

Article

Process Parameter Optimization and Removal Depth Prediction for Robotic Adaptive Hydraulically Controlled Grinding of Aircraft Skin Primer

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Abstract

The removal of primer from aircraft skin epoxy resin primer plates was investigated by using an adaptive hydraulically controlled polishing tool in conjunction with an industrial robot. This study examined the effects of several key process parameters—grinding force, rotational speed, feed speed, and abrasive grit size—on primer removal depth and surface roughness. Through both single-factor analysis and response surface methodology (RSM), the variation patterns of removal depth and surface roughness with respect to these parameters were elucidated. RSM was employed to develop regression models for the primer removal depth and removal rate. The relative errors of these regression models were found to be within 8%, while the maximum relative error of the backpropagation neural network prediction model for surface roughness R_a is 9.5%. These models exhibit high accuracy in predicting the material removal depth, material removal depth rate, and surface roughness of the primer plates. The optimal parameters for the adaptive hydraulically controlled polishing tool were identified as flows: a polishing force of 20 N, a feed speed of 40 mm·s^{−1}, a rotational speed of 2000 rpm, and 80-grit sandpaper. Under these conditions, the maximum removal depth reaches 27.5 μm, the highest removal rate is 5.501 μm·s^{−1}, and the surface roughness R_a is 1.897 μm.

Keywords: hydraulically controlled polishing robot; epoxy resin primer; removal depth; response surface methodology; BP neural network



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1. Introduction

Aircraft are routinely exposed to extreme environmental conditions during flight, including extreme temperatures (both high and low), intense radiation, and hypersonic airflow, which can significantly impact the aircraft's performance and durability. Consequently, the types and properties of coatings applied to the aircraft skin play a critical role in determining the aircraft's service life [1]. The typical thickness of aircraft skin ranges from 2 to 4 mm, while civil aviation manufacturers such as Boeing and Airbus generally specify that the total thickness of the coating system must not exceed 200 μm. Within this system, the primer layer typically measures 20 to 30 μm. Among the various coatings, aircraft skin epoxy primer functions as a vital underlayer in the overall coating system [2]. Aircraft skin coatings are multifunctional and can be categorized into three primary types based on

their specific functions: (1) The decorative layer, which displays visual identifiers such as aviation logos and registration numbers while also enhancing aerodynamic performance; (2) The functional layer, primarily designed to provide corrosion resistance [3], oxidation resistance [4], ultraviolet protection, anti-icing capabilities [5], lightning strike resistance [6], wear resistance, and stealth performance (for military aircraft); (3) The base layer, typically composed of aluminum or carbon fiber, which mainly provides structural support and mechanical strength to the airframe. Among these materials, aluminum alloys are the predominant choice for aircraft base structures due to their favorable strength-to-weight ratio, superior fatigue resistance, and cost-effectiveness [7–9].

The service environment of aircraft is complex and dynamic, causing the aircraft's paint layer to suffer significant wear and damage over extended flight durations. To ensure both structural safety and flight performance, partial or complete removal of the composite coating from the aircraft skin is necessary [10]. Current methods for removing aircraft skin coating include manual paint stripping, mechanical paint stripping, chemical paint stripping, and laser paint stripping [11–13]. Among these, manual grinding and paint stripping offer flexibility; however, the quality and efficiency of the process are heavily dependent on the operator's skill and experience. Chemical paint stripping, while more efficient than manual methods, involves the use of highly polluting chemicals, which are incompatible with increasingly stringent environmental regulations [14,15]. Laser paint stripping, an advanced aviation technology, has emerged as a promising solution. Hu et al. [16] investigated the use of an infrared nanosecond pulse laser for paint layer stripping, adjusting the laser energy density to evaluate its impact on the skin structure and wear performance, with favorable results. Despite such advancements, the laser stripping process is divided into three distinct stages and still faces notable limitations, including reduced effectiveness on certain coating materials and the high cost of required equipment.

Given the labor intensity, environmental concerns, and cost-effectiveness issues associated with aircraft paint stripping, this study proposes developing an automated mechanical paint removal method, aiming to achieve an efficient and sustainable solution for aircraft coating removal. Compared to other paint removal methods, automated grinding and polishing offers significant advantages in aircraft maintenance, particularly in terms of efficiency, precision, and cost control [17]. Traditionally, pneumatic automatic grinding has been employed; however, challenges in controlling the pneumatic grinding force often lead to a reduced grinding precision [18]. Vladareanu et al. [19] addressed the problem of hybrid force-position control in robotic grinding by applying the principles of linear and nonlinear attractive points, along with a network of attractive curves, to generate position and force parameters. Chen et al. [20] developed a decoupled robotic grinding system consisting of an industrial robot and an end effector for robotic grinding of curved parts, which substantially reduced the grinding depth errors. Zhang et al. [21] demonstrated, through adaptive control and force modeling of a flexible grinding head, that controlling the grinding force could indirectly regulate both the material removal rate and grinding quality. Xu et al. [22] integrated a hybrid stiffness mechanism, developed a comprehensive model, and optimized parameters to maximize the constant force stroke by addressing the force overshoot problem during the contact phase of the robot end effector. Senthilkumar et al. [23] applied response surface methodology to simultaneously optimize multiple processing parameters, including flank wear, material removal rate, and surface roughness. Xie et al. [24] optimized process parameters such as polishing force, feed speed, and rotational speed, and established a surface roughness prediction model to enhance the surface quality of robot-polished mold steel. Yang et al. [25] proposed a novel surface roughness prediction model, VSG-FC, which integrates genetic algorithm-driven virtual sample generation (GA-VSG) and genetic programming-driven feature construction (GP-PC) to overcome

data scarcity and achieve accurate surface roughness predictions. Shan et al. [26] developed a prediction model for material removal rate using mathematical regression models and neural networks, which were optimized via genetic algorithm (GA) to improve model accuracy. This model converted material removal rate into material removal depth per unit time and area, based on the mass difference before and after removal.

The constant-force polishing tool, based on electro-hydraulic actuator technology, offers stable polishing force control and adaptive flexible end-contact capabilities. The system integrates a servo motor, hydraulic pump, micro oil tank, hydraulic valve assembly, sensing elements, and a controller, enabling high-precision control of robotic mechanical motion through the conversion of electrical drive to hydraulic energy. This configuration allows seamless switching between “force” and “position” control modes, making it suitable for various application scenarios, including grinding, polishing, and deburring.

This study employs an adaptive hydraulically controlled polishing tool to investigate the grinding performance of Al2024 aluminum alloy plates coated with epoxy primer. The influence of various process factors on removal depth and surface roughness was examined via single-factor experiments [27], and the concept of material removal depth rate was introduced to align with industrial requirements [28]. Prediction models for three response variables were developed using response surface methodology, followed by the application of a BP neural network to optimize surface roughness, thereby achieving comprehensive optimization of process parameters.

2. Materials and Methods

The test material employed in this study was an Al2024 aluminum alloy flat plate coated with epoxy primer, with dimensions of 300 mm × 200 mm × 3 mm. The robotic grinding and polishing setup, as shown in Figure 1, comprised an eight-axis KUKA KR20 robot, an adaptive grinding and polishing (AGP) tool (Model: AGP1A-750, Shanghai Saiwider Robot Co., Ltd., Shanghai, China), a grinding disc, and sandpaper. The eight-axis KUKA KR20 robot consists of a six-axis manipulator with two additional axes, featuring a maximum load capacity of 20 kg, which enables flexible grinding and polishing across all regions of the aircraft skin. The AGP tool has a maximum rotational speed of 5500 rpm, a spindle radial floating range of 0–20 mm with a resolution of 0.01 mm, and an adjustable grinding force range of 5–120 N with a resolution of 1 N. A sandpaper disc with a diameter of 51 mm (or 2 inches) and corresponding 3M 775L sandpaper were selected. And the latter is composed of triangular ceramic alumina abrasive, which maintains sharpness, provides strong cutting force, and ensures consistent grinding performance.

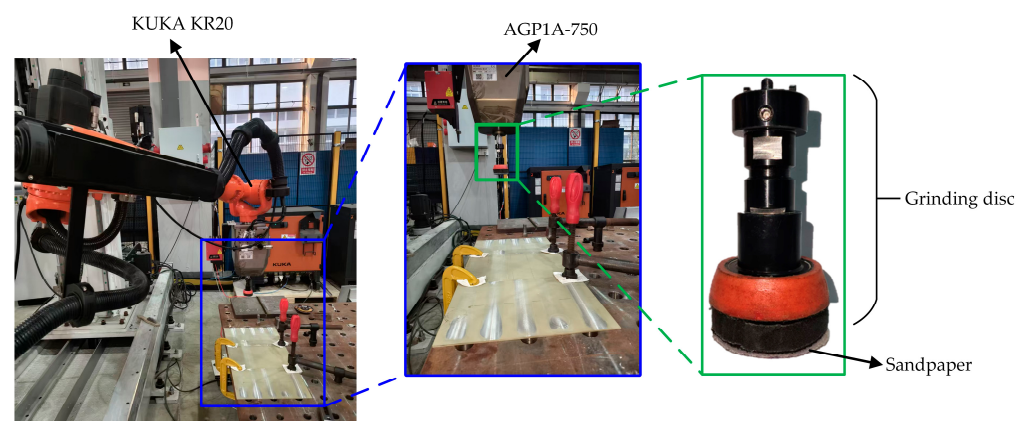


Figure 1. Photo of robotic grinding and polishing setup.

The AGP tool was mounted on the sixth axis of the KR20 robot. The feed speed was regulated by the KR20 robot, while the rotational speed and grinding force were regulated by the AGP tool. The sandpaper disc was attached to the spindle end of the AGP, with sandpaper affixed to its surface. Surface roughness R_a was measured using a JITAI810 surface roughness tester (Beijing Jitai Keyi Testing Equipment Co., Ltd., Beijing, China), which offers a measurement range of 0.005–16 μm and a resolution of 0.001 μm . When measuring the surface roughness R_a , the JITAI 810 tester employs a Gaussian (GAUSS) filter, with a measurement speed of 1 $\text{mm}\cdot\text{s}^{-1}$. The cutoff length is identical to the sampling length, both being 2.5 mm. The measurement length (also known as the evaluation length) is 12.5 mm, which is exactly 5 times the sampling length. The coating removal depth was determined using a TT260 coating thickness gauge (Beijing Shidai Chuanghe Technology Co., Ltd., Beijing, China), with a measurement range of 0–1250 μm and a resolution of 0.1 μm .

During the experiment, the width direction of the experiment plate was designated as the feed direction for the grinding path. Along this width direction, the plate was divided into 5 grinding regions of 200 mm $\times$ 50 mm with a 10 mm interval. For measurements, the centerline of each region served as the measurement path. The coating thickness and surface roughness R_a were measured at 50 mm, 100 mm, and 150 mm along the grinding feed direction, respectively. Each measurement was repeated 5 times, and the average value was adopted as the valid result, with error bars representing one standard deviation.

A 0-level test was conducted to establish the baseline parameters for the single-factor experiments. The 0-level test conditions were set as follows: a grinding force of 15 N, a feed speed of 60 $\text{mm}\cdot\text{s}^{-1}$, a rotational speed of 1500 rpm, and a 180-grit sandpaper. The single-factor test scheme for grinding and polishing the epoxy primer plate was summarized in Table 1. Based on the results of the single-factor test, the effects of the key process parameters on material removal depth and surface quality were analyzed.

Table 1. Single-factor experimental scheme for grinding and polishing epoxy primer plates.

No.	Grinding Force, F/N	Feed Speed, $v_f/\text{mm}\cdot\text{s}^{-1}$	Rotational Speed, n/rpm	Grit Size, M
1	5, 10, 15, 20, 25	60	1500	180
2	15	20, 40, 60, 80, 100	1500	180
3	15	60	500, 1000, 1500, 2000, 2500	180
4	15	60	1500	80, 120, 180, 240, 320

In industrial grinding applications, the efficiency of grinding and polishing processes is of critical importance. To quantitatively evaluate this aspect, this study introduces the concept of material removal depth rate (MDR), defined as the removal depth of the sample after a single complete grinding cycle divided by the grinding time. M_{DR} can be further expressed as the material removal depth per unit time and unit length, with the corresponding conversion relationship given as follows:

$$M_{DR} = M_D \frac{v_f}{L} \quad (1)$$

where M_{DR} represents material removal depth rate, M_D represents material removal depth, v_f represents the robot's feed speed, and L is the grinding length.

The analysis of the initial experimental design indicated that the quadratic effects of grinding process parameters play an important role in both material removal depth and surface roughness. Therefore, considering the interaction and quadratic effects among process parameters, a response surface methodology (RSM) experimental scheme was developed using the Central Composite Design (CCD). The factors considered included

grinding force, feed speed, rotational speed, and abrasive size, while the response variables were material removal depth, material removal depth rate, and surface roughness.

The coded levels of RSM factors are shown in Table 2. With the number of test factors $m = 4$, the distance between the axial points and the center point was determined as $\gamma = 2$. For clarity and convenience, both the RSM experimental design and the corresponding analysis of the RSM results are consolidated in Table 3.

Table 2. Coded levels of RSM factors for epoxy primer samples.

Level	Grinding Force, F (N)	Feed Speed, v_f ($\text{mm} \cdot \text{s}^{-1}$)	Rotational Speed, n (rpm)	Grit Size, M
	A	B	C	D
2	25	100	2500	320
1	20	80	2000	240
0	15	60	1500	180
−1	10	40	1000	120
−2	5	20	500	80

Table 3. Response surface test scheme and results for epoxy primer samples.

No.	Grinding Force, F (N)	Feed Speed, v_f ($\text{mm} \cdot \text{s}^{-1}$)	Rotational Speed, n (rpm)	Grit Size, M	M_D (μm)	M_{DR} ($\mu\text{m} \cdot \text{s}^{-1}$)	Ra (μm)
	A	B	C	D			
1	1	1	1	1	12.4	4.96	1.052
2	1	1	1	−1	14.0	5.60	1.571
3	1	1	−1	1	9.1	3.64	1.267
4	1	1	−1	−1	8.8	3.52	2.455
5	1	−1	−1	1	15.5	3.10	1.023
6	1	−1	−1	−1	15.5	3.10	1.818
7	1	−1	1	1	22.9	4.58	0.967
8	1	−1	1	−1	24.7	4.94	1.361
9	−1	1	1	1	5.5	2.20	1.124
10	−1	1	1	−1	8.6	3.40	1.674
11	−1	1	−1	1	5.5	2.20	1.036
12	−1	1	−1	−1	5.2	2.08	2.316
13	−1	−1	−1	1	11.8	2.36	1.136
14	−1	−1	−1	−1	12.4	2.48	1.886
15	−1	−1	1	1	11.7	2.34	1.047
16	−1	−1	1	−1	15.7	3.14	1.495
17	2	0	0	0	16.9	5.07	1.541
18	−2	0	0	0	6.7	2.01	1.591
19	0	2	0	0	7.8	3.90	1.729
20	0	−2	0	0	26.0	2.60	1.203
21	0	0	2	0	13.0	3.90	1.128
22	0	0	−2	0	6.1	1.83	2.458
23	0	0	0	2	7.7	2.31	0.954
24	0	0	0	−2	13.1	3.93	2.946
25	0	0	0	0	9.2	2.76	1.227
26	0	0	0	0	8.5	2.55	1.562
27	0	0	0	0	9.4	2.82	1.492
28	0	0	0	0	9.7	2.91	1.312
29	0	0	0	0	8.8	2.64	1.363
30	0	0	0	0	10.4	3.12	1.302

The experimental design outlined in Table 3 comprises 16 factorial point experiments, 8 axial point experiments, and 6 center point experiments. Center point experiments serve

two main purposes: first, to estimate experimental errors with a particular focus on pure errors, and second, to validate the stability of the model near the center point. In a typical CCD experiment, 3 center point experiments are conventionally employed. However, in this study, 6 center point experiments were conducted to achieve two key objectives. On one hand, it improves the accuracy of error estimation and reduces the impact of random fluctuations in an individual experiment; on the other hand, it enhances the robustness of the model. This ensures that the subsequent regression-based model, incorporating both quadratic terms and interaction terms, exhibits more stable predictive performance across the entire factor space.

3. Results and Analysis

3.1. Results and Analysis of Single-Factor Tests

3.1.1. Influence of Grinding Force on Material Removal Depth and Surface Roughness

The influence of grinding force on material removal depth M_D and surface roughness R_a is illustrated in Figure 2. As the grinding force increases, the removal depth exhibits an overall upward trend, whereas the surface roughness first decreases and then increases. Specifically, when the grinding force increases from 5 N to 25 N, the removal depth increases from 5.2 μm to 16.7 μm .

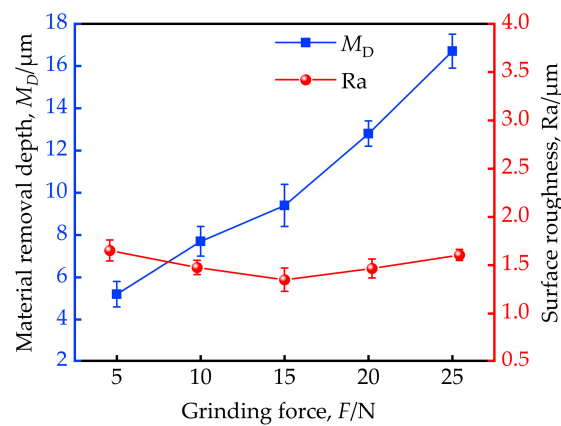


Figure 2. Influence of grinding force on material removal depth and surface roughness.

In the elastic grinding and polishing material removal model, Preston's empirical formula is widely adopted [29], with its equation expressed as:

$$\frac{dM_D}{dt} = k_p \cdot p(x, y, t) \cdot v_m(x, y, t) \quad (2)$$

where dM_D denotes the material removal depth at point (x, y) within a given interval dt ; dt represents the grinding residence time; k_p is the correction coefficient of the equation, which depends on factors such as workpiece material, tool material, abrasive type, temperature, robot operating conditions; $p(x, y, t)$ is the force at the grinding contact point (x, y, t) ; and $v_m(x, y, t)$ is the relative speed between the contact point (x, y, t) and the workpiece surface.

Vertical sandpaper grinding involves circular flexible contact, which conforms to Hertz contact theory, with the force distribution approximated by the semi-ellipsoidal law. Given the relatively small grinding force, the resulting deformation is minimal, allowing the contact area to be regarded as a circle, as illustrated in Figure 3a [30]. Accordingly, the grinding force at time t for point $A(x, y)$ can be expressed as:

$$p(x, y, t) = \frac{F}{\pi R^2} \sqrt{1 - \left(\frac{x}{R}\right)^2 - \left(\frac{y}{R}\right)^2} \quad (3)$$

where R is the radius of grinding disc.

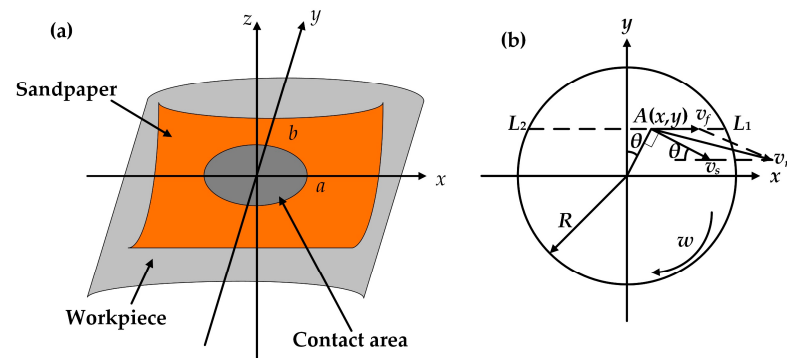


Figure 3. Schematic diagram of (a) the contact area between sandpaper and workpiece, and (b) composition of speed vectors.

In Figure 3b, since $v_s = \omega \sqrt{x^2 + y^2} = 2\pi n \sqrt{x^2 + y^2}$, according to the composition of speed vectors, the relative speed v_m can be expressed as:

$$v_m = \sqrt{v_s^2 + v_f^2 + \frac{2yv_s v_f}{\sqrt{x^2 + y^2}}} = \sqrt{v_f^2 + 4\pi^2 n^2 (x^2 + y^2) + 4\pi v_f n y} \quad (4)$$

Therefore, the total material removal depth M_D at point $A(x, y)$ can be expressed as the summation of material removal depths contributed by all micro-elements along segment $L_1 L_2$, such that [31]:

$$M_D = \frac{2k_p F}{\pi R^2 v_f} \int_0^{\sqrt{R^2 - y^2}} \sqrt{1 - \left(\frac{x}{R}\right)^2 - \left(\frac{y}{R}\right)^2} \sqrt{v_f^2 + 4\pi^2 n^2 (x^2 + y^2) + 4\pi v_f n y} \, dl \quad (5)$$

where v_f is the robot's feed speed, n is the rotational speed, and F is the grinding force.

Equation (5) demonstrates the trend observed in Figure 1, indicating that the material removal depth M_D increases with the grinding force F .

Figure 1 also shows that as the grinding force increases from 5 N to 15 N, the surface roughness R_a of the sample decreases from 1.653 μm to 1.350 μm ; however, when the grinding force increases from 15 N to 20 N, the surface roughness R_a rises from 1.350 μm to 1.606 μm . This behavior is attributed to the fact that the increased grinding force enlarges the cutting depth of abrasive grains, causing more pronounced scratches on the workpiece surface and consequently reducing surface quality. Moreover, higher grinding force generates increased cutting heat. Since the coating material is an epoxy resin primer—and resin-based materials exhibit strong adhesiveness [32]—the elevated cutting temperature promotes adhesion of the paint layer to both the workpiece surface and the sandpaper. This adhesion degrades the workpiece's surface quality and impairs the sandpaper's grinding performance.

3.1.2. Influence of Feed Speed on Material Removal Depth and Surface Roughness

The influence of the robot's feed speed on material removal depth and surface roughness is illustrated in Figure 4.

As shown in Figure 4, when the robot's feed speed increases from 20 $\text{mm} \cdot \text{s}^{-1}$ to 100 $\text{mm} \cdot \text{s}^{-1}$, the material removal depth decreases from 33.3 μm to 5.7 μm , while the surface roughness R_a increases from 1.219 μm to 1.924 μm , exhibiting an upward trend. According to Equation (5), this phenomenon can be explained as follows. With the increase in feed speed v_f , the grinding time per unit length of the workpiece is reduced, which decreases the number of interactions between abrasives and weakens the cutting effect,

thereby lowering the material removal depth. Additionally, the shortened contact time between each abrasive grain and the workpiece intensifies the sliding and plowing actions on the workpiece surface, leading to an increase in surface roughness.

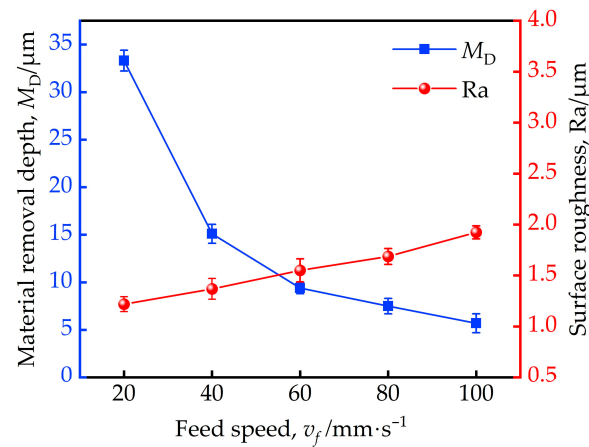


Figure 4. Influence of feed speed on material removal depth and surface roughness.

3.1.3. Influence of Rotational Speed on Material Removal Depth and Surface Roughness

The effect of the grinding disc's rotational speed on material removal depth and surface roughness is presented in Figure 5.

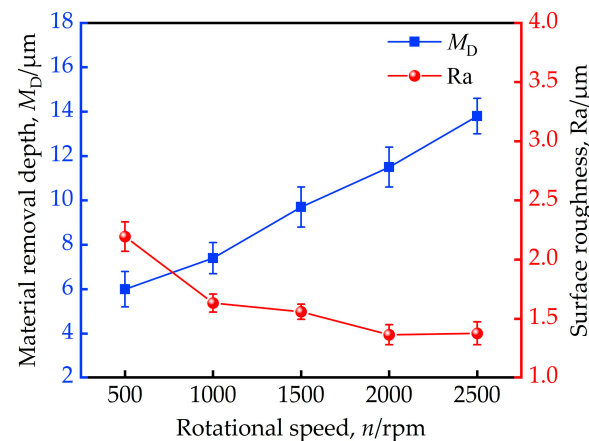


Figure 5. Influence of rotational speed on material removal depth and surface roughness.

As observed from Figure 5, increasing the rotational speed from 500 rpm to 2500 rpm results in an increase in material removal depth from 6 μm to 13.8 μm . With regard to surface roughness R_a , it decreases from 1.663 μm to 1.365 μm as the rotational speed increases from 500 rpm to 2000 rpm. Upon reaching 2500 rpm, the surface roughness R_a experiences a slight increase to 1.377 μm , which remains within the range of the error bars. As outlined in Equation (5), the increase in rotational speed enhances the material removal depth. This is because, with the robot's feed speed remaining constant, a higher rotational speed increases the number of abrasive grains interacting with the workpiece per unit time, thereby increasing the material removal depth. Additionally, the more frequent abrasive interactions reduce the residence time of each grain, minimizing the height of grooves formed by plowing and improving surface finish. However, as indicated by Equation (4), further increases in rotational speed significantly raise the relative speed v_m , which in turn elevates the workpiece surface temperature. This can cause the epoxy primer to adhere to both the sandpaper and the workpiece, degrading the surface quality. Consequently, to

maintain optimal surface finish, the rotational speed for grinding the paint layer should not exceed 2000 rpm.

3.1.4. Influence of Grit Size on Material Removal Depth and Surface Roughness

The influence of grit size on material removal depth and surface roughness is depicted in Figure 6.

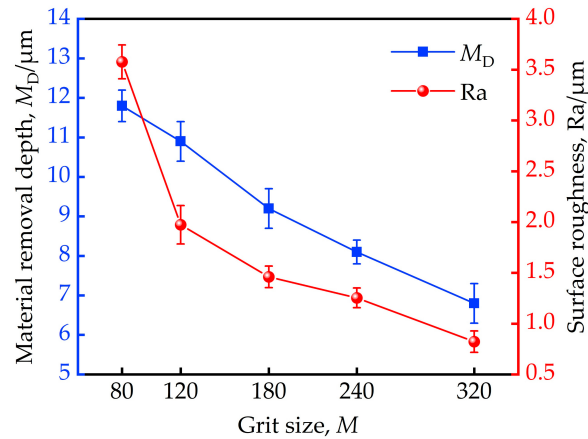


Figure 6. Influence of grit size on material removal depth and surface roughness.

As illustrated in Figure 5, when the sandpaper grit size increases from 80 to 320, the material removal depth decreases from 11.8 μm to 6.8 μm , while surface roughness Ra decreases significantly from 3.577 μm to 0.823 μm . With the finer abrasive grit, the abrasive grains on the sandpaper have smaller diameters and heights, which reduces their penetration depth into the workpiece and weakens the sliding and plowing effects. As a result, both the material removal depth and surface roughness decrease, leading to the improved surface quality. Notably, when the grit size increases from 80 to 120, the material removal depth decreases slightly from 11.8 μm to 10.9 μm , whereas the surface roughness Ra is substantially reduced from 3.577 μm to 1.974 μm . This indicates a significant improvement in surface finish with minimal loss in material removal.

3.2. Results and Analysis of Response Surface Methodology

The response surface methodology results for epoxy primer samples are displayed in Table 3.

Design-Expert 13.0 was employed to carry out regression analysis on the experimental data presented in Table 3. Given the influence of interaction and coupling effects between factors, a quadratic regression model was adopted in this study [33]:

$$Y = \beta_0 + \sum_{i=1}^4 \beta_i x_i + \sum_{i=1}^4 \sum_{j=1, j < i}^4 \beta_{ij} x_i x_j + \sum_{i=1}^4 \beta_{ii} x_i^2 \quad (6)$$

where Y represents the response variables, specifically M_D , M_{DR} , and Ra ; β_0 , β_i , β_{ij} , and β_{ii} denote the constant term, linear coefficient of each factor, interaction coefficient between factors, and quadratic coefficient of each factor, respectively; x_i and x_j stand for the independent factors, i.e., one of the factors A , B , C , D .

The credibility of the regression model was verified through the multiple correlation coefficient R^2 and analysis of variance [34,35]. The outcomes of material removal depth are compiled in Tables 4 and 5.

Table 4. Variance and correlation coefficients of material removal depth based on response surface regression.

Source	Sum of Squares	df	Mean Square	F-Value	p-Value
Model	833.02	14	59.50	56.94	<0.0001
A	187.04	1	187.04	179.00	<0.0001
B	396.91	1	396.91	379.85	<0.0001
C	85.88	1	85.88	82.19	<0.0001
D	19.74	1	19.74	18.90	0.0006
AB	3.42	1	3.42	3.28	0.0904
AC	21.62	1	21.62	20.69	0.0004
AD	1.10	1	1.10	1.06	0.3206
BC	4.00	1	4.00	3.83	0.0693
BD	0.36	1	0.36	0.34	0.5660
CD	6.76	1	6.76	6.47	0.0225
A ²	11.13	1	11.13	10.65	0.0052
B ²	100.33	1	100.33	96.02	<0.0001
C ²	0.15	1	0.15	0.14	0.7091
D ²	2.04	1	2.04	1.96	0.1822
Residual	15.67	15	1.04	—	—
Lack of fit	13.40	10	1.34	2.95	0.1222
Pure error	2.27	5	0.45	—	—
Cor total	848.69	29	—	—	—

$R^2 = 0.9815$, $R^2_{adj} = 0.9643$, $R^2_{pred} = 0.8985$

Table 5. Variance and correlation coefficients of material removal depth rate based on response surface regression.

Source	Sum of Squares	df	Mean Square	F-Value	p-Value
Model	28.77	14	2.06	25.42	<0.0001
A	15.62	1	15.62	193.19	<0.0001
B	0.72	1	0.72	8.92	0.0092
C	6.85	1	6.85	84.71	<0.0001
D	1.69	1	1.69	20.91	0.0004
AB	0.37	1	0.37	4.60	0.0487
AC	1.42	1	1.42	17.52	0.0008
AD	0.08	1	0.08	0.97	0.3403
BC	0.04	1	0.04	0.45	0.5141
BD	0.01	1	0.01	0.08	0.7823
CD	0.61	1	0.61	7.53	0.0151
A ²	1.13	1	1.13	13.97	0.0020
B ²	0.47	1	0.47	5.77	0.0297
C ²	0.03	1	0.03	0.39	0.5395
D ²	0.23	1	0.23	2.80	0.1147
Residual	1.21	15	0.08	—	—
Lack of fit	1.01	10	0.10	2.46	0.1658
Pure error	0.20	5	0.04	—	—
Cor total	29.99	29	—	—	—

$R^2 = 0.9596$, $R^2_{adj} = 0.9218$, $R^2_{pred} = 0.7626$

A higher F-value, lower p-value, and R^2 value closer to 1 indicate greater model accuracy [36]. Specifically, a p-value < 0.05 denotes statistical significance, a p-value < 0.01 indicates higher significance, and an $R^2 > 0.9$ suggests a reliable regression equation. As shown in Table 4, both R^2 and R^2_{adj} of the material removal depth prediction model exceed 0.9, confirming the model's significance. However, a considerable discrepancy between

R^2_{pred} and R^2 indicated the presence of some redundant terms, which were subsequently eliminated. Specifically, the p -values of terms A , B , C , D , AC , and CD , as well as quadratic terms A^2 and B^2 , were less than 0.05, while the p -values of interaction terms AB and BC were between 0.05 and 0.1, warranting their retention in the model. Therefore, the terms AD , BD , C^2 , and D^2 were removed. The response surface prediction regression equation for material removal depth M_D obtained using Design-Expert 13.0 is as follows:

$$M_D = 28.65167 - 0.575200A - 0.619842B + 0.003708C \\ + 0.018189D - 0.004625AB + 0.000465AC - 0.000050BC \\ - 0.000022CD + 0.023784A^2 + 0.004674B^2 \quad (7)$$

In the analysis of variance for the refined model, the values are as follows: $R^2 = 0.9774$, $R^2_{adj} = 0.9654$, and $R^2_{pred} = 0.9349$. Although R^2 shows a slight decrease and R^2_{adj} exhibits a minor increase, the R^2_{pred} increases substantially. This indicates that the reliability and predictive accuracy of the model have been significantly improved after the elimination of redundant terms.

In addition, the F -values presented in Table 4 reflect the relative influence of each factor on the material removal depth, with the ranking as $B > A > B^2 > C > AC > D > A^2 > CD$. Correspondingly, the factors affect the material removal depth in the following order: feed speed > force > quadratic term of feed speed > rotational speed > interaction between force and rotational speed > quadratic term of force > sandpaper grit size > interaction between rotational speed and sandpaper grit size. The interactions between feed speed and force, as well as between force and rotational speed, exhibit only minor effects on the material removal depth. Meanwhile the interaction between feed speed and sandpaper grit size has the least influence, and the interaction between force and sandpaper grit size has a negligible influence on the material removal depth.

The outcomes of material removal depth rate are shown in Table 5.

Both R^2 and R^2_{adj} of the material removal depth rate prediction model exceed 0.9, indicating that the model is significant, although R^2_{pred} is relatively low. Using the same optimization approach as described previously, the terms AD , BC , BD , C^2 , and D^2 were eliminated. The refined model yields $R^2 = 0.9475$, $R^2_{adj} = 0.9239$, and $R^2_{pred} = 0.8622$, with the difference between R^2_{pred} and R^2 remaining below 0.1, confirming the model's reliability. The response surface regression equation for material removal depth rate M_{DR} obtained using Design-Expert 13.0 is expressed as follows:

$$M_{DR} = 4.18548 - 0.333833A - 0.048750B + 0.000453C \\ + 0.005611D + 0.001525AB + 0.000119AC \\ - 0.000065CD + 0.007506A^2 + 0.000288B^2 \quad (8)$$

The F -values presented in Table 5 reflect the relative influence of each factor on the material removal depth rate, ranked as $A > C > D > AC > A^2 > B > CD > B^2 > AB$. Accordingly, the factors affect removal depth rate in the following order: grinding force > rotational speed > sandpaper grit size > interaction between force and rotational speed > quadratic term of force > feed speed > interaction between rotational speed and sandpaper grit size > quadratic term of feed speed > interaction between force and feed speed. The interactions between force and sandpaper grit size, between feed speed and rotational speed, and between feed speed and sandpaper grit size exhibit negligible influence on the material removal depth rate and therefore can be disregarded.

The response surface regression model for surface roughness was analyzed using the same methodology. The analysis indicates that the p -value of the optimized model is 0.0002, confirming its statistical significance. However, the coefficients of determination—

$R^2 = 0.8333$, $R^2_{adj} = 0.7986$, and $R^2_{pred} = 0.7051$ —are all below 0.9, indicating that the model lacks sufficient reliability for accurate prediction.

Given the poor performance of the surface roughness regression model, if only the maximum material removal depth and maximum material removal rate are taken as optimization objectives, the optimal process parameters obtained by Design Expert 13.0 are as follows: a grinding force of 25 N, a feed rate of $40 \text{ mm} \cdot \text{s}^{-1}$, a rotational speed of 2500 rpm, and an 80# sandpaper grit size.

3.3. BP Neural Network Prediction Model for Surface Roughness and Removal Depth

Given the limited predictive accuracy of the surface roughness regression model established via response surface methodology, a BP neural network was adopted to predict surface roughness R_a and material removal depth M_D . Since the construction of a BP neural network requires a substantial dataset, 25 groups of experimental data, as presented in Table 6, were incorporated into the response surface test data results.

Table 6. Additional experimental data for establishing BP neural network.

No.	Grinding Force, $F(\text{N})$	Feed Speed, $v_f (\text{mm} \cdot \text{s}^{-1})$	Rotational Speed, $n (\text{rpm})$	Grit Size, M	$M_D (\mu\text{m})$	$R_a (\mu\text{m})$
1	5	20	500	80	6.3	4.434
2	5	40	1500	240	5.1	1.106
3	5	60	2500	120	9.7	1.539
4	5	80	1000	320	2.7	1.285
5	5	100	2000	180	8.7	2.010
6	10	20	2500	240	19.2	0.718
7	10	40	1000	120	12.7	1.993
8	10	60	2000	320	11.2	1.093
9	10	80	500	180	8.7	2.458
10	10	100	1500	80	9.9	5.818
11	15	20	2000	120	34.1	1.725
12	15	40	500	320	8.9	1.555
13	15	60	1500	180	10.2	1.245
14	15	80	2500	80	12.6	3.166
15	15	100	1000	240	8.8	1.530
16	20	20	1500	320	31.8	0.714
17	20	40	2500	180	25.1	1.263
18	20	60	1000	80	17.1	5.355
19	20	80	2000	240	14.8	1.052
20	20	100	500	120	5.8	3.270
21	25	20	1000	180	32.3	1.471
22	25	40	2000	80	35.8	4.709
23	25	60	500	240	8.3	1.719
24	25	80	1500	120	13.4	1.739
25	25	100	2500	320	11.6	1.180

The BP neural network is a multilayer feedforward neural network trained by the error backpropagation algorithm, consisting of an input layer, a hidden layer, and an output layer [37]. The number of nodes in the hidden layer has an impact on the prediction accuracy and is typically determined by the following empirical formula [38]:

$$N = \text{round}(\sqrt{p + q} + a) \quad (9)$$

where N is the number of hidden layer nodes; p is the number of input layer nodes, q is the number of output layer nodes, and a is a constant ranging from 1 to 10.

In this study, the BP neural network model was implemented using MATLAB 2024b and configured with a three-layer structure. The transfer functions from the input layer to the hidden layer and from the hidden layer to the output layer are both set as *tansig*, and the training algorithm adopted is *trainlm*. The input layer contained four nodes, representing the grinding force F , feed speed v_f , rotational speed n , and sandpaper grit size M , respectively. The output layer included two nodes, corresponding to surface roughness R_a and material removal depth M_D . According to Equation (9), the number of hidden layer nodes N is considered within the range of 3–12. Optimal performance was achieved when $N = 7$. The network was trained for 1000 iterations, with a learning rate of 0.01 and a minimum training error target of 0.00001.

From the 30 CCD experimental sets, 23 were randomly selected, with the constraint that they include exactly 3 randomly chosen center point experiments. Furthermore, 17 were randomly selected from the 25 supplementary experiments. These 40 groups collectively form the training set. The remaining 15 groups—consisting of 7 from the CCD experiments and 8 from the supplementary experiments—make up the test set.

The training results indicate that the coefficient of determination R^2 is 0.9315 for surface roughness R_a and 0.9650 for material removal depth. Figure 7 presents the error plots for both surface roughness R_a and material removal depth M_D , where both relative errors are less than 9.5%, and they are well within the acceptable range. This indicates a strong consistency between the BP model's predicted and experimental values. These results confirm that the established BP neural network model possesses high predictive accuracy and stability.

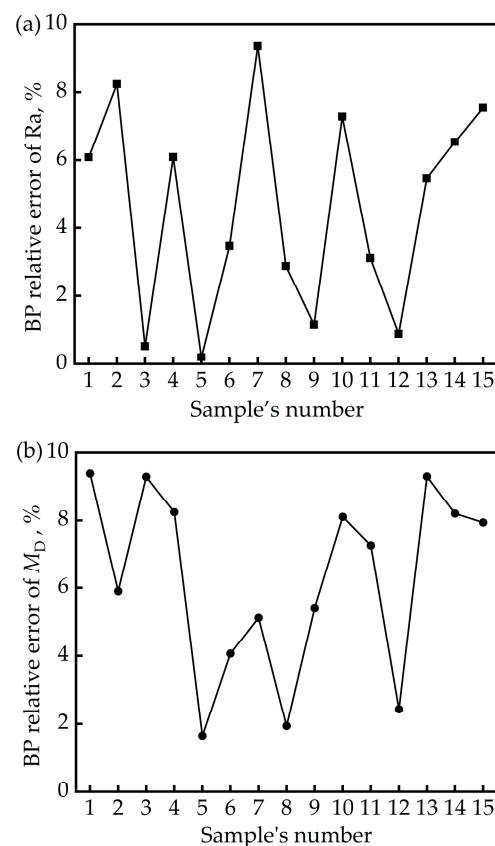


Figure 7. Error diagrams of BP neural network model prediction results: (a) surface roughness; (b) material removal depth.

For the prediction of material removal depth, the BP neural network model yields an R^2 value of 0.9650, which is slightly lower than that of the regression model ($R^2 = 0.9815$).

In contrast, for surface roughness prediction, the BP neural network achieves an R^2 value of 0.9315, which is substantially higher than that of the regression model ($R^2 = 0.8719$). These results indicate that the BP neural network model exhibits superior predictive performance for surface roughness, whereas its performance in predicting material removal depth is comparable to that of the regression model.

To further validate the model accuracy of models and obtain the optimal process parameters, experiments were performed using the optimal parameters initially determined by maximizing both material removal depth and material removal rate (i.e., a grinding force of 25 N, a feed rate of $40 \text{ mm} \cdot \text{s}^{-1}$, a rotational speed of 2500 rpm, and a sandpaper grit size of 80). However, the experimental results indicated that excessive primer layer adhesion on the sandpaper surface led to poor durability, allowing only one grinding cycle. Consequently, to enhance sandpaper lifespan, the grinding process parameters were further reduced. After multiple iterative tests, a revised parameter set (grinding force: 20 N, feed rate: $40 \text{ mm} \cdot \text{s}^{-1}$, rotational speed: 2000 rpm, sandpaper grit size: 80) was selected. This revised set, together with 4 additional random process parameter sets as specified in Table 7, was adopted for subsequent experiments. The experimental results were compared with the corresponding predictions from models, as shown in Table 8.

Table 7. Process parameters used for model prediction and test verification.

No.	Grinding Force, F (N)	Feed Speed, v_f ($\text{mm} \cdot \text{s}^{-1}$)	Rotational Speed, n (rpm)	Grit Size, M
W1	20	40	2000	80
W2	16	68	1742	180
W3	13	42	2093	240
W4	15	79	1472	320
W5	7	54	1064	120

Table 8. Comparison between model predicted values and test values.

No.	M_{DR} ($\mu\text{m} \cdot \text{s}^{-1}$)		Error (%)	M_D (μm)			Reg-Error (%)	BP-Error (%)	Ra (μm)		Error (%)
	Test	Reg-Pred.		Test	Reg-Pred.	BP-Pred.			Test	BP-Pred.	
W1	5.501	5.316	3.4	27.5	25.467	29.198	7.4	6.2	1.897	1.731	8.8
W2	3.434	3.519	2.5	10.1	9.841	9.718	2.6	3.8	1.436	1.503	4.7
W3	2.772	2.574	7.1	13.2	14.211	12.227	7.7	7.4	1.126	1.084	3.7
W4	2.371	2.526	6.5	6.0	6.356	6.392	5.9	6.5	1.183	1.295	9.5
W5	2.295	2.114	7.9	8.5	8.089	9.346	4.8	10.0	2.037	2.171	6.6

As shown in Table 8, the maximum relative error of the material removal depth rate regression model is 7.9%, and that of the removal depth regression model is 7.4%, both of which are below 8%. The maximum relative error of the surface roughness Ra predicted by the BP neural network model is 9.5%, indicating that the established models can reliably predict the material removal depth rate, material removal depth, and surface roughness. For material removal depth, the maximum relative error of the regression model is 7.4%, compared to 10.0% for the BP neural network model, showing a certain discrepancy. Nevertheless, when comparing the predicted material removal depth values under the five different grinding process parameters, the two models exhibit comparable accuracy, with the regression model performing slightly better. Therefore, the regression model is suitable for predicting the material removal depth and material removal depth rate, while the BP neural network model is more appropriate for predicting the surface roughness.

Additionally, from the standpoint of primer layer removal efficiency, W1 in Table 8 corresponds to the experimental results under the optimal process parameters ($F = 20 \text{ N}$,

$v_f = 40 \text{ mm}\cdot\text{s}^{-1}$, $n = 2000 \text{ rpm}$, $M = 80$). Specifically, this parameter set yields a maximum material removal depth of $27.5 \text{ }\mu\text{m}$, a maximum removal rate is $5.501 \text{ }\mu\text{m}\cdot\text{s}^{-1}$, and a corresponding surface roughness R_a is $1.897 \text{ }\mu\text{m}$.

4. Conclusions

- (1) The study reveals that the material removal depth of the sample increases with the elevation in grinding force, whereas the surface roughness first decreases and then increases. As the feed speed rises, the material removal depth declines rapidly, with the rate of decrease slowing down significantly when exceeding $60 \text{ mm}\cdot\text{s}^{-1}$. In contrast, the surface roughness shows a consistent upward trend. An increase in the rotational speed enhances the material removal depth while gradually reducing surface roughness. Moreover, finer abrasives lead to a pronounced reduction in both material removal depth and surface roughness, highlighting their significant influence on surface quality.
- (2) Owing to the inherent adhesiveness of resin materials, the surface quality of the ground workpiece is impaired, and the material removal depth is reduced. The optimal process parameters were identified as $F = 20 \text{ N}$, $v_f = 40 \text{ mm}\cdot\text{s}^{-1}$, $n = 2000 \text{ rpm}$, and $M = 80$. Under these conditions, the maximum material removal depth is $27.5 \text{ }\mu\text{m}$, the maximum material removal depth rate is $5.501 \text{ }\mu\text{m}\cdot\text{s}^{-1}$, and the corresponding surface roughness R_a is $1.897 \text{ }\mu\text{m}$.
- (3) The maximum relative errors of the material removal depth rate and material removal depth regression models are both below 8%, and the maximum relative error of the surface roughness R_a predicted by the BP neural network model is less than 9.5%. These results indicate that the established models can reliably predict material removal depth rate, material removal depth, and surface roughness. Although the regression model for material removal depth exhibits slightly better accuracy than the BP neural network model, the maximum relative errors of both models remain below 10%, confirming their overall predictive reliability.

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