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MODELING OF SURFACE FINISH IN SELECTIVE LASER MELTING OF 316L STAINLESS STEEL BY APPLYING STATISTICAL MULTI-PARAMETER ANALYSIS AND ARTIFICIAL NEURAL NETWORKS

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Abstract: *This work explores the effect of laser power and laser speed as crucial selective laser melting (SLM) process-related parameters on surface finish indicators; average surface roughness, Ra, ten-point height, Rz, maximum roughness, Rt and mean spacing at mean line, Sm. A multi-level factorial design of experiments followed by a custom response surface design was established to generate 21 experiments with reference to the experimental levels determined for laser power and laser speed. Results were analyzed using analysis of variance (ANOVA) whereas full quadratic models were developed to correlate the selected SLS-related parameters with two out for the five roughness parameters studied; Ra and Rt. Contour plots for Ra and Rt roughness responses were examined for identifying laser power and laser speed effects as well as their variations. Several neural network architectures (ANNs) were examined to model the SLS process and obtain results for future research related to optimization approaches.*

Key words: *Selective Laser Melting, surface roughness, multi-parameter analysis, neural networks.*

1. INTRODUCTION

Additive manufacturing (AM) is an ongoing technology which it serves both as rapid prototyping operation as well as typical manufacturing process. Its applications spectrum involves automobile, aerospace, medical and other important production fields where part accuracy, mechanical properties (i.e. part strength) and surface integrity [1-3] are key criteria to be met.

Among the different methods and technologies of AM, selective laser melting (SLM) is a quite promising end-use AM method where powder materials are selectively melted and then solidified “layer-by-layer”. As it occurs to all production methods and materials processing technologies, determining beneficial settings for process-related control parameters is essential in order to meet product requirements [4-7].

When it comes to SLM a number of parameters need to be examined and set to achieve requirements related to functionality and aesthetics of fabricated components [8-12]. The purpose of searching for a beneficial (or even optimal) range of process-related parameters is accomplished by designing experiments and applying the different optimization approaches reported in the broader literature [13-16]. Among the different optimization approaches implemented for modeling or optimizing the independent process parameters with regard to one or more optimization criteria, intelligent algorithms and neural networks are distinguished [17-20].

This work considers two main SLM-related control (input) parameters; namely laser power, LP (W) and laser speed, LS (mm/s) for study-ing and modeling their effect on surface finish with emphasis to major roughness indicators. The main scope of the work is to correlate surface finish with observations related to part strength referring to tensile properties σB (MPa) and elasticity modulus, E (MPa). Studies concerning this correlation are to be presented in future work. The main reason for this concept is that SLS/SLM components lack of high or even acceptable surface quality whilst in the majority of cases is far away from achieving the required value. As a consequence the implementation of post-processing techniques is necessary and thus, the total manufacturing time is significantly increased. Stainless steel 316L powder was selected to fabricate experimental specimens as per the experimental design protocol adopted. Average surface roughness (Ra) and maximum rough-ness (Rt) where further investigated by performing statistical analysis and regression modeling. Simulations to test various neural network topologies were conducted to decide for the best network topology for Ra and Rt.

2. EXPERIMENTAL

Experimental specimens were manufactured using an iDEN® 160, Zrapid-Tech® SLM apparatus by maintaining the same part orientation (parallel to the machine's X-axis). The spherical 316L stainless steel powder with an average particle size between 15 and 53 μm and 158 HB hardness was used to build the experimental dog-bone samples.

Experimental samples were of a standard geometry and dimensions. The sequence of experiments was formulated by implementing a multi-level factorial design with two independent SLM process-related control parameters; laser power, LP (W) and laser speed, LS (mm/sec). Three discrete levels were assigned to laser power whereas seven levels were assigned to laser speed. As responses, four of the numerous surface roughness parameters were selected; namely average surface roughness (Ra), ten point height (Rz), maximum roughness (Rt) and mean spacing at mean line, (Sm). The definitions and the mathematical formulae of these parameters are well established; see for example Ref. [21]; therefore they are not presented here.

Experimental runs were divided to three discrete groups according to laser power level implemented for their production. Group-A involved the experiments performed with 130 W (experiments from No.1 to No.7); group-B with 140 W laser power (experiments from No.8 to No.14) and group-C with 150 W laser power (experiments from No.15 to No.21). Roughness measurements were obtained by using a Taylor Hobson® roughness tester with 0.8 mm cut-off length. To maintain rigorous results in term of roughness parameter results, five independent measurements were taken on each sample from top and bottom surfaces at different points. Finally the average value from each group of five roughness measurements was calculated to represent the final output. The three series of experimental specimens produced with SLM are tabulated in Table 1.

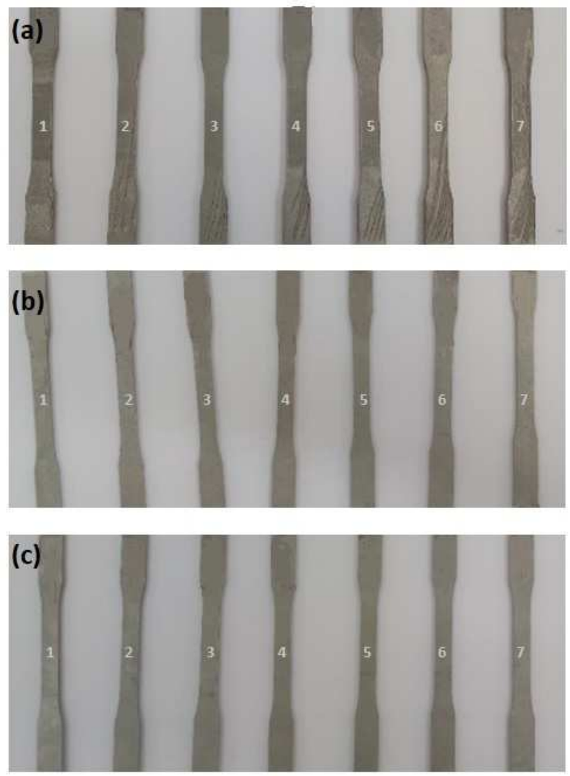


Fig. 1. Groups of experimental SLM specimens: (a) LP: 130 W; (b) LP: 140 W and (c) LP: 150 W.

2.1 Results and analysis

Table 1 and Table 2 summarize the experimental design and the results obtained for surface roughness measurements, respectively.

Table 1.

Design of SLM experiments.

Exp.No.	SLM parameters	
	LP (W)	LS (mm/s)
1	130	800
2	130	850
3	130	900
4	130	950
5	130	1000
6	130	1050

7	130	1100
8	140	800
9	140	850
10	140	900
11	140	950
12	140	1000
13	140	1050
14	140	1100
15	150	800
16	150	850
17	150	900
18	150	950
19	150	1000
20	150	1050
21	150	1100

Table 2.

Results for roughness parameters.

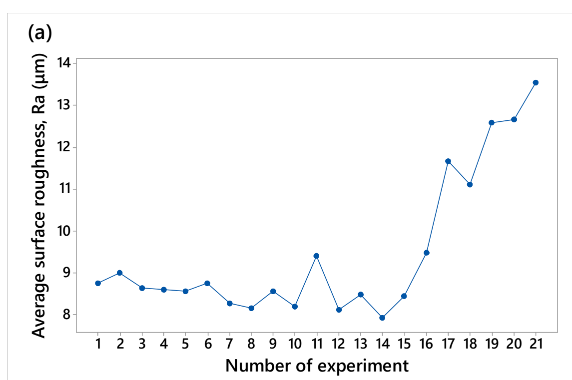
Responses			
Ra (μm)	Rz (μm)	Rt (μm)	Sm (μm)
8.76	49.2	64.4	121.2
9.00	47.6	61.2	125.6
8.64	51.0	65.4	117.4
8.60	49.2	64.8	121.2
8.56	48.4	61.6	113.8
8.76	47.6	63.2	114.2
8.28	48.4	62.2	120.6
8.16	44.6	55.8	120.0
8.56	48.6	66.8	152.0
8.20	47.0	70.2	133.0
9.40	50.8	66.2	134.0
8.12	47.0	61.0	131.4
8.48	48.6	66.8	119.2
7.92	44.6	59.6	122.0
8.44	46.0	70.0	135.6
9.48	54.6	69.6	101.6
11.68	62.8	79.2	153.6
11.12	61.2	80.2	129.0
12.60	65.8	88.4	137.8
12.68	67.2	92.8	168.2
13.56	71.8	96.0	162.8

Fig. 2 shows the variation of roughness parameters, Ra (Fig. 2a); Rz (Fig. 2b); Rt (Fig. 2c) and Sm (Fig. 2d) for the different levels of laser speed and laser power according to the multi-level factorial design. First observations indicate that the experiments performed using the lowest experimental level for laser power i.e., 130 W (experiments from 1 to 7) exhibit a constant trend with relatively low results for average surface roughness Ra (Fig. 2a). Next experiments yield variations in their results with the 14th experiment to exhibit the lowest output for mean surface roughness (laser power, LP=140 W; laser speed, LS=1100 mm/sec; Ra=7.92 μm). Mean surface roughness increases dramatically from 15th to 21st experiment; i.e., in group-C, where results lies in the range between 8.44 μm and13.56 μm.

The same trend is exhibited for the ten point height, Rz (Fig. 2b). However lowest results for Rz are shown in 8th and 14th experiments with 55.8 μm and 59.6 μm respectively. A relatively stable behavior in terms of Rz are indicated in 4th up to 7th experiment (laser power, LP 130W; variable laser speed, LS from 950 to 1100 mm/sec). The variation of the results obtained for maximum surface roughness Rt, is shown in Fig. 2c. It can be seen that Rt follows an irregular pattern whilst the lowest Rt result is reported in 8th experiment (LP: 140 W, LS: 800 mm/sec, Rt: 55.8 μm).

Fig. 2d presents the observed trend of measured values for mean spacing at mean line, Sm (μm). It is evident that Sm variation is relatively low for the experiments conducted with the fist level for laser power, LP=130W (group-A). There is also a relatively stable variation for Sm in experiments no. 10; 11 and 12. The lowest Sm value is measured in 16th experiment (Sm=101.6 μm, LP: 150 W, LS: 850 mm/sec).

Further analysis concerning ANOVA and modeling by applying different ANN architectures is conducted for average surface roughness Ra and maximum roughness Rt, as the most important and often-adopted indicators to characterize surface finish [21], while the rest of roughness parameters discussed are yet to be statistically analyzed and modeled under the same methodology adopted for examining Ra and Rt roughness parameters.



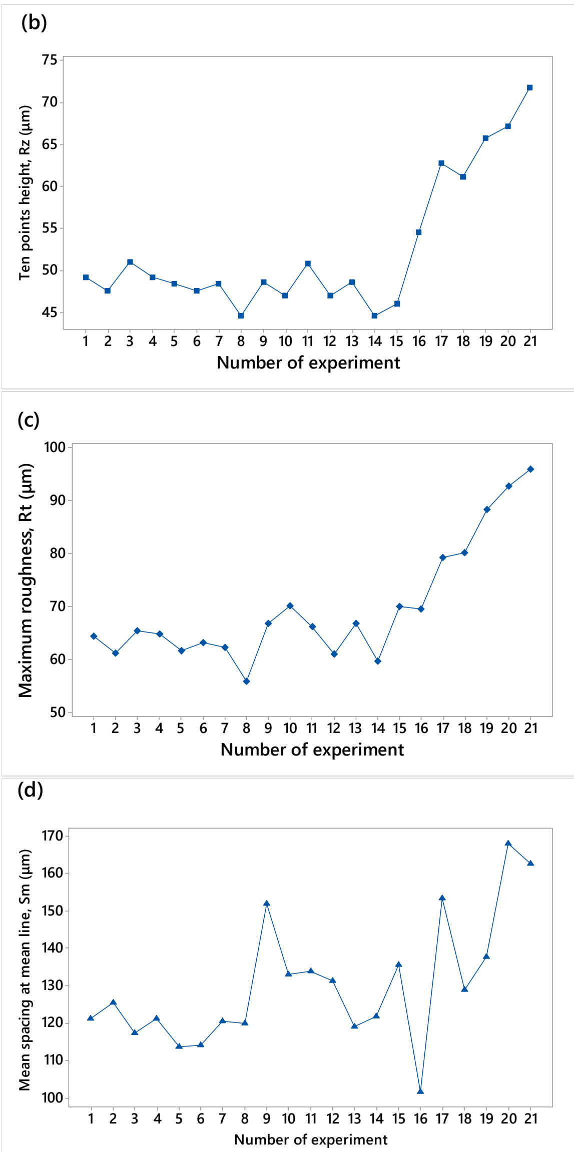


Fig. 2. Experimental results for roughness parameters: (a) average surface roughness Ra; (b) ten-point height Rz; (c) maximum roughness Rt and (d) mean spacing at mean line, Sm.

2.2 Statistical analysis and regression modeling for Ra and Rt.

To acquire a meaningful understanding concerning the effect of laser power, LP (W) and laser speed, LS (mm/sec) in surface finish referring to the selective laser melting of 316L stainless steel, a statistical analysis was conducted using MINITAB® 17 software. As response representation model, the full-quadratic mathematical expression was implemented (Eq.1).

$$y = \beta_0 + \sum_{i=1}^{k}\beta_i x_i + \sum_{i=1}^{k}\beta_{ii} x_i x_i + \sum_{i<j}\sum \beta_{ij} x_i x_j \qquad (1)$$

The above mathematical expression involves the linear terms (process-related variables as independent control parameters), the quadratic terms of independent control parameters and their two-way interactions whose number depends on the number of independent variables in the experiment. With "Y" the responses of average surface roughness Ra (µm) and maximum roughness, Rt (µm) are represented whereas the number of independent variables (LP and LS) is depicted as x_i (i^{th} variable). The model's adequacy in terms of response prediction is validated by either F or p-values. Increased F values should normally correspond to reduced p-values and vice-versa. Low p-values ($p<0.05$) found in analysis of variance (ANOVA) suggest that their corresponding variables hold significant influence on the responses under question. As far as lack-of-fit is concerned, it should be insignificant enough for the model to well-fit the experimental results, therefore large p-values are preferred. The results obtained by the analysis of variance (ANOVA) with reference to the experimental outputs for Ra and Rt, indicated that both regression models can adequately explain variation with calculated values R^2=90.37 % and R^2=89.68 significance.

According to ANOVA's p-values, it was shown that average surface roughness Ra, is primarily affected by linear and square terms (30.31 %, 21.48 % contributions respectively) followed by their interactions (2-way interaction between LP and LS, with 18.19 % contribution to the experiment). Individual significance of each term is computed by t-test at 95 % confidence level. This implies the significance of terms with p-value lower than 0.05. Coefficient of determination (R^2) shows the total variation percentage in the studied response explained by the terms in the model. Results concerning the analysis of this non-linear problem referring to SLM of 316L metallic powder, involve the representation of 2D graphical regions known as contour plots. These plots illustrate the beneficial sub-regions where independent variables favor the response under interest through their proper settings. Moreover contour plots reveal the resulting trend of the response examined owing to the interaction existing between the two independent variables (X and Y axes). Fig. 3a and Fig. 3b illustrate the experimental regions and the effects of laser power LP (W) and laser speed, LS (mm/sec) on the responses of average surface roughness, Ra (μm) and maximum roughness Rt (μm) respectively.

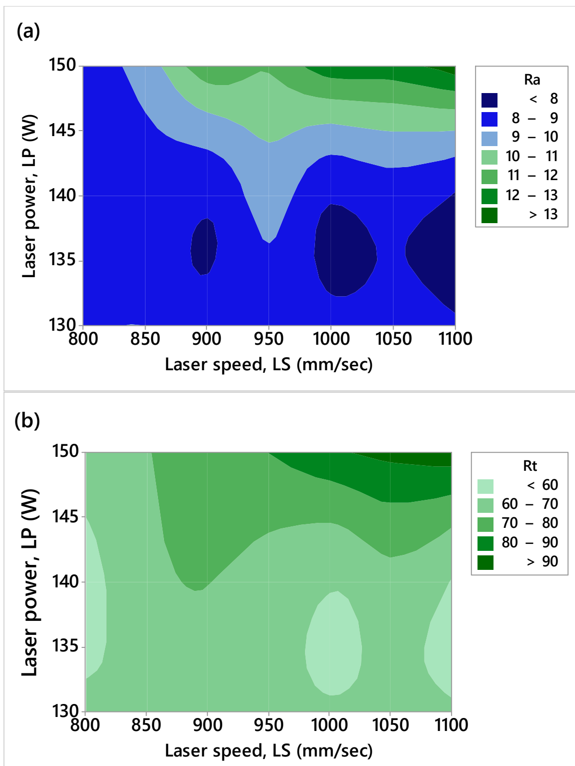


Fig. 3. Contour plots for LP and LS independent parameter effects on: (a) average surface roughness Ra; (b) maximum roughness, Rt.

Anderson-Darling normality test can evaluate the model's suitability and justify its usage for practical applications. If the resulting p-value referring to residuals is found lower than the confidence interval's (CI) pre-specified value; i.e. 0.05, then residuals won't follow normality and will question the regression model's reliability. Therefore p-value for this test should occur away beyond 0.05 to justify insignificance of residuals' effect. In the current experiment, ANOVA reveals that regression models created for predicting mean surface roughness Ra and ten points height, Rt are adequate enough; having p-value for Ra residuals equal to 0.189 (Fig. 4a) and for Rt residuals equal to 0.682 (Fig. 4b) verifying that the regression model's validity despite its lower R^2 value when compared to that of Ra regression model.

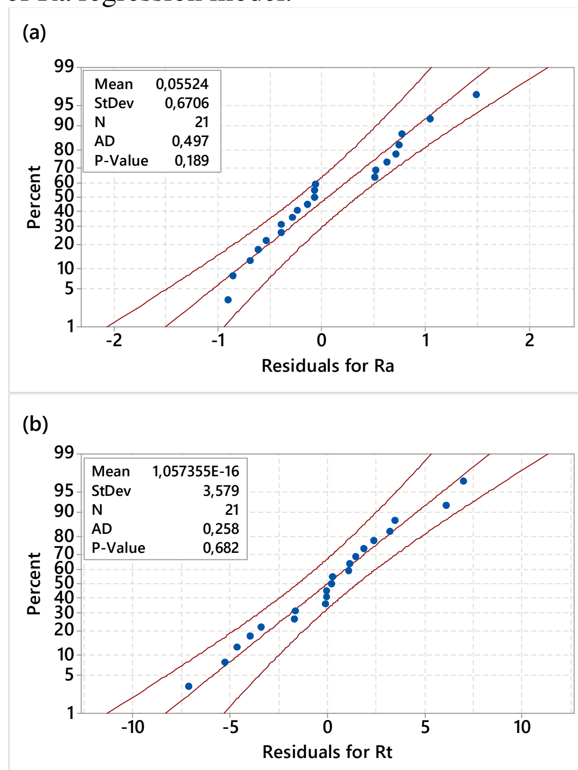


Fig. 4. Normality plots of residuals using Anderson-Darling test: (a) residuals for average surface roughness Ra; (b) residuals for maximum roughness, Rt.

3. PREDICTION OF RESPONSES USING NEURAL NETWORKS

It has been shown that SLM of 316L stainless steel powder exhibits high complexity despite the fact that only two independent variables have been considered (laser power and laser speed). This complexity may introduce difficulties in accurate response predictions using conventional approaches.

To further examine the potentials of accurate response prediction at least for Ra and Rt roughness indicators, several neural network architectures were tested in order to select a reliable neural network model capable of predicting both responses. Laser power LP and laser speed LS were the two input parameters whilst Ra and Rt were the two outputs. Each of the parameters is represented by a single neuron and consequently the input layer in the neural network structure comprises two neurons. The neural network architecture and topology finally adopted is depicted in Fig. 5.

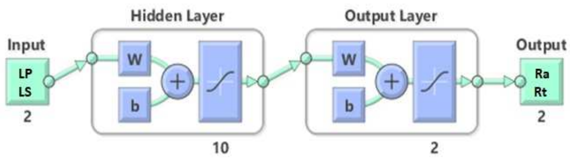


Fig. 5. ANN architecture and topology for modeling Ra and Rt roughness parameters.

To introduce a reliable database to the network the experimental results were considered referring to the outputs and the independent variables along with their limit ranges. Results for Ra and Rt were used for training the network and further examining input-output correlation. The database has been divided to three discrete datasets, namely the training, testing and validation (random selection of data division; 70 % for training, 15 % for validating and 15 % for testing). Training set has been thoroughly used for adjusting the weights, testing set was used for examining the network's accuracy in its predictions and validation set was used for validating the results according to the training procedure. Consequently, the experiments were divided into three sets; 15 for training, 3 for validation and 3 for testing. Neural network training deals with the update in its connected weights so that the error among predicted and actual experimental outputs is minimized. The neural network architectures examined were tested using the standard back propagation algorithm found in Mathworks® MATLAB® R2014b. In order to decide the final number of neurons referring to the hidden layer, several structures under a varying number of neurons were tested. Activation level for neurons was determined by the tan-sigmoid transfer function while "TRAINLM" was the training function. An important aspect for designing neural network models model to predict responses with reference to the independent process parameters-inputs is overfitting. Overfitting occurs when neural network topologies exceed a reasonable accuracy on training data; however a lack of adequate predictability is exhibited on testing data. In general when overfitting occurs, the neural network model adopts the training data noise instead of the actual relation among process parameters and responses (inputs and outputs). To avoid overfitting, several methods are implemented i.e., the "weight decay regularization" and the "dropout" [22-25]. Such methods were considered and employed to the neural network topologies examined in this research to ensure that the final topology is capable of reliably predicting surface roughness parameters Ra and Rt with reference to the two input variables; laser power LP and laser speed LS. Note that a neural network topology should successfully be able to generalize the results predicted beyond the experimental domain from which training, testing and validation operations have been applied. Understanding the generalization process of neural network models on unexplored results is imperative for designing trustworthy and reliable topologies among inputs hidden layers and outputs.

It was found that 2-10-2 network topology was the most beneficial among others examined. Fig. 6 depicts the best validation performance for topology giving the best output equal to 6.8905 at epoch 3 after 200 iterative evaluations.

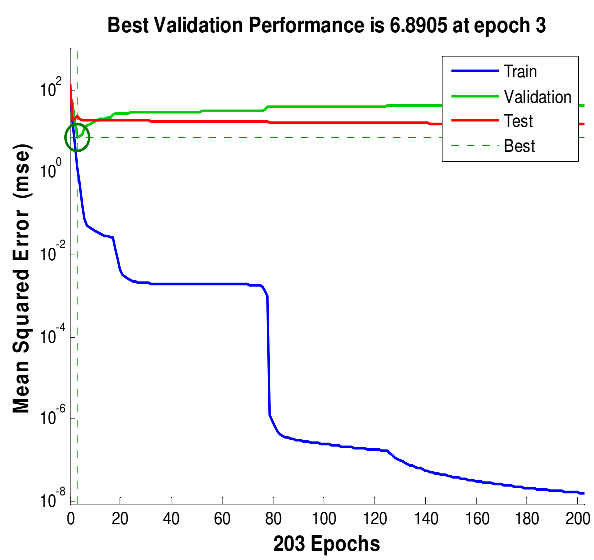
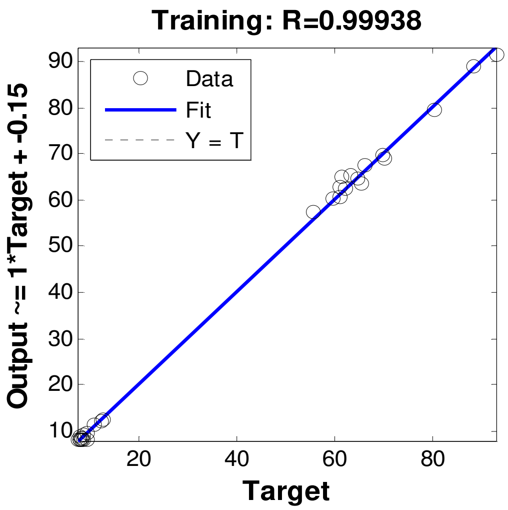
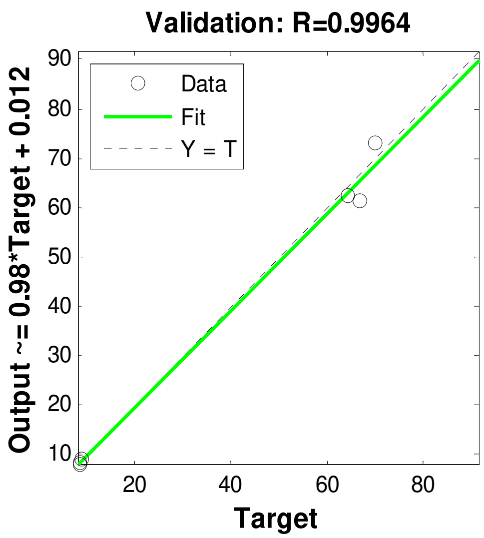
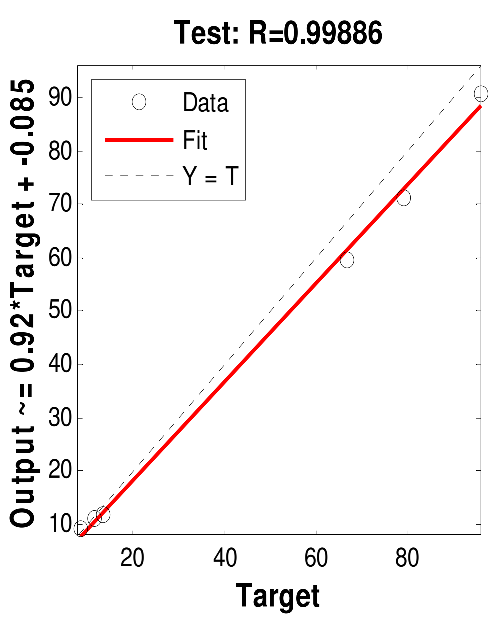


Fig.6. Regression analysis for the results obtained by 2-10-2 ANN topology.

To verify the prominence of this trained ANN architecture, the training set was presented to the ANN. Fig. 7 depicts the regression analysis for the ANN implemented.







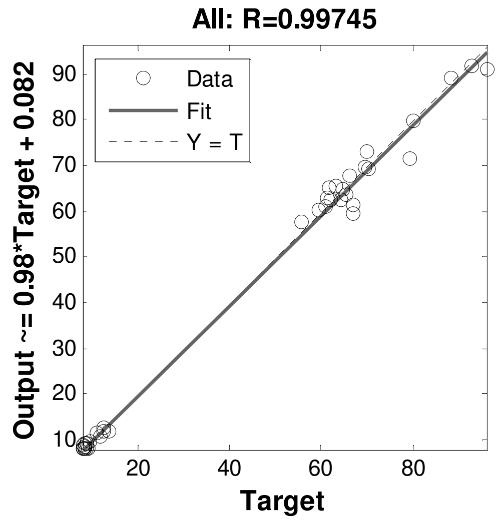


Fig.7. Regression analysis results obtained by the ANN architecture adopted, based on its validation performance.

It can be stated that the high correlation coefficient (R^2) among outputs (predicted results) and targets (Ra and Rt) verify the sufficient ANN's performance.

4. CONCLUSION

This work examined the effect of laser power and laser speed on surface finish of SLM 316L stainless steel fabricated specimens. The roughness parameters investigated were average surface roughness Ra, ten-point height Rz, maximum roughness Rt and mean spacing at mean line, Sm. Experimental runs were determined by following a multi-level factorial response surface design involving 21 experiments according the number of levels for each independent SLM parameter. The results obtained were analyzed for Ra and Rt roughness parameters for which regression and neural network modeling were applied. The conclusions of this work are summarized as follows:

- Maintaining surface finish in SLM additive manufacturing is a challenging process where irregularities and large variations among roughness outputs occur. This conclusion is in line with latest findings and observations of the scientific literature.
- Although the SLM process exhibits a highly non-linear behavior concerning laser power

LP (W) and laser speed LS (mm/s) as the major independent process-related parameters, Ra and Rt roughness parameters can be adequately correlated when applying regression analysis with emphasis to full quadratic models.

- Successive modeling of Ra and Rt parameters through regression and neural networks is an encouraging outcome, however; more surface roughness indicators should be extensively investigated to come up with reliable outputs and guarantee a solid characterization of SLS-manufactured components in terms of their surface quality.

As a future perspective the authors plan to look further ahead on examining and providing a distinct link between surface finish parameters and tribological behavior of SLM-fabricated 316L stainless steel components.

5.ACKNOWLEGEMENT

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MODELLIERUNG DER OBERFLÄCHENBESCHICHTUNG BEIM SELEKTIVEN LASERSCHMELZEN VON EDELSTAHL 316L DURCH ANWENDUNG STATISTISCHER MULTIPARAMETERANALYSE UND KÜNSTLICHER NEURONALER NETZWERKE

bstrakt: Diese Studie untersucht den Einfluss von Laserleistung und Lasergeschwindigkeit als entscheidende Parameter des Selective Laser Melting (SLM) auf Oberflächenqualitätsindikatoren;

mittlere Oberflächenrauheit, Ra, Zehn-Punkt-Höhe, Rz, maximale Rauheit, Rt und mittlerer Abstand bei der mittleren Linie, Sm. Ein mehrstufiges faktorielles Versuchsdesign, gefolgt von einem maßgeschneiderten Response-Surface-Design, wurde erstellt, um 21 Experimente in Bezug auf die für die Laserleistung und Lasergeschwindigkeit bestimmten experimentellen Stufen durchzuführen. Die Ergebnisse wurden mittels Varianzanalyse (ANOVA) analysiert, während vollständige quadratische Modelle entwickelt wurden, um die ausgewählten SLS-bezogenen Parameter mit zwei der fünf untersuchten Rauheitsparameter zu korrelieren; Ra und Rt. Konturdiagramme für die Ra- und Rt-Rauheitsreaktionen wurden untersucht, um die Auswirkungen von Laserleistung und Lasergeschwindigkeit sowie deren Variationen zu identifizieren. Mehrere Architekturen neuronaler Netze (ANNs) wurden untersucht, um den SLS-Prozess zu modellieren und Ergebnisse für zukünftige Forschungen im Zusammenhang mit Optimierungsansätzen zu erhalten.

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