Enhancement of Surface Quality of DMLS Aluminium Alloy using RSM Optimization and ANN Modelling

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ABSTRACT

Direct Metal Laser Sintering (DMLS) is an additive manufacturing technology gaining popularity due to its ability to produce near net-shaped functional components. As there is a great need to improve the surface quality of DMLS components to upgrade their dynamic properties, an attempt was made to study the influence of process parameters like laser power, scan speed, and overlap rate on the surface quality of DMLS Aluminum alloy (AlSi10Mg) in as-built condition. The optimized process window to generate the best surface quality was achieved using Response Surface Method (RSM). Artificial Neural Network (ANN) modeling is also developed to map the influence of process parameters on surface quality. Conclusively, Scan speed is found to be most influential over surface quality as per the F and P test results. The optimized process parameters for best surface quality (3.52 µm) were 300 W laser power, 600 mm/sec scan speed, and 25% overlap rate. Both RSM and ANN models were accurate in

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prediction. However, ANN is recorded as superior with the highest coefficient of correlation (R).

Keywords: *DMLS; Aluminum alloy; Surface quality; RSM and ANN*

Nomenclature

DMLS-Direct Metal Laser Sintering
LP- Laser Power
SS-Scan Speed
OR-Overlap Rate
SR-Surface Roughness
R- Coefficient of correlation

Introduction

The most preferred technology of today's manufacturing sector is an additive manufacturing (AM) due to its aptitude for producing end-use products. In this technology, the desired product can be produced in a layer-by-layer manner. Selective laser melting (SLM)/direct metal laser sintering (DMLS) is one of the metal additive manufacturing technology in which, final part can be produced by melting metal powder using a laser at designed points as per the stereolithography file. It has many advantages like near net shape, low cycle time, and litheness in the design of the product. The AM process has its application in aerospace, automobile, and biomedical industries due to the possibility of producing functional components [1]. Since the metal is being melted in a layer-by-layer approach, the conduction of heat takes place from the molten zone to the surrounding material quickly. Due to the high solidification rate in the DMLS process, the microstructure is usually fine and has several phases. So, better mechanical properties can be achieved than the conventional processes like casting and forging [2]. However, by choosing the proper combination of process parameters, one can tailor the microstructure and thereby final properties. This is the area of research interest to look up the quality of this AM product through process parameters optimization and by applying statistical models.

The present area of interest is to make components for aerospace and automobile industries using lightweight, high-strength materials to meet the challenges. Aluminum alloy AlSi10Mg is the trending material for these applications. The manufacturing of this material using the DMLS process attracted more attention from the industry due to the versatile character of the process. The AlSi10Mg has high strength, hardness, and better dynamic properties. Lore Thijs et al. [3] reported that the SLM AlSi10Mg product has a very fine microstructure consisting of FCC Aluminum cells covered with diamond-like silicon phase due to unique process conditions. This peculiar microstructure of SLM AlSi10Mg offers more mechanical advantages. The laser sintering process has inherent defects that depend on process parameters, building orientation, and powder characteristics. The process parameters like laser power, scan speed, hatch distance, and layer thickness, etc., have a significant influence over the quality of a product. Mainly in AlSi10Mg, an oxide layer will readily be formed due to residual oxygen present on the surface of the DMLS part, which decreases wettability and generates a lack of fusion defect by obstructing molten metal flow between deposited layers [4]. The rapid heating and cooling of metal powder will create high residual thermal stresses, leading to the generation of micro-cracks, which will always originate from the surface. These residual thermal stresses will compromise AM part tensile and fatigue strengths [5]. The surface defects were responsible for crack instigation during fatigue loading in laser sintered Al-Si alloys [6]. The majority of failures in AM products are due to surface-initiated cracking [7].

The surface quality of DMLS AlSi10Mg is less than that of the conventionally made component. This is probably due to the balling effect associated with the laser sintering process, which leads to the formation of discontinuous tracks and prevents the even allocation of a new powder layer. This phenomenon will lead to the formation of porosity and delamination defects [8]. The poor surface quality of the as-built DMLS part has a detrimental effect on the mechanical and tribological properties [9]. So, there is concern that remained open for research to improve its surface quality to enhance its fatigue life [10]. The surface treatments like sandblasting, vibratory polishing, micro-shot peening [11], and electrochemical etching [12] were applied to improve the surface quality of AM specimens. But, adopting these kinds of post-processes will increase time and expenses, and thereby AM process losing its advantage of producing complex shapes with ease. AM machine makers are trying hard to produce machine quality that can turn out good quality products [13]. However, employing advanced machines and post processes could not completely eliminate these defects [10].

So, continuous research is required to find optimized process parameters to minimize or nullify these defects. Since it is a costly affair, careful and effective experiments are required to use optimized process parameters to give reliable and best results. So, the adoption of statistical and modeling tools to this DMLS process could be a better option to research. Different optimization tools like Taguchi, Screening, Factorial, Response surface, etc are widely used by the researchers [14, 15] and reveal that these methods will reduce the overall experimental runs results in low experimental costs. Compared to other optimization techniques response surface method (RSM) is popular due to its prediction ability. Also, it can reveal the interaction effect of important process parameters, which show a significant effect on the output results.

As per the latest studies, the application of artificial neural network (ANN) modeling is gaining wide popularity and it could possibly decrease the complexity of the process. ANN empirical modeling uses both experimental data and statistical theory [16]. This modeling uses the data from experiments to create a correlation function between process parameters and ultimate properties like surface roughness and fabrication time. This function helps in adjusting process parameters to produce parts as per user requirements Mallikharjun et al. [17] developed an ANN model to suggest process parameters and to estimate build time in the SLM process. The more data is fed to ANN, the more precisely it can anticipate the results. Munguia et al. [18] applied an ANN model to estimate build time in the SLS process.
From the available literature, it is found that different authors investigated the suitability of DMLS AlSi10Mg for specific engineering applications, generally static applications but very limited works were reported on its dynamic behavior. However, the adaptability of advanced statistical and optimization with modeling tools in the evolution of its dynamic properties are still in an infant state. The present research work aims at revealing the dynamic behavior of DMLS AlSi10Mg. For this purpose, RSM optimization and ANN modeling are performed to enhance the surface quality of as-built DMLS AlSi10Mg.

Material and Methods

This section describes the material procurement, fabrication, and experimental procedure carried out to get the surface roughness values and application of RSM and ANN methods applied for analysis purposes.

Material

The material AlSi10Mg is known for its applications in structural components of space vehicles, airplanes, and automobiles due to versatile characteristics like high strength, lightweight, good thermal properties, and corrosion resistance and is also available at low cost [19]. Though it is a prominent material with many advantages, fewer works reported on this alloy produced using the DMLS route. So, it still needs further exploration. The gas atomized metal powder AlSi10Mg_200C is received from EOS GmbH; Germany is used in this experiment. The particle size ranges from 10-90 microns. It is not desirable to have fine powder particles due to the agglomeration problem. Large size powder particles will form voids [20]. So, broad dissemination of both size powder particles will give better product density. The SEM image of the powder material used for this experiment is shown in Figure 1. The powder particle of 10-micron size and almost spherical shape can be seen in the same image. The spherical particles will give the advantage of even spreading the powder layer.

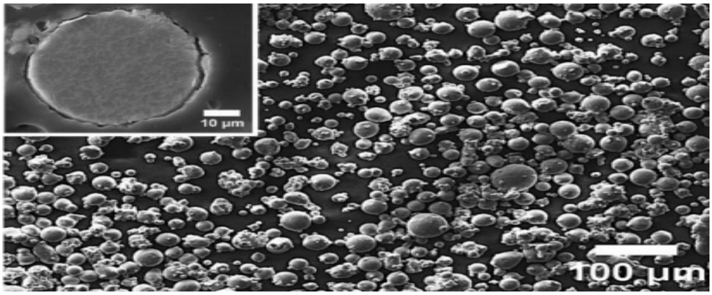

Figure 1: SEM image of AlSi10Mg powder used in the experiment.

The EOS Aluminum alloy AlSi10Mg is processed at a build platform temperature of 200 ^{0}C. Preheating built platforms will reduce the effect of residual thermal stresses that generally arise due to the rapid heating and cooling of metal powder [21]. The rapid melting and resolidification of the DMLS process will affect the microstructural features and corresponding mechanical properties. Since the DMLS is a layer-wise building process, anisotropy is a common problem in the product. Some post-treatments are necessary to decrease/ eliminate this anisotropy.

The AlSi10Mg castings normally require some post-heat treatment processes like T6 to improvise its mechanical properties. But, the definite heat treatment cycles were not yet prescribed for this laser sintered Aluminum AlSi10Mg alloy. To date, minor research works were conducted to study the effect of various heat treatment cycles on the mechanical and metallurgical properties of DMLS AlSi10Mg. But, seemingly, they were not sure about improving aimed properties [22]. The chemical composition of AlSi10Mg_200C metal powder is shown in Table 1. The AlSi10Mg mechanical properties provided by the material supplier are shown in Table 2. These values were obtained from the tensile test conducted according to ISO 6892-1:2009 (B) Annex D.

Table 1: AlSi10Mg metal alloy powder chemical composition

Element	Al	Si	Mg	Fe	Cu	Zn	Ti	Mn	Ni	Pb
Weight (%)	Bal.	9 - 11	0.2 - 0.45	≤ 0.55	≤ 0.55	≤ 0.10	≤ 0.15	≤ 0.45	≤ 0.05	≤ 0.05

Table 2: Mechanical Properties of AlSi10Mg Powder

Build orientation	Tensile strength (MPa)	Yield Strength (MPa)	Modulus of elasticity (GPa)	Elongation at break (%)
Horizontal	360	220	70	8
Vertical	390	210	70	6

Methodology

Design of experiments

In order to achieve better output results with limited usage of resources, well-planned experiments are essential. Therefore, in the present investigation, Box-Behnken assisted response surface method (RSM) optimization technique was used to study the effect of three process variables of laser power (LP), scan speed (SS), and overlap rate (OR) on the surface quality of DMLS aluminum alloy (AlSi10Mg). A statistical software Minitab-19 was employed and 27 experiments were conducted by varying the three process variables of laser power, scan speed, and overlap rate as shown in Table 3.

Table 3: Experimental input parameter conditions

S. No	Input Parameters	Units	Levels
1	Laser power (LP)	Watt	320, 360, 380
2	Scan Speed (SS)	mm/sec	500, 600, 700
3	Overlap Rate (OR)	%	25, 30, 35

Specimen preparation and surface roughness measurement

The EOSINT M 280 machine is used for the fabrication of specimens is shown in Figure 2. The maximum build volume is 250×250×325 mm. The laser used is a Ytterbium fiber laser with a maximum power of 400 W. The argon inert medium is provided here to avoid the oxidation of powder material during the process.

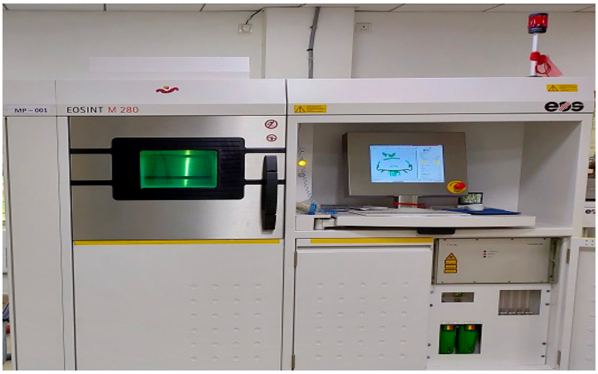

Figure 2: EOSINT M280 DMLS Machine used for manufacturing.

The strict management of process parameters is necessary to improve the quality of the DMLS AlSi10Mg product [23]. The process parameters chosen for our experiment are presented in Table 3. The process parameters altered are laser power, scan speed, and overlap rate at three different levels. The fixed layer thickness of 30 microns is used in the fabrication of all specimens. The build orientation is vertical, i.e., perpendicular to the build platform. A total of 27 specimens with dimensions 10×8×12 mm are prepared as per the design matrix in Table 3 to find out surface roughness.

The specimens are cleaned in acetone for 15 minutes before the test to ensure that the surface is perfectly clean. The average surface roughness is measured for all specimens by using the Mitutoyo instrument with a conisphere stylus of 4 µm diameter. The parameters in the test are taken as per EN ISO 4287 standard. The surface roughness values are measured at three random positions of each specimen. The R_a value is taken as the arithmetic mean of absolute ordinates from the mean line of roughness profile.

Since DMLS is a multivariable process, the Response Surface Method (RSM) can be a better option to optimize process parameters in order to develop superior quality products. These influencing factors are independent in nature and the response is a dependent variable [24]. RSM offers an advantage by defining the interaction between independent variables and developing a mathematical model. RSM method examines the relationship between input and output and marks the optimized response of the system of interest. The experimental data is evaluated to fit a statistical model. It may be a linear, quadratic or cubic model [25]. Therefore in the present experimental investigation, the RSM optimization technique was used to study the three process variables of laser power, scan speed, and overlap rate on the surface quality of DMLS aluminum alloy (AlSi10Mg). Based on the design conditions from Table 3, 27 experiments are conducted randomly by varying the three process variables and the surface roughness (SR) was measured with a Talysurf surface meter. Table 4 represents the experimental as well as RSM surface roughness results.

Table 4: The process parameters combinations as per DoE

Specimen	LP	SS	OR	SR(Exp)	SR(RSM)
1	300	500	0.25	4.17	4.106
2	300	500	0.3	4.25	4.534
3	300	500	0.35	3.64	3.691
4	300	600	0.25	3.52	3.448
5	300	600	0.3	4.23	4.114
6	300	600	0.35	3.91	3.508
7	300	700	0.25	4.24	4.094
8	300	700	0.3	5.14	4.998
9	300	700	0.35	4.32	4.629
10	340	500	0.25	5.18	5.373
11	340	500	0.3	5.82	5.530
12	340	500	0.35	4.52	4.415
13	340	600	0.25	5.87	5.680
14	340	600	0.3	6.66	6.075
15	340	600	0.35	4.52	5.197
16	340	700	0.25	7.25	7.292
17	340	700	0.3	7.26	7.924
18	340	700	0.35	7.69	7.283
19	380	500	0.25	5.36	5.009
20	380	500	0.3	4.37	4.894
21	380	500	0.35	3.75	3.507
22	380	600	0.25	5.89	6.281
23	380	600	0.3	6.71	6.404
24	380	600	0.35	4.95	5.254
25	380	700	0.25	8.96	8.857
26	380	700	0.3	9.25	9.218
27	380	700	0.35	8.49	8.306

ANN Modeling

The industries of today's manufacturing sector are heartening the integration of information technology with their system to improve their efficiency and to reduce cost and time. For this purpose, optimization and modeling tools are popular in vogue. These tools are known for solving the complex problems of the manufacturing process by utilizing the limited available resources more efficiently with limited experimental runs [26]. In recent times, artificial intelligence (AI) modeling is gaining wide popularity among other statistical techniques due to its exceptional prediction capabilities. The available studies [27] show that optimization and modeling tools can unveil the informative relationship between the important variables in the manufacturing process. However, a clear and definite relationship between process parameters and the product's final quality is not yet defined in DMLS. Therefore artificial neural network (ANN) model in MATLAB®2019 is used in the present endeavor.

The experimental results from RSM are trained in the ANN network to predict better surface roughness values. For this purpose, the three process variables (laser power, scan speed, and overlap rate) are trained to the input layer and surface roughness to the output layer as shown in Figure 3. The hidden layer was trained with 20 neurons based on trial and error techniques. In the first layer i.e. input layer, three neurons (process parameters) are trained; the hidden layer will process the input data and the data is trained continuously by trial and error until a low mean square error (MSE) is achieved. Out of 100% data, 70% data is used for training, 15% for testing, and 15% for validation purposes. Levenberg-Marquardt feed-forward backpropagation training algorithm was used due to the complex nonlinear problem-solving capability and high precision accuracy of the algorithm [28].

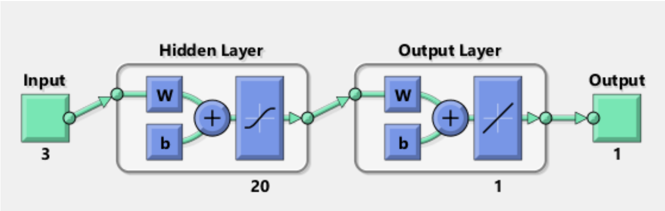

Figure 3: ANN network model.

Results and Discussions

Analysis of Variance (ANOVA)

With the advent of powerful statistical tools, the best outputs are predicted within limited experiments, which are considered a time and cost-saving, that play a vital role, especially in manufacturing. Apart from the cost and time, the prediction capabilities of these software tools are also appreciable. Naiju et al. [29] revealed that the important contributing parameters that are significant during the manufacturing process pecan be assessed by analyzing variance (ANOVA). In ANOVA analysis, the significance of process parameters can be verified with the P and F test. Lower the P-value indicates strong evidence against the null hypothesis. The F-value can measure the statistical significance of the parameter or model. So, the parameter with more F-value and low P-value is the most significant factor. Minitab®2019 software is used for statistical analysis of the model. Table 5 shows LP, SS, and OR process parameters' influence on the surface quality of DMLS parts is given from the ANOVA model.

As per the F-test and P-test, SS is recorded as the most influential parameter with the highest F-value (152.67) and lowest P-value (<0.0001), followed by LP with 139.77 and <0.0001 (F and P values). The possible reasons may acclaim due to the increase in scan speed might have created lower energy density and resulted in partial melting, whereas too low scan speeds will create balling effect due to over melting of the pool. These findings are also agreed with by Calignano et al. [30]. The ANOVA results for surface roughness are presented in Table 5. The coefficient of correlation (R^2) for the model is 96.17% and the adjusted coefficient of correlation (R^2) is 94.15% (Equations 1-3). These values can be considered an accurate model since the model developed by Arfan Majeed et al. [31] given a coefficient of determination (R^2) value of 56.75% only. The regression equation to forecast the surface roughness for a given set of input parameters is given below. The regression equation in uncoded units is:

*SR = -23.9 + 0.2715LP - 0.1626SS + 165.5OR - 0.000510LP*LP + 0.000065 SS*SS - 254.4 OR*OR + 0.000241 LP*SS - 0.1358 LP*OR + 0.0475SS*OR*

$$R = \frac{\sum_{i=1}^{n}(X_{p,i}-X_{p,ave})(X_{a,i}-X_{a,ave})}{\sqrt{[\sum_{i=1}^{n}(X_{p,j}-X_{p,avg})^2][\sum_{i=1}^{n}(X_{a,i}-X_{a,avg})^2]}} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(X_{a,i}-X_{p,i})^2}{\sum_{i=1}^{n}(X_{p,i}-X_{a,avg})^2} \tag{2}$$

$$Adj.R^2 = 1 - [(1 - R^2) \times \frac{n-1}{n-k-1}] \tag{3}$$

where X_j and Y_p were input to node j and P respectively. W was the weight of linking neutron. The number of experimental data and input variables were given by n and k respectively. Xp,i was the estimated value, Xa,i was the experimental values, Xa,avg was the average experimental values.

Table 5: ANOVA results

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	72.1395	8.0155	47.47	<0.0001
Linear	3	50.4259	16.8086	99.56	<0.0001
LP	1	23.5985	23.5985	139.77	<0.0001
SS	1	25.7762	25.7762	152.67	<0.0001
OR	1	1.0512	1.0512	6.23	0.023
Square	3	8.9764	2.9921	17.72	<0.0001
LP*LP	1	3.9962	3.9962	23.67	<0.0001
SS*SS	1	2.5524	2.5524	15.12	0.001
OR*OR	1	2.4278	2.4278	14.38	0.001
2-Way Interaction	3	12.7372	4.2457	25.15	<0.0001
LP*SS	1	11.1747	11.1747	66.19	<0.0001
LP*OR	1	0.8856	0.8856	5.25	0.035
SS*OR	1	0.6769	0.6769	4.01	0.061
Error	17	2.8702	0.1688		
Total	26	75.0097			
Model Summary	S	R^2	R^2 (adj)	R^2 (pred)	
	0.410897	96.17 %	94.15 %	91.25 %	

A Pareto chart is used to visualize the parameters that are most critical in the given process. The parameters which contain 20% can be treated as critical/significant factors. In this model, scan speed (A) and laser power (B) are shown in Figure 4 as critical factors which is already evident from ANOVA results Table 5.

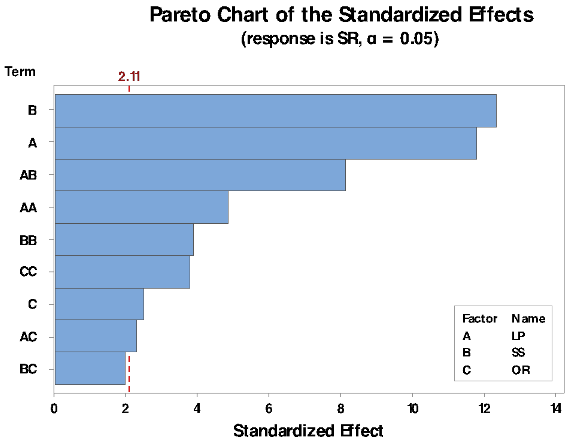

Figure 4: Pareto chart showing significant process parameters.

A normal probability plot is drawn to check whether the data fit a normal distribution or not. From Figure 5, it is clear that all points are fall on a straight line indicating that the data obtained fit a normal probability distribution. Almost all points fall below the confidence level of 95%. Hence, this model developed is accurate enough to predict surface roughness.

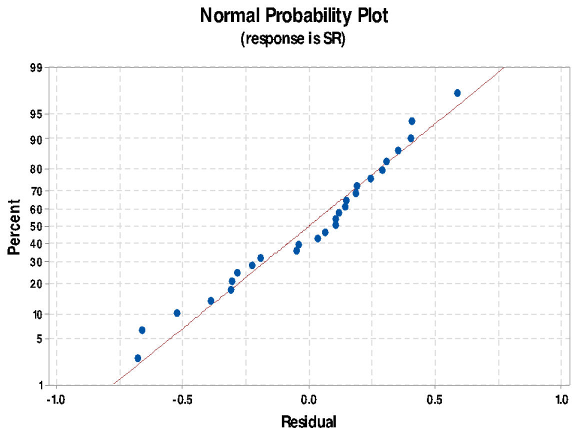

Figure 5: Normal probability of residuals for surface roughness (SR).

The effect of process parameters on surface roughness

From Figure 6, it can be observed that increasing laser scan speed resulted in track instability that increased surface roughness. Low laser power (300 W) with medium scan speed (600 mm/s) resulted in better surface roughness. This is probably due to the fact that sufficient laser intensity is applied with good track steadiness. Too low laser power and high scan speed will create unmelted regions, due to which the surface roughness will be more. However, high laser power and high scan speed result in balling effect due to over melting. This effect will also generate a rough surface. This analysis is carried at a constant overlap rate of 30%.

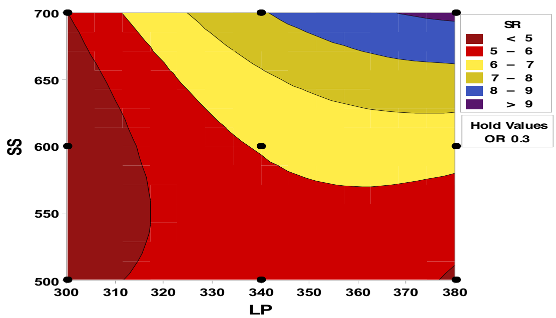

Figure 6: LP vs SS on Surface Roughness (SR).

The percentage area that is influenced by repeated melting with the laser beam is known as the overlap rate. The combined effect of overlap rate and scan speed over surface roughness at a constant laser power of 340 W revealed that higher overlap rate and lower scan speeds lead to forming a smooth surface. The overlap rate is higher means the scanning tracks are overlapping on each other largely. At the same time, low scan speed has made the laser power concentrate on the same area for an adequate time. This can be attributed to the generation of smooth surfaces. However, low overlap rate and higher scan speeds will lead to form higher surface roughness that is evident from Figure 7. The reason is higher scan speeds will generate a distortion effect in the melt pool.

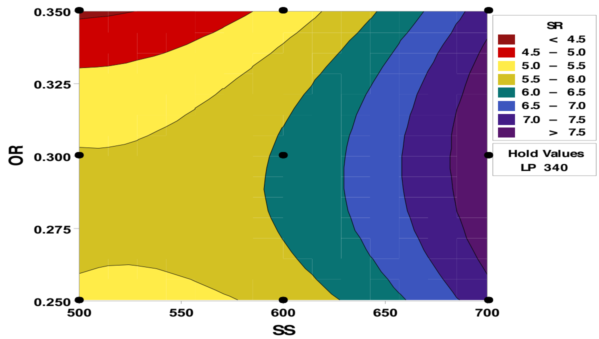

Figure 7: SS vs OR on Surface Roughness (SR).

It is clear from Figure 8 that when laser power increased, the surface roughness is also increased. This might be due to the waving of the melt pool. The laser power of 300 W with an overlap rate of 25% resulted in the best surface quality, i.e., 3.52 µm when laser scan speed is 600 mm/s, which is an optimum value. The surface roughness value is below 4 µm for laser power 300 W at low and high overlap rates of 25% and 35% and an optimum scan speed of 600 mm/s.

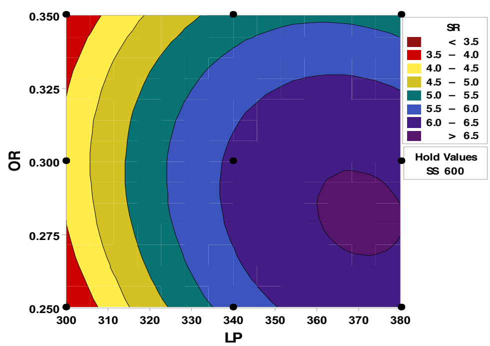

Figure 8: LP vs OR on Surface Roughness (SR).

Based on the analysis of results, it is clear that optimum values of process parameters will result in the excellent quality of the final product. These optimized process parameters resulted in the best surface quality of the DMLS product. The optimized values with experimental and predicted values of surface roughness are shown in Table 6. It can be noted that the difference between experimental and predicted surface roughness values is very less. Hence, it is clear that the experimental results obtained are accurate and in good agreement with model values.

Table 6: Optimized process variables and recorded response

Purpose	Optimum values of process variables	Experimental surface roughness (R_a)	ANOVA Predict surface roughness (R_a)
Reducing surface roughness of DMLS AlSi10Mg	LP = 300 W SS = 600 mm/s OR = 25%	3.52 μm	3.448 μm

Prediction capabilities of ANN and RSM

The 27 experimental results of laser power (LP), scanning speed (SS) overlap rate (OR), and surface roughness (SR) from Table 4 are used for ANN modeling. A supervised learning mechanism is adapted, and 20 hidden neurons are used during the training of the ANN model. Neuron selection plays a vital role in ANN modeling as the numbers of hidden neurons are more than there is a possibility of losing the ANN ability to generalize. On the other hand, fewer neurons will inhibit appropriate pattern classification. Therefore optimum hidden neurons of 20 are selected based on trial and error technique. "Levenberg- Marquardt" backpropagation algorithm is used to determine the relationship between surface quality and laser input parameters (LP, SS, OR) of the DMLS process.

Figure 9 shows the correlation coefficient (R) plots for training, validation, and testing. The corresponding R values obtained are 0.9969, 0.9959, and 0.9989. Thus, the R values for validation and testing are high, denoting a significant correlation between the experimental and estimated results. The comparison of surface roughness values obtained from experimental, RSM, and ANN are plotted in Figure 10. It is evident that the experimental results are in good agreement with both models RSM and ANN.

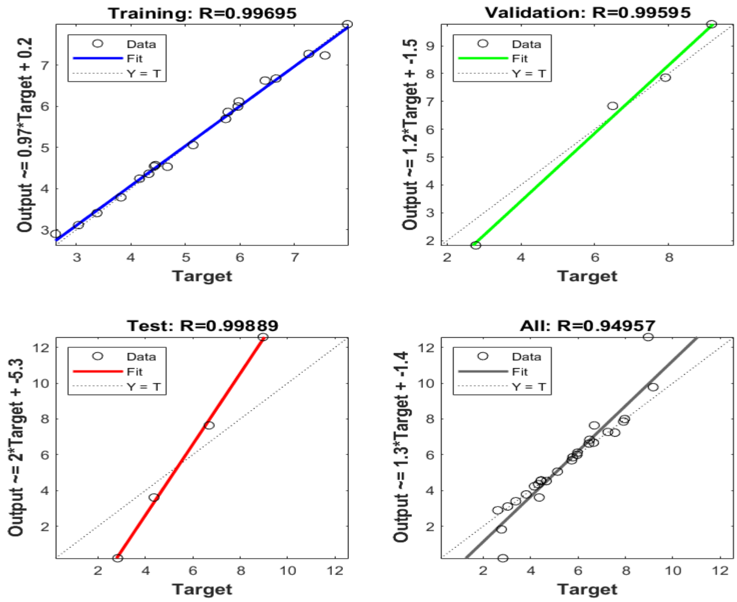

Figure 9: Coefficient of correlation (R) values for ANN.

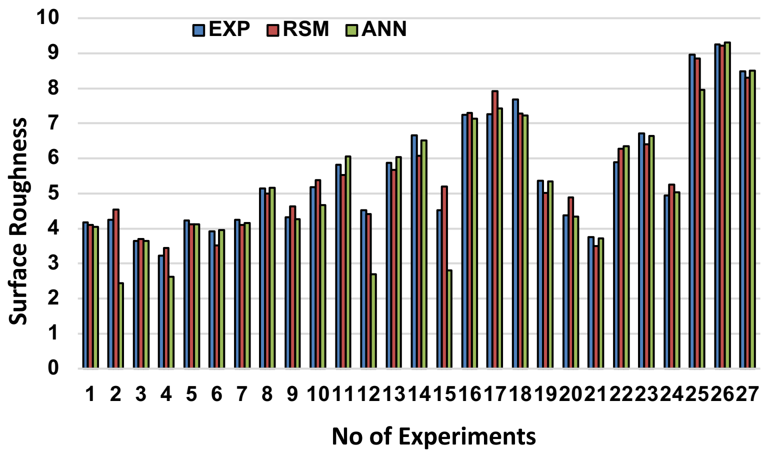

Figure10: Surface roughness values comparison graph of experimental, RSM and ANN models.

Conclusions

From this experiment, the set of optimized process parameters that can give good surface quality are explored. The RSM is used to design a set of experiments and ANOVA is used to identify significant process parameters. The regression analysis is done to generate an equation that can be used to predict surface roughness values for any set of process parameters. The following conclusions can be drawn from the observed results.

i. The optimum process parameters are laser power 300 W, laser scan speed 600 mm/s, and overlap rate of 25% when the layer thickness is constant at 30 µm.
ii. The surface quality has deteriorated when high laser powers and high scan speeds are used. This is because increases in laser power and scan speed will cause the over-melting of the melt pool, resulting in possible adverse effects like balling.
iii. The small overlap rate (25%) with low laser power (300 W) leads to good surface quality due to the formation of favourable temperature gradients within the melt pool.
iv. High laser power (380 W) and overlap rate (35%) with lower scan speed (500 mm/s) also resulted in better surface quality. This might be due to the higher laser energy density (LED) available in the melt pool since LED is directly proportional to laser power and inversely proportional to scan speed.
v. From the ANOVA analysis, the most influential parameter is identified as scan speed.
vi. The prediction capabilities of ANN are observed superior to RSM based on the coefficient of correlation values (R)
vii. RSM and ANN are given the best model to achieve good surface quality for DMLS AlSi10Mg alloy.

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