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Simulation Research On Surface Roughness Of Process Parameters Of Selective Laser Melting Ti-6Al-4V Based On Response Surface Optimization Method

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Abstract: *Selective Laser Melting (SLM) technology has been widely applied in fields such as material science, aerospace, biomedicine, and industrial production. In particular, the titanium alloy Ti-6Al-4V, due to its outstanding mechanical properties and biocompatibility, has garnered extensive attention. However, the surface roughness produced during the SLM process can significantly influence the performance and application scope of the components. Thus, optimizing the SLM process parameters to achieve the desired surface roughness has become a challenging topic in current research. Given the cost-effectiveness and efficiency of numerical simulation in optimizing SLM, this paper primarily investigates the impact of SLM process parameters on the surface roughness of Ti-6Al-4V through numerical simulations and conducts a simulation study based on the response surface optimization method. Furthermore, this paper simulates the optimal surface roughness of laser-melted Ti-6Al-4V using the response surface optimization method. The anticipated results are expected to provide theoretical references and practical guidance for the optimization and application of SLM.*

Background*: Selective Laser Melting (SLM) technology is a prominent method for producing metal parts with complex geometries. The surface roughness of SLM parts is influenced by various factors, including laser power, scanning speed, and hatch spacing. Simulation technology offers an economical and efficient approach to study these factors. Simulations reduce experimental costs, offer high flexibility, and allow researchers to model and analyze complex physical processes. This study introduces the principles of obtaining surface roughness in SLM technology and the primary factors affecting it. The response surface optimization method is used to simulate the surface roughness of laser-melted Ti-6Al-4V.*

Materials and Methods*: This research employed the three-factor Box-Behnken response surface design for simulation experiments. Key process parameters considered were Laser power, Scanning speed, and Hatch spacing. The levels for these parameters were set, and using the Design-Expert software, an experimental design was established with 15 experimental combinations. Surface roughness measurements were conducted on the 15 SLM-simulated melt tracks. The response surface optimization method, grounded in statistics, considers interactions between various parameters. By establishing a response surface model, it identifies the optimal combination of influencing factors, conserving experimental costs and enhancing optimization efficiency.*

Results*: The derived model from the response surface experiment showed that as laser power, scanning speed, and hatch spacing parameters change, surface roughness follows a parabolic trend. The optimized process parameters were identified as laser power at 207.459W, scanning speed at 1112.43mm/s, and hatch spacing at 0.09557mm.*

Conclusion: *The study revealed that variations in laser power, scanning speed, and hatch spacing significantly influence surface roughness in SLM. Excessive or insufficient laser power and scanning speed can adversely affect surface quality. The research successfully established a regression model to predict and optimize surface roughness.*

Key Word*: Selective Laser Melting; Ti-6Al-4V, Surface Roughness; Response Surface; Numerical Simulation*

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I. Introduction

With the continuous advancement of modern manufacturing technologies, additive manufacturing has been playing an increasingly pivotal role in many crucial sectors[1,2,3]. As an advanced manufacturing technique, selective laser melting has been extensively applied in domains such as materials science, aerospace, biomedicine, and industrial production[4,5]. Among these applications, the use of selective laser melting for the titanium alloy Ti-6Al-4V has drawn significant attention due to its exceptional mechanical properties and biocompatibility[6,7]. However, the surface roughness generated during the selective laser melting process significantly influences the performance and application scope of the parts[8,9]. Thus, optimizing laser melting parameters to achieve desired surface roughness has become a challenging topic of current research. Laser power, scanning speed, and hatch spacing are the three primary parameters affecting surface roughness during the laser melting process. First, laser power can influence melting depth and cooling rate, thereby altering the shape and size of the melt pool, subsequently impacting the surface roughness[10,11]. Next, scanning speed also affects the shape and cooling speed of the melt pool, leading to changes in surface roughness[12,13]. Lastly, hatch spacing determines the coverage area and overlap degree of a single scan; an inappropriate hatch spacing can result in surface unevenness, increasing surface roughness[14]. Zhang et al.[15] achieved notable improvements in the surface quality of 316L material by adjusting these three key parameters, achieving optimal surface quality when laser power was set to 90W, scanning speed to 1200mm/s, and hatch spacing to 0.07mm. Gong et al.[16] noted that during the selective laser melting process, as the scanning speed increased, the size of the melt pool gradually diminished. With constant hatch spacing, this reduction in melt pool size led to decreased overlap, thereby worsening the surface roughness. Majeed et al.[17] optimized the laser power, scanning speed, and hatch spacing for AlSi10Mg selective laser melting, achieving a best surface roughness of 3.57μm. They discovered that, post solution heat treatment (SHT), the lowest average surface roughness was 3.05 microns, indicating a 17% reduction in average surface roughness. Cao et al.[18] performed a detailed analysis and discussion of experimental results using machine learning, uncovering that laser power, scanning speed, and layer thickness significantly affected surface roughness and dimensional accuracy. They also employed the Whale Optimization Algorithm (WOA) for global optimal process parameter search, confirming the optimization through experimental validation. Khorasani et al.[19] in their study on selective laser melting of Ti-6Al-4V found that the factors influencing surface roughness, in descending order of significance, were: heat treatment > laser power > scan pattern angle > hatch spacing > scanning speed. They utilized artificial neural network techniques to develop predictive models for selective laser melting process parameters.

In recent years, many researchers have sought to explore the factors affecting surface roughness in the SLM process through experimental means, and have subsequently optimized processing parameters based on these findings. However, this method is costly, constrained by experimental conditions, and inefficient[20]. Simulations, as a scientific research method, offer unique advantages. Firstly, simulations significantly reduce experimental costs. Compared to traditional physical experiments, simulation experiments do not require expensive equipment and materials; with ample computational resources and the appropriate simulation software, complex physical processes can be modeled and analyzed[21]. This not only saves substantial material and equipment costs but also avoids experimental errors caused by equipment failures or operational mistakes. Secondly, simulation experiments offer high flexibility. Researchers can easily modify various parameters, such as laser power, scanning speed, and hatch spacing, to simulate the melting process under different conditions[22]. This not only allows a deeper understanding of the physical mechanisms of the melting process but also helps in identifying the optimal processing parameters. In summary, simulation technology offers an effective, economical, and efficient method for the optimization research of selective laser melting, promising to further advance this field[23].Zhang et al.[24] built a finite element analysis model (FEM) to evaluate the thermal characteristic parameters of the melt zone temperature field. They also studied how laser energy density affects the surface quality and mechanical properties of SLM SS316L components, providing theoretical support for optimizing the processing parameters of complex components. Alghamdi[25] and his team demonstrated that simulation could predict thermally induced defects based on input geometric shapes, with a strong correlation found between experimental and numerical data. Moreover, in studies on the surface roughness of selective laser melted Ti-6Al-4V based on the response surface optimization method, due to complex interactions between parameters, it is challenging to obtain a global optimal solution through a single experimental design. To address this challenge, this study will use Design-expert software to apply the response surface optimization method to simulate the surface roughness of laser-melted Ti-6Al-4V tracks. The response surface optimization method, grounded in statistics, considers the interactions between various parameters. By establishing a response surface model, it effectively identifies the optimal combination of multiple influencing factors. This method not only conserves experimental costs but also enhances optimization efficiency and accuracy. Deng et al.[26] employed the response surface method to study the density and surface roughness of 316L stainless steel components manufactured by SLM, with process parameters including laser power, scanning speed, and hatch spacing. They successfully constructed a statistical model describing the relationship between process parameters and manufacturing quality. Waqas et al.[27] examined the surface quality and dimensional accuracy of SLM-manufactured AlSi10Mg components. They used the Response Surface Method (RSM) to determine the impact of layer thickness and process parameters (such as laser power, scanning speed, and hatch spacing) on components and assessed the surface roughness and dimensional accuracy of the samples using ANOVA techniques. This paper initially introduces the fundamental principles of obtaining surface roughness in selective laser melting technology and the primary factors affecting surface roughness. It then elaborates on the basic theory and application of the response surface optimization method, culminating in a simulated study of the surface roughness of laser-melted Ti-6Al-4V using the response surface optimization method. The findings are expected to offer theoretical references and practical guidance for the optimization and application of selective laser melting.

II. Material And Methods

Analytical method: This study utilized the FLOW-3D software to simulate the powder bed after selective laser melting and subsequently acquired the STL (stereolithography) file of the melted powder bed. The obtained STL file was imported into MATLAB to attain a uniformly distributed scatter plot of the melt track surface within a specified range. After importing the three-dimensional coordinate data of these scatter points into an Excel file, they were fed into a MATLAB script. Using surface roughness calculation formula 1, we derived the numerical value of the three-dimensional surface roughness and obtained topographical maps of the melt track surface. Both the scatter plot and the topographical map of the melt track are shown in Figure 1. In the x-direction, the simulated limited length is 84μm. To eliminate the surface roughness error at the beginning and end of the melt track, the data was taken starting from 5μm and stopped at 79μm in the x-direction. The y-direction width of the melt track was determined based on its actual width.

$$R_a = \frac{1}{MN}\sum_{k=0}^{M-1}\sum_{l=0}^{N-1}\left| Z(x_k, y_l) - \frac{1}{MN}\sum_{k=0}^{M-1}\sum_{l=0}^{N-1} Z(x_k, y_l)\right| \quad (1)$$

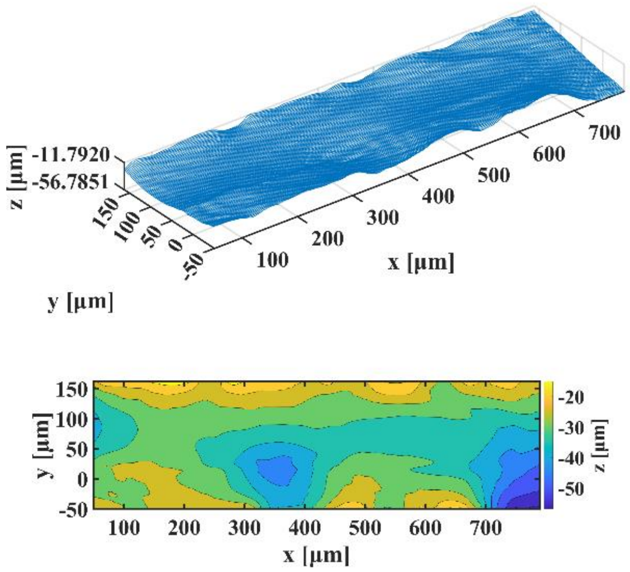


Figure 1: Scatter diagram and terrain diagram of melt channel

Simulation parameters: The material used for this simulation was Ti-6Al-4V. Table 1 lists all the thermophysical properties used in this simulation.

Table 1: Simulation parameters of Ti-6Al-4V

Physical Properties	Value	Reference
Laser absorptivity	70%	**Error! Reference source not found.**
Melting temperature(K)	1900K	**Error! Reference source not found.**
Liquidus temperature(K)	1923K	**Error! Reference source not found.**
Solidus temperature(K)	1877K	**Error! Reference source not found.**
Surface tension coefficient(Nm-1)	1.4	**Error! Reference source not found.**
Evaporation temperature(K)	3315K	**Error! Reference source not found.**
Latent heat of evaporation(J/kg)	9.83×106 K	**Error! Reference source not found.**
Liquid density(kg/m3)	3920-0.68(T-1923 K)	**Error! Reference source not found.**
Solid density(kg/m3)	4420-0.154(T-298 K)	**Error! Reference source not found.**
Specific heat(J/(kg K))	483.04+0.215 T(T≤1268 K)	**Error! Reference source not found.**
	412.7+0.1801 T(1268 K<T≤1923 K)	

	831.0(1923 K<T<3315 K)	
Dynamic viscosity(Pa·s)	3.25×10-3(1923 K) 3.03×10-3(1973 K)	**Error! Reference source not found.**
	2.66×10-3(2073 K) 2.36×10-3(2773 K)	
Thermal conductivity(W/(m K)	1.2595+0.0157 T(T≤1268 K)	**Error! Reference source not found.**
	3.5127+0.0127 T(1268 K<T≤1923 K)	
	-12.752+0.024 T(1923 K<T<3315 K)	

Optimized method: This paper utilized Design-Expert for response surface optimization. Design-Expert is a software developed by Stat-Ease, Inc. for experimental design and response surface optimization. This software offers a comprehensive set of tools commonly used for experimental design, data analysis, and optimization. Response Surface Methodology (RSM) is an empirical statistical technique used to optimize responses in multi-variable systems. Based on a series of designed experiments, RSM can establish an empirical model between a target or response variable and one or more factors. Typically, the response surface model can be expressed as:

$$Y = f(X_1, X_2, \dots, X_k) + \varepsilon$$

Wherein, Y is the response or target variable, X_i is the factor influencing the response, ε is the random error term, and f is an unknown function, usually approximated by a polynomial function. To determine f, experiments need to be designed and conducted. Common experimental designs include Central Composite Design, Box-Behnken Design, and Doehlert Design, among others.

III. Result

A three-factor, five-level orthogonal experiment was first designed for the Ti-6Al-4V material. The surface roughness of the SLM-formed Ti-6Al-4V melt track was measured using MATLAB, with the results shown in Table 2. From the surface roughness values in Table 2, it can be observed that when the laser power is 210W, the scanning speed is 1200mm/s, and the hatch spacing is 0.1mm, the specimen has the minimum surface roughness. After categorizing and summing each process parameter, taking their corresponding average values and further analyzing, the main effect plots of each process parameter on surface roughness are shown in Figure 2. From the figure, it can be seen that the influence of the three process parameters on the surface roughness of the melt track all exhibit a trend of first decreasing and then increasing.

Table 2: Three-factor, five-level orthogonal experiment

Serial number	Laser power(W)	Scanning speed(mm/s)	Hatch spacing(mm)	Melting channel width(μm）	Surface roughness(μm)
1	150	800	0.07	(-68, 150)	4.65
2	150	1000	0.085	(-56, 158)	4.50
3	150	1200	0.1	(-50, 154)	4.91
4	150	1400	0.115	(-50, 158)	6.33
5	150	1600	0.13	(-40, 176)	6.38
6	180	800	0.085	(-76, 190)	4.63
7	180	1000	0.1	(-62, 182)	4.51
8	180	1200	0.115	(-50, 180)	3.89
9	180	1400	0.13	(-44, 184)	5.00
10	180	1600	0.07	(-44, 122)	6.61
11	210	800	0.1	(-76, 200)	4.61
12	210	1000	0.115	(-62, 204)	4.01
13	210	1200	0.13	(-62, 200)	3.97
14	210	1400	0.07	(-54, 140)	4.50
15	210	1600	0.085	(-40, 142)	4.93
16	240	800	0.115	(-90, 222)	4.31
17	240	1000	0.13	(-76, 220)	4.64
18	240	1200	0.07	(-62, 158)	4.23
19	240	1400	0.085	(-48, 150)	4.51
20	240	1600	0.1	(-52, 164)	4.44
21	270	800	0.13	(-98, 240)	5.35
22	270	1000	0.07	(-84, 176)	4.47
23	270	1200	0.085	(-68, 180)	4.65
24	270	1400	0.1	(-62, 176)	3.72
25	270	1600	0.115	(-52, 190)	4.14

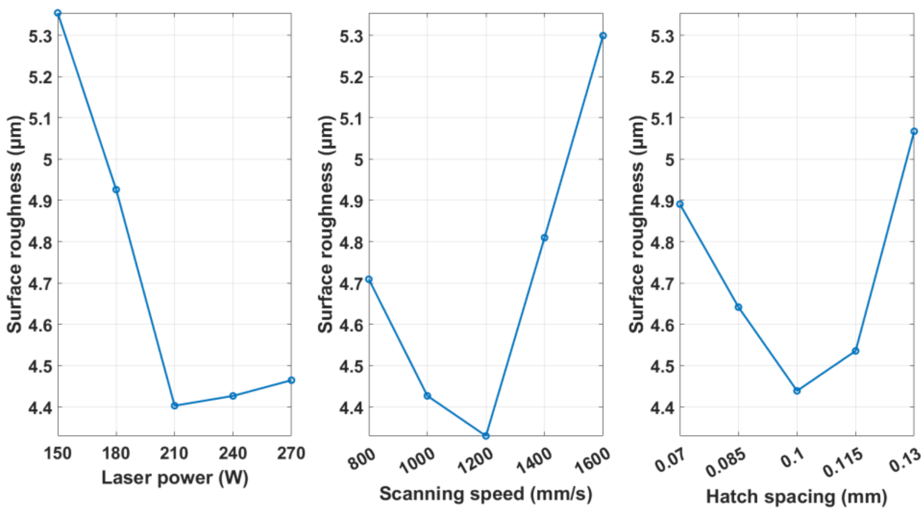


Figure 2: Main effect plot of process parameters on surface roughness

During the SLM process, Laser power, Scanning speed, and Hatch spacing are three critical parameters, significantly influencing the surface roughness of the formed parts. Firstly, insufficient Laser power might lead to incomplete melting of the metal powder, resulting in discontinuous melt pools and an increased surface roughness. Furthermore, defects such as pores and unmelted areas might form. Excessively high Laser power might lead to over-melting, producing deep melt pools. This could result in unstable melt pools and spattering, further increasing the surface roughness. Secondly, a low Scanning speed could cause over-melting due to the laser lingering too long in one spot, possibly destabilizing the melt pool and exacerbating surface roughness. A high Scanning speed might lead to incomplete melting, forming discontinuous melt pools and surface defects, thereby elevating the surface roughness. Finally, a low Hatch spacing might lead to repetitive or over-melting due to increased overlap between adjacent scanning paths, potentially increasing surface roughness. A high Hatch spacing might cause discontinuous melting between metal powders, as there might be unmelted areas between scanning paths, leading to a rougher surface.

In optimizing the surface roughness of Ti-6Al-4V, orthogonal experiments can precisely determine the influence trend of each factor. However, for scenarios with complex non-linear relationships and interactions between factors, the analytical potential of orthogonal experiments is limited. Although orthogonal experiments allow for considering interactions, dealing with these interactions might become more intricate in multi-factor, multi-level designs, potentially leading to only local optimal solutions. In contrast, the Response Surface Methodology (RSM) can find a global optimal solution by fitting a polynomial model to describe the relationship between responses and factors. Based on the characteristics of mathematical models, RSM can also predict responses under untested conditions. To delve deeper into this issue, this study employed a three-factor Box-Behnken response surface design for simulation experiments. In the research, Laser power, Scanning speed, and Hatch spacing were selected as key process parameters. The three levels of Laser power were set at 180W, 210W, and 240W; the Scanning speed levels were 1000mm/s, 1200mm/s, and 1400mm/s; and the levels for Hatch spacing were 0.085mm, 0.1mm, and 0.115mm. By evaluating the impact of these process parameters on melt track surface roughness, the optimal processing conditions were determined.

Using the Design-Expert software, an experimental design was established by adding 3 central points, resulting in a total of 15 experimental combinations. Subsequently, surface roughness measurements were conducted on the 15 SLM-simulated melt tracks. The related experimental design and results are shown in Table 3, while the analysis of variance results are presented in Table 4. Observing the data from Table 3, it is evident that there is a minimal difference between the actual and predicted surface roughness values. This further verifies that the multivariate quadratic regression model derived from the Box-Behnken Design (BBD) response surface methodology possesses excellent predictive accuracy.

When evaluating the model's quality, the primary metrics taken into account are the values of R^2, Adj-R^2, and Pred-R^2, as well as the analysis of lack-of-fit terms. Generally, the closer the values of R^2, Adj-R^2, and Pred-R^2 are to 1, the more significant the model. In this study, the value of R^2 is 0.9972, Adj-R^2 is 0.9922, and Pred-R^2 is 0.9581. As the difference between Adj-R^2 and Pred-R^2 is less than 0.2, it demonstrates a good fit of the model. Based on statistical analysis, when the p-value is less than 0.05, the model term can be considered significant. Therefore, in this study, both Laser power and Scanning speed have a notable influence on the surface roughness of the Ti-6Al-4V melt track. Concurrently, the significance of the interaction terms AC and BC further indicates a substantial interaction effect between Hatch spacing, Laser power, and Scanning speed.

Table 3: BBD Response Surface Design

Serial number	Laser power(W)	scanning speed(mm/s)	Hatch spacing(mm)	actual value(μm）	Predictive value(μm)
1	210	1000	0.085	4.05	4.04
2	180	1200	0.115	4.47	4.48
3	210	1200	0.1	3.40	3.42
4	240	1000	0.1	4.08	4.10
5	210	1000	0.115	4.18	4.55
6	180	1000	0.1	4.52	4.55
7	240	1200	0.085	3.71	3.70
8	240	1400	0.1	3.62	3.59
9	210	1400	0.115	3.84	3.85
10	210	1200	0.1	3.43	3.42
11	180	1200	0.085	4.35	4.33
12	210	1200	0.1	3.42	3.42
13	210	1400	0.085	3.41	3.45
14	180	1400	0.1	4.19	4.17
15	240	1200	0.115	4.06	4.08

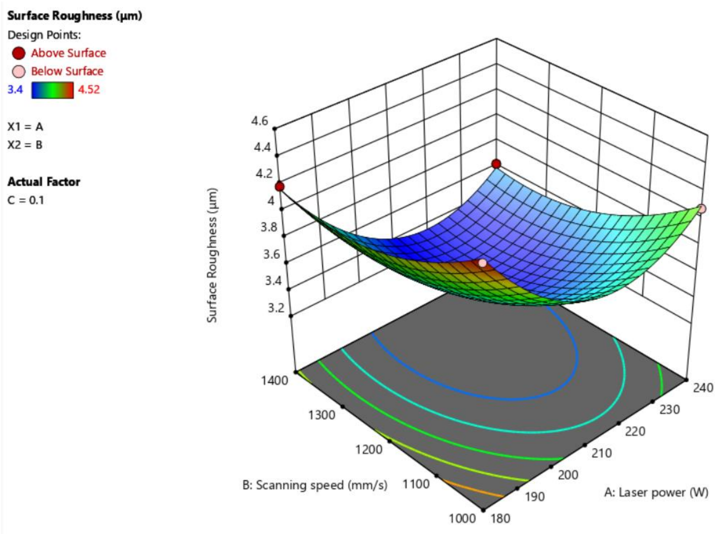
Using the Design-Expert software to analyze the surface roughness of the Ti-6Al-4V melt track, the multivariate quadratic regression equation for its surface roughness is derived as: $SR = 3.42 - 0.2575A - 0.2213B + 0.1287C - 0.0325AB + 0.0575AC + 0.075BC + 0.4817A^2 + 0.2042B^2 + 0.292C^2$

Where SR represents the theoretical predicted value of the surface roughness for the simulated melt track of Ti-6Al-4V, the coefficients indicate the degree of influence, A denotes Laser power, B signifies Scanning speed, and C corresponds to Hatch spacing.

Table 4: Response Surface Analysis of Variance

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	2.2	9	0.2450	197.81	< 0.0001	significant
A-Laser power	0.5305	1	0.5305	428.36	< 0.0001	
B-Scanning speed	0.3916	1	0.3916	316.24	< 0.0001	
C-Hatch spacing	0.1326	1	0.1326	107.09	0.0001	
AB	0.0042	1	0.0042	3.41	0.124	
AC	0.0132	1	0.0132	10.68	0.0222	
BC	0.0225	1	0.0225	18.17	0.008	
A^2	0.8566	1	0.8566	691.76	< 0.0001	
B^2	0.1539	1	0.1539	124.29	0.0001	
C^2	0.2292	1	0.2292	185.11	< 0.0001	
Residual	0.0062	5	0.0012			
Lack of Fit	0.0057	3	0.0019	8.18	0.1109	not significant

Using the Design-Expert software for multivariate regression fitting, the quadratic equation response surface obtained is illustrated in Figure 3.



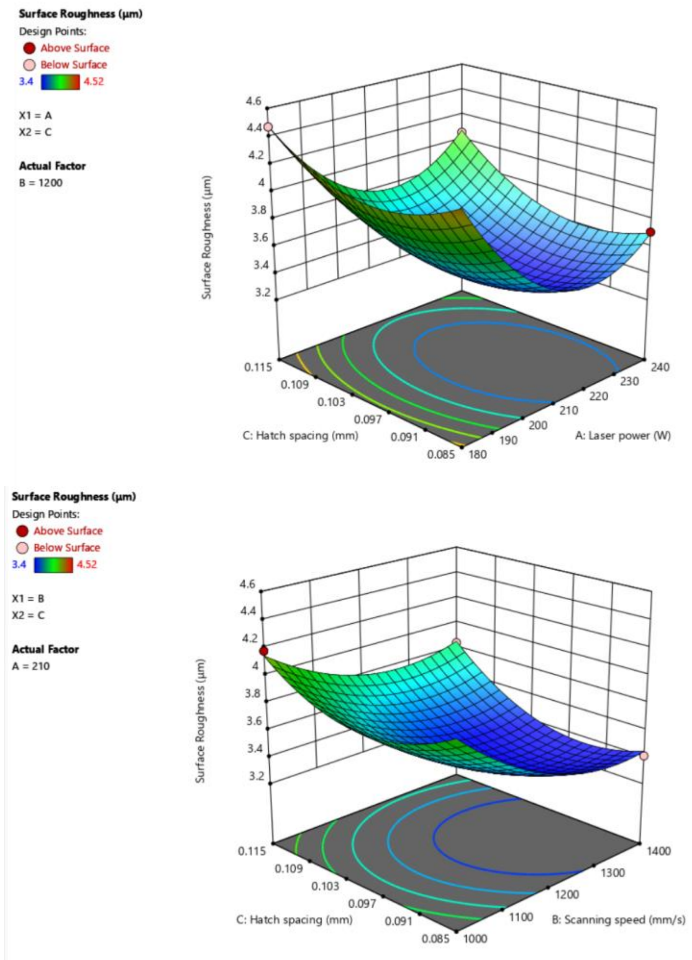


Figure 3: Response surface of the interaction of laser power, scanning speed and scanning distance for the simulated surface roughness of Ti-6Al-4V melt channel

From Figure 3, it can be observed that the interactions among laser power, scanning speed, and hatch spacing on the melt track of Ti-6Al-4V exhibit a parabolic trend, with the response surfaces all having a minimum value.

After optimization using the response surface methodology, the best surface roughness parameters determined by the Design-Expert software are as follows: laser power is set to 207.459W, scanning speed at 1112.43mm/s, and hatch spacing at 0.09557mm. The predicted optimal surface roughness is 3.3934μm, with a confidence level of 97%.

IV. Discussion

Selective Laser Melting technology, especially when applied to the titanium alloy Ti-6Al-4V, has been a focal point of research due to the alloy's exceptional mechanical properties and biocompatibility. One of the significant challenges in SLM is achieving the desired surface roughness, as it can significantly influence the performance and application scope of the components. The study highlighted the three primary parameters affecting surface roughness during the laser melting process: laser power, scanning speed, and hatch spacing. Each of these parameters has a distinct influence on the melting depth, cooling rate, shape, and size of the melt pool, which subsequently impacts the surface roughness. Previous research has shown improvements in surface quality by adjusting these parameters. Traditional experimental methods to explore the factors affecting surface roughness in the SLM process can be costly and inefficient. In contrast, simulations offer a cost-effective and efficient alternative. The study leveraged simulations to understand the physical mechanisms of the melting process better and identify optimal processing parameters.

The paper employed the response surface optimization method, grounded in statistics, to address the challenge of obtaining a global optimal solution through a single experimental design. This method considers the interactions between various parameters and identifies the optimal combination of multiple influencing factors. The results from the study's orthogonal experiments and response surface methodology provided insights into the influence of laser power, scanning speed, and hatch spacing on the surface roughness of Ti-6Al-

4V. The findings suggest that there exists an optimal combination of these parameters that minimizes surface roughness. The use of numerical simulations and the response surface optimization method provides a comprehensive understanding of the factors influencing surface roughness. The anticipated results from this study are expected to serve as a theoretical reference and practical guidance for further optimization and application of SLM.

V. Conclusion

The study on the surface roughness of selective laser melting Ti-6Al-4V has provided valuable insights into the optimization of SLM process parameters. The research has identified laser power, scanning speed, and hatch spacing as the three primary parameters that significantly influence the surface roughness during the SLM process. Through the use of numerical simulations, the study has demonstrated the cost-effectiveness and efficiency of this approach in optimizing SLM, as opposed to traditional experimental methods which can be costly and inefficient. The application of the response surface optimization method, grounded in statistics, has proven to be a robust tool in this research. By considering the interactions between various parameters, this method has effectively identified the optimal combination of multiple influencing factors. The results from the study's orthogonal experiments and response surface methodology have provided a comprehensive understanding of the factors influencing surface roughness, suggesting an optimal combination of parameters that minimizes surface roughness. In essence, this research has not only advanced our understanding of the SLM process for Ti-6Al-4V but has also provided a practical guide for its optimization. The findings are expected to have significant implications for the broader field of additive manufacturing, offering a pathway to produce components with desired surface properties.

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