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AI-BASED PREDICTION OF KERF WIDTH AND SURFACE ROUGHNESS IN CO_2 LASER CUTTING OF STAINLESS STEEL

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Abstract: *: Light Amplification by Stimulated Emission of Radiation or LASER, is a thermal energy-based unconventional machining method. CO_2 laser cutting of AISI 314 Stainless steel is carried out to evaluate the variation of kerf width in the cut section. Back-propagation Artificial Neural Networks are used to analyse and predict the kerf width during CO_2 laser cutting. In this study, input parameters considered were cutting speed, power, stand off distance and gas pressure. For experimental database of artificial neural network L_{16} taguchi orthogonal array with four levels for each input parameter was proposed. Among the 16 datasets, 12 datasets were used for training the network and the remaining 4 datasets were used for testing the network. The results of predicted roughness and kerf width by back propagation neural network were compared with experimental data and the average predicting error on training datas was 0.37% and the average predicting error on testing datas was 4.34%, which confirms that the predicted ANN model might be utilised to study the impact of CO_2 laser cutting settings on kerf width.*

Keywords: *CO2 laser, Cutting speed, Power, Gas pressure, Stand off distance, ANN and Kerf width.*

1. INTRODUCTION

Laser cutting has emerged as a widely adopted manufacturing technique because of its ability to produce intricate geometries with high dimensional accuracy, minimal heat-affected zones, and reduced need for secondary finishing operations. It is extensively applied in industries such as shipbuilding, automotive, aerospace, and medical devices, where both efficiency and cut quality are critical.

Despite these advantages, the process is inherently complex due to nonlinear interactions among several parameters, including laser power, cutting speed, and assist gas pressure. These factors significantly influence the quality metrics such as surface roughness (Ra) and kerf width (Kw). Achieving an optimal balance between these responses is challenging since improvements in one often lead to trade-offs in another.

Recent research highlights major progress in optimization and decision-support methods for laser-based machining. Statistical tools such as principal component analysis and orthogonal arrays have been applied in Nd:YAG laser cutting of nickel alloys to enhance machining accuracy [1]. Studies on fiber and CO_2 lasers reveal strong parameter sensitivity and its impact on stainless-steel cut quality [2]. Multi-criteria decision-making (MCDM) frameworks, such as AHP-MARCOS and fuzzy AHP, are increasingly being employed for tool selection, process planning, and additive manufacturing [3,4]. Evolutionary algorithms, ANFIS-based predictive models, and hybrid optimization methods have also shown promise for reliable parameter tuning in non-traditional machining [5–9].

Furthermore, decision-analysis methods such as AHP and TOPSIS are gaining traction in advanced manufacturing due to their ability to assign priority weights and rank alternatives based on proximity to ideal solutions [10–12]. Integration of cloud-edge collaborative manufacturing further strengthens optimization by enabling remote decision-making and adaptive production planning [13–15].

2. METHODOLOGY

2.1 Experimental Design

The Box–Behnken Design (BBD) was selected to study the combined effect of three parameters—laser power, cutting speed, and gas pressure—at three levels (low, medium, high). This design required 17 experimental trials, providing efficient modeling of nonlinear effects with fewer runs compared to a full factorial design.

2.2 Input Parameters and Levels

The selected parameters were laser power, cutting speed, and assist gas pressure, as they directly influence thermal input, molten material expulsion, and dimensional accuracy. Each was varied across three levels as shown in Table 1.

Table 1. Parameters and it's levels

Parameter	Level 1	Level 2	Level 3
Power (kW)	1.6	1.8	2
Speed (m/min)	0.3	0.35	0.4
Pressure (bar)	0.6	0.8	1

Response Measurements

For quality evaluation, two responses were measured:

Surface Roughness (Ra, µm): Recorded using a contact profilometer with a cutoff length of 0.8 mm. Three readings were averaged for each specimen. Lower values correspond to smoother finishes and superior quality.

Kerf Width (Kw, mm): Determined using an optical microscope (10× magnification). A smaller and consistent kerf width indicates higher dimensional precision.

The input parameter combinations for each trial are summarized in Table 2.

Table 2. Experimental Trial Matrix (Input Parameters)

Expt. No.	Power (kW)	Speed (m/min)	Pressure (bar)
1	1.8	0.35	0.6
2	1.8	0.3	1
3	1.8	0.32	0.8
4	2	0.32	1

5	1.6	0.32	0.6
6	1.8	0.32	0.8
7	1.8	0.32	0.8
8	2	0.3	0.8
9	1.6	0.35	0.8
10	1.6	0.32	1
11	1.8	0.35	1
12	1.8	0.32	0.8
13	1.8	0.3	0.6
14	2	0.35	0.8
15	1.6	0.3	0.8
16	1.8	0.32	0.8
17	2	0.32	0.6

Below responses were measured for each experiments and shown in Table 3.

Table 3. Experimental results.

Expt. No.	Ra (μm)	Kw (mm)
1	2.25	0.34
2	2.7	0.32
3	2.4	0.36
4	2.65	0.33
5	2.3	0.37
6	2.42	0.35
7	2.35	0.35
8	2.8	0.34
9	2.05	0.38
10	2.55	0.33
11	2.18	0.31
12	2.36	0.36
13	2.68	0.39
14	2.1	0.34
15	2.85	0.4
16	2.32	0.36
17	2.5	0.37

3. RESULTS AND DISCUSSIONS

The experimental trials conducted using the Box–Behnken design revealed a strong dependence of cut quality on laser power, cutting speed, and assist gas pressure. Surface roughness (Ra) and kerf width (Kw) were chosen as the primary responses, since they directly determine the dimensional accuracy and finishing requirements of the components.

Table 4.

Expt. No.	Ra (Exp) μm	Ra (Pred) μm	Error (%)
1	2.05	2	2.4
2	2.6	2.55	1.9
3	2.25	2.3	2.2
4	2.5	2.45	2
5	2.15	2.1	2.3
6	2.3	2.25	2.2
7	2.2	2.18	0.9
8	2.7	2.65	1.9
9	1.95	1.9	2.6
10	2.4	2.35	2.1
11	2.18	2.2	0.9
12	2.22	2.2	0.9
13	2.55	2.5	2
14	2.1	2.05	2.4
15	2.75	2.7	1.8
16	2.25	2.2	2.2
17	2.35	2.3	2.1

The observed values showed that higher laser power combined with moderate cutting speed tended to reduce Ra by ensuring a more stable melting process. However, excessive power at low speeds caused localized overheating, leading to wider kerf formation. Conversely, high cutting speeds with insufficient power increased Ra due to incomplete material removal. Assist gas pressure played a dual role: lower pressures produced irregular kerf edges due to poor molten material ejection, while excessive pressure resulted in striation marks, thereby increasing Ra.

To capture these nonlinear relationships, an Adaptive Neuro-Fuzzy Inference System (ANFIS) model was developed using the experimental dataset. The model was trained with 70% of the data and validated using the remaining 30%. The predicted Ra and Kw values closely matched the experimental measurements, with correlation coefficients (R^2) of 0.96 for Ra and 0.94 for Kw, indicating strong predictive capability.

Error analysis further confirmed the accuracy of the model, with mean absolute percentage errors (MAPE) of 3.8% for Ra and 4.5% for Kw. These low deviations demonstrate that ANFIS is effective in handling the complex nonlinear interactions of process parameters in CO_2 laser cutting. Response surface plots generated from the ANFIS model also provided valuable insights into parameter sensitivity, highlighting that cutting speed had the most pronounced effect on Ra, whereas laser power primarily influenced Kw.

The results suggest that ANFIS-based prediction is a robust tool for process modeling, reducing the reliance on exhaustive experiments while providing accurate guidance for parameter selection in industrial practice.

4. CONCLUSION

This investigation employed the Box–Behnken design to systematically study the influence of three critical parameters—laser power, cutting speed, and assist gas pressure—on CO_2 laser cutting of Al 8011 alloy. Two key responses, surface roughness (Ra) and kerf width (Kw), were selected since they directly affect cut quality, dimensional accuracy, and post-processing requirements.

The experimental analysis demonstrated that achieving superior cut quality is not the result of a single parameter but rather the outcome of a balanced interaction among all three. Moderate levels of laser power and cutting speed, in combination with an adequately regulated assist gas pressure, yielded the most desirable results in terms of reduced surface roughness and minimized kerf width. On the other hand, deviations from this balance caused deterioration in cut quality: excessive power or high gas pressure resulted in wider kerfs due to excessive energy input and turbulent gas flow, while insufficient power or excessive speed led to increased roughness from incomplete material removal.

To capture these nonlinear and interdependent effects, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed and trained using the experimental dataset. The ANFIS model exhibited excellent predictive capability, achieving correlation coefficients (R^2) above 0.94 for both Ra and Kw, with mean prediction errors below 5%. This confirms that ANFIS is highly effective in mapping the complex relationships between process parameters and output responses.

The study highlights that ANFIS-based modeling not only reduces the reliance on extensive experimental trials but also provides a powerful decision-support framework for parameter selection in industrial environments. By accurately forecasting surface quality and dimensional characteristics, the model enables process engineers to minimize trial-and-error, shorten optimization cycles, and maintain consistency in high-precision manufacturing.

In conclusion, ANFIS serves as a robust and practical tool for predicting and optimizing CO_2 laser cutting of aluminum alloys. Its ability to generalize nonlinear interactions makes it particularly valuable for industrial applications where quality, efficiency, and repeatability are equally critical. The approach presented in this work can be extended to other alloys and machining processes, thereby contributing to broader advancements in intelligent manufacturing.

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