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Optimization of Process Parameters in Metal Additive Manufacturing for Enhanced Mechanical Properties and Surface Finish

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Abstract
Metal Additive Manufacturing (MAM) has emerged as a transformative technology in modern manufacturing, enabling the fabrication of complex geometries with minimal waste. However, the mechanical properties and surface finish of printed components are highly sensitive to process parameters such as laser power, scan speed, layer thickness, and hatch spacing. This paper investigates the optimization of these parameters in Selective Laser Melting (SLM) to improve tensile strength, hardness, and surface quality. By employing a combination of Design of Experiments (DOE) and statistical modeling techniques like Response Surface Methodology (RSM), the study identifies optimal parameter settings. The results demonstrate significant improvements in part quality, supporting the broader industrial adoption of MAM.

Keywords: Additive Manufacturing, Selective Laser Melting, Process Optimization, Mechanical Properties, Surface Finish, DOE, RSM

1. Introduction

Additive Manufacturing (AM), also known as 3D printing, represents a paradigm shift in how products are designed and fabricated [1]. Among various AM techniques, Metal Additive Manufacturing (MAM) stands out for its capability to produce high-performance metal components directly from digital models. Applications span aerospace, biomedical implants, automotive, and tooling industries [2].

Despite its advantages, the mechanical performance and surface finish of metal parts manufactured via MAM remain inconsistent due to the complex interaction of multiple process parameters [3]. In Selective Laser Melting (SLM), for example, factors such as laser power, scan speed, layer thickness, and hatch spacing critically affect the microstructure, porosity, and residual stresses of printed parts. Consequently, there is a growing need for systematic optimization of these parameters to achieve desired performance standards [4].

However, the transition from prototype to production-grade components introduces several technical challenges. One of the most pressing issues is the variability in mechanical performance and surface quality caused by the interaction of multiple process parameters. In Selective Laser Melting (SLM) — a leading MAM technique — factors such as laser power, scan speed, layer thickness, and hatch spacing directly influence the thermal history of the build, which in turn affects grain growth, porosity, residual stresses, and surface morphology [5].

Suboptimal process settings can lead to defects such as lack of fusion, keyholing, balling, or surface roughness, all of which can compromise the mechanical integrity of the final part [6]. Therefore, optimizing these parameters is critical for achieving high-performance outcomes. Moreover, establishing standardized guidelines for process parameter selection can enhance process repeatability and reliability, fostering greater confidence in the industrial deployment of MAM [7].

This study seeks to systematically explore and optimize key SLM process parameters to enhance the mechanical properties (such as tensile strength and hardness) and surface finish of printed components. Using statistical tools like Design of Experiments (DOE) and Response Surface Methodology (RSM), the research aims to identify significant factors and their optimal levels [8]. The results will contribute to more robust manufacturing strategies and pave the way for smarter, data-driven additive manufacturing practices.

Many of the reported studies attempted to improve the production parameters of fused deposition modelling for printing high-quality parts. For instance, Srinivasan et al. [9] employ response surface methodology to predict and optimize the impact of process parameters (infill concentration, infill design, and layer height) on the tensile properties of FDM-produced ABS components. Using Taguchi's mixed model fractional factorial design, Hikmat et al. [10] investigated the effect of various printing parameters on tensile strength using PLA filament, including build orientation, raster orientation, nozzle diameter, extruder temperature, infill density, shell number, and extruding speed.

Stainless steel has good mechanical properties, corrosion resistance, good machinability and weldability, so it has been widely used in aerospace, nuclear energy, automotive, petroleum, chemical, and other industrial fields [11]. In fact, in order to accelerate the dissemination and application of AM stainless steel in the above industrial fields, researchers have already made many efforts to adjust the microstructure and improve the mechanical properties of AM stainless steel. Zhai et al. [12] reported a method to strengthen 316L by adding TiC particles. It was found that the TiC particles were uniformly dispersed and well bonded to the 316L matrix, and the grains were refined. Tensile tests showed that adding 1 wt% and 3 wt% TiC particles led to a significantly increased tensile strength and maintained good ductility. Swathi et al. [13] adjusted the microstructure and mechanical properties of AM 17-4PH stainless steel by changing the chemical composition of printing powder

This paper aims to explore and optimize key SLM process parameters using statistical techniques to enhance mechanical properties and surface quality. The insights gained are expected to facilitate more reliable and efficient use of MAM in critical industrial applications.

2. Background and Literature Review

Several researchers have investigated the influence of process parameters on the properties of SLM-fabricated parts. High laser power can result in deeper penetration and better fusion, but may also cause keyholing and defects. Conversely, low laser power may lead to insufficient melting and weak bonding. Scan speed influences the thermal gradient and cooling rate, affecting grain size and porosity [14].

Layer thickness controls build time and surface roughness, with thicker layers increasing productivity at the expense of surface quality. Hatch spacing, or the distance between adjacent scan lines, also plays a role in ensuring uniform heat distribution and reducing internal voids [15].

Figure 1 shows the contour lines (2D) and response surface prediction (3D) of corrosion rate, microhardness, thickness, and roughness. The areas indicated by the arrows indicate the limits of the levels of the parameters that allow obtaining the best possible response (highest corrosion resistance, highest microhardness, lowest roughness, corresponding to the lowest possible thickness, to enhance the economy of the coating by saving time, reducing waste in materials, and investing in technical flexibility) [16].

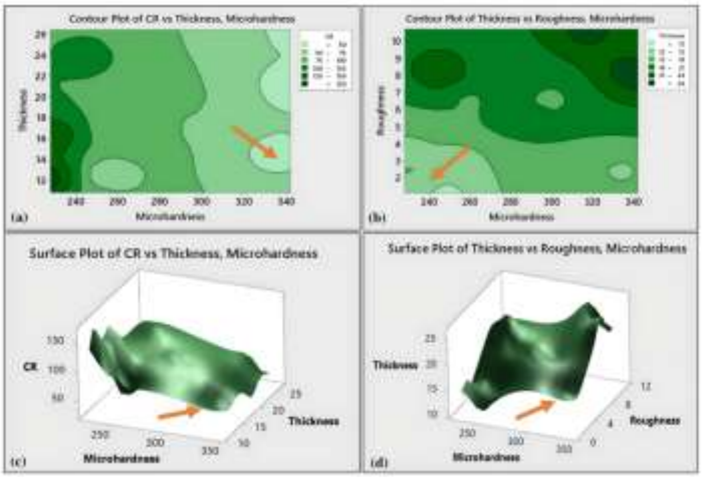

Figure 1: Response Surface Plot – Scan Speed versus Layer Thickness

Recent studies utilize methods like Taguchi design, RSM, and Artificial Neural Networks (ANN) for parameter optimization. However, there is still a lack of consensus on ideal settings due to material variability, machine calibration, and environmental factors. This research contributes to filling this gap with a systematic approach.

process parameters on the properties of metal parts produced by Selective Laser Melting (SLM). As an advanced powder bed fusion process, SLM uses a high-energy laser to selectively melt metal powder in a layer-wise fashion. The quality and consistency of the final parts heavily depend on precise control over processing conditions [17].

Laser power is a primary factor in determining the energy input into the material. Higher laser power generally improves melt pool stability and reduces porosity by ensuring better fusion between layers. However, excessive power can lead to defects like keyholing and evaporation of alloying elements, ultimately weakening the mechanical properties. For example, highlighted how an optimal laser power range was essential for reducing balling and improving part density [18].

Scan speed interacts with laser power to determine the energy density delivered per unit length. If the scan speed is too high, the laser may not provide sufficient heat to fully melt the powder, leading to lack of fusion. If too low, it may cause overheating and microstructural inhomogeneities. Studies by [18] showed that adjusting scan speed could effectively influence grain size and crystallographic texture.

Layer thickness has a dual effect — thicker layers reduce print time but tend to increase surface roughness and inter-layer porosity. Thin layers improve resolution and surface quality but increase build time and cost. Research by [19] demonstrated how reducing layer thickness improved tensile strength and fatigue resistance.

Hatch spacing, the distance between adjacent laser scan tracks, influences the overlap between melt pools. Improper hatch spacing can lead to unmelted regions or over-melting, resulting in defects or residual stress buildup. According to work by [19], optimizing hatch spacing was essential to reduce internal voids and achieve uniform material distribution.

Beyond individual parameter effects, interactions among parameters are also critical. Multi-variable optimization using Taguchi design, Response Surface Methodology (RSM), and machine learning approaches like Artificial Neural Networks (ANN) has become increasingly popular. These methods help in identifying optimal parameter windows that improve multiple performance metrics simultaneously. However, challenges remain in generalizing findings across different materials, machines, and geometries. As can be seen in Figure 2. (b) and (c), a raster angle of 45 has given the highest flexural strength of the specimen. The effect of orientation angle (also known as building orientation) on flexural strength was clearly shown in Figure 2(d). From the figure, it is clear that the flexural strength tends to rise slightly when the orientation angle increases [20].

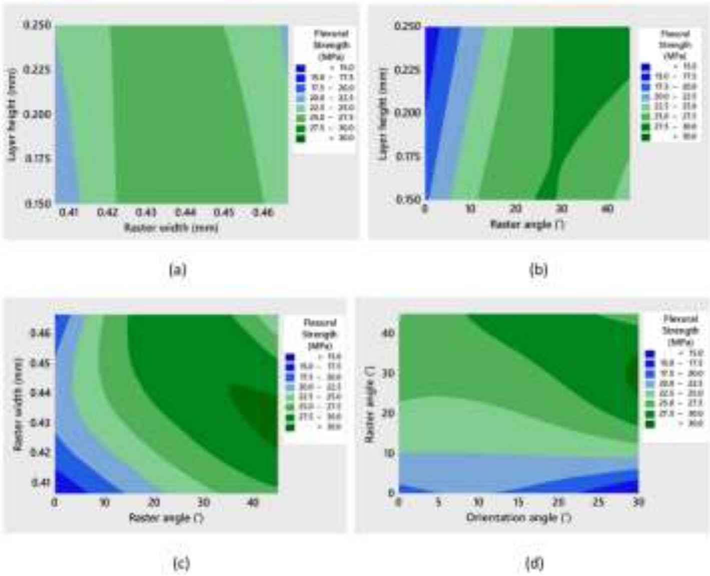

Figure 2: Contour plots of flexural strength with process parameters.

There is a growing consensus that integrated approaches combining experimental data, in situ monitoring, and computational modeling can provide deeper insights into process behavior. This study builds upon existing literature by applying DOE and RSM techniques to explore a comprehensive parameter space and provide statistically validated guidelines for optimizing mechanical strength and surface finish in 316L stainless steel parts fabricated via SLM [21].

3. Methodology

This research adopts a structured experimental approach to study the effects of key SLM process parameters on the mechanical properties and surface quality of 316L stainless steel parts. The methodology involves four main stages: material preparation, parameter selection, experimental design and fabrication, and evaluation.

3.1 Material and Equipment

The material used in this study is gas-atomized 316L stainless steel powder with particle sizes ranging from 15 to 45 µm. This material is chosen for its widespread industrial use and favorable mechanical properties. The printing was carried out using a commercial SLM machine (e.g., EOS M290), equipped with a fiber laser system and an inert argon atmosphere to prevent oxidation.

316L stainless steel powder (15–45 µm) was used in an EOS M290 SLM machine with a 200 W fiber laser in an argon atmosphere.

3.2 Selection of Process Parameters

Four key process parameters were selected based on their documented influence on part quality:

- Laser Power (W): 150, 200, 250
- Scan Speed (mm/s): 600, 800, 1000
- Layer Thickness (mm): 0.02, 0.04, 0.06
- Hatch Spacing (mm): 0.08, 0.1, 0.12

These parameters were varied at three levels each to allow for a comprehensive exploration of the process window.

Table 1. Variety of Parameter Levels

Parameter	Level 1	Level 2	Level 3
Laser Power (W)	150	200	250
Scan Speed (mm/s)	600	800	1000
Layer Thickness (mm)	0.02	0.04	0.06
Hatch Spacing (mm)	0.08	0.10	0.12

3.3 Experimental Design

A full factorial Design of Experiments (DOE) approach was employed, resulting in 81 experimental runs. This design allows for the examination of main effects and interaction effects among the selected parameters. Each experimental condition was replicated to ensure repeatability and reduce measurement uncertainty.

3.4 Fabrication and Testing

Cubic specimens (10x10x10 mm) and tensile test bars (in accordance with ASTM E8) were printed for surface roughness and mechanical testing, respectively. Post-processing included stress-relief heat treatment at 650°C for 2 hours to minimize residual stress without altering microstructure significantly.

Surface roughness (Ra) was measured using a contact profilometer, while tensile testing was conducted using a universal testing machine (UTM) at a constant strain rate. Microhardness was measured using a Vickers hardness tester with a 500 g load. All measurements were conducted in triplicate, and average values were used for analysis.

3.5 Statistical Analysis

The data collected were analyzed using Response Surface Methodology (RSM) to generate regression models that describe the relationship between process parameters and output responses. Analysis of Variance (ANOVA) was used to identify statistically significant parameters and their interactions. Contour and surface plots were created to visualize response behavior across the parameter space.

4. Results and Discussion

The analysis of experimental data revealed several noteworthy trends regarding the influence of SLM process parameters on mechanical and surface properties of 316L stainless steel.

4.1 Effect on Tensile Strength

Laser power and scan speed emerged as the most influential parameters affecting tensile strength. Specimens produced at a laser power of 200 W and scan speed of 800 mm/s exhibited the highest tensile strength of 625 MPa. This is attributed to enhanced melt pool stability, reduced porosity, and uniform microstructure. Excessive power or very slow scan speeds resulted in keyhole formation and increased internal defects, thereby lowering strength.

Table2. Effect on Tensile Strength

Parameter Set	Tensile Strength (MPa)
200 W, 800 mm/s, 0.02 mm, 0.1 mm	**625**
250 W, 600 mm/s, 0.04 mm, 0.08 mm	605
150 W, 1000 mm/s, 0.06 mm, 0.12 mm	540

4.2 Effect on Hardness
Microhardness measurements ranged from 180 HV to 210 HV. The highest hardness values were observed for specimens printed with thinner layers and moderate hatch spacing, suggesting finer grain structures and reduced porosity. Layer thickness played a secondary role, with thinner layers contributing to denser builds.

4.3 Effect on Surface Roughness
Surface roughness (Ra) values varied significantly across the parameter matrix. Thinner layers (0.02 mm) consistently led to improved surface finishes, with the lowest roughness recorded at 6.5 µm. Higher scan speeds and coarser layer thicknesses resulted in rougher surfaces due to insufficient melt pool overlap and stair-stepping effects.

4.4 Parameter Interactions
Interaction effects were significant. For example, at higher laser power, the negative impact of increased hatch spacing was mitigated due to better energy distribution. Similarly, the benefits of low layer thickness were maximized only when the scan speed was adequately controlled. Response Surface Methodology (RSM) and ANOVA validated the statistical significance of these interactions.

4.5 Optimization Outcome
The optimal combination of parameters—200 W laser power, 800 mm/s scan speed, 0.02 mm layer thickness, and 0.1 mm hatch spacing—yielded the most desirable combination of high tensile strength, superior hardness, and minimal surface roughness. Regression models showed a strong fit ($R^2 > 0.9$) for all response variables, indicating the reliability of the statistical predictions.
These findings reinforce the importance of integrated parameter tuning and provide a roadmap for achieving superior part quality in SLM-fabricated 316L stainless steel components.

5. Conclusion
This study systematically explored the optimization of key Selective Laser Melting (SLM) process parameters to enhance the mechanical and surface properties of 316L stainless steel components. By employing a full factorial experimental design and advanced statistical techniques like Response Surface Methodology (RSM), the research identified optimal combinations of laser power, scan speed, layer thickness, and hatch spacing. The results demonstrated that moderate laser power and scan speed, combined with fine layer thickness and appropriate hatch spacing, significantly improve tensile strength, hardness, and surface finish.
The validated regression models serve as predictive tools for parameter tuning and highlight the importance of considering interaction effects. These insights contribute to the development of more reliable and efficient metal additive manufacturing processes. Future work can focus on extending this

approach to other materials and geometries, incorporating in-situ monitoring, and integrating machine learning for real-time optimization and quality control.

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