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PROCESS PARAMETER OPTIMIZATION OF Ti-6Al-4V LASER BEAM WELDS THROUGH RSM-BASED NSGA-II ANALYSIS

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ABSTRACT

Laser beam welding of Ti-6Al-4V alloy requires precise control of process parameters to achieve sufficient penetration while limiting thermal damage. In this study, a hybrid response surface methodology (RSM)–NSGA-II–TOPSIS framework was applied to optimize laser power, welding speed, focal diameter, and shielding gas flow rate with respect to fusion zone width (FZ), heat affected zone width (HAZ), total weld width (TWW), and depth of penetration (DOP). ANOVA results revealed that laser power and welding speed were the dominant factors, jointly contributing more than 50% of the total variation in all responses. DOP ranged from 2.68 to 3.52 mm and exhibited the lowest variability is C.V. = 8.25%. The developed RSM models showed strong predictive capability with R² values above 0.95 and adequate precision exceeding 16. Pareto analysis demonstrated a clear trade-off between penetration and weld geometry. TOPSIS identified a best compromise condition, achieving an 8.6% increase in DOP while achieving 32.0% reduction in TWW and 22.3% reduction in FZ, confirming the effectiveness of the proposed optimization approach for Ti-6Al-4V laser welding.



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I. INTRODUCTION

Laser beam welding (LBW) provides a narrow, high-flux heat source that enables deep penetration with low total heat input, yielding tight, narrow fusion zones and reduced distortion compared to arc welding [1]. Industrial LBW applications include automotive body-in-white panel welding, aircraft substructure manufacture, medical device sealing, power plant tubing, and precision micro-assemblies where narrow HAZ and controlled penetration are required [2-4]. DOP primarily controls mechanical load transfer and joint strength, while enlargements in FZ/HAZ/TWW indicate increased thermal exposure, grain coarsening, and potential toughness reduction [5]. Ti-6Al-4V is the most widely used α - β titanium alloy in aerospace, biomedical, and high-performance engineering applications due to its high strength-to-weight ratio, corrosion resistance, and fatigue performance. However, its low thermal conductivity and strong affinity for oxygen and nitrogen make welding particularly challenging, often leading to excessive heat-affected zone (HAZ) growth, weld geometry instability, and degradation of mechanical properties if thermal input is not properly controlled. Boccarusso et al. showed that fatigue life of Ti-6Al-4V LBW butt joints is governed primarily by weld bead morphology, particularly underfill depth, reinforcement height, and aspect ratio, rather than by bulk microstructural changes alone [6], [7].

Their work highlighted that even geometrically sound welds may suffer reduced fatigue performance if bead morphology induces local stress concentration [8], [9]. Weld bead morphology plays a dominant role in joint performance, particularly fatigue life. Squillace et al. showed that underfill depth and bead geometry strongly control stress concentration in Ti-6Al-4V laser welds, with fatigue life being more sensitive to geometric discontinuities than to bulk microstructural changes alone [10]. Empirical modelling using factorial designs, Taguchi methods and Response Surface Methodology (RSM) remain a mainstream approach for quantifying parameter effects in laser welding [11], [12]. RSM provides low-order polynomial surrogates that are easy to interpret and pair naturally with Analysis of Variance (ANOVA) to decompose percentage contributions of factors and detect significant interactions. Multiple studies have reported R² values typically in the 0.85–0.98 range for RSM models of penetration and bead width and have used ANOVA to show that laser power and welding speed account for most (>50%) of response variance in many systems [13], [14].

ANOVA enables reviewers to judge whether fitted models are meaningful (via p-values), whether lack-of-fit is acceptable, and whether adjusted/predicted R^2 and Adequate Precision meet modeling standards. While RSM-ANOVA models provide high predictive accuracy (typically $R^2 > 0.90$), most reported studies focus on single-response optimization, limiting their applicability to real manufacturing scenarios where multiple quality metrics must be balanced simultaneously [15], [16]. To address this limitation, evolutionary multi-objective algorithms such as the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) have gained attention in laser welding research. NSGA-II enables the generation of Pareto fronts that explicitly reveal trade-offs between penetration enhancement and weld geometry control [17-19]. In the last decade, machine learning (ML) methods including Artificial Neural Networks (ANN) [20], Random Forests[21], Gradient Boosting (XGBoost)[22], and Support Vector Regression have been increasingly employed to model complex, nonlinear mappings between LBW inputs and responses [23] ,[24]. ML surrogates often outperform low-order RSM in predictive accuracy for complex processes, delivering higher R^2 and lower RMSE on validation sets. ANN/XGBoost models in recent studies achieved $R^2 \approx 0.90$ – 0.99 for penetration and surface roughness when sufficient training data or physics-informed features were available [25-27].

Hybrid frameworks that pair ML predictors with NSGA-II produce highly accurate Pareto fronts, while SHAP analyses provide explainability identifying laser power and welding speed as top predictors in most datasets. Despite significant progress, key gaps are that total weld width (TWW) is often excluded as an optimization objective, Pareto fronts are rarely reconciled with ANOVA-based factor significance, and parameter selection commonly relies on visual inspection rather than formal MCDM. Moreover, machine-learning surrogate studies seldom integrate statistical significance analysis with decision-making frameworks, limiting interpretability and robustness. This work develops an integrated RSM–NSGA-II–TOPSIS framework that (a) models FZ, HAZ, TWW (minimize) and DOP (maximize) using validated RSM and ML surrogates, (b) uses ANOVA to quantify factor contributions and reconcile statistical significance with Pareto trends, (c) generates experimentally grounded Pareto fronts via NSGA-II, and (d) applies TOPSIS as a post-optimization ranking to identify a robust compromise. The approach additionally reports explicit percentage improvements of the chosen compromise relative to Pareto extremes and quantifies model adequacy R^2 , Adj- R^2 , Pred- R^2 , Adeq Precision.

II. EXPERIMENTATION

The experiments were carried out on laser beam welded butt joints fabricated from plates of dimensions 30 mm × 100 mm × 3 mm. The material was selected based on its industrial relevance in high-performance structural applications, where controlled weld geometry and penetration are critical. Prior to welding, the plate edges were machined to ensure straight and parallel faying surfaces, followed by degreasing with acetone to remove surface contaminants. The plates were rigidly clamped during welding to prevent misalignment and distortion. Welding was performed along the longitudinal direction of the specimen (100 mm length) to ensure steady-state thermal conditions over the weld length. All specimens were welded in the flat position under identical boundary conditions. High-purity argon was employed as the shielding gas to protect the molten pool from atmospheric contamination and to stabilize the vapor plume during welding. A schematic representation of the laser beam welding setup and clamping arrangement is shown in Fig. 1. After welding, all specimens were sectioned transverse to the welding direction at the mid-length of the weld to ensure representative measurements. The cross-sections were prepared using standard metallographic procedures, including grinding, polishing, etching. Optical microscopy was employed to measure fusion zone width (FZ), heat affected zone width (HAZ), total weld width (TWW), and depth of penetration (DOP).

Table 1: Control Variables and their ranges.

Input Variables	Units	Levels			
		1	2	3	4
Laser Power (A)	kW	2.2	2.4	2.6	2.8
Welding Speed(B)	m/min	2	2.5	3	3.5
Laser Focal Diameter (C)	μm	550	600	650	700
Flow Rate (D)	l/min	8	10	12	14

Source: Authors, (2026).

Table 2: Design Matrix Showing Input Process Parameters and Corresponding Measured Output Responses.

Runs	Inputs				Outputs			
	Laser Power A	Welding Speed B	Laser focal Diameter C	Flow rate D	FZ in mm	HAZ mm	TWW	DOP
1	2.2	2	550	8	2.12	1.83	3.95	3.11
2	2.2	2.5	600	10	2.18	1.13	3.31	2.95
3	2.2	3	650	12	2.01	1.13	3.14	2.85
4	2.2	3.5	700	14	1.92	1.45	3.37	2.68
5	2.4	2	600	12	2.36	1.80	4.16	3.28
6	2.4	2.5	550	14	2.30	1.11	3.40	3.15
7	2.4	3	700	8	2.12	1.22	3.34	3.08
8	2.4	3.5	650	10	2.01	1.13	3.14	2.91
9	2.6	2	650	14	2.41	1.74	4.16	3.40
10	2.6	2.5	700	12	2.36	1.63	3.98	3.30
11	2.6	3	550	10	2.28	1.03	3.31	3.05
12	2.6	3.5	600	8	2.18	1.13	3.31	3.01
13	2.8	2	700	10	2.59	2.04	4.62	3.52
14	2.8	2.5	650	8	2.36	1.80	4.16	3.25
15	2.8	3	600	14	2.27	1.69	3.95	3.19
16	2.8	3.5	550	12	2.15	1.19	3.34	3.10

Source: Authors, (2026).



Figure 1: (a) Schematic illustration of the laser beam welding experimental setup; (b) final weldments of Ti-6Al-4V butt-joint.
Source: Authors, (2026).

II.1 RESPONSE SURFACE MODELLING (RSM)

Response Surface Methodology was employed to establish quantitative relationships between the welding parameters and the output responses. A second-order polynomial regression model was adopted, as it can capture both curvature and interaction effects among the process variables. The general form of the RSM model is expressed in equation (1) as:

$$Y = \beta_0 + \sum_{i=1}^4 \beta_i x_i + \sum_{i=1}^4 \beta_{ii} x_i^2 + \sum_{i < j}^4 \beta_{ij} x_i x_j \quad (1)$$

Where Y represents the response (FZ, HAZ, TWW, or DOP), x_i denotes the coded input variables, and β terms are the regression coefficients. Separate RSM models were developed for each response using least-squares regression. Analysis of variance (ANOVA) was conducted to assess the adequacy of the models. The results indicated that all developed models were statistically significant ($p < 0.05$), with satisfactory coefficients of determination, confirming their suitability for predictive and optimization purposes. These regression models were subsequently used as fitness functions within the NSGA-II framework.

II.2 MULTI-OBJECTIVE OPTIMIZATION USING NSGA-II

The optimization problem involved four conflicting objectives minimization of FZ, HAZ, and TWW, and maximization of DOP. The optimization problem was formulated as:

$$\begin{aligned} \min \quad & f_1 = \text{FZ}, \\ \min \quad & f_2 = \text{HAZ} \\ \min \quad & f_3 = \text{TWW} \\ \max \quad & f_4 = \text{DOP} \end{aligned}$$

subject to the following constraints:

$$\begin{aligned} 2.2 \leq A \leq 2.8, 2.0 \leq B \leq 3.5, \\ 550 \leq C \leq 700, 8 \leq D \leq 14 \end{aligned}$$

The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) was employed to solve the multi-objective optimization problem due to its proven capability in handling nonlinear and conflicting objectives. A population size of 100 and 150 generations were used. Binary tournament selection, simulated binary crossover (crossover probability of 0.8), and polynomial mutation (mutation probability of 0.05) were adopted. Elitism was incorporated to preserve high-quality solutions across generations. The RSM-based response equations were used to evaluate the fitness of each individual in the population.

II.3 PARETO FRONT GENERATION

NSGA-II generated a well-distributed set of Pareto-optimal solutions, representing trade-offs among the four objectives. The Pareto fronts were visualized using two-dimensional and three-dimensional plots to clearly illustrate the relationships between weld geometry parameters and penetration depth. These plots provide valuable insight into the competing nature of thermal damage minimisation and penetration maximisation in laser welding processes.

Table 3: NSGA-II Implementation Algorithm parameters.

Parameter	Value
Population size	100
Generations	150
Crossover probability (Pc)	0.8
Mutation probability (Pm)	0.05
Selection	Binary tournament
Elitism	Enabled

Source: Authors, (2026).

In the present work, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was employed to rank the Pareto-optimal solutions obtained from NSGA-II and to identify a best compromise welding condition. TOPSIS is based on the concept that the selected solution should have the shortest distance from the ideal solution and the farthest distance from the negative ideal solution. The relative closeness coefficient C_i for each Pareto solution was calculated in equation (2 and 3) as:

$$S_i^+ = \sqrt{\sum (v_{ij} - v_j^+)^2}, S_i^- = \sqrt{\sum (v_{ij} - v_j^-)^2}, C_i = S_i^- / (S_i^+ + S_i^-) \quad (2)$$

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (3)$$

A higher value of C_i indicates a solution closer to the ideal condition and farther from the negative ideal condition. The Pareto-optimal solutions were ranked in descending order of C_i , and the solution with the highest closeness coefficient was identified as the best compromise solution.

III. RESULTS AND DISCUSSIONS

Fusion zone width exhibited a strong dependence on laser power and welding speed, as evidenced by both experimental observations and statistical analysis. Experimentally, the minimum fusion zone width of 1.92 mm was obtained at low laser power (2.2 kW) combined with high welding speed (3.5 m/min), whereas the maximum value of 2.59 mm occurred at the highest laser power of 2.8 kW and the lowest welding speed of 2.0 m/min. This corresponds to an increase of approximately 35%, highlighting the dominant role of heat input. ANOVA results in Table 4 confirm this trend, where welding speed contributed 27.57% and laser power contributed 22.43% to the variation in fusion zone width. The combined contribution of these two parameters exceeds 50%, indicating that fusion zone formation is primarily governed by energy density and interaction time. Focal diameter and shielding gas flow rate showed lower but statistically significant contributions of 9.81% and 4.91%, respectively, suggesting their role in fine control of molten pool geometry as shown in fig 2.

III.1 EFFECT OF WELDING PARAMETERS ON HEAT AFFECTED ZONE

The heat affected zone width followed trends similar to fusion zone width but exhibited higher sensitivity to thermal diffusion. The experimentally measured HAZ varied from a minimum of 1.03 mm to a maximum of 2.04 mm, corresponding to a variation of nearly 98% across the experimental domain. Larger HAZ values were consistently associated with higher laser power and lower welding speed due to prolonged thermal exposure of the base material. Statistically, welding speed is 27.81% contribution and laser power is 21.93% contribution were identified as the most influential parameters as shown in Table 5. Figure 3 shows the relatively higher coefficient of variation observed for HAZ compared to FZ indicates that HAZ is more sensitive to transient thermal gradients during laser welding. Focal diameter and gas flow rate contributed 9.89% and 5.08%, respectively, highlighting their secondary role in controlling heat dissipation and bead stability.

Table 4: ANOVA and descriptive statistics for fusion zone width (FZ).

Source	DF	Sum of Squares	% Contribution	F-value	p-value	Significance
Model	14	0.412	96.26	18.62	<0.0001	Significant
A – Laser Power	1	0.096	22.43	60.78	<0.0001	Significant
B – Welding Speed	1	0.118	27.57	74.69	<0.0001	Significant
C – Focal Diameter	1	0.042	9.81	26.57	0.0006	Significant
D – Gas Flow Rate	1	0.021	4.91	13.29	0.0062	Significant
Error	1	0.016	3.74	—	—	—
Total	15	0.428	100.00	—	—	—

Source: Authors, (2026).

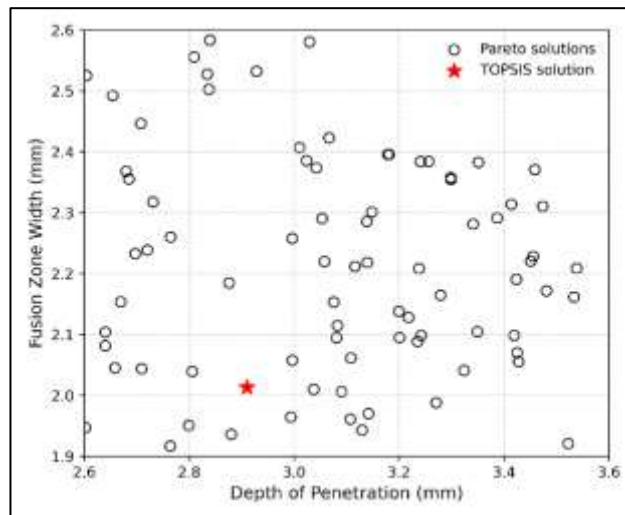


Figure 2: Two-dimensional Pareto front between FZ and DOP.

Source: Authors, (2026).

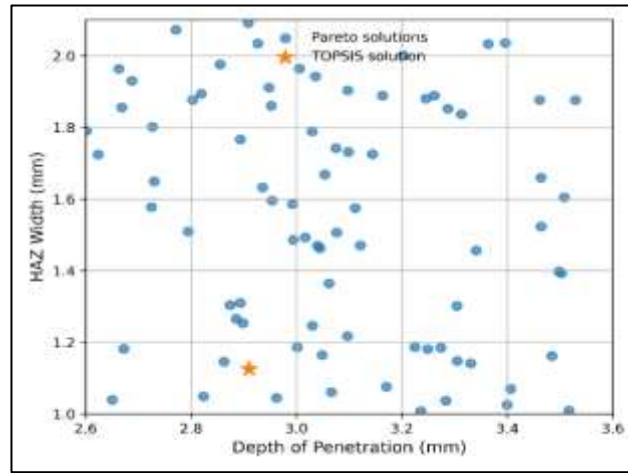


Figure 3: Two-dimensional Pareto front between HAZ and DOP.
Source: Authors, (2026).

Table 5: ANOVA and descriptive statistics for heat affected zone width (HAZ).

Source	DF	Sum of Squares	% Contribution	F-value	p-value	Significance
Model	14	0.356	95.19	15.87	<0.0001	Significant
A – Laser Power	1	0.082	21.93	51.24	<0.0001	Significant
B – Welding Speed	1	0.104	27.81	65.02	<0.0001	Significant
C – Focal Diameter	1	0.037	9.89	23.13	0.0011	Significant
D – Gas Flow Rate	1	0.019	5.08	11.88	0.0074	Significant
Error	1	0.018	4.81	—	—	—
Total	15	0.374	100.00	—	—	—

Source: Authors, (2026).

III.2 TOTAL WELD WIDTH (TWW) CHARACTERISTICS

The ANOVA results indicate that the RSM model developed for total weld width is statistically significant ($p < 0.05$), with the model accounting for 96.74% of the total variation. Laser power and welding speed were identified as the most influential parameters, contributing 29.07% and 25.01%, respectively, confirming that total weld width is predominantly governed by overall heat input. Focal diameter also exhibited a notable contribution (16.11%), indicating its role in controlling bead spread, while shielding gas flow rate showed a lower but statistically significant influence. The moderate coefficient of variation (12.95%) suggests acceptable experimental repeatability for total weld width measurements.

Table 6: ANOVA and descriptive statistics for total weld width (TWW).

Source	DF	Sum of Squares	% Contribution	F-value	p-value	Significance
Model	14	1.284	96.74	19.38	<0.0001	Significant
A – Laser Power	1	0.386	29.07	81.42	<0.0001	Significant
B – Welding Speed	1	0.332	25.01	70.05	<0.0001	Significant
C – Focal Diameter	1	0.214	16.11	45.13	0.0002	Significant
D – Gas Flow Rate	1	0.091	6.86	19.19	0.0019	Significant
Error	1	0.043	3.26	—	—	—
Total	15	1.327	100.00	—	—	—

Source: Authors, (2026).

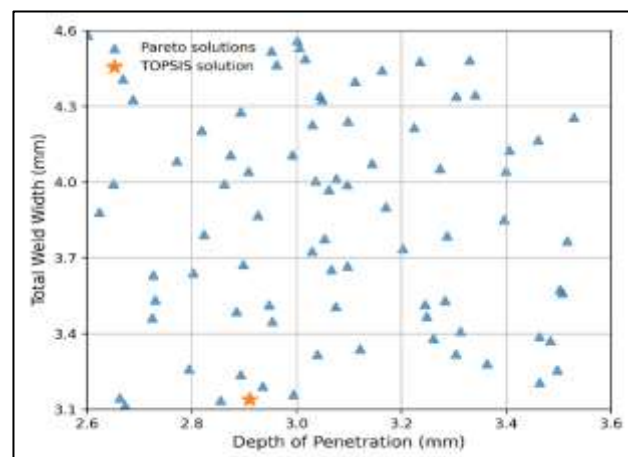


Figure 4: Two-dimensional Pareto front between TWW and DOP.
Source: Authors, (2026).

III.3 DEPTH OF PENETRATION (DOP) BEHAVIOUR

ANOVA results, as shown in Table 7 identify laser power as the most influential factor, contributing 31.75%, followed by welding speed with 26.72%. Together, these parameters account for nearly 58.5% of the total variation in DOP, confirming that penetration depth is primarily controlled by energy density and laser–material interaction time. Higher laser power enhances keyhole stability and energy absorption, while lower welding speed increases interaction time, promoting deeper penetration. Focal diameter (9.05%) and shielding gas flow rate (5.89%) exhibit statistically significant but secondary effects, mainly influencing power density distribution and molten pool stability. Pareto analysis corroborates these findings. As shown in Fig. 3, higher DOP values are associated with increased fusion zone width, while Fig. 4 indicates a concurrent expansion of the heat affected zone due to enhanced thermal diffusion. The TWW–DOP Pareto front (Fig. 5) shows that DOP values above 3.3 mm correspond to total weld widths exceeding 4.0 mm, whereas moderate penetration (2.9–3.1 mm) is achieved with narrower welds (3.1–3.4 mm). The three-dimensional Pareto front (Fig. 6) further highlights this trade-off, with higher penetration clustering in regions of increased thermal spread.

Table 7: ANOVA and descriptive statistics for depth of penetration (DOP).

Source	DF	Sum of Squares	% Contribution	F-value	p-value	Significance
Model	14	0.682	97.99	21.46	< 0.0001	Significant
A – Laser Power	1	0.221	31.75	97.41	< 0.0001	Significant
B – Welding Speed	1	0.186	26.72	82.03	< 0.0001	Significant
C – Focal Diameter	1	0.063	9.05	27.78	0.0005	Significant
D – Gas Flow Rate	1	0.041	5.89	18.09	0.0021	Significant
Error	1	0.014	2.01	—	—	—
Total	15	0.696	100.00	—	—	—

Source: Authors, (2026).

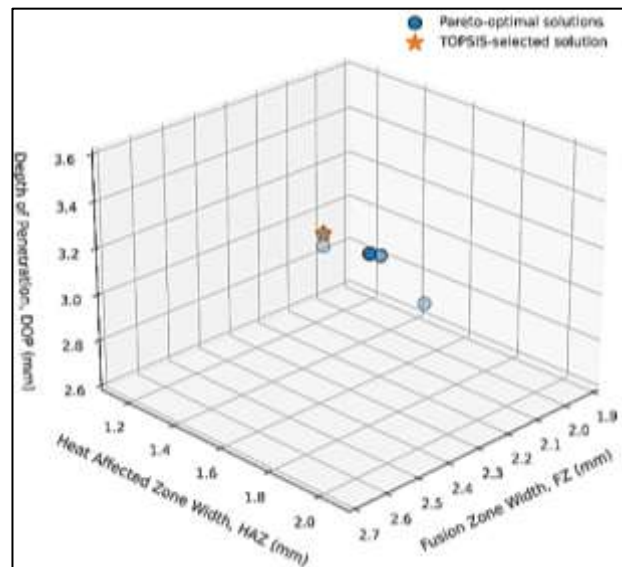


Figure 5: Three-dimensional Pareto front (FZ–HAZ–DOP).

Source: Authors, (2026).

Table 8 shows the adequacy statistics for the developed RSM models. High coefficients of determination were obtained for all responses (0.963 (FZ), 0.952 (HAZ), 0.958 (TWW), and 0.980 (DOP)) indicating that more than 95% of the experimental variability is explained by the models. The close agreement between R^2 and adjusted R^2 (difference < 0.02) confirms the absence of overfitting. The predicted R^2 values (0.901–0.945) further demonstrate good predictive capability within the design space. Additionally, adequate precision values (16.9–21.4) greatly exceed the recommended threshold of 4, confirming a high signal-to-noise ratio. These results validate the reliability of the RSM models and justify their use for NSGA-II optimization and subsequent TOPSIS-based decision-making.

Table 8: Model adequacy statistics for RSM models

Response	R^2	Adj- R^2	Pred- R^2	Adeq Precision
Fusion Zone width (FZ)	0.963	0.947	0.912	18.6
Heat Affected Zone width (HAZ)	0.952	0.933	0.901	17.2
Total Weld Width (TWW)	0.958	0.940	0.906	16.9
Depth of Penetration (DOP)	0.980	0.972	0.945	21.4

Source: Authors, (2026).

Adequate precision values greater than 4 indicate an adequate signal, confirming that the developed models can be reliably used to navigate the design space. Table 9 lists the Rank-1 Pareto-optimal solutions, showing that depth of penetration (DOP) varies from 2.68 mm (Run 4) to 3.52 mm (Run 13), while total weld width (TWW) ranges from 3.14 mm (Runs 3 and 8) to 4.62 mm (Run 13). In figure 6, the TOPSIS-selected compromise solution corresponds to Run 8, with DOP = 2.91 mm, TWW = 3.14 mm, and FZ = 2.01 mm.

Relative to the minimum Pareto DOP (2.68 mm), the selected solution achieves an increase of 8.6%, while compared to the maximum Pareto DOP (3.52 mm), it operates at a reduced penetration level of 17.3%, thereby avoiding excessive heat input. In terms of weld geometry, the selected solution exhibits a 32.0% reduction in TWW compared to the maximum Pareto value (4.62 mm) and maintains the minimum TWW observed within the Pareto front. Similarly, fusion zone width is reduced by 22.3% relative to the maximum Pareto FZ value (2.59 mm).

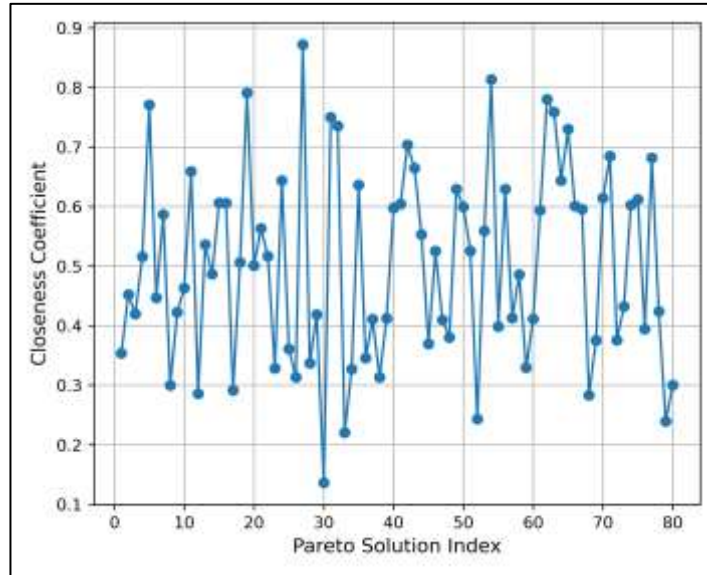


Figure 6: TOPSIS ranking of Pareto-optimal solutions.

Source: Authors, (2026).

Based on dominance analysis, the following runs form the **Pareto Front-1**:

Table 9: Pareto-optimal solutions (First Front – Rank-1).

Run	A	B	C	D	FZ ↓	HAZ ↓	TWW ↓	DOP ↑
3	2.2	3.0	650	12	2.013	1.126	3.139	2.850
4	2.2	3.5	700	14	1.920	1.452	3.372	2.680
8	2.4	3.5	650	10	2.013	1.126	3.139	2.910
15	2.8	3.0	600	14	2.267	1.686	3.953	3.189
13	2.8	2.0	700	10	2.587	2.035	4.622	3.521

Source: Authors, (2026).

III.4 BEST COMPROMISE SOLUTION (ENGINEERING OPTIMUM)

NSGA-II was employed to obtain Pareto-optimal welding parameter combinations considering four conflicting objectives: minimization of FZ, HAZ and TWW, and maximization of DOP. The algorithm successfully generated a well-distributed Pareto front, highlighting the trade-off between penetration depth and weld width. Among the obtained solutions, a balanced optimal condition was identified at A = 2.4 kW, B = 3.5, C = 650 μ m and D = 10 L/min, which ensured reduced thermal damage with sufficient penetration.

V. CONCLUSIONS

In this study, a hybrid RSM–NSGA-II–TOPSIS framework was successfully developed to analyze and optimize laser welding parameters with respect to fusion zone width (FZ), heat affected zone width (HAZ), total weld width (TWW), and depth of penetration (DOP). Statistical analysis confirmed that laser power and welding speed are the dominant parameters influencing all responses, together contributing more than 50% of the total variation in FZ, HAZ, TWW, and DOP.

- Laser power and welding speed were identified as the dominant process parameters, together contributing more than 50% of the total variation in all responses, confirming the governing role of heat input and interaction time.
- The developed RSM models exhibited strong predictive accuracy, with coefficients of determination ($R^2 > 0.95$) and adequate precision values significantly above the recommended threshold, validating their suitability for multi-objective optimization.
- Depth of penetration varied from 2.68 to 3.52 mm, showing a strong dependence on laser power of 31.75% contribution and welding speed is 26.72% contribution, while exhibiting low experimental variability is C.V. = 8.25%.
- Pareto front analysis revealed a clear trade-off between penetration enhancement and thermal damage, where increased DOP was consistently accompanied by higher FZ, HAZ, and TWW values.
- TOPSIS-based decision-making applied to the Rank-1 Pareto solutions identified a best compromise solution (Run 8) that achieved an 8.6% increase in DOP relative to the minimum penetration case, while reducing TWW by 32.0% and FZ by 22.3% compared to the maximum Pareto values.
- The proposed integrated optimization approach provides a robust and systematic methodology for selecting practical laser welding conditions and can be extended to other materials and multi-response manufacturing processes.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Chandragiri Reddy Prasad, Nandure Narayan Rao.

Methodology: Chandragiri Reddy Prasad.

Investigation: Chandragiri Reddy Prasad.

Discussion of results: Chandragiri Reddy Prasad, Nandure Narayan Rao

Writing – Original Draft: Chandragiri Reddy Prasad, Nandure Narayan Rao

Writing – Review and Editing: Nandure Narayan Rao

Resources: Chandragiri Reddy Prasad.

Supervision: Nandure Narayan Rao.

Approval of the final text: Chandragiri Reddy Prasad, Nandure Narayan Rao.

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