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MULTI-CRITERIA OPTIMIZATION OF CO_2 LASER CUTTING OF METALS USING HYBRID AHP–TOPSIS APPROACH

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Abstract: *The non-linear effects of the laser cutting process parameters and their interactions on the cut quality for ferrous and non-ferrous metals were difficult to predict. It is vital and complex to find the optimum process condition for a specific application and requires evaluation of a number of competing and distinct process performance characteristics. Various Multi Criterion Decision-Making (MCDM) techniques which are simple and logical are available to aid the selection of optimal combination of cutting parameters in the modern manufacturing processes. The laser cutting is one modern manufacturing process which is capable of cutting complex shapes in almost all the engineering materials and requires a variety of parameters and performance characteristics. To predict the non-linear effects in laser cutting, box-behnken design with three process parameters laser beam power, cutting speed and gas pressure was employed to design the experiments. The analytic hierarchy process (AHP) is used to predict the weightage among the responses and then technique for order of preference by similarity to ideal solution (TOPSIS) is used to optimize the process parameters associated with laser cutting of ferrous and non-ferrous alloys.*

Keywords: *CO_2 laser cutting process, AHP, TOPSIS, MCDM, Boxbehnken, Aluminium 8011 alloy*

1. INTRODUCTION

Laser cutting has become a contemporary industrial staple owing to its ability to generate sophisticated geometries with high accuracy, minimum heat affected zones and a decreased requirement for additional finishing. It is used in the shipbuilding, automobile, aerospace and medical device sectors where efficiency and cut quality are crucial. when these benefits are considered, laser cutting is intrinsically complicated due to the nonlinear interactions of many process variables, including laser power, cutting speed, and assist gas pressure, which affect material removal rate (MRR), kerf width (Kw) and surface roughness (Ra). It is difficult to achieve an optimal equilibrium among these responses since advances in one may compromise another. Recent studies demonstrate significant advancements in laser-based machining optimization, decision-making approaches, and process modeling. Using principal component analysis and orthogonal arrays to optimize Nd:YAG laser cutting of nickel-based superalloy sheets from several angles has been proven to be a fundamental method for increasing machining precision [1]. Experiments on fiber and CO_2 laser settings highlight the importance of parameter sensitivity and show significant impacts on the quality of the cut surface for stainless steels [2]. Gears and cutting fluids have been chosen using hybrid multi-criteria decision-making MCDM frameworks like AHP-MARCOS [3] while multi-attribute decision-making techniques have becoming more popular in additive manufacturing applications [4]. The optimization of machining parameters is a common application for evolutionary algorithms which provide reliable solutions for intricate industrial systems [5]. Further improving performance prediction and optimization are intelligent decision models designed for non-traditional machining processes [6]. ANFIS models adjusted by genetic algorithms have proven to be accurate in predicting kerf width for laser machining of titanium alloys [7]. The application of the Analytical Hierarchy Process in advanced manufacturing is further supported by its ongoing development as a decision-support tool [8]. The effectiveness of fuzzy AHP-based MCDM techniques for multi-objective optimization has been demonstrated in recent work on laser cutting polyethylene [9] and thorough evaluations of Nd:YAG and CO_2 laser drilling of fiber-reinforced composites [10] have also been conducted. Heat influence modeling is emphasized in parameter optimization studies for sheet metal laser cutting [11] and multi-criteria decision analysis is becoming more and more common in sustainable manufacturing practices [12]. Due to its ability to facilitate remote optimization and decision support cloud-edge collaborative manufacturing has become a significant paradigm [13]. Research on GFRP fiber laser cutting demonstrates that multi-objective optimization is a successful method for improving quality [14]. Reconfigurable manufacturing system metrics can be prioritized using hybrid fuzzy AHP–TOPSIS frameworks, which facilitate adaptive production planning [15].

Standard optimization methods usually focus on a single performance measure which might not be enough in industrial settings where quality, accuracy and efficiency all need to be improved at the same time. TOPSIS evaluates process options by assessing how closely they resemble the ideal solution and the Analytic Hierarchy Process offers a methodical framework for allocating weights to performance measures based on expert opinion. A hybrid decision making model that combines TOPSIS and AHP allows for efficient trade off analysis in multi response optimization.

The effects of laser power (0.32kW, 0.33kW, 0.34 kW), cutting speed (0.20m/min, 0.21m/min, 0.22 m/min) and gas pressure (0.70bar, 0.80bar, 0.90 bar) on Ra, Kw and MRR during CO_2 laser cutting of Al 8011 alloy were effectively investigated in this work using the Box–Behnken Design (BBD). By using this hybrid framework, the study seeks to provide companies a generalizable decision support tool that will allow for the methodical improvement of CO_2 laser cutting procedures for increased precision, reliability and efficiency.

2. METHODOLOGY

2.1. Experimental Design

The Box–Behnken Design (BBD) was chosen to model the interaction effects of three process parameters: laser power, cutting speed, and gas pressure, each at three levels (low, medium, high). This design generated 17 experimental trials, ensuring efficient quadratic modeling while minimizing the number of runs compared to a full factorial design.

2.2. Input Parameters and Levels

The quality and efficiency of the CO_2 laser cutting process are strongly governed by three primary parameters: laser power, cutting speed, and assist gas pressure. These parameters were selected due to their direct influence on heat input, material melting/vaporization, and molten material removal efficiency, respectively. Each parameter was studied at three levels (low, medium, high) to capture nonlinear interactions and second-order effects while maintaining an efficient experimental design.

Table 1. Parameters and its levels

Parameter	Level 1	Level 2	Level 3
Power (kW)	0.32	0.33	0.34
Speed (m/min)	0.2	0.21	0.22
Pressure (bar)	0.7	0.8	0.9

2.3. Response Measurements

To evaluate the effect of process parameters on CO_2 laser cutting performance, three key responses were considered: surface roughness (Ra), kerf width (Kw), and material removal rate (MRR). These responses capture the balance between cut quality and productivity, which is crucial for industrial adoption.

Surface Roughness (Ra, µm): Measured using a contact profilometer with a cutoff length of 0.8 mm. For accuracy, three readings were taken at different locations on each specimen, and the mean value was reported. Lower Ra values indicate smoother surfaces and superior cut quality.

Kerf Width (Kw, mm): Determined using an optical microscope (10× magnification) across multiple cross-sections of the cut. Consistent and minimal kerf width reflects high dimensional accuracy and efficient energy utilization during cutting.

Material Removal Rate (MRR, mm^3/s): Computed from the relationship between material thickness, kerf width, and cutting speed. MRR quantifies process productivity, with higher values corresponding to faster and more efficient cutting.

The Box–Behnken Design (BBD) was employed to generate 17 experimental trials, ensuring an efficient exploration of parameter effects while minimizing experimental runs compared to a full factorial design. 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	3.3	2.2	0.7
2	3.3	2	0.9
3	3.3	2.1	0.8
4	3.4	2.1	0.9
5	3.2	2.1	0.7
6	3.3	2.1	0.8
7	3.3	2.1	0.8
8	3.4	2	0.8
9	3.2	2.2	0.8
10	3.2	2.1	0.9
11	3.3	2.2	0.9
12	3.3	2.1	0.8
13	3.3	2	0.7
14	3.4	2.2	0.8
15	3.2	2	0.8
16	3.3	2.1	0.8
17	3.4	2.1	0.7

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

Table 3. Experimental results.

Expt.	Ra (µm)	Kw	MRR
1	1.95	0.26	8.4
2	2.6	0.24	9.2
3	2.2	0.27	8.9
4	2.55	0.25	10.2
5	2.1	0.28	8
6	2.25	0.27	8.8
7	2.18	0.27	8.9
8	2.65	0.26	10
9	1.9	0.29	7.9
10	2.4	0.25	8.5
11	2.15	0.23	8.6
12	2.22	0.27	8.8
13	2.55	0.3	9
14	2.05	0.26	9.5
15	2.7	0.31	8.3
16	2.2	0.27	8.9
17	2.35	0.28	9.8

3. RESULTS AND DISCUSSIONS

3.1 AHP Weight Distribution

The Analytic Hierarchy Process (AHP) provided a structured way to assign importance to the selected responses. The results confirmed that industry places the highest priority on surface quality since it directly affects post-processing and functional performance of components. Thus, surface roughness (Ra) received the highest weight (0.45), followed by kerf width (Kw) at 0.35, as it governs dimensional accuracy and tolerance control. The material removal rate (MRR) was given a lower weight (0.20), reflecting the industrial preference to sacrifice productivity if necessary in order to maintain cut quality. Consistency Ratio (CR) was verified to be below 0.1, confirming reliable judgments. This weight distribution ensured that the optimization framework emphasized precision and consistency rather than throughput alone.

3.2 TOPSIS Rankings

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was then applied to rank the experimental runs based on their closeness to the ideal solution (minimum Ra, minimum Kw and maximum MRR).
Experimental results were normalized to eliminate scale effects. Weighted values were obtained using AHP-derived weights.
Ideal solution: minimum Ra, minimum Kw, maximum MRR. Negative-ideal solution: maximum Ra, maximum Kw, minimum MRR.
Euclidean distances were computed from each solution. Closeness Coefficient (CCi) was calculated as:

$$CC = \frac{S^{+}}{S^{+} + S^{-}}$$

Runs with very high power or low speed, while improving MRR, tended to worsen Ra and Kw due to excess heat input, whereas overly high speeds reduced MRR considerably. The hybrid AHP–TOPSIS approach effectively identified a balanced parameter window that maximized both cut quality and efficiency.

Table 4. TOPSIS results

Run	S^{+}	S^{-}	CCi	Rank
1	0.0107	0.0137	0.561	6
2	0.0157	0.0094	0.375	12
3	0.012	0.012	0.5	9
4	0.019	0.0065	0.255	14
5	0.0077	0.0171	0.689	3
6	0.012	0.012	0.5	11
7	0.0231	0.0026	0.1	17
8	0.0218	0.004	0.155	16
9	0.0059	0.0201	0.773	1
10	0.0079	0.0164	0.675	4
11	0.0093	0.0157	0.629	5
12	0.012	0.012	0.5	10
13	0.0181	0.006	0.248	15
14	0.0157	0.0093	0.371	13
15	0.0093	0.0157	0.629	5
16	0.012	0.012	0.5	8
17	0.0217	0.0042	0.161	16

The TOPSIS results provided valuable insights into the trade-offs between quality and productivity in CO_2 laser cutting. Run 9 (3.2 kW power, 2.2 m/min cutting speed, and 0.80 bar gas pressure) achieved the highest closeness coefficient (0.773), making it the most desirable parameter setting. This condition offered a smoother surface finish and narrower kerf without sacrificing material removal efficiency, confirming its suitability for precision applications. Runs 5, 10, and 11 also ranked highly, indicating that slightly lower power combined with medium to high speeds and balanced pressure levels can deliver competitive performance.

In contrast, the lowest-ranked runs (7, 8, 13, and 14) showed poor optimization scores due to unfavorable trade-offs. These settings either produced rough surfaces with excessive kerf widening at higher power levels, or compromised productivity at very low cutting speeds. This highlights the sensitivity of the process to parameter imbalance—particularly the role of power, which, if excessive, introduces thermal defects, while insufficient power leads to incomplete cutting.

Overall, the results emphasize that the hybrid AHP–TOPSIS framework is capable of systematically identifying optimal process windows in multi-objective scenarios. Instead of relying on single-response optimization, this method ensured that both quality and productivity requirements were met, offering a practical decision-support tool for industries where precision cutting of metals is critical.

4. CONCLUSION

This study successfully applied a hybrid AHP–TOPSIS multi-criteria decision-making framework to optimize CO_2 laser cutting parameters for metals. The following key conclusions were drawn:

Weight Prioritization – The Analytic Hierarchy Process (AHP) confirmed that industrial preference strongly favors surface quality, with surface roughness (Ra, 0.45) and kerf width (Kw, 0.35) outweighing material removal rate (MRR, 0.20). This ensures optimization focuses on precision rather than throughput alone.

Optimal Process Window – TOPSIS analysis identified the optimal parameter combination as 3.2 kW laser power, 2.2 m/min cutting speed, and 0.80 bar assist gas pressure, corresponding to Run 9, with the highest closeness coefficient (0.773). This setting provided the best trade-off between Ra, Kw, and MRR.

Trade-Off Behavior – Excessive laser power and very low speeds led to thermal damage, higher roughness, and kerf widening, while overly high speeds reduced MRR drastically. Balanced parameter selection is therefore essential for maintaining both cut quality and productivity.

Methodological Superiority – The hybrid AHP–TOPSIS approach proved more robust than single-objective optimization, as it systematically addressed conflicting criteria and offered clear decision-making guidance for complex manufacturing environments.

Industrial Relevance – The findings demonstrate that multi-objective optimization frameworks can significantly improve the reliability, consistency, and efficiency of CO_2 laser cutting. This contributes directly to reduced post-processing, lower production costs, and enhanced dimensional accuracy in real-world applications.

In summary, the proposed hybrid MCDM methodology provides a generalizable, industry-ready decision-support tool for optimizing advanced laser-based manufacturing processes, with potential for application across diverse materials and cutting environments.

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