

Article

Investigation into Process Parameter Optimization of Selective Laser Melting for Producing AlSi12 Parts Using ANOVA

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Abstract: In this study, AlSi12 alloy samples were produced via the selective laser melting (SLM) technique to produce high-density components with complex and customized parts for railway applications. Nonetheless, the production of dense samples necessitates the optimization of production process parameters. As a statistical design of the experimental method, response surface methodology was applied to optimize different combinations of SLM parameters. The outcomes were analyzed via analysis of variance (ANOVA) and signal-to-noise(S/N) ratios. The relationship between the hardness response to the process parameters (scanning speed and laser power) for determining the optimal processing conditions were examined. A hardness value of 133 HV was obtained. The process parameters were successfully optimized and the relationship between the parameters and the structures of the fabricated samples were reported.

Keywords: selective laser melting; ANOVA; mechanical properties; microstructure; response surface methodology



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1. Introduction

Aluminum and its alloys are known for their outstanding characteristics, including being light in weight, weldable, and corrosion resistant. These properties make them ideal to be applied in different industrial engagements such as aerospace, defense, automotive, etc. Aluminum-silicon-based alloys (Al-Si), notably AlSi12, AlSi10Mg, A357 (AlSi7Mg0.7), and A356 (AlSi7Mg0.3), have been hugely employed in the selective laser melting (SLM) mechanism due to their fabricability [1]. However, AlSi12 alloy still has many disadvantages such as a high content level of silicon and being weaker and susceptible to wear, tear, and thermal expansion [2]. To break the bottleneck, new manufacturing techniques like selective laser melting have been developed [3]. SLM is the mostly utilized technique for AlSi12 material. In this additive manufacturing process, metal powder is melted via a laser. The laser passes over the powder, forming a solid object one layer at a time. During selective laser melting, the AlSi12 alloy goes through rapid melting and solidification cycles. These cycles allow for grain refining, which is necessary for producing a strong alloy. The SLM method enables the creation of almost completely dense materials. This is crucial for reducing porosity and improving the mechanical features of the alloy. The SLM process includes layering the AlSi12 alloy. This can result in direction-dependent mechanical characteristics. This attribute can vary along and perpendicular to the building's direction [2]. A recent review on selective laser sintering/melting (SLS/SLM) of aluminum alloy powders found that processing parameters, powder properties, and the type of laser used do contribute to the densification of the produced part. Gosh et al. [4] investigated a multi-component reinforced aluminum-based metal matrix composite produced in situ by SLS process. Laser

power, layer thickness, scanning speed, powder combination, and scanning speed were varied to optimize the parameters and achieve components with higher density and lower porosity. Their results revealed that the density of the component is mainly influenced by the scan spacing layer thickness and composition, while scan spacing, laser power, and layer thickness are the parameters of importance that influence the porosity. On the other hand, According to Read et al. [5], the porosity development in the AlSi10Mg alloy structures treated by SLM is significantly influenced by laser power, scan speed, and the interplay between scan speed and scan spacing. In the work by Olakanmi et al. [6], the density of a part was decreased by using a constant laser power of 240 W, with an increase in hatch spacing.

It was discovered that the statement made by Olakanmi et al. [6] (that densification improves with increasing laser power and with decreasing scan speed) was also valid for other materials using SLM. In fact, scanning speed had a bigger impact on the mechanical qualities and microstructure of the produced components than hatch spacing or powder layer thickness [7]. Nigon et al. [8] used the SLM approach to create 2205 samples with a densification of 98.6% by optimizing the scanning speed range. Davidson et al. [9] discovered a considerable rise in the SLM 2507 material's Vickers hardness as the scanning speed was reduced.

In the investigation of the impact of scanning speed on the mechanical and microstructure characteristics of SLM-formed Inconel 718 specimens, Wang et al. [10] discovered that the grain size could be influenced by the high laser scanning speeds, thereby lessening the mechanical properties' anisotropy and decreasing the intensity of the <001> texture. Liu et al. [11] studied the 316 L samples, which had an overall elongation to failure of 55% and good ductility. It was found that reduced scanning speed removed melting pool borders and remaining pores, which resulted in excellent ductility of the samples.

To minimize porosity, numerous research have optimized the SLM parameters for various materials. Most of them produce cubes and tensile samples with varying SLM parameters, then choose the ones that ultimately result in the maximum density, as determined by Archimedes' density technique. Dilip et al. [12] used this process for HY100 steel. Read et al. [5] also utilized the processes using AlSi10Mg, and Wen et al. [13] used tungsten. This procedure takes a lot of time and materials to make and test all these cubes; thus, this process is inefficient. Furthermore, it is possible that ideal parameters will not be shown in the end.

On the other hand, it has been demonstrated that design of experiment (DOE) methods like the response surface method (RSM) and statistical analysis employing the analysis of variance (ANOVA) are helpful ways to investigate the impact of numerous aspects in material processing applications. The importance of the selective laser sintering (SLS) process factors on surface roughness has been investigated using the response surface design of experiment and ANOVA approach [14]. Similarly, Carter [15] optimized SLM for CMSX-486 Ni-superalloy using the response surface approach and ANOVA methodologies, examining the effects of process parameters (laser power, scan speed, scan spacing, and island size) on crack density and porosity percentage.

Optimizing system performance and process yield while keeping costs down are critical goals. The standard procedure for identifying the ideal operating conditions while maintaining the others at a steady level involves a parameter adjustment. The term "one-variable-at-a-time technique" describes this. This technique's main drawback is that it excludes the impacts of interactions between the variables and, therefore, fails to show all the effects that the parameters have on the process. Response surface methodology can be utilized in optimization studies to solve this issue.

According to Montgomery et al. [16], RSM is a sort of statistical and mathematical method suitable for the analysis and modeling of problems in which an interest response is affected by various parameters, and the goal is to optimize this response. Ti6Al4V, Invar36 and SS316L, iron-based powders, maraging steel, AlSi12, and other materials were

subjected to this process. Using DOE has the advantages of potentially showing the optimal parameters and requiring less time than the previous method.

The DOE approach is commonly streamlined using the single scan track (SST) method, which preliminarily screens the process parameters. SST refers to a laser track being scanned on a single powder layer that has been previously dispersed over a substrate. This method relies on the concept that powder bed fusion–laser beam/metal (PBF-LB/M) parts are composed of overlapping SSTs; as a result, the geometry of each SST and their interactions with one another determine the part's attributes. When producing the SSTs, only laser power (P) and scanning speed (v) can be changed, but, because of their quick production and analysis, a large variety of their combinations can be investigated. While a DOE of bulk samples is still necessary for full optimization with this methodology, Gheysen et al. [17] and Bosio et al. [18] provided a further simplification of the process by creating a way to determine the best hd value taken straight from SSTs. The optimal hd value is normally obtained from calculating the width of the SSTs and reflecting on the suitable overlapping among them. According to research conducted by Martucci et al. [19], the SST technique cannot properly forecast events related to the layer-by-layer scanning typical of PBF-LB/M manufacturing, even while it excludes parameters that might cause scan track problems. This issue is more noticeable in aluminum-based alloys that are prone to cracking. Consequently, it seems that the problem of optimizing the PBF-LB/M process parameters without resulting in huge DOEs of bulk samples remains unsolved.

In this study, the AlSi12 multi-scan track samples were built using the SLM technique to ensure the consistency of sample behavior in the layer by layer of the built part, and hardness properties and microstructure variations were observed. To obtain denser samples, the SLM processing parameters were optimized using the factorial design and statistical design of experiment using response surface methodology and analysis of variance (ANOVA), thus developing the processing map for the AlSi12 alloy.

2. Experimental Method

2.1. Equipment and Materials

The AlSi12 powder, with the composition shown in Table 1, was supplied by Applied Engineering Materials (AEM).

Table 1. AlSi12 powder chemical composition.

Elements	Si	Fe	Mn	Zn	Al	Cu	Mg	Pb	Sn	O
Wt%	11.0–13.3	≤ 0.25%	≤ 0.1%	≤ 0.2%	Balance	≤ 0.3%	≤ 0.1%	≤ 0.02%	≤ 0.02%	< 0.05%

Figure 1 illustrates a scanning electron microscopy (SEM) micrograph of the powder. It is evident from the image that the powder particles are evenly spherical, which indicates a good powder flowability.

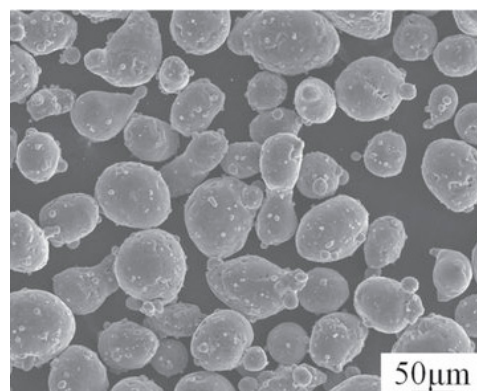


Figure 1. SEM morphology of AlSi12 powder.

Selective Laser Melting Machine

All samples were fabricated using a Concept Laser Mlab 200R SLM machine which is manufactured by Concept Laser based in Lichtenfels, Germany. The Mlab200R system is equipped with a Yb-fiber laser, which can produce up to 200 W of laser power, 150 μm of laser track width, and 7000 mm/s of laser scan speed. To create the specimens, stripe scanning strategy was used in order to achieve samples with low porosity.

2.2. Methodology

The steps taken in the methodology are listed in the flow diagram below on Figure 2, identifying the design of experiment, manufacturing, characterization, and statistical analysis.

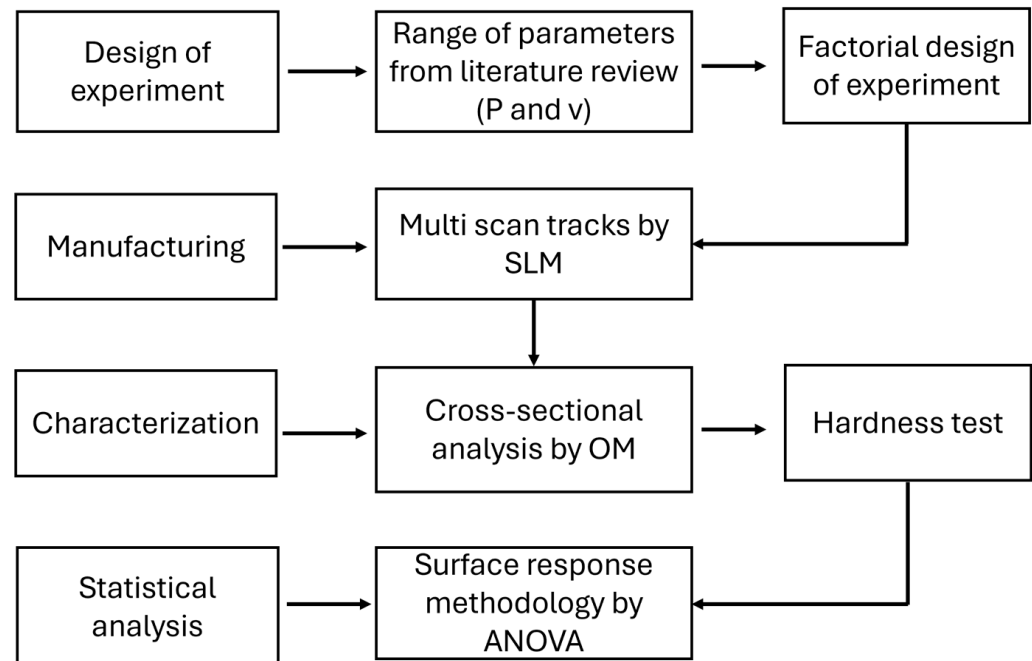


Figure 2. Methodology followed to fulfill the experimental work.

2.3. Design of Experiments (DOEs)

The parameters were achieved by obtaining a range of parameters from the literature. The factorial design of experiment was performed to select the parameters to streamline the range of fabrication experiments and validate the methodology. Gheysen et al. [17] reported that the use of factorial design of experiments does decrease the costs of experiments. The software STAT EASE Design Expert Version 13 was used to perform the DOE.

Later, the statistical design of experiment using response surface methodology was used. ANOVA was used in this regard. An approximation model between the input and output parameters was found using the response surface methodology, a statistical technique used to develop an experimental design that maximizes process responses. It is an assortment of mathematical and statistical techniques for simulating and analyzing engineering issues. The primary goal of this method is to maximize the response surface, which is affected by several process variables.

The response surface methodology's experimental design process can be summed up as follows:

- Determining the essential process variable.
- Deciding on the upper and lower limit process parameters
- Choosing the output response.
- Creating the matrix for the experimental design.
- Following the design matrix when conducting the studies.
- Noting the response from the output.

- Creating a mathematical model to connect the output response and the process parameters.
- Making the model more optimal via a genetic algorithm.

2.4. Building of Samples and Preparation

Using a fractional factorial DOE, 16 parametric combinations were employed to create samples to execute the DOE and parametric optimization. Sixteen multi-track samples were produced; each sample had numerous tracks (10×) and was 50 mm in length. This type of DOE was used to determine at what levels of inputs the outputs would be optimized. The range and amounts of the important process variables under investigation are displayed in Table 2.

Table 2. Range of matrix building parameters.

Parameter	Units	Levels			
Scanning speed	mm/s	200	500	850	1000
Laser power	W	50	100	150	200

2.5. Hardness Testing

In determining the isotropy and mechanical property of the AM products, the microhardness test is an important test for this determination. Vickers microhardness was determined via an indenter made of a diamond pyramid with 100 gf applied force for 10 s dwelling. Five measurement values were recorded randomly from each specimen and the average was calculated.

2.6. Microstructural Analysis

The samples were cut on a cross-sectional area, ground, and polished according to standard procedures. They were etched using Keller's solution comprising 96.22% distilled water, 2.59 nitric acid, 0.64% hydrochloric acid, and 0.55% hydrofluoric acid for 10 s. The microstructures were examined via a BX51 polarizing microscope (OM, Olympus, Tokyo, Japan).

3. Results and Discussion

This section includes the experimental data pertaining to the microhardness measurement, the response's analysis of variance (ANOVA), and the response's optimization in relation to the processing parameters.

3.1. Microhardness and Microstructure Analysis

Table 3 gives the experimental outcomes of the measured microhardness (HV). The varying hardness values with the variation in laser power and scanning speed for AlSi12 is depicted in Figure 3. The laser power was discovered to greatly affect the fabricated samples' hardness. The hardness steadily declined from 131 HV to about 97 HV (B1-1 to C1-1) as the laser power reduced from 200 W to 50 W. The maximum hardness value of about 131 HV was observed at a laser power of 200 W and a scanning speed of 1000 mm/s, while the hardness obtained by high-pressure casting was 72 HV (reported by Aksoy et al. [20]). The processing parameters for Sample D1-1 and D1-2, as shown in Figure 4, could not fabricate any specimen, solely due to the combination of very low laser power and high scanning speed. Figure 5 shows the OM micrographs describing the microstructure of the SLM-fabricated AlSi12 specimen from a laser power of 200 W and scanning speed of 200–1000 mm/s. All samples showed similar micrographs. Figure 5a represents the sample with the maximum hardness of 131.48 HV. The observed microstructures were not uniform throughout the material but exhibited the typical laser tracks of SLM processing also observed by Su and Yang (2012) [21] and Thijs et al. [22]. The tracks consisted of scale-like morphology, which was also detected by Liu et al. [23]. The cellular and dendrite growth within the grain was also seen in the work by Prashanth et al. [24], which

they ascribed to the eutectic silicon particles being located at the cellular boundaries. The boundaries in Figure 5 match the portions where two unlike laser tracks overlapped (revealing a hatch overlap), which were hence melted two times. There were some porosities that were observed that may have been caused by the printing parameters. In Figure 5a,b,d, the pores are indicated by the dark areas. It is possible for gases to become trapped in the material when the metal solidifies during fabrication. This may cause the microstructure to develop pores or voids. Thus, porosity may be attributed to the solidification process. No cracks were observed.

Table 3. Microhardness values of SLM-built AlSi12 alloy.

Sample No	Material AlSi12	LP (W)	SS (mm/s)	Hardness Value
1	A1-1	150	1000	107.32
2	A1-2	150	850	116.27
3	A1-3	150	500	110.75
4	A1-4	150	200	124.40
5	B1-1	200	1000	131.48
6	B1-2	200	850	128.82
7	B1-3	200	500	120.36
8	B1-4	200	200	121.23
9	C1-1	100	1000	75.15
10	C1-2	100	850	103.48
11	C1-3	100	500	108.70
12	C1-4	100	200	118.02
13	D1-1	50	1000	-
14	D1-2	50	850	-
15	D1-3	50	500	97.66
16	D1-4	50	200	109.34

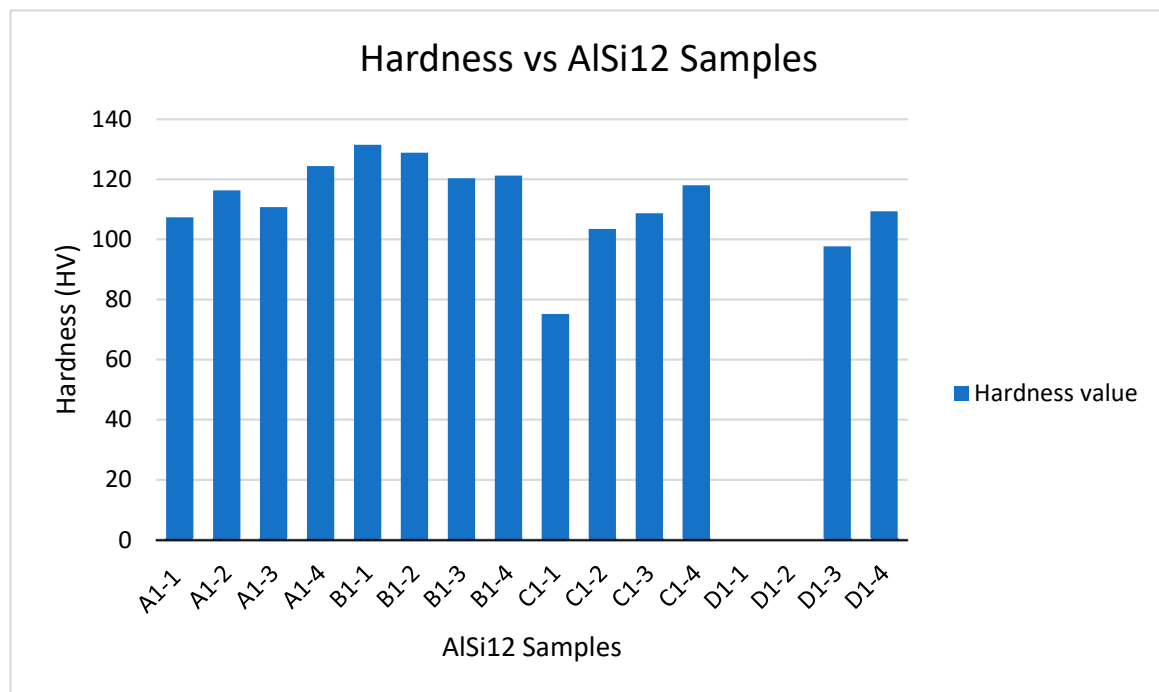


Figure 3. Hardness values of SLM-built AlSi12 alloy.

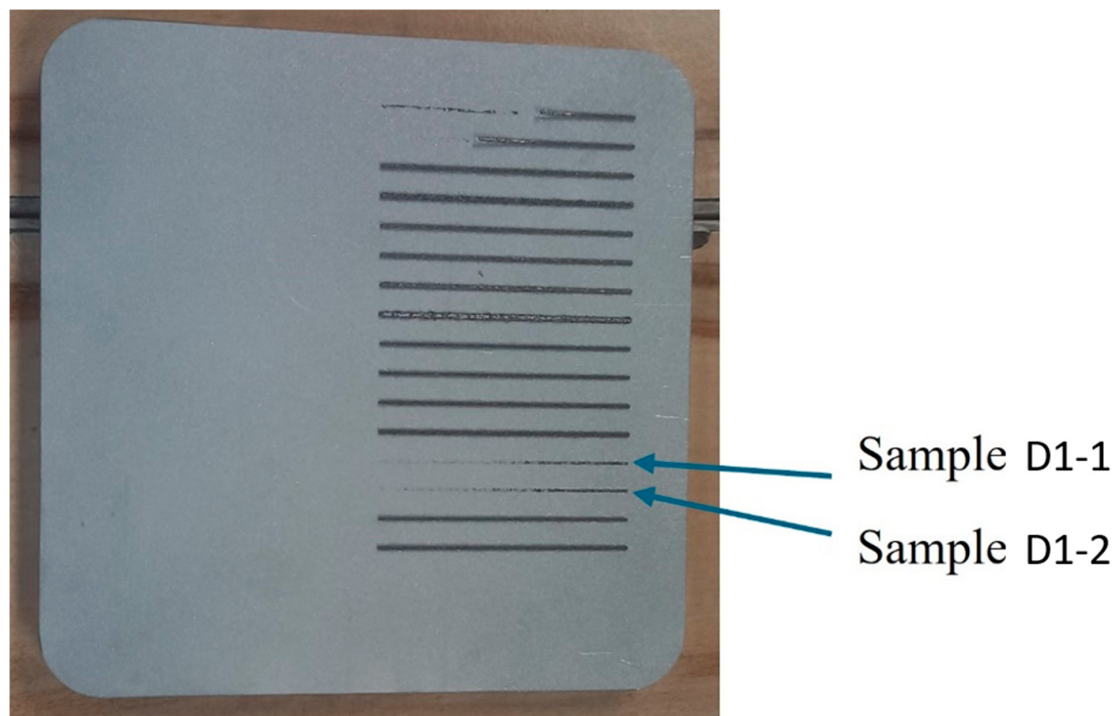


Figure 4. As-built samples.

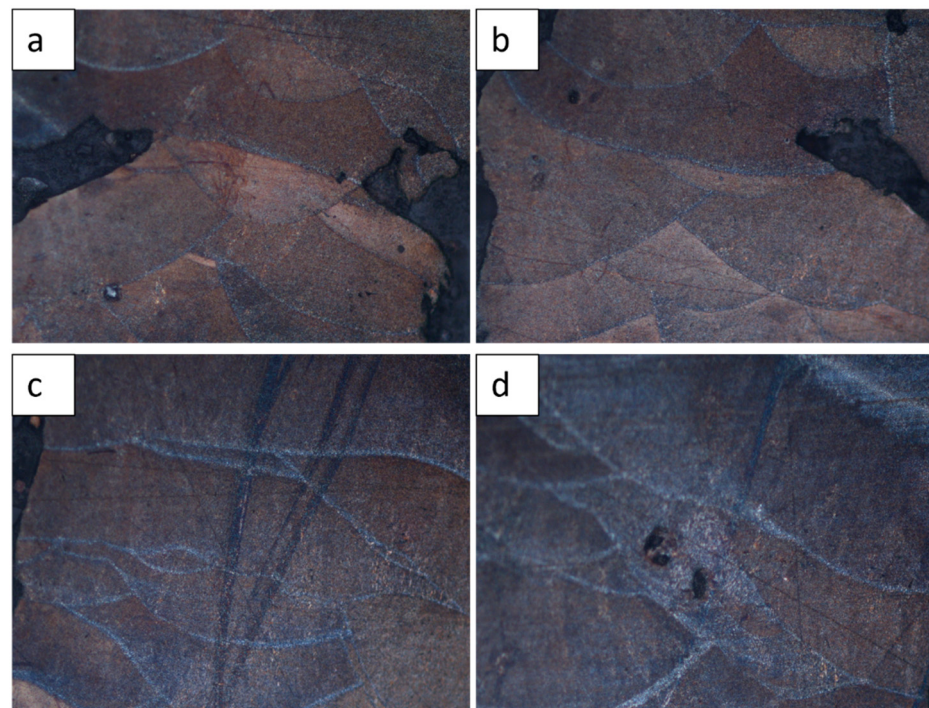


Figure 5. Optical microscopic (OM) images of cross-sectional multiple tracks of SLM-built samples (a) B1-1, (b) B1-2, (c) B1-3, and (d) B1-4.

3.2. Results on the ANOVA

The relationship between processing control parameters and manufacturing performance can be shown through statistical analysis. The statistical method of ANOVA was applied to the measured data to determine the impact of the input factors on the overall variation of responses. The STAT EASE Design Expert 13 program was used for response optimization and statistical analysis to establish the design matrix, as revealed in Table 4.

Table 4. Design matrix and experimentally recorded responses. ⁽¹⁾ Observation with leverage $> 2.00 \times (\text{average leverage})$. ⁽²⁾ Exceeds limits).

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Cook's Distance	Influence on Fitted Value DFFITS	Standard Order
1	107.32	101.39	5.93	0.177	0.360	0.346	0.007	0.161	11
2	116.27	104.97	11.30	0.110	0.659	0.643	0.013	0.226	4
3	110.75	113.32	−2.57	0.090	−0.148	−0.142	0.001	−0.045	10
4	124.40	120.47	3.93	0.223	0.245	0.235	0.004	0.126	8
5	131.48	144.65	−13.17	0.413	−0.946	−0.942	0.157	−0.789	7
6	128.82	140.03	−11.21	0.257	−0.716	−0.700	0.044	−0.412	5
7	120.36	129.25	−8.89	0.209	−0.550	−0.534	0.020	−0.275	13
8	121.23	120.01	1.22	0.521 ⁽¹⁾	0.097	0.093	0.003	0.097	6
9	75.15	58.13	17.02	0.177	1.033	1.036	0.057	0.480	12
10	103.48	69.90	33.58	0.110	1.959	2.274	0.119	0.800	1
11	108.70	97.38	11.32	0.090	0.653	0.637	0.010	0.200	3
12	118.02	120.93	−2.91	0.223	−0.182	−0.174	0.002	−0.094	2
13	0.0000	14.86	−14.86	0.413	−1.067	−1.074	0.200	−0.901	9
14	0.0000	34.84	−34.84	0.257	−2.224	−2.777	0.427	−1.632 ⁽²⁾	14
15	97.66	81.44	16.22	0.209	1.004	1.004	0.067	0.516	15
16	109.34	121.39	−12.05	0.521 ⁽¹⁾	−0.959	−0.955	0.250	−0.997	16

Owing to the analyzed outcomes, the SLM method behavior was enhanced via the optimizing process control conditions. The aim of optimization was to improve the product hardness value, which was made via the SLM technique. Table 5 highlights the optimal values of the processing parameters for hardness performance measurement. Furthermore, the expected outcomes were obtained via the model by engaging varying processing parameters.

Table 5. Predicted and actual measured results of optimized processing parameters.

Objective	Optimized Processing Parameter	Predicted Value	Experimental Value
Maximize hardness	Laser power = 200 W Scanning speed = 1000 mm/s	144.65	131.48

Process control parameter optimization improved the performance of the SLM process according to the analysis findings. Maximizing the hardness value of the produced samples using SLM technology was the aim of optimization. Table 5 lists the ideal settings for the processing parameters to measure hardness performance. Values of hardness that were anticipated and measured in the experiment confirmed the validity of the numerical optimization. By adjusting the processing parameters, this model allowed for the achievement of the necessary hardness results.

The developed model was then tested for adequacy by applying the ANOVA technique. The F-value and the *p*-values in Table 6 show that the input parameters, laser power, and scanning speed were significant regarding microhardness. From the outcomes of using this technique, it can be noted that the model was significant, showing $p < 0.05$, and that with an F value 21.0, there was only a 0.01% chance that an F-value this large could occur due to noise. For further illustration of adequacy, the hardness model was established via the regression analysis that was contingent on significant processing parameters.

Table 6. ANOVA table for output.

Source	Sum of Squares	df	Mean Square	F-Value	p-Value	
Model	20,831.78	3	6943.93	21.03	<0.0001	significant
A-laser power	9029.59	1	9029.59	27.35	0.0002	
B-scan speed	4054.14	1	4054.14	12.28	0.0043	
AB	5778.18	1	5778.18	17.50	0.0013	
Residual	3961.39	12	330.12			
Cor Total	24,793.17	15				

Based on important processing factors, regression analysis was used to build the hardness model.

The coefficient of determination (R^2) for the R_a model was 0.8402, R^2 adjusted was 0.8003, and predicted R^2 was 0.7168, as shown in Table 7. The predicted R^2 of 0.7168 was in realistic concordance with the adjusted R^2 of 0.8003; meaning the variation was <0.2. Adeq Precision calculated the signal to noise ratio. A ratio beyond 4 was obtainable. The obtained ratio of 14.287 revealed a satisfactory signal. The developed validity of regression model was further tested by plotting a scatter diagram, as shown in Figure 6, showing the predicted values and actual values of the responses scattered close to the 45° line, revealing a practically perfect fit of the developed empirical model. Via an approximate correlation between predicted and adjusted values, the model stability was validated. Hence, the model can be capably used to estimate the SLM product hardness, especially for any sort of processing parameters within this experimental research.

Table 7. R^2 Test for hardness regression model.

Std. Dev.	18.17	R^2	0.8402
Mean	98.31	Adjusted R^2	0.8003
C.V.%	18.48	Predicted R^2	0.7168
		Adeq Precision	14.2870

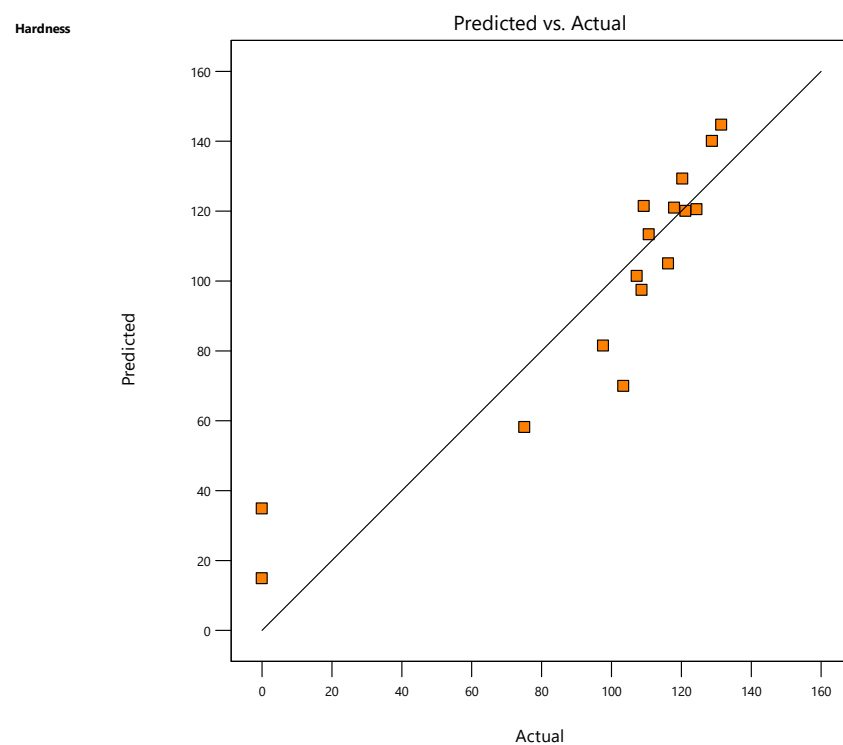


Figure 6. Predicted values vs. actual values of hardness.

The tight correlation between the adjusted and anticipated values supported the stability of the model. The model may thus be effectively used to predict the hardness of SLM products for any set of processing parameters that fall within the scope of this experimental investigation.

Figure 7 represents the influence of controlling parameters on the microhardness of the SLM-built samples. When the laser power and scan speed was elevated, the hardness was at its highest. The laser power had a much bigger impact on the hardness than the scanning speed. It was observed that, even at the lower laser power, the hardness that was closer to the maximum hardness was obtained.

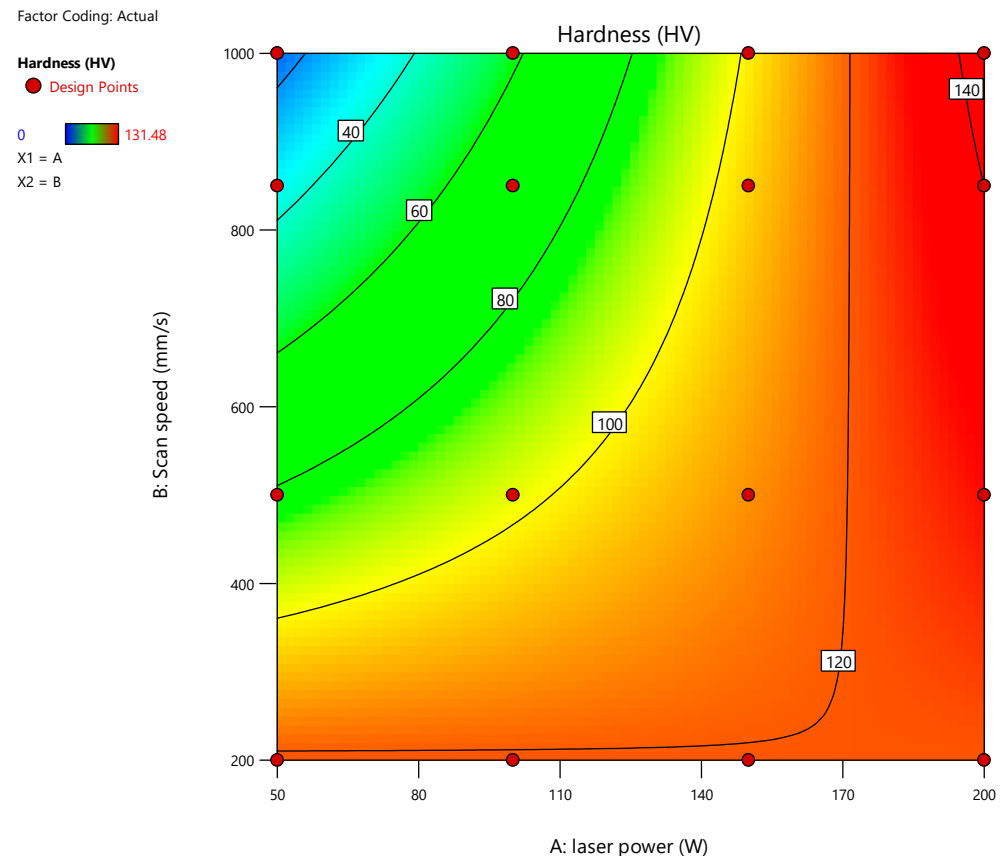


Figure 7. Contour plot of laser power and scanning speed for hardness.

4. Conclusions

This study elaborates the influence of processing parameters on the hardness of SLM-built AlSi12 alloy samples based on a full factorial DoE technique. Also, the determined experimental outcomes were achieved via regression and ANOVA analysis. In maximizing the hardness, regression analysis was employed. From the results achieved, the following important conclusions can be drawn:

- Increasing the laser power consequently makes the hardness increase because of the increment in laser beam intensity.
- Scanning speed does not have much impact on the resultant hardness.
- Optimized processing parameters are achieved, giving a hardness value of 131.48 Hv.

Future research should focus on enhancing the obtained optimized AlSi12 alloy hardness and looking into the microstructural evolution and other mechanical properties by using Cu and Mg additives. This proposed alloy may be applicable to the railway industry, since, recently, aluminum has become very crucial in modernizing trains and boosting energy efficiency.

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