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Research Article

Optimization of Laser Cutting Parameters for Mild Steel Using Regression Analysis and Differential Evolution Algorithm

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ABSTRACT

The primary objective in the production of parts is to optimize the manufacturing process. As the industry recognizes the roughness of the cut product as one of the key criteria, it becomes critical to select the correct laser settings with minimum trial, error and at the lowest possible cost while using reliable techniques to achieve the desired surface finish. Due to the nonlinear nature of laser cutting, statistical analysis is necessary to obtain a satisfactory surface finish. In this study, experimental data sourced from literature were subjected to analytical processes. In the experimental design, L25 orthogonal array was used. The optimization process for the laser cutting parameters (laser power, cutting speed, and assist gas pressure) was implemented using regression analysis and a differential evolution algorithm. The regression model, with an R^2 value of 83.21%, accurately predicted roughness based on these parameters. The model's effectiveness was further supported by the high correlation (R^2 = 86.6%) between the experimental and predicted results. Using the differential evolution optimization method, the minimum surface roughness was calculated as 0.442 µm. This study provides a method for identifying optimal laser settings to achieve the desired surface roughness based on the obtained results.

Keywords: *Laser Cutting, Differential Evolution, Roughness, Regression Analysis, Stochastic Optimization*

I. INTRODUCTION

Identifying optimal criteria is essential prior to employing optimization techniques, such as Differential Evolution (DE) and other evolutionary algorithms, in product development. To determine the effective parameters utilized during production, optimization techniques have been developed in the manufacturing sector (Nas & Özbek, 2020). Differential Evolution is an optimization algorithm known for its simplicity and robustness and is widely used to solve complex optimization problems (Kocak et al., 2024; Ozdemir et al., 2017; SHAH & Karabulut, 2022). DE, developed by (Storn & Price, 1997), is a population-based method in the evolutionary algorithms (EA) family (Ahmad et al., 2022). Unlike other traditional methods, DE generates new generations by recombining solutions with scaled difference vectors, and if the new solution outperforms the existing solution, the existing solution is replaced by this new generation (Price et al., 2006). The algorithm relies on a few specific parameters such as the scaling factor, crossover rate mutation and crossover are observed to play an important role in search performance (Qin et al., 2009). In another study (Y. Wang et al., 2024), a model for surface roughness prediction was proposed based on the DE algorithm combined with ensemble learning, aiming to explain the relationship between the machining parameters and surface roughness. Experiments on 3D-printed

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components made of 316L stainless steel demonstrated that the proposed algorithm is more effective than other algorithms, with an average absolute percentage error approximately 42% lower than that of other algorithms. The DE algorithm is known for its straightforwardness and reliability in addressing non-linear and multi-modal optimization challenges. Unlike other algorithms such as Genetic Algorithms (GA) or Particle Swarm Optimization (PSO), DE is less sensitive to parameter settings and often provides better convergence in fewer iterations, making it more efficient for laser cutting parameter optimization.

Laser cutting is an important application of lasers in industry, especially for the processing of materials that are difficult to cut. In contrast to traditional machining methods, laser cutting is characterized by minimal material removal (Xiao et al., 2024), localized precise heat application to the workpiece (Madhava, 2024), minimal distortion (Samantaray et al., 2024), and the absence of tool wear (Begic-Hajdarevic et al., 2016). This technique uses a laser beam to supply thermal energy, which is then transformed into heat. Because the laser beam is electromagnetic radiation, it does not require mechanical cutting force, tool wear, or vibration, and can be focused on the material surface to an extremely small point. Thus, laser beam cutting can be used to cut soft or hard materials (Genna et al., 2020). In laser cutting, a localized increase in the surface temperature occurs due to the interaction of the laser beam with the electrons of the material, which absorb some of the energy. Melting, vaporization, or other chemical changes in the material may result from this increase. The wavelength and power density of the laser, as well as the chemical and physical properties of the material, such as thermal conductivity and absorption capacity, influence these phenomena, which in turn determine the laser-material interaction (Shugaev et al., 2020; Tamrin et al., 2021).

Surface roughness is a technical requirement for mechanical products and is used to measure product quality (Çaydaş & Hasçalik, 2008; Kasman, 2023; Suhail et al., 2010). One of the most important aspects of the functional performance of a part is ensuring the desired surface quality (Magdum et al., 2022; Zdravković et al., 2020). Production costs are significantly impacted by product surface roughness, which is a measure of product quality (Anuja Beatrice et al., 2014; Suhail et al., 2010). Higher manufacturing costs correlate with lower desired surface roughness (Ratnam, 2017). Prior to the production process, the selection of the appropriate cutting parameters is necessary to achieve the expected surface roughness (Aslan et al., 2007; Sharma et al., 2012; Tseng et al., 2016) Although it is usually desirable to reduce surface roughness in industry, the opposite situation may be desired in some studies. Ghalandarzadeh et al. (2023) found that zirconia samples treated with different laser power densities exhibited higher surface roughness compared to untreated samples. This increase in surface roughness corresponded to an increase in hydrophobicity, indicating a potential relationship between surface texture and wettability.

Laser surface treatment is a highly nonlinear process (Ozbey & Tıkız, 2024; Tamanna et al., 2019). Optimization of laser parameters and analysis of the changes that occur on the surface of the laser-machined material are of great importance for the manufacturing industry (2022; Ürgün et al., 2024). Accurate adjustment of these parameters plays a critical role in bringing the material properties to the desired level and increasing the efficiency of the production processes (Rouf et al., 2022). In literature, laser material interaction has been studied experimentally and analytically from different perspectives (Um et al., 2022; G. Wang et al., 2021). The various forms of selective laser–material interaction approaches and their properties utilized in biomedical devices and materials were presented by Um et al (2022). G. Wang et al. (2021) utilized laser direct deposition, an additive manufacturing technique, to produce W–Cu composite material. Experimental and simulation analyses were conducted to investigate laser-powder interaction and particle transport phenomena. The microstructure of mild steel samples was altered through the use of a diode laser with a maximum power output of 3.3 kW, combined with electrochemical processes in another study (Speidel et al., 2016). The findings showed that the exposed surface textures and the chemistry of the surfaces can be modified by combining laser pretreatment with EJM. In this case, the machined surface roughness was shown to increase from approximately 0.45 µm for untreated surfaces to roughly 18 µm for surfaces subjected to intensive laser pretreatment. In another study (Salleh et al., 2020), mild steel was subjected to surface hardening with a fiber laser with a wavelength of 1060 nm. It was observed that higher laser power increased the surface hardness, but higher scanning speeds decreased the surface hardness. Laser material interaction can be studied with various optimization techniques. (Fan et al., 2023) used Taguchi Methods and Response Surface Method to improve surface roughness in laser-assisted rapid tool servo (LAM-FTS) machining of glass-ceramic materials. The results showed that the most effective parameters were laser power, spindle speed, feed rate and piezoelectric frequency, respectively. In other study (G. Wang et al., 2024), the optimal cleaning parameters were determined using the response surface method and the second-generation non-dominated sequencing genetic algorithm (NSGA-II) to improve the surface quality during laser removal of rust layers on Q390 steel. In the study, a mathematical model was established between input variables (laser power, cleaning speed, scanning speed and repetition frequency) and target values (surface oxygen content, rust layer removal rate and surface roughness). As a result of the study, surface corrosion was effectively removed, a distinct metal brightness was achieved, and a pre-weld surface treatment standard was achieved.

In this study, regression analysis and stochastic optimization were carried out for the laser cutting of mild steel. Experimental data were obtained from the literature and analytical processes were examined in detail. The laser parameters (laser power, cutting speed and assist gas pressure) were specified as inputs in 5 levels, and the response was considered roughness. The measurement analysis results were examined using Minitab 19 software for a 0.05 significance level ($\alpha = 0.05$) with an L25 Orthogonal Array. The regression equation was determined, and the surface roughness was optimized using the differential evolution algorithm. The originality of this study lies in the combination of regression analysis and DE algorithm to optimize the surface roughness during laser cutting. This combination offers an innovative and effective approach to optimize critical parameters such as surface roughness in laser cutting processes. While statistical analyses reveal the relationship between cutting parameters and surface roughness by modeling the effects of independent variables, the DE algorithm optimizes these parameters to improve both accuracy and efficiency in manufacturing processes. Unlike existing methods in literature, this novel approach allows for a more effective handling of nonlinear manufacturing processes.

II. MATERIAL METHODS

In this study, experimental data were obtained from (Madić & Radovanović, 2013). Madić and Radovanović used a 2.2 kW CO_2 laser for the laser cutting of commercial mild steel sheets with a thickness of 2 mm. The chemical compositions, (Samatham et al., 2017) mechanical and physical properties (Khan et al., 2013; Villavicencio & Guedes Soares, 2011) of mild steel are given in Table 1.

Table 1. Chemical composition (wt.%) (Samatham et al., 2017), physical and mechanical properties of mild steel (Khan et al., 2013; Villavicencio & Guedes Soares, 2011).

Chemical composition (wt.%)					
Sample	Fe	Si	Mn	P	C
Mild Steel	98.7	0.2	0.54	0.16	0.17

Mechanical properties				
Yield strength	Tensile strength	Hardness	Young's modulus	Poisson's ratio
275 MPa	475 MPa	143 HB	206 GPa	0.3

Physical properties			
Density	Thermal conductivity	Specific heat capacity	Melting Point
7850 kg/m3	51.9 W/m. K	0.472 J/g °C	1523 °C

The cutting process was performed in Gaussian distribution beam mode using 99.95% pure oxygen as the protective gas. With a 127 mm focal length focusing lens, the laser beam was focused on the sample surfaces. A conical nozzle (HK10) with a 1 mm diameter, a consistent stand-off distance of 0.7 mm was used to maintain between the nozzle and the workpiece. The parameters, including the focusing lens specifications, nozzle diameter, focus position, stand-off distance and sheet thickness, were held constant throughout the experiment (Madić & Radovanović, 2013). In their study, Madić and Radovanović (Madić & Radovanović, 2013) investigated the roughness of mild steel by varying laser parameters such as the laser power, cutting speed , and assist gas pressure. The specific process variables and their levels are listed in Table 2.

Table 2. Process parameters and experimental design levels (Madić & Radovanović, 2013).

Variables	Levels				
	1	2	3	4	5
Cutting speed, v (mm/min)	3000	4000	5000	6000	7000
Laser power, P (W)	700	900	1100	1300	1500
Assist gas pressure, p (bar)	3	4	5	6	7

This study employed five levels and three main laser parameters, namely, cutting speed, laser power, and assist gas pressure, to optimize the cutting process. The experimental design was created using an L25 orthogonal array, and MINITAB (Version 19) was employed as the statistical tool for its development. The experimental results and input parameters are given in Table 3.

Table 3. Experimental results (Madić & Radovanović, 2013).

Exp. No	Cutting speed (mm/min)	Laser Power (W)	Assist gas Pressure (bar)	Surface Roughness (μm)
1	3000	700	3	1.487
2	3000	900	4	1.29
3	3000	1100	5	2.073
4	3000	1300	6	2.477
5	3000	1500	7	2.937
6	4000	700	4	1.78
7	4000	900	5	1.707
8	4000	1100	6	2.337
9	4000	1300	7	3.307
10	4000	1500	3	1.19
11	5000	700	5	2.013
12	5000	900	6	2.017
13	5000	1100	7	2.603
14	5000	1300	3	1.173
15	5000	1500	4	1.38
16	6000	700	6	1.66
17	6000	900	7	1.71
18	6000	1100	3	0.963
19	6000	1300	4	1.007
20	6000	1500	5	1.143
21	7000	700	7	1.587
22	7000	900	3	0.832
23	7000	1100	4	0.903
24	7000	1300	5	0.88
25	7000	1500	6	1.073

Differential evolution is a powerful stochastic real parameter optimizing algorithm (Islam et al., 2012). DE is sensitive to the choice of mutation strategy and the settings of control parameters such as crossover rate, scale factor and population size (Mallipeddi & Suganthan, 2010; Saad et al., 2024) . Because of these features, DE generates better optimal solutions for optimization issues involving experimental work and time constraints (Ahmed et al., 2020). The mathematical modeling of the Differential Evolution (DE) algorithm was done using Wolfram Mathematica. The steps used in the program are given below (Ceylan et al., 2023; Dash et al., 2023; Rubal & Kumar, 2018):

1. Define a population consisting of h points $\{a_1,a_2,\ldots,a_h\}$, ensuring that h exceeds the total number of design variables.
2. Generate the population points randomly.
3. Utilize the real scaling factor *rsf*, defined as $a_{rsf} = a_w+rsf\cdot(a_u-a_v)$, to generate new iteration points based on the existing population.
4. Update a by modifying its *j-th* coordinate from a_{rsf} according to the probability P. In this stage, the "CrossProbability" parameter within Mathematica is set within the range [0,1]. If the constraint $f(a_i)>f(a_{new})$ is satisfied, the original point is retained instead of the newly generated point.
5. Evaluate the convergence by comparing the difference between the two most recently generated points. If this difference is below the specified tolerance, the algorithm halts. This hybrid approach can address problems involving integer variables or cases where the objective function is non-numeric.

The steps of the Differential Evolution Algorithm are presented in Figure 1.

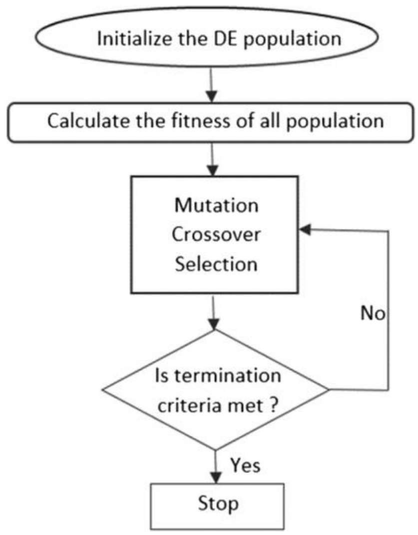

Figure 1. Steps for Differential Evolution Algorithm (Rubal & Kumar, 2018).

III. RESULTS AND DISCUSSION

In this study, it is aimed to determine the laser parameters that would improve the surface properties of mild steel using statistical methods. To achieve the highest surface quality, surface roughness should be minimized. In the first part of this study, the response (roughness) values were assessed using the normality test. Probability charts are vital for examining whether a dataset matches a particular theoretical distribution. These plots compare the actual dataset with a theoretical distribution to test the hypothesis that a statistical sample derives from a specified distribution (Ferré, 2009). As shown in Figure 2, the P-value is greater than 0.05; therefore, the response values are normally distributed and follow almost a straight line; thus, surface roughness data can be used in statistical analysis.

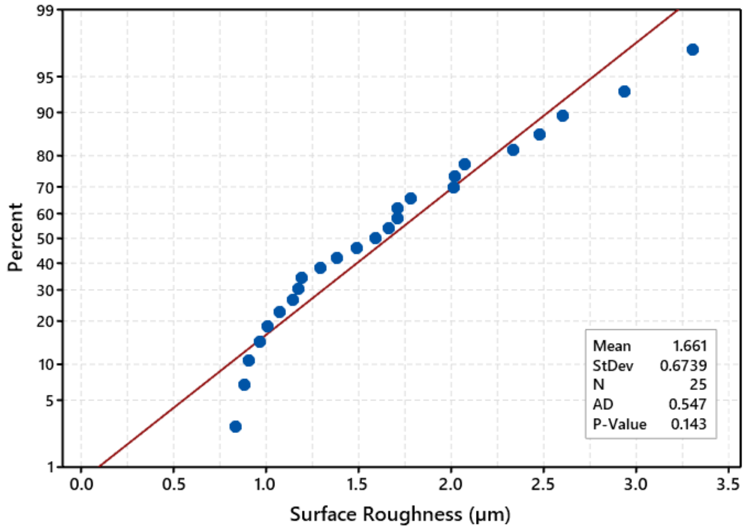

Figure 2. Probability plot of roughness.

Table 4 presents the correlation matrix. There is an inverse, moderate and statistically significant relationship between cutting speed and surface roughness, a strong and statistically significant relationship between assist gas pressure and surface roughness as in reference (Zeilmann & Conrado, 2022), and a weak and statistically insignificant relationship between laser power and surface roughness. In addition, as in reference (Erkan, 2023), while surface roughness decreases with increasing cutting speed, surface roughness increases with increasing assist gas pressure.

Table 4. Correlation matrix ((*. Correlation is significant at the 0.05 level (2-tailed)) and (**. Correlation is significant at the 0.01 level (2-tailed))).

		Cutting Speed	Laser Power	Assist Gas Pressure	Surface Roughness
Cutting Speed	Pearson Correlation	1	0	0	-0.398*
	Sig. (2-tailed)		1	1	0.049
	N	25	25	25	25
Laser Power	Pearson Correlation	0	1	0	0.093
	Sig. (2-tailed)	1		1	0.657
	N	25	25	25	25
Assist Gas Pressure	Pearson Correlation	0	0	1	0.526**
	Sig. (2-tailed)	1.000	1.000		0.007
	N	25	25	25	25
Surface Roughness	Pearson Correlation	-0.398*	0.093	0.526**	1
	Sig. (2-tailed)	0.049	0.657	0.007	
	N	25	25	25	25

The multicollinearity between independent variables was checked. The variance inflation factor (VIF) < 10 and the condition index (CI) < 30 indicate that there is no multicollinearity problem among the independent variables.

Statistical regression analysis was performed to characterize the interaction between one or more independent variables and dependent variables. The objective of regression analysis is to determine how independent factors affect the dependent variable (Arnab, 2017; Freund et al., 2010; Thomasian, 2022). The regression equation (R^2= 83.21%) for the laser cutting process was determined in Equation 1 using Minitab 19.

$$\text{Surface Roughness } (\mu m) = 1.458 - 0.000276 \text{ Cutting speed (mm/min)} - 0.000032 \text{ Laser power (W)} + 0.3240 \text{ Assist gas pressure (bar)} \quad (1)$$

Contour and surface plots for surface roughness are given in Figures 3 and 4 respectively. The analysis shows that the laser parameters have a significant effect directly on the roughness and in interaction with each other. In contour plots, laser power and cutting speed have been observed to reduce roughness beyond a certain threshold value. Similarly, the roughness exhibits different trends with increasing pressure. In the surface plots, the relationship between these parameters is revealed in more detail and low roughness regions are identified.

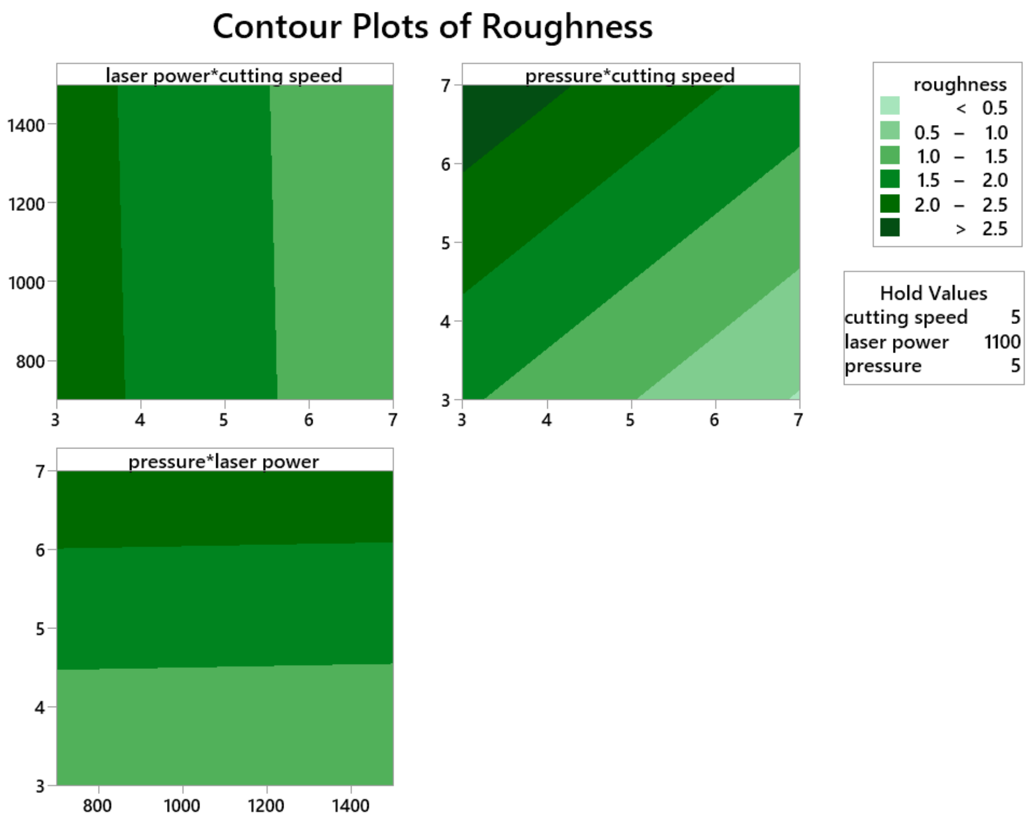

Figure 3. Contour plots of roughness.

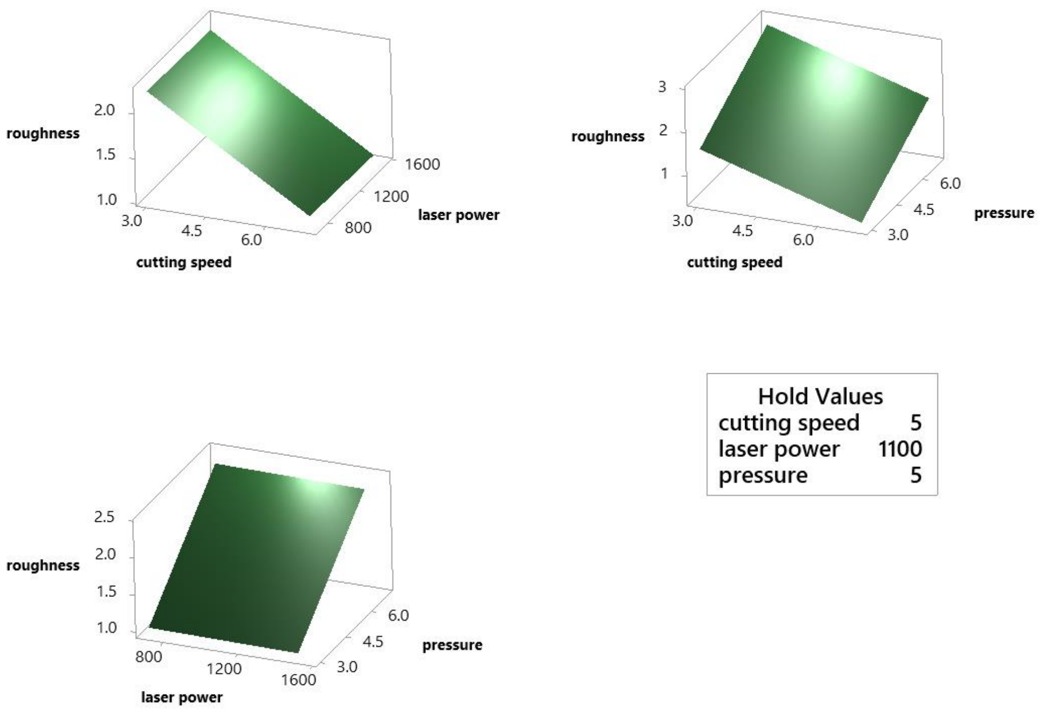

Figure 4. Surface plots of roughness.

After regression analysis, the estimated roughness was determined and compared with the experimental results. experimental and estimated results obtained by the second-order regression analysis are compared in Figure 5. The figure demonstrates a strong correlation between actual test results and predicted outcomes. The calculated coefficient of determination (R^2) values, reaching 86.6 %, for the equations used to determine the surface roughness, signify a high degree of accuracy. Consequently, the second-order regression model was effective for estimating surface roughness within the 95% CI.

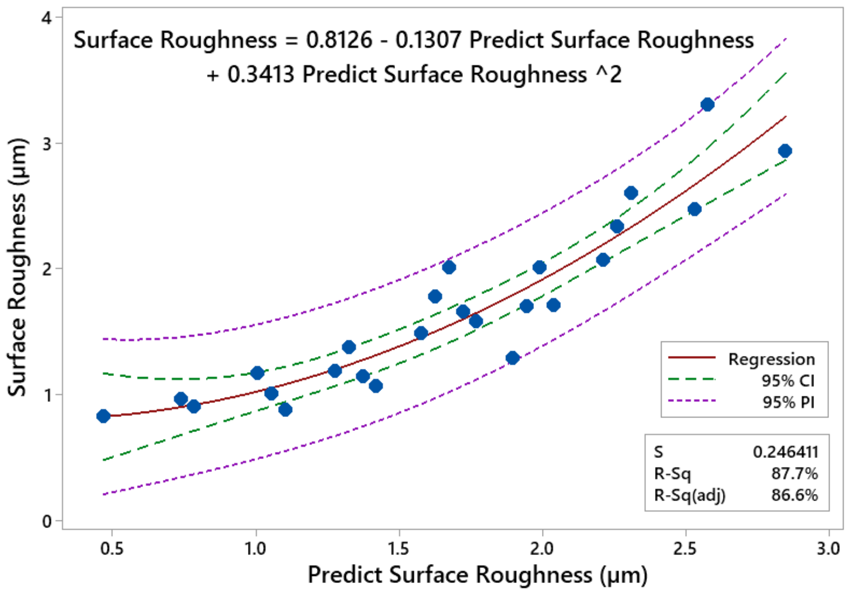

Figure 5. The quadratic regression model compared with the experimental roughness results.

In order to understand the effect of the laser parameters on the surface roughness, a Pareto chart is provided in Figure 6. In the Pareto chart, the standardized effect represents the magnitude and significance of the effect of each factor on the response variable (Hashem et al., 2018; Makableh et al., 2021). The red dashed line in the figure represents a boundary with a value of 2.080, which indicates the level of statistical significance (95% confidence interval). The laser parameter that has the most influence on the surface roughness is assist gas pressure and the second most influential parameter is the cutting speed. The laser power is statistically below the analytical limit of 22.080, i.e. the laser power does not have a statistically significant effect on the surface roughness. Possible reasons for the lack of effect of laser power on surface roughness could be the power range used or the type of laser used in the study. It can be concluded from these results that future studies should focus on laser parameters such as gas pressure and laser cutting speed of mild steel.

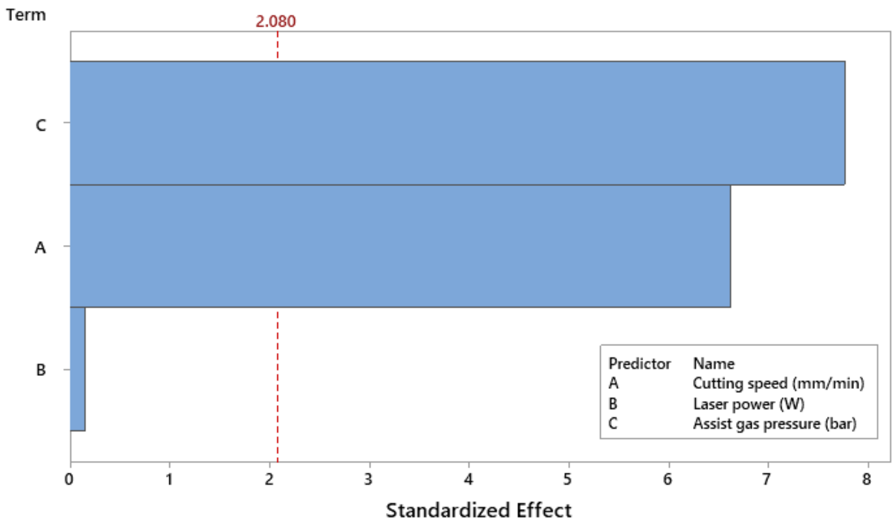

Figure 6. Pareto Chart of the Standardized Effects for Surface Roughness (α = 0.05).

Differential evolution is a stochastic, population-based heuristic search approach for continuous domains, which is a subfield of evolutionary programing. Differential evolution is a straightforward, user-friendly, fast, and reliable heuristic technique (Karci, 2017). Table 5 shows the optimization results obtained using the differential evolution algorithm, which minimizes the surface roughness during laser cutting. The results show that the optimal parameter settings to achieve a minimum roughness value of 0.442 µm are a cutting speed of 7000 mm/min, laser power of 1500 W, and gas pressure of 3 bar.

Table 5. Optimization results of the differential evolution algorithm for roughness (a: Cutting speed (mm/min), b: Laser power (W), and c: Assist gas pressure (bar)).

Objective Function	Constrains	Min Roughness (µm)	Suggested Design
1.458 - 0.000276 a - 0.000032 b + 0.3240 c	3000≤ a ≤7000 700≤ b ≤1500 3≤ c ≤7	0.442	a = 7000 b = 1500 c = 3

Figure 7 shows how the differential evolution algorithm optimizes the objective function value during the iteration process. In the first iteration, there is a rapid decrease in the value of the objective function, and the solution stabilizes at about the 40th iteration. This indicates that the algorithm has reached an optimal solution. Differential Evolution is an efficient solution method for engineering design, hyperparameter optimization and similar problems.

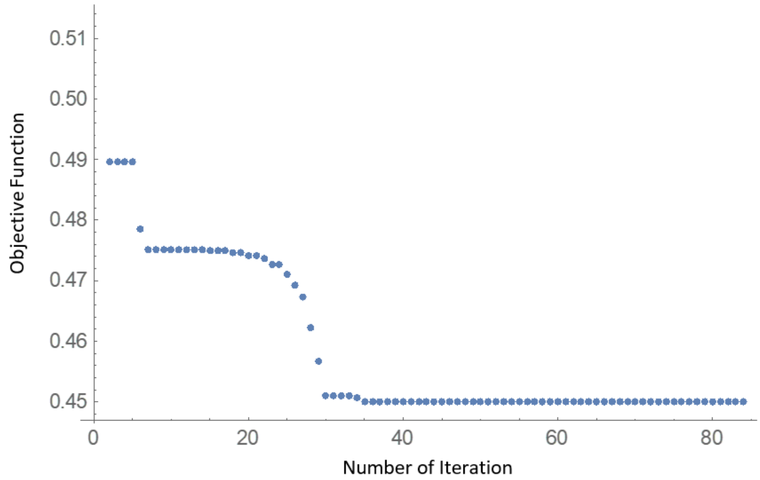

Figure 7. Convergence graphic for differential evaluation algorithm.

In this study, it was observed that increasing laser power led to a significant increase in surface roughness. However, when laser power decreased, surface roughness showed a tendency to decrease as well. This is consistent with previous studies (Kim et al., 2022), where lower laser power resulted in minimal changes in surface roughness. In industrial applications, these findings can enhance the efficiency of laser cutting machines. For example, the combination of low laser power and high cutting speed can save time in rapid prototyping and mass production.

IV. CONCLUSIONS

The aim of this study was to determine the optimum cutting settings for achieving superior surface finish in laser cutting processes. First, normality tests confirmed that the surface roughness data followed a normal distribution, indicating their suitability for statistical analysis. Regression analysis showed a strong relationship between surface roughness and independent variables (cutting speed, laser power and auxiliary gas pressure), resulting in a regression equation with an R^2 value of 83.21%. The predictions of the model are in close agreement with the experimental results and demonstrate high accuracy, as evidenced by the R^2 value of 86.6%. Optimization by means of the DE algorithm determined the optimal parameters for the minimum surface roughness as 7000 mm/min cutting speed, 1500 W laser power, and a 3-bar auxiliary gas pressure, resulting in a minimum roughness of 0.442 µm. The results of this study are highly relevant for industries that utilize the laser cutting process for precision manufacturing, such as automotive, aerospace and metal fabrication. The combined use of regression analysis and differential algorithms can be applied to nonlinear manufacturing processes, offering a reliable and cost-effective parameter optimization approach. Overall, this study could contribute to reducing production costs and improving product quality in industrial settings. By optimizing laser cutting parameters, particularly for high-volume production, it is possible to achieve faster processing times, reduce energy consumption, and minimize material waste.

DECLARATIONS

Author Contributions: Conceptualization, S.O.; methodology, S.O. and A.K.; validation, S.O., I.T. and A.K.; research, S.O. ; references, S.O., I.T. and A.K; data editing S.O., I.T. and A.K; writing-original drafting, S.O. ; writing-review and editing, S.O., I.T. and A.K; checking, S.O., I.T. and A.K. All authors have read and accepted the published version of the manuscript.

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Use of AI Tools: Artificial intelligence tools used for language and readability improvements

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