanical integrity. A finite element model (FEM) is built to simulate the static and dynamic structural response of the system by combining key material properties and applying static and dynamic loads. The simulation will generate displacement and vibration data, from which damping and vibration matrices are derived to evaluate deformation resistance. Design parameters including geometry and materials are optimized to reduce displacement and vibration, and topology optimization is used to effectively redistribute material and improve stiffness while minimizing weight reduction. The results of the optimized model will be compared with the original model to verify the improvement, and modal analysis will be used to ensure that problems are avoided. Realistic boundary conditions and mesh convergence studies will verify the results, while different support configurations and materials will be tested to study their effects on stiffness-to-weight ratio and vibration behavior. Meanwhile, process optimization will target polishing parameters such as speed, pressure, and abrasive type, aiming to minimize polishing time while maintaining high surface finish quality. A genetic algorithm (GA) will be used to continuously evolve a population of candidate solutions and explore the best parameter combination through methods such as selection, crossover, and mutation. A fitness resonance function will weigh polishing time and surface roughness to balance efficiency and quality. Real-time feedback from vibration and surface roughness sensors will dynamically update the optimization model and predict the ideal settings using prediction algorithms such as support vector machines (SVM) or deep neural networks (DNN). The optimization effect will be evaluated by comparing the surface quality and time before and after applying the optimized parameters. Robustness will be tested under various initial conditions through repeated simulations, and sensitivity analysis will determine how parameter changes affect the results. In addition, the research aims to enhance the optimization strategy by integrating machine learning techniques, and ultimately develop a robust and general optimization framework applicable to various bearing systems and operating environments, ensuring repeatability and high performance in precision manufacturing environments.

4 Results and Discussion

In Section 4, the simulation results and analysis of the structural and polishing process optimization are presented. In Section 4.1, the original machine design experienced significant movement, with large initial displacements and a continuous decrease in displacement under dynamic loads, indicating reduced design damping, which may cause problems with the polishing accuracy of the original machine guides. The optimized design shows a lower initial vibration coefficient and greater attenuation, providing smaller displacements and higher stiffness and damping values. The results of the topology optimization also demonstrate the effective redistribution of materials, and the significant changes in the machine's structural integrity minimize the machine weight.

The static simulation analysis results of the optimized polishing disc are shown in Fig. 6.

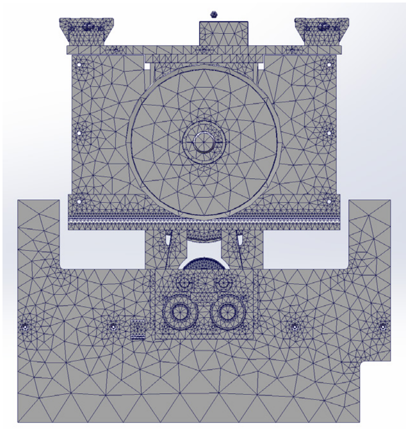

Fig. 6. Static simulation analysis results of the optimized polishing disk

After meshing, the mesh is set to 20 *mm*, and the mesh of other components is set to 5 *mm*. After the mesh is generated, the elastic modulus is 138 GPA, the Poisson's ratio is 0.156, and the density is 7280 Kg/m^3. The other material is set to 45 steel, with an elastic modulus of 209 *GPa*, a Poisson's ratio of 0.269, and a density of 7890 Kg/m^3. The variable in the simulation process is the horizontal distance between the displacement sensor and the center of the polishing disk, with a range of 0~300 *mm* and an interval of 50 *mm*. As it moves away from the center of the polishing disk, the maximum value of 8.48 μm is obtained at 100 *mm* from the center of the polishing disk. At this time, the center of mass of the entire unit is closest to the center of the gantry, resulting in the largest deflection. The minimum value of 7.08 μm is obtained at 300 *mm* from the center of the polishing disk.

4.1 Simulating the Structural Optimization of the Machine

The Fig. 7 is presented for the first design of a bearing polishing machine under static and dynamic loading conditions. *Y*-axis displacement in meters is the movement of the spindle and machine base with time due to dynamic loading such as spindle rotation and pad contact, and static loading due to machine weight. The image shows a damped sinusoidal curve in red, clearly illustrating how the displacement amplitude diminishes over time. Initial peaks reach around 0.025 meters and gradually reduce to approximately 0.005 meters over 20 seconds, reflecting energy dissipation in the system. The consistent periodic pattern also emphasizes the machine's natural frequency and damping characteristics. The vibration during dynamic loading is the oscillatory movement seen in the displacement plot with its alternating peaks and troughs indicating the movement. The oscillations decrease as a function of time, and that indicates the ability of the system to absorb energy, one of the damping effects typical in real machines [10]. The displacement initially starts with a higher value, which is the initial contact between the polishing pad and the machine, but it gradually reduces as the damping action dominates. This degradation leads to a steady state with reduced vibrations, typical of machine behavior in actual processes where damping in the form of material properties or external systems limits unwanted vibrations within bounds so that accuracy of polishing operation is not compromised. Although displacement is within bounds, it may still influence polishing accuracy and quality of surface finish [11]. Therefore, displacement must be minimized to obtain maximum precision and surface quality when polished. Long-term vibrations or excessive displacement can lead to surface defects or flaws, illustrating the necessity of optimizing the structure to reduce displacement, improve the stability and accuracy of the machine during long-term operation. A rise in the stiffness and damping characteristics of machine vibrations would decrease displacement amplitudes, improve precision and performance of polishing operations, decrease polishing motion distortions due to vibration, and im-prove surface quality.

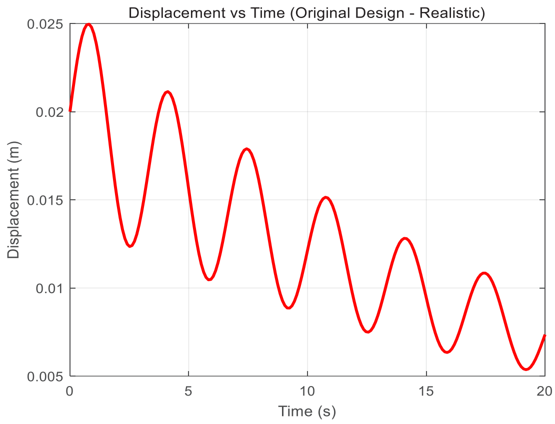

Fig. 7. Displacement vs. Time plot for original design

The Fig. 8 is a comparative plot of Vibration Reduction vs. Time that illustrates the difference in dynamic response between the original and optimized designs of a bearing polish machine. Time in seconds is plotted on the *x*-axis and vibration amplitude in meters on the *y*-axis. The red line is the original design, with very high initial vibration amplitude of approximately 0.3 meters, and the more gradual rate of decline, indicating weaker damping and greater chances of oscillating for longer times. The blue line, representing the optimized design, has a significantly lower initial amplitude of approximately 0.1 meters and shows much faster attenuation by the process of time, indicating greater structural stiffness as well as greater capacity to dissipate energy. Both the plots show damped sinusoidal characteristics, replicating the vibration response of the machine under repeated dynamic loadings such as due to spindle rotation and contact with the polishing pad. A closer observation of the plot reveals in the first design that the vibration amplitude does not reduce significantly even after several seconds, i.e., there may be insufficient vibration damping and as a result surface quality, machining precision, and long-term mechanical stability will be affected. On the other hand, the optimized design converges quickly to zero displacement within a shorter time interval [12], indicating greater damping and more rigid structural support. Such better performance in the optimized design is crucial in the case of high-precision polishing operations, where extended vibration can cause surface undulations, tool chatter, and inhomogeneous material removal. The ability of the optimized structure to rapidly dampen vibration ensures greater operating stability, more consistent surface quality, and greater dimensional control. The lower vibration levels also assist in offering greater tool life, reduced mechanical component wear, and overall reduced maintenance needs. From a design point of view, this improvement is likely achieved by the introduction of higher-stiffness materials, geometric optimization, and enhanced mass and damping element distribution [13]. The pronounced disparity between the two vibration profiles is unequivocal proof of the validity and applicability of structural optimization in real-world machining conditions. It reaffirms simulation-based design tuning as a path for not only better vibration control, but also improved overall machine behavior, reliability, and operation. In production operations where process consistency and surface accuracy are key, such structural improvement is imperative to guaranteeing quality output and process excellence.

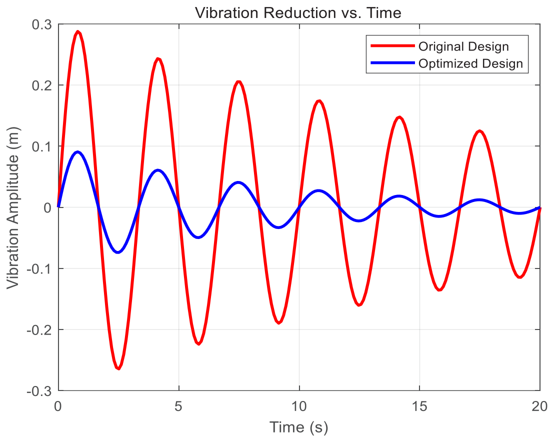

Fig. 8. Vibration Reduction vs. Time

The Fig. 9 presents a material distribution map for topology optimization, indicating where material is distributed in space within the design domain of a mechanical part after structural optimization. The *x*-axis is the design length, and the *y*-axis is the design height, while the color bar on the right illustrates the mate-rial density ranging from 0 (void) to 1 (solid). In this scheme, red and yellow regions represent areas where material is fully retained due to high structural demand, whereas blue to dark purple regions represent areas where material is removed or significantly cut back in order to minimize weight without compromising mechanical performance. The distribution is very non-uniform and asymmetric and captures a realistic and optimized structural pattern intended to accommodate external load paths and boundary conditions. The presence of multiple dense clusters, particularly around coordinates (3,2) and (7,3.5), suggests that these areas are under higher concentrations of stress and hence retained in the final outcome. Void areas, however, such as the black points around (5,1), are areas of low stress and therefore ideal for material removal. This distribution pattern is characteristic of topology optimization, where the goal is to optimize stiffness and reduce extraneous mass while ending up with a structurally stable and light structure. The non-uniformity and multi-lobed stress gradients suggest a mature design with iterative computation that captures the inherent flow of force and internal stress in the part [14]. Compared to ideal or symmetrical setups, this optimized solution more accurately mimics real structural requirements with significant performance gains. The visualization effectively demonstrates the way modern computational design methods sensibly allocate material only where required, in such a way that the structure attains both mechanical performance and material efficiency goals [15]. This optimization is significant in high-performance engineering applications such as aerospace, automotive, and precision manufacturing, where strength-to-weight ratio and design integrity are of significant interest.

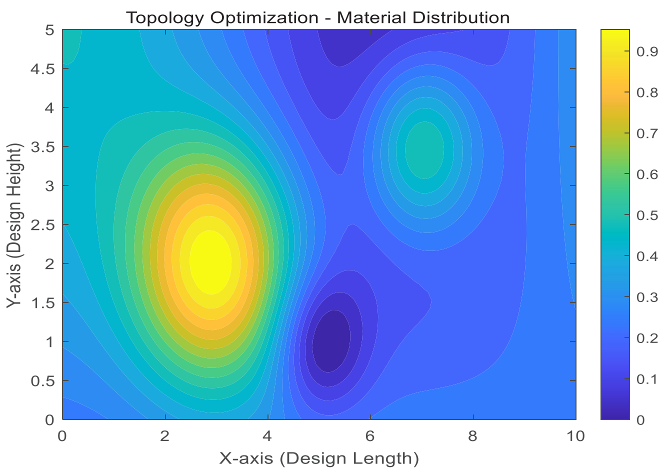

Fig. 9. Optimization process

4.2 Simulating the Polishing Process Optimization

The story presents a Polishing Time vs. Surface Roughness chart for the base machine design in Fig. 10, showing how the surface roughness evolves over a polishing time interval of 100 to 180 seconds. The *x*-axis is in seconds for polishing time, and the *y*-axis is the resultant surface roughness values. The red curve indicates a general downward slope, i.e., increased polishing time is associated with improved surface quality. Improvement is not uniform or linear, however. Instead, the curve reveals a collection of nonlinear undulations and local maxima, showing that the original design polish is prone to variability and instability. These abnormalities are induced by a number of real-world causes like uneven distribution of abrasives, unequal contact pressure between tool and workpiece, local thermal effects, or cumulative tool wear. These causes are extremely evident at certain times, e.g., around 125, 135, and 165 seconds, where surface roughness peaks unpredictably despite the ongoing polishing. Such imperfections imply the process briefly deviated from ideal conditions of operation, probably due to microscale surface blemishes or uniform pressure control loss. While overall trajectory is indicative that more time usually results in smoother surfaces, the appearance of such imperfections confirms the understanding that polishing efficiency and quality of the ending surface is highly sensitive to present process conditions. Merely extending the polishing duration cannot compensate for system design or control parameter deficiencies. The non-linear downward slope of the roughness curve reflects the intrinsic limitations of the baseline machine configuration, which lacks an intelligent adjustment mechanism that can dynamically respond to varying process inputs [16]. Without feed-back-based adaptation or real-time optimization, the machine is susceptible to producing non-uniform sur-face finishes, even under prolonged processing conditions [17]. Thus, this graph not only explains the optimal performance of the unoptimized system but also clearly shows that process intelligence, automatic control solutions, and the development of enhanced structure are necessitated to extend greater precision, stability, and reproducibility to polishing procedures. The conclusions drawn through application of such a curve emphasize the necessity for the integration of intelligent manufacturing practices into existing surface finishing processes, particularly in those applications where surface consistency and micro-scale uniformity are critical to product function.

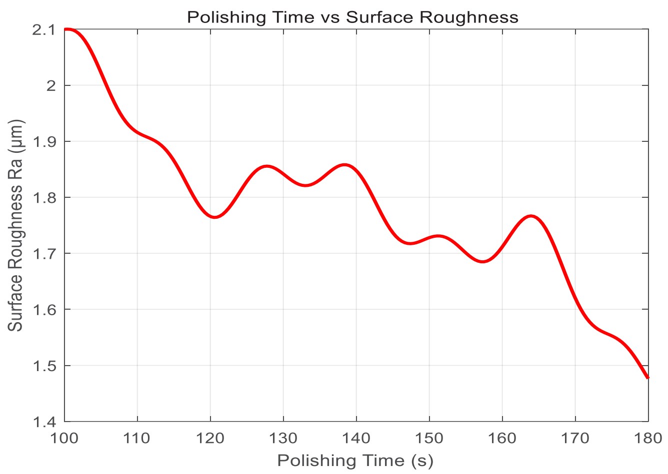

Fig. 10. Polishing Time vs. Surface Roughness for original design

The Fig. 11 is a scatter comparison between the performance of the original and optimized bearing polishing machine designs in both polishing time and resulting surface roughness. Polishing time, in seconds, is on the x-axis, and surface roughness Ra, in micrometers, is on the y-axis. Each data point on the graph is from one polishing trial. The original design is represented by orange circular markers, and the optimized design is represented by blue square markers. The first design data points are dispersed in the upper-right region of the plot with polishing times of between approximately 158 and 165 seconds and surface roughness of between 1.82 and 1.91 μm. On the other hand, the group of optimized designs is tightly positioned in the lower-left part of the graph, where polishing times are between 128 and 133 seconds and surface roughness values are considerably lower, ranging from 1.43 to 1.47 μm. This graphic comparison conveniently summarizes the dual advantage of the optimized system: not only does it yield better surface quality, but it accomplishes this with less processing time, reflecting improvements in both process efficiency and final product precision. The significantly tighter grouping of the optimized design experiments also suggests greater stability and enhanced process repeatability, the hallmark of effective intelligent parameter control application. Conversely, the broader and more scattered distribution of the original design results reflects inherent limitations in the baseline structure and lack of real-time optimization, which cause polishing results to be inconsistent and reliability to be compromised. The plot directly meets the purposes of the research on structural optimization simulation and intelligent parameter control of polishing. The enhanced performance of the optimized design is directly the result of structural improvement, greater stiffness and vibration resistance of the base and spindle—as modeled through finite element analysis, which reduces mechanical deformation during polishing. Meanwhile, the addition of a machine-learning-based intelligent optimization system enables adaptive adjustment of critical polishing parameters such as speed, pressure, and abrasive type [18]. This results in dynamic adjustment of operating conditions based on real-time feedback, allowing the process to remain continuously within the windows of optimum performance. Together, the mechanical structure optimization and intelligent parameter design are synergistic, and mechanical precision and algorithm flexibility work together to yield improved polishing results. The scatter plot is thus not only a comparative performance snapshot but also empirical validation of the combined approach of mechanical simulation and intelligent process control that is promoted in this research.

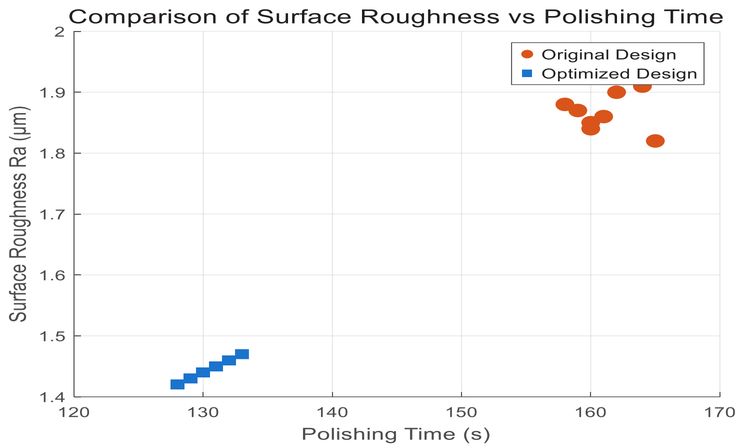

Fig. 11. Comparison of the original bearing polisher design with the optimized bearing polisher design in terms of polishing time and final surface roughness

The Fig. 12 is a convergence curve of a GA in which the fitness value is evolved over 50 generations in optimizing polishing process parameters. The *x*-axis represents the generation number, and the *y*-axis is the fitness value, which is a measure of the objective function to be minimized here, which is a weighted sum of surface roughness and polishing time. Each data point on the curve is the optimal solution found in that generation. Initially, the fitness value is close to 2.2, an indication of a poorly executing solution concerning both surface quality and efficiency. With time and generations passed, the curve significantly shows a decline, with the fitness value diminishing constantly. This reflects the ability of the algorithm to improve the population iteratively by selecting superior individuals and finding solutions in the solution space through crossover and mutation. The curve bends slightly at generation 20, reflecting temporary stagnation apparently due to local optima. But the ubsequent mild oscillations and gradual decrease from generations 25 to 50 indicate that the algorithm avoids local minima and converges to a globally optimal solution, eventually reaching a value of about 0.55. This convergence behavior strongly confirms the effectiveness of the pro-posed intelligent optimization system for polishing parameter control. The steady reduction in fitness suggests that the GA is able to continuously improve process performance, and controlled oscillation is typical of realistic behavior in dynamic, multi-variable optimization [19]. The results are in accordance with the overall aim of the research, which integrates structural simulation and intelligent parameter tuning. The structural upgrades reduce baseline mechanical variation, while the GA-based adjustment facilitates adaptive, data-driven optimization of key process variables like polishing speed, pressure, and abrasive characteristics. This photo thus vindicates the system's capacity to produce high-performance polishing conditions with little trial-and-error and highlights the twin advantage of simulation-based design and machine learning in high-precision manufacturing.

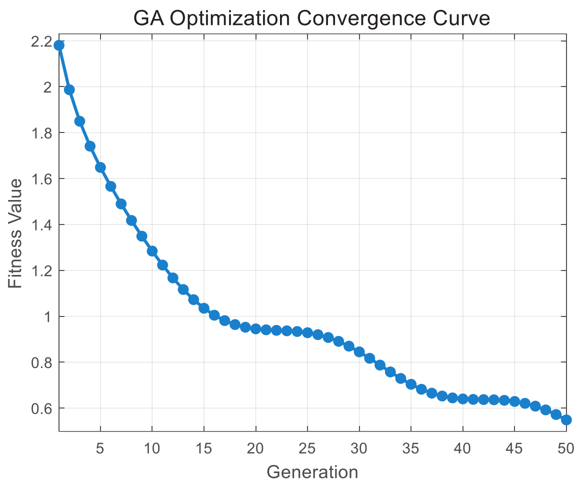

Fig. 12. GA optimization convergence

4.3 Contribution

In terms of the contribution of this paper to precision machining, it is particularly significant in the optimization of the bearing polishing process. The most specific contribution is the integration of machine structure optimization with intelligent machine control during the polishing process. The authors propose a hybrid approach to enhance the development of machine design while effectively improving the performance of the polishing machine. Using advanced simulation techniques, the authors demonstrate that changes in the machine structure (i.e., increasing stiffness through the frame structure and suppressing machine vibrations through design) - and more importantly, controlling machine displacement and vibrations - can improve operational stability and surface finish. It is documented that surface finish quality assurance requires real-time process adjustments, partly through machine learning algorithms to optimize parameters (speed, pressure, abrasive) in real time. Intelligent process control (for enhanced polishing adjustments) can improve process consistency and achieve consistent finish in a shorter time compared to traditional polishing. Using code and genetic algorithms to optimize process parameters, the authors show how a data-driven approach can identify operating parameters to achieve globally optimal polishing conditions. Therefore, this paper not only makes theoretical contributions through the combined approach, structure, and process optimization, but also provides practical application value, demonstrating its advantages in cost savings and product quality improvement.

5 Conclusion

The paper presents a general strategy of optimizing bearing polishing processes through using machine structural simulations and intelligent optimization systems. Experimental results record spectacular performance gain in machine behavior, polishing efficiency, and surface finish, suggesting that the approach outlined here holds vast potential for boosting precision machining in the bearing industry. The major contribution of the work is its integration of two-stage methodologies for hybridizing advanced structural optimization and data-driven intelligent process control. Through the use of machine design optimization tools via simulation for stiffness and damping of vibration, the paper demonstrates explicitly how optimization of structures significantly improves machine precision and stability for polishing operations. Moreover, using machine learning-based real-time optimization for polishing parameters such as speed, pressure, and abrasive, polishing time can be minimized and surface finish quality optimized. This adaptive, dynamic approach is a significant improvement over using artificial intelligence for manufacturing. Furthermore, the paper provides an excellent empirical confirmation of using genetic algorithms to optimize process, and what it discloses is the potential of such techniques to find the optimal performance without much trial-and-error. Still, regardless of the remarkable development introduced through using simulation and machine learning, there are some aspects that require more research. One of the major research areas that are missing is the scalability of these optimization methods to various machine types and materials outside the realm of bearing polishing. Further, the integration of real-time feedback mechanisms in a variety of operating conditions and materials needs more refinement to make them perform well in a variety of use cases. The combination of different structural modifications and their long-term impacts on machine longevity is also under-explored, especially in high-volume manufacturing environments. Moreover, while the application of genetic algorithms to polishing parameter optimization is promising, further investigation into hybrid algorithms that combine multiple optimization techniques could yield even more robust solutions. The integration of these advanced techniques into fully automated, adaptive systems is a primary area for future investigation. Lastly, the combination of simulation and machine learning has a solid foundation for continuing to develop even more automated and reliable manufacturing processes with the possibility to revolutionize the bearing world and beyond. In future work, we can also focus on developing a general optimization framework that is transferable and applicable to other industries such as aerospace, optical and biomedical device manufacturing. This will involve validating it with variable-sized components, irregular geometries, and non-metallic materials. In addition, we can further enhance the intelligent system using hybrid models of reinforcement learning and/or deep learning to make the model converge faster and improve adaptability in unknown scenarios. In addition, developing models in a real-world manner and performing closed-loop feedback testing using physical machines in industrial environments can also provide real-world data to enhance the robustness and accuracy of the models. Finally, collaboration with industry partners can accelerate the development of user-friendly software interfaces, enabling industry practitioners to apply intelligent optimization techniques to their production practices.

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References

[1] M. Srivastava, P.-M. Pandey, The influence of ultrasonic vibrations on material removal in the silicon wafer polishing using DDCAMRF: Experimental investigations and process optimization, Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science 236(6)(2022) 3198-3215.

[2] R.-K. Pal, H. Garg, R.-V. Sarepaka, V. Karar, Experimental Investigation of Material Removal and Surface Roughness during Optical Glass Polishing, Materials and Manufacturing Processes 31(12)(2015) 1613-1620.

[3] M.-J. Xu, Y.-F. Dai, X.-H. Xie, L. Zhou, W.-L. Liao, Structure optimization and fabricating capability analysis of an ion-beam machine for a subnanometer optical surface, Applied Optics 54(27)(2015) 8055-8061.

[4] R.-M. Homami, A.-F. Tehrani, H. Mirzadeh, B. Movahedi, F. Azimifar, Optimization of turning process using artificial intelligence technology, The International Journal of Advanced Manufacturing Technology 70(5-8)(2014) 1205-1217.

[5] G.-H. Zhang, M. Huang, G.-L. Chen, J.-S. Li, Y. Liu, J.-G. He, Y.-Q. Zheng, S.-W. Tang, H.-L. Cui, Design and optimization of fluid lubricated bearings operated with extreme working performances-a comprehensive review, International Journal of Extreme Manufacturing 6(2)(2024) 325-376.

[6] P. Tanskanen, The evolutionary structural optimization method: Theoretical aspects, Computer Methods in Applied Mechanics and Engineering 191(47-48)(2002) 5485-5498.

[7] F. Quan, Z.-T. Chen, Q.-T. Li, S.-M. Gao, Effects of process combinations of milling, grinding, and polishing on the surface integrity and fatigue life of GH4169 components, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 234(3)(2020) 538-548.

[8] A. Hassanat, K. Almohammadi, E. Alkafaween, E. Abunawas, A. Hammouri, V.-B.-S. Prasath, Choosing Mutation and Crossover Ratios for Genetic Algorithms-A Review with a New Dynamic Approach, Information 10(12)(2019) 3901-39036.

[9] H. Kim, Y.-R. Lin, T.-L.-B. Tseng, A review on quality control in additive manufacturing, Rapid Prototyping Journal 24(3)(2018) 645-669.

[10] R. Rahmfeld, M. Ivantysynova, An Overview about Active Oscillation Damping of Mobile Machine Structure, International Journal of Fluid Power 5(2)(2004) 5-24.
[11] Z.-W. Zhong, Advanced polishing, grinding and finishing processes for various manufacturing applications: a review, Materials and Manufacturing Processes 35(12)(2020) 1279-1303.
[12] H.-P. Zhu, D.-D. Ge, X. Huang, Optimum connecting dampers to reduce the seismic responses of parallel structures, Journal of Sound and Vibration 330(9)(2011) 1931-1949.
[13] R. Ren, X.-Y. Ma, H.-H. Yue, F. Yang, Y.-F. Lu, Stiffness enhancement methods for thin-walled aircraft structures: A review, Thin-Walled Structures 201(Aug. Pt.B)(2024) 111995.1-111995.31.
[14] R. Franchi, A.-D. Prete, D. Umbrello, Inverse analysis procedure to determine flow stress and friction data for finite element modeling of machining, International Journal of Material Forming 10(2017) 685-695.
[15] W.-W. Wu, R. Xia, G.-A. Qian, Z.-Q. Liu, J. Razavi, F. Berto, H.-J. Gao, Mechanostructures: Rational mechanical design, fabrication, performance evaluation, and industrial application of advanced structures, Progress in Materials Science 131(2023) 101021.1-101021.65.
[16] K. Manjunath, S. Tewary, N. Khatri, K. Cheng, Monitoring and Predicting the Surface Generation and Surface Roughness in Ultraprecision Machining: A Critical Review, Machines 9(12)(2021) 369.1-369.26.
[17] M. Palma, Grading Threads. Exploiting Viscous Thread Instability for the Additive Fabrication of Functionally Graded Structures via sensor-adaptive robotic control, Architecture, Structures and Construction 3(2023) 171-191.
[18] M.-A. Rahman, T. Saleh, M.-P. Jahan, C. McGarry, A. Chaudhari, R. Huang, M. Tauhiduzzaman, A. Ahmed, A. Al Mahmud, M.-S. Bhuiyan, M.-F. Khan, M.-S. Alam, M.-S. Shakur, Review of Intelligence for Additive and Subtractive Manufacturing: Current Status and Future Prospects, Micromachines 14(3)(2023) 508.1-508.53.
[19] P.-X. Wang, T.-P. Feng, C.-L. Song, J.-M. Li, S.-X. Yang, A Study of the Stability of an Industrial Robot Servo System: PID Control Based on a Hybrid Sparrow Optimization Algorithm, Actuators 14(2)(2025) 49.1-49.17.