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CUTTING OF 316L STAINLESS STEEL FOR METAL MESH IMPLANT USING CO_2 LASER CUTTING: ANALYSIS AND OPTIMIZATION

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ABSTRACT

This study investigates the effects of CO_2 laser cutting parameters on the quality of 316L stainless steel used for metal mesh implants. A Taguchi L9 orthogonal array was employed to design the experiments with three factors: laser power (100-200 W), cutting speed (50-150 mm/min), and gas pressure (3-9 bar). The dimensions (Dim) and heat-affected zone (HAZ) of the cuts were analyzed using both Taguchi and Hybrid Taguchi-Grey Relational Analysis (T-GRA) methods. Results from Taguchi analysis identified the optimal parameters for minimizing Dim as 100 W, 100 mm/min, and 6 bar, and for HAZ as 100 W, 50 mm/min, and 6 bar. ANOVA indicated that laser power significantly influenced both Dim (41.11%) and HAZ (28.10%). T-GRA optimization predicted the optimal parameters as 200 W, 50 mm/min, and 3 bar, confirmed through validation experiments with a Grey Relational Grade (GRG) of 0.969. The study concludes that laser power is the most critical parameter, followed by gas pressure and cutting speed, providing a comprehensive optimization strategy for laser cutting 316L stainless steel for medical implants.

Keywords: taguchi-grey relational analysis (T-GRA), dimension, heat affected zone (HAZ), parameter optimization.

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INTRODUCTION

Stainless steel mesh implants are widely used in medical applications due to their strength, durability, and excellent biocompatibility. These implants provide robust structural support in orthopedic, cranial, maxillofacial, and spinal surgeries. Stainless steel is particularly valued for its corrosion resistance, ensuring that implants remain intact and functional over long periods without degradation [1-3].

Stainless steel meshes can be customized through advanced manufacturing methods, such as 3D printing and laser cutting, to meet the specific needs of individual patients. Laser cutting, in particular, offers precise and intricate designs, enhancing the implant's fit and performance. Despite their advantages, such as high mechanical strength and low risk of adverse reactions, potential drawbacks include the risk of metal allergies and fatigue over time. However, continuous advancements in materials science and medical engineering are improving the performance and biocompatibility of stainless steel mesh implants, making them essential in modern surgical procedures [1, 2, 4, 5].

Laser cutting technology has been applied to process stainless steel for many objectives. Muhammad et al. [6] applied laser cutting for profiling thin tubular materials of 316L stainless steel with diameter < 4 mm and wall thickness < 200 μm. They compared the performance of wet and dry fibre laser cutting to produce the medical coronary stent. It was reported that under damp conditions, back wall damage was prevented, and the heat affected zone (HAZ), kerf width, surface roughness, and dross deposition had also been improved compared to the dry condition. Aimed to study the relation of the cutting-edge quality parameters with the process parameters in CO_2 laser cutting of 316L stainless steel, Eltahwani *et al*. [7] applied the overall optimization to find out the optimal cutting setting that would enhance the quality or minimize the operating cost. Mathematical models were developed to determine the relationship between the process parameters and the edge quality features and process parameters' effects on the quality features had been defined. It was reported that the optimal laser cutting conditions had been found at which the highest quality or minimum cost could be achieved. In a similar study but limited to the effect of cutting speed on surface quality (surface roughness and HAZ) when CO_2 laser cutting was applied to cut 316L stainless steel [8], it was reported that cutting speed showed a visible effect on surface roughness, the width of the HAZ and presence of macro-irregularities, such as presence of dross, molten and burnt material. The use of a cutting speed of 16.5 mm/s produced cut surfaces with good roughness and negligible heat-affected zone. The cutting speed of 9.17 mm/s produced a surface with lower roughness, but at the expense of visible HAZ, taking up approximately 20% of the cut surface. Besides 316L stainless steel, the study on the effect of process parameters on the quality of cutting was done on 304 stainless steels, and similar results were reported [9,10]. The more comprehensive information regarding the process parameters of the cutting quality in laser cutting is reviewed and reported in [11, 12].

Modeling and simulation in laser cutting of stainless steel are reviewed and reported in [13] while optimization is in [13, 14]. Anghel *et al*. [15] reported the results of the investigation conducted on CO_2 laser cutting of miniature gears of 304 stainless steel. The optimization process was studied using Response Surface Methodology (RSM) and the results showed that the optimum laser parameters were obtained at a laser power of 2407 Watts, cutting speed of 1.25 m/min, focal point of 2.4 mm, and gas pressure of 12.5 bar. At the optimum laser parameters, the best value of surface roughness was recorded at Ra = 0.43 μm. Using the RSM technique but focused on modeling, Parthiban *et al*. [10] developed a mathematical model considering laser process parameters (power, cutting speed, gas pressure) while HAZ was the response. They reported that the model could be used to predict the response and satisfy the confirmation test. The optimization of laser machining parameters of 314 stainless steel using the RSM technique was reported in [16]. In the study of Parthiban et al. [10], it was reported that RSM suggested a quadratic regression equation for surface roughness prediction in terms of process parameters. The optimum process parameters obtained were at a power of 1.2 kW, gas pressure of 0.579 bars, and cutting speed of 2.4 m/min. At the optimum condition, the surface roughness was recorded at Ra = 2.132 μm. The other optimization studies are reported in [17, 18] and focus is mainly on surface roughness.

In the work reported in this paper, the CO_2 laser cutting is applied in cutting 316L stainless steel with a case study on cutting the feature of metal mesh implant. The dimension and HAZ of the feature are analyzed based on the results of the experimental study by Taguchi design while then; the optimization of the process parameters is carried out using the hybrid Taguchi-Grey Relational Analysis (T-GRA) technique.

MATERIALS AND METHODS

The design of the metal mesh implant for the case study of the application of CO2 laser in cutting 316L stainless steel in this study is shown in Figure 1. The design is the repetition of a feature called a diamond feature. For the case study, the small diamond feature in Figure 1 is taken as the sample to be processed by CO2 laser cutting. The dimension of the small diamond feature is (6 x 10) mm. The width of the diamond feature profile (thick black line in Figure-1) is 1 mm while the thickness of the feature is 0.5 mm or the same as the thickness of workpiece material 316L stainless steel. There are 2 (two) reasons why the small diamond feature is taken as the focus, they are the accuracy and the difficulty of cutting the small size of the detail feature for the metal mesh implant.

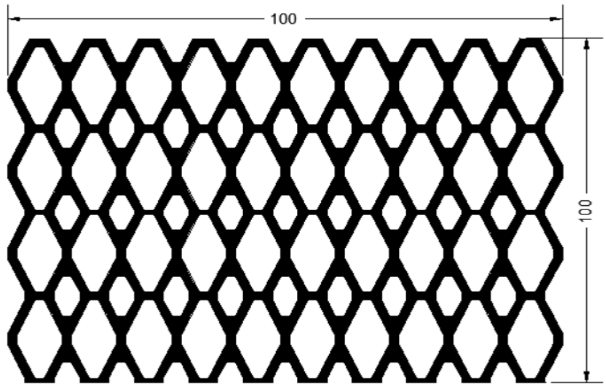

Figure-1. Design of metal mesh implant (unit size in mm).

A stainless steel grade of 316 L sheet metal with a thickness of 0.5 mm is used as the workpiece material in this study. The chemical composition of 316L stainless steel is C 0.03%, Mn 2%, Cr (17-19) %, Ni (13-15.5) %, Mo (2-3) %, Si 0.75%, Cu 0.50%, N 0.1%, P 0.025%, S 0.01%, and the remaining is Fe.

A CNC CO_2 laser cutting machine with a laser power maximum of 300 Watts and equipped with a servo motor for the movement of the laser nozzle or cutting speed of 1000 mm/min is used in this study. The machine has an external water chiller for cooling. During the laser cutting process, a continuous wave is applied with the assistance of Argon gas.

The experiment is based on the Taguchi method with 3 replications. The factors and levels are shown in Table-1. The stand-off is kept constant at 3 mm. The response variables in this study are dimension and heat-affected zone (HAZ). Both response variables are observed using a digital microscope Dino-Lite Edge AM7915MZT. The measurements related to the dimension of feature and HAZ are also taken by using the digital microscope. Four measurements are taken for the representation of the dimension of feature and HAZ from each sample, and the average values are recorded. The measurement of the dimension of the feature is presented as the difference value between the width of the feature profile (1 mm = 1000 μm) and the width of the cutting product. For example, if the average value of the width of the feature profile is 800 μm, so the data recorded becomes (1000 – 800) μm = 200 μm. But, for HAZ, the data recorded is the thickness of HAZ observed along the profile of the feature.

The optimization in this study is done by using the hybrid Taguchi and Grey Relational Analysis (T-GRA) technique. The combination of the Taguchi method and GRA in the T-GRA technique enhances the robustness and effectiveness of optimization and decision-making processes in engineering applications. T-GRA is a useful optimization technique when dealing with systems characterized by limited or uncertain data. Evaluation of the correlation between different factors by measuring their similarity or proximity can be done by this technique

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[19-23]. There are 5 (five) steps carried out for the implementation of T-GRA technique in this study:

a) Running the experimentation using Taguchi design L9 (33) as per Table-1.
b) Performing Taguchi analysis. Note that the characteristic of both response variables is smaller the better.
c) Performing the GRA analysis. Calculating the Signal-to-Noise (S/N) ratio value and normalizing the value of the S/N ratio.
d) Calculating the delta values and the gamma values (grey relational coefficient / GRC).
e) Calculating the value of grey relational grade (GRG) for predicting the optimal combination of process parameters that resulting the optimum values for response variables and verifying result thru confirmation experiment.

Table-1. Factors and levels of Taguchi design L9 (3^3).

Factors	Unit	Symbol	Code	Level 1	Level 2	Level 3
Laser power	Watts	*P*	A	100	150	200
Cutting speed	mm/min	*v*	B	50	100	150
Gas pressure	bar	*p*	C	3	6	9

Taguchi analysis in this study has been done with the aid of the Minitab package while the calculations for the implementation of the T-GRA technique by the development of a Python line program. The tool for the development of the program is Python 3.0 with Jupyter Notebook which runs in Anaconda version 1.9.12. The output of the program is saved in MS Excel format.

RESULTS AND DISCUSSIONS

A total of 27 samples of diamond features resulted from the experiment. Each sample was then observed and measured for data collection. The evidence of observation and measurement on the sample resulted from cutting at laser power (P) of 150 Watts, cutting speed (v) of 150 mm/min, and gas pressure (p) of 3 bar is shown in Figures 2 and 3.

Figure-2. Measurement of the width (dimension/Dim.) of the diamond feature profile.

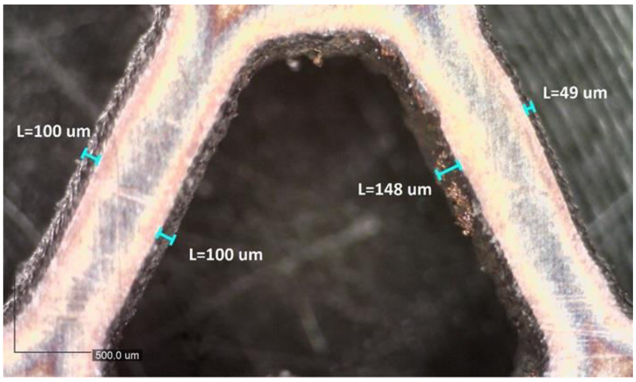

Figure-3. Measurement of the HAZ along the diamond feature profile.

Taguchi Analysis

The data collected from the measurement of all samples are summarized and presented in Table-2. Before analyze the data by the Taguchi method, the distribution of data was checked through a probability plot, and the results are shown in Figure-4. The plots in Figures 4(a) and 4(b) show that data are scattered along the diagonal line and none out of the border. It indicates that the distribution of data is good and follows the normal distribution. The goodness-of-fit of data is explained by the value of the Anderson-Darling (AD) test and the P-value as well. Both values indicate that the data comes from a normal distribution. Based on this fact, it can be concluded that the Dimension (Dim.) and HAZ data resulting from the experiment are feasible for further analysis.

The results of Taguchi analysis are given in the main effect plot for the Signal-to-Noise (S/N) ratio for Dimension and HAZ as presented in Figure-5. For the analysis of response Dimension, the optimum is given by the combination process parameter A1 B2 C2 or associated with laser power (*P*) of 100 Watts, cutting speed (*v*) of 100 mm/min, and gas pressure (*p*) of 6 bar.

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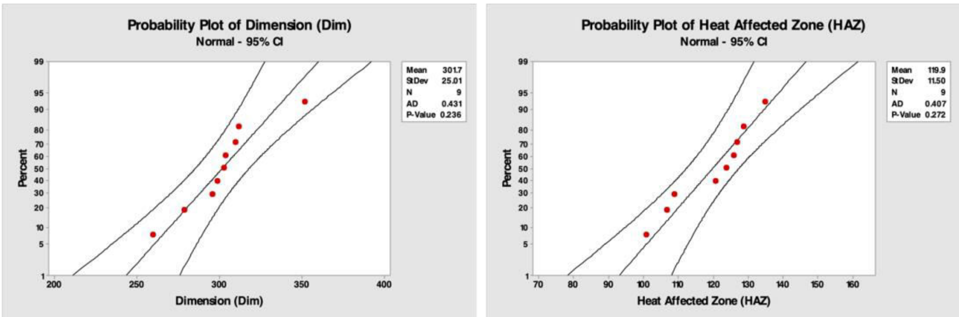
For HAZ, the optimum is given by the combination process parameter A1 B1 C2 or associated with laser power (*P*) of 100 Watts, cutting speed (*v*) of 50 mm/min, and gas pressure (*p*) of 6 bar. From these results, it can be learned that the Taguchi method provides the optimum condition of each response at a certain combination of process parameters. Unlike the capability of GRA, Taguchi provides only one optimum response variable at a time of analysis and cannot provide simultaneously the optimum combination of process parameters for all response variables.

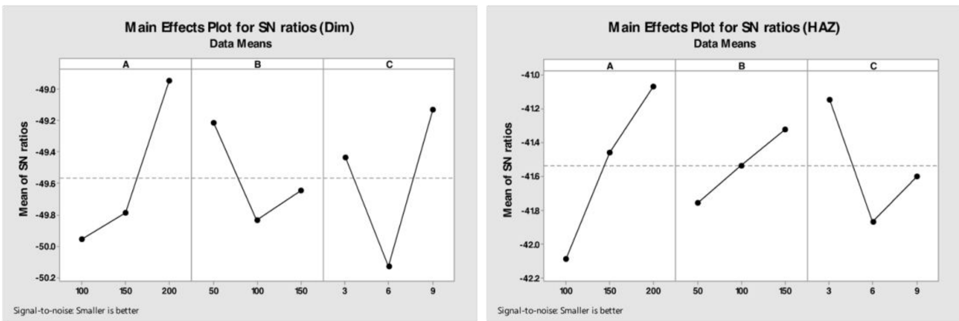
Table-2. Summary of data resulting from the experiment.

Run	*P*	*v*	*p*	Dim.	HAZ
	Watts	mm/min	bar	μm	μm
1	100	50	3	299	135
2	100	100	6	352	121
3	100	150	9	296	126
4	150	50	6	310	127
5	150	100	9	304	129
6	150	150	3	317	100
7	200	50	9	260	107
8	200	100	3	279	109
9	200	150	6	303	124



(a) (b)

Figure-4. Probability plot of data: (a) Dimension, and (b) HAZ.



(a) (b)

Figure-5. Taguchi analysis (the smaller the better) for: (a) Dimension, and (b) HAZ.

In addition to the Taguchi analysis, the analysis of variance (ANOVA) was performed for both response variables. The results of ANOVA show that for Dimension (Dim.) versus process parameters, the effect of laser power (*P*) is significant with a 41.11% contribution, followed by gas pressure (*p*) with 38.95%, and cutting speed (*v*) contributes 14.86%. For the model, the coefficient of determination score is $R^2 = 0.9493$ indicating the fit of the

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experimental data is satisfactory. Moreover, for HAZ versus process parameters, the effect of laser power (*P*) contributes 28.10%, followed by gas pressure (*p*) of 11.73%, and cutting speed (*v*) of 5.12%. The score of R^2 = 0.4495 which is less than the model resulted in analysis of Dimension. From the ANOVA, so far, it can be concluded that for both response variables Dim. and HAZ, as per Taguchi analysis, the laser power (*P*) is the most influencing factor compared to gas pressure (*p*) and cutting speed (*v*).

Hybrid Taguchi-Grey Relational Analysis (T-GRA)

The aforementioned results of Taguchi analysis show that the optimum for response variables Dim. and HAZ are at A1 B2 C2 and A1 B1 C2, respectively. Even the characteristic of response is the same at the smaller the better, but the process parameters for optimum response are different. In this section, the hybrid T-GRA technique is applied to find the process parameters that resulting the optimum response. The hybrid T-GRA analysis is presented step by step in the following.

Steps 1 and 2 have been described in the previous section of Taguchi analysis. Now, for step 3, the results of the calculation of the S/N ratio and the normalizing value of the S/N ratio for both response variables are presented in Table-3.

Table-3. The values of S/N ratio and normalizing S/N ratio for Dim. and HAZ.

Run	S/N Ratio		Normalize S/N Ratio	
	Dim	HAZ	Dim	HAZ
1	-49.513	-42.607	0.539	0.000
2	-50.931	-41.656	0.000	0.365
3	-49.426	-42.007	0.572	0.230
4	-49.827	-42.076	0.419	0.204
5	-49.657	-42.212	0.484	0.151
6	-50.021	-40.000	0.346	1.000
7	-48.299	-40.588	1.000	0.775
8	-48.912	-40.749	0.767	0.713
9	-49.629	-41.868	0.495	0.283

Before the GRC and GRG calculations, a calculation of the correlation coefficient between both response variables is checked. The previous probability plots in Figures 4(a) and 4(b) show that visually the data points fall along a straight line, indicating normality. Therefore, the Pearson correlation coefficient can be used to measure a numerical value that indicates the strength and direction of the linear relationship between Dim and HAZ. The result of the calculation is 0.23 as the score of the correlation coefficient between variables Dim and HAZ. This value suggests a weak positive linear relationship between variables Dim and HAZ. It means that, in general, as Dim increases, HAZ tends to increase slightly as well, but the relationship is not strong.

The results of the calculation for the delta, gamma (Grey Relational Coefficient / GRC) values (step 4), and the Grey Relational Grade (GRG) (step 5) are presented in Table-4. From the table, the highest value of GRG = 0.845 indicates that the combination value of process parameters in Run 7 at A3 B1 C3 is the initial optimum process parameter. The analysis was then continued to calculate the average GRG value to determine the optimum condition (prediction) for each factor. For this purpose, the average value of GRG for each level is calculated and presented in Table-5. The results in Table 5 show that the highest values of each factor are A = 0.653 (level 3), B = 0.565 (level 1), and C = 0.601 (level 1). As a result, the process parameters of A3 B1 C1 are considered as the prediction optimum condition with a GRG value of 0.75. Moreover, the main effect of each factor on GRG shows an agreement with the ANOVA result that the laser power (factor A) has the most significant effect on the multiple quality characteristics of both response variables Dim and HAZ.

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Table-4. The values of delta, gamma (GRC), and GRG.

Run	Delta (Absolute diff.)		Gamma (GRC)		GRG	Rank
	Dim	HAZ	Dim	HAZ		
1	0.461	1.000	0.520	0.333	0.427	7
2	1.000	0.635	0.333	0.440	0.387	9
3	0.428	0.770	0.539	0.394	0.466	4
4	0.581	0.796	0.463	0.386	0.424	8
5	0.516	0.849	0.492	0.371	0.431	6
6	0.654	0.000	0.433	1.000	0.717	2
7	0.000	0.225	1.000	0.689	0.845	1
8	0.233	0.287	0.682	0.635	0.659	3
9	0.505	0.717	0.497	0.411	0.454	5

Table-5. The average values and optimum values of GRG.

Level	Factors		
	A	B	C
1	0.427	0.565	0.601
2	0.524	0.492	0.422
3	0.653	0.546	0.581
Max	0.653	0.565	0.601
Min	0.427	0.492	0.422
Diff	0.226	0.073	0.179
Rank	1	3	2

Table-6. Summary of results of the hybrid T-GRA and the confirmation experiment.

Optimum parameter	Initial	Optimum condition	
		Prediction	Confirmation
	A3 B1 C3	A3 B1 C1	A3 B1 C1
Dim	260	-	245
HAZ	107	-	101
GRG	0.845	0.75	0.969

Finally, the prediction optimum condition at process parameters of A3 B1 C1 is verified through a confirmation test. In this case, the process parameters A3 B1 C1 or associated with laser power (P) of 200 Watts, cutting speed (v) of 50 mm/min, and gas power of (p) of 3 bar were applied for confirmation experiment. The confirmation experiment was carried out with 3 replications. The average values of Dim and HAZ from the confirmation experiment are shown in Table-6. The corresponding GRG is at 0.969. This result shows that the optimum values of Dim and HAZ are provided by the process parameters A3 B1 C1 and the values are lower than the initial optimum condition at process parameters A3 B1 C3.

CONCLUSIONS

This study systematically analyzed the impact of CO_2 laser cutting parameters on the quality of 316L stainless steel, specifically focusing on dimensions and heat-affected zones. The Taguchi method identified optimal conditions for individual responses, while the T-GRA provided a multi-response optimization. The Taguchi analysis revealed that the optimal parameters for minimizing the cut dimensions were 100 W, 100 mm/min, and 6 bar, whereas for minimizing HAZ, the optimal conditions were 100 W, 50 mm/min, and 6 bar. ANOVA results confirmed that laser power had the most significant effect on both response variables, with contributions of 41.11% for dimensions and 28.10% for HAZ.

The hybrid T-GRA approach predicted optimal parameters as 200 W, 50 mm/min, and 3 bar, validated through confirmation tests. This method proved effective in optimizing multiple quality characteristics simultaneously, yielding a GRG of 0.969. The results indicate that higher laser power, combined with lower cutting speed and gas pressure, enhances cutting performance, reducing both dimensions and HAZ.

The findings underscore the importance of laser power as the primary factor influencing cut quality, followed by gas pressure and cutting speed. The study recommends adopting the hybrid T-GRA approach for multi-response optimization in laser cutting applications, particularly for materials used in medical implants. Future research should explore the effects of additional parameters, such as laser frequency and pulse duration, to further refine the cutting process. Implementing these optimized parameters in industrial settings can improve the quality and efficiency of manufacturing medical implants, ensuring better performance and biocompatibility.

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