

Article

Hybridization of Principal Component Analysis-Entropy-TOPSIS Techniques for Minimization of Angular Deviation in Gas Metal Arc Welded Stainless Steel Plates

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Abstract: The current study involves optimizing gas metal arc welding input parameters by hybridization techniques such as principal component analysis, entropy, and TOPSIS for minimizing the angular distortion resulting from the welding process. Structural steel has been considered as the research material by varying the process parameters such as electrode angle with workpiece, time gap between passes, wire feed rate, and welding speed, each varying with five levels. Experimental layout has been prepared through response surface methodology with 125 experimental trials combining different parameters. The measured angular distortion of the welded plates has been considered for multi-criteria decision making to find the optimal parameter combination for reducing the angular distortion. The optimal combination comprising 110 degrees of electrode to workpiece angle, 25 min time gap, 5.75 mm/min wire feed rate, and 10.8 cm/min welding speed is found to hold top ranking (A2B2C1D2) from both PCA and entropy weighted values through TOPSIS technique. The closeness coefficient value has been trained and tested through supervised ML techniques. AdaBoost algorithm outperformed other regression algorithms with excellent evaluation scores. The microstructure analysis of the welded plates reveals the presence of coarse and fine structures in the welded area.

Keywords: GMAW; supervised ML techniques; PCA; entropy; TOPSIS



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1. Introduction

Welding is a well-known fabrication technique that joins similar or dissimilar materials by applying pressure and heat to create both basic and intricate structures. By using the right welding technique, it is possible to create extremely economical structures out of structures ranging from massive aircrafts to machine structures that can be joined together with ease and at a lower cost. Wire welding, also referred to as gas metal arc welding (GMAW), is one of the most used forms of welding. The GMAW method heats the metal pieces by creating an electric arc between the metal and a wire electrode. The procedure involves the generation of an electric arc, which is established and maintained between a base material and continuously-fed wire electrode in order to fuse and melt the workpieces together to form a tight bond. The main benefits of GMAW are its high deposition efficiency, lack of slag or spatter formation, capacity to weld thin material sheets, and low hydrogen deposit in the weld. Notwithstanding the advantages it offers, welded products typically have a number of drawbacks, such as the welded plate's deformation. When the angular distortion from the welding process surpasses the tolerance level, it is a general problem that could lead to the workpiece being rejected. The choice of ideal welding parameters is essential for reducing process-related distortion and for improving the quality of the weld with increased strength in the welded area. Numerous scholars have concentrated on a range of problems resulting from GMAW welded structures, as well as on optimizing the welding settings to reduce or completely eradicate the relevant faults.

Paulo et al. [1] have adopted ASTM A36 structural steel plates to predict angular distortion with 16 mm and 19 mm thickness through the butt welding process with multiple passes. The authors have varied the heat inputs and developed different analytical models. The model which adopted the lowest heat input is found to be efficient in predicting the distortion. Samal et al. [2] adopted the factorial approach for evaluating the angular distortion in TIG welded high strength low alloy steels. The factors welding current and torch angle have an influence on angular distortion, and welding speed has a detrimental effect. Mayank et al. [3] studied the effect of process parameters over the angular distortion of MIG welded stainless steel 202 plates. The mathematical model developed is effective in identifying the angular distortion at different combinations of input factors. Through optimal parameter combination, the angular distortion is reduced to 2.75 degrees. Hang et al. [4] have analyzed the effect of welding input factors over angular distortion, residual stresses, and lamellar tearing tendency in low alloy steel thick plates. The authors have recommended the TJ-F joint pass arrangement as it produces lower angular distortion and tendency of lamellar tearing. Mehran et al. [5] were involved in studying the residual stresses and angular distortion in high strength steel plates. The authors have performed simulation studies using 3D FE models using ABAQUS FE code. The distortion of welded stainless steel sheets that happened through gas tungsten arc welding has been studied by Hafiza et al. [6]. The authors have reported that when the welding current is high, angular distortion is also high due to more heat flow in the weld region. Lucas et al. [7] investigated the effect of welding orientation over angular distortion in steel plates through GMAW with multiple passes. The authors have suggested an alternative orientation which reduces the angular distortion in a better way. Woo et al. [8] have observed the characteristics of distortion in multi-layer butt welding. The authors have concluded that the angular distortion is a function of the number of passes and groove geometry. Liu et al. [9] optimized welding parameters towards distortion and stress in high strength steel thin plate structures. The deformation has been lowered by 5.4% using the ideal mixture of parameters. Following optimization, the pump arm's warpage volume and side bending volume decreased by 9.56% and 4.06%, respectively and welding deformation is significantly reduced. Zubairuddin et al. [10] hybridized both experimental and numerical simulation for understanding residual stress formation and distortion in modified steel welded through gas tungsten arc welding process. The application of large distortion theory has produced better accuracy in output response prediction.

Multi-criteria decision making (MCDM) techniques are adopted in different domains of engineering and management when multiple criteria arise in a situation where decision making becomes crucial. MCDM techniques such as TOPSIS, COPRAS, ARAS, and GRA have been adopted in many industrial scenarios to obtain an optimal solution when conflicting criteria are involved and considerable results have been attained in the past studies. Chatterjee et al. [11] adopted COPRAS- and ARAS-based approaches for the material selection for gears. The authors have made a comparison of the ranking performance of both methods involved. Singaravel et al. [12] have applied the ARAS method for optimizing the turning process parameters to minimize surface roughness and to enhance micro hardness and material removal rate. Wang et al. [13] have applied MCDM methods for solar power plant site selection in Indonesia. The objective of the study is to identify a location which is cost effective. Vinodh and Shinde et al. [14] applied the MOORA method for optimizing the 3D printing process parameters and compared the ranking of alternatives with TOPSIS. Srinivasan et al. [15] have adopted the grey relational analysis and TOPSIS methods for optimizing the end milling process parameters.

Machine learning algorithms are capable of predicting future outcomes when they have trained with an initial dataset. In today's scenario, machine learning algorithms have been applied in many fields which include finance, medicine, and engineering. Dogra et al. [16] have adopted machine learning algorithms for parameter optimization of the welding process. Algorithms such as neural network, genetic algorithm, and support vector machines have been employed for predictions. The accurate prediction of welding param-

eters can result in enhanced bead quality, improved mechanical properties, and overall efficiency. Mongan et al. [17] combined ANN and the genetic algorithm for optimizing the input factors of ultrasonic welding process used for joining aluminium alloys. The authors have optimized the initial weights of ANN model through the genetic algorithm and the developed model has been used for training through 27 datasets. The validation datasets consisted of 10 experimental data and the model has performed better with an R-square value of 0.9827. The process parameter optimization of friction stir welded joints through regression machine learning algorithms have been carried out by Eyob et al. [18]. Algorithms such as random forest, decision trees, and gradient boosting have been employed to determine the ultimate tensile strength of aluminium 6061 AA 5 mm sheets. Random forest algorithm has outperformed other algorithms with a higher R-square value of 0.926. Tiago et al. [19] deployed machine learning algorithms for optimizing the input factors of the robotic welding process. The study has adopted the random forest algorithm for weld classification and Monte Carlo method for identifying the best suitable future weld iteration. Vinayak and Divya [20] exploited the benefits of data-driven framework in the assessment of weldability and parameter optimization of resistance welding process. The solutions obtained from teaching the learning-based optimization algorithm seems to be promising in attaining a better weld quality and it has been evaluated through three performance measures such as root mean square error, mean square error, and R-square.

The literature survey carried out indicates the emergence of angular distortions in GMAW welded plates, which is a serious concern as it affects the acceptance of the final product. The optimization study focuses on predicting the ideal parameter combination which can reduce the angular distortion through the application of MCDM techniques and machine learning algorithms. Through the application of PCA-Entropy-TOPSIS techniques, the input factor combination comprising 110 degrees of electrode to workpiece angle, 25 min time gap, 5.75 mm/min wire feed rate, and 10.8 cm/min welding speed is found to hold top ranking (A2B2C1D2). Regression results indicate that the factors of electrode to workpiece angle and time gap between the passes are significant with p -value less than 0.05. Figure 1 represents the research methodology adopted in the current study.

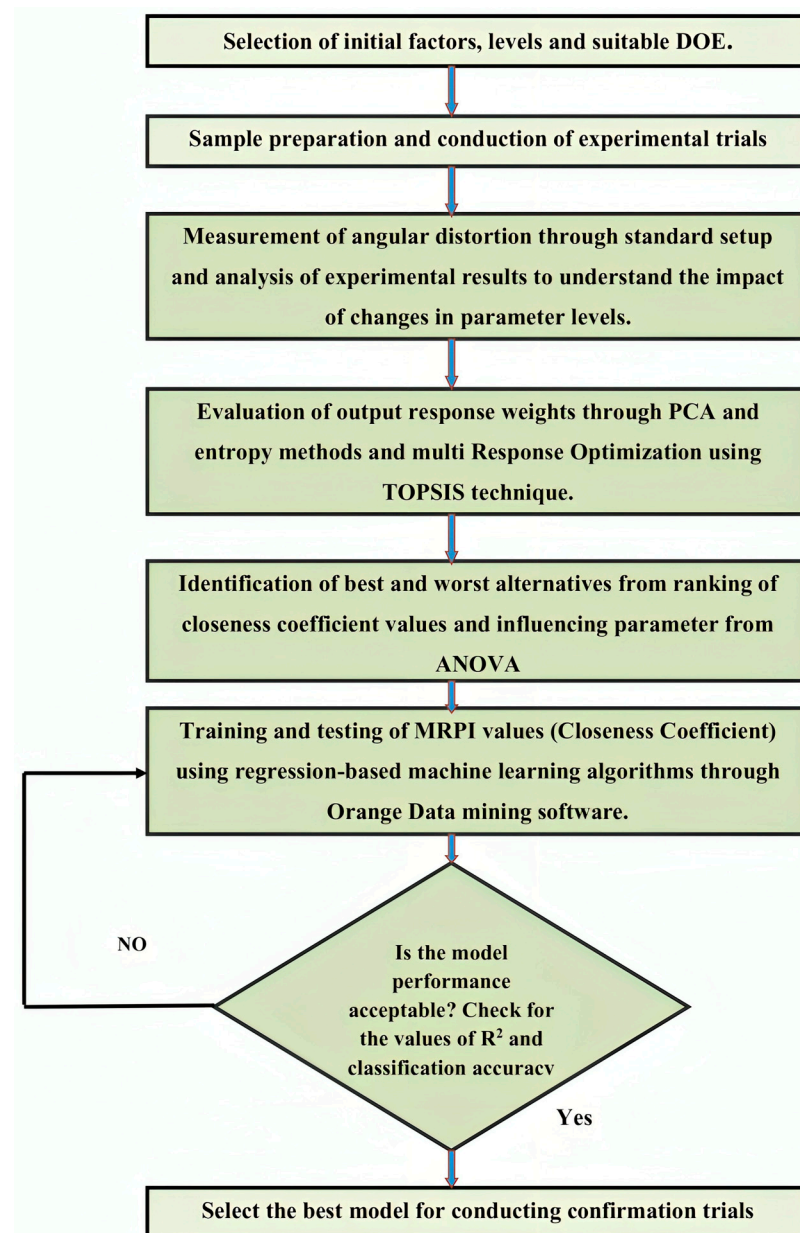


Figure 1. Proposed research methodology.

2. Materials and Methods

The current study has adopted IS2062 (Grade A) structural steel made by Steel Authority of India Limited (SAIL) as the base metal for investigation. Structural steel in plate form has been set as the material for research. Different shapes, including I-beam, Z-shaped, hollow structural section, angle, C-section, and T-shaped cross section, are available for commercial structural steels. Owing to its positive benefits such as high ratio of strength to weight, durability, sustainability and very good ductility, structural steel has been considered in the making of buildings, towers, bridges, and structures like warehouses and industrial plants. Despite the positive characters it holds, it has certain disadvantages such as higher susceptibility to corrosion and it involves high fire resistance cost. Table 1 shows the elemental composition of IS2062 A structural steel.

Table 1. Elemental composition of IS2062 A structural steel.

Fe%	C%	Si%	Mn%	P%	S%	N%
97.8	0.23	0.23	0.4	1.5	0.05	0.05

The sample material has iron as the major constituent in structural steel with 97.8% elemental composition. The carbon content of 0.23% indicates low carbon steel category, and other alloying elements such as silicon, manganese, sulfur, nitrogen, and phosphorous are present at different percentages. The considered structural steel has been used in fields such as automobiles, machine building, fabrication, and general engineering.

The current research has been considered for different welding parameters such as angle between the electrode and workpiece (θ), time gap between the passes (t), wire feed rate (F), and welding speed (S). Each parameter considered has been varied in five levels to create the experimental design layout. Table 2 shows the GMAW control factors and its levels. Totally, 125 experimental trials have been prepared through response surface methodology.

Table 2. GMAW control factors and levels.

Input Factors	S.I Unit	Symbol	Levels				
			−2	−1	0	1	2
Electrode angle to workpiece	Degrees	θ	70	80	90	100	110
Time gap between passes	min	T	5	10	15	20	25
Wire feed rate	m/min	F	5	5.25	5.5	5.75	6
Welding speed	cm/min	S	8.4	9	9.6	10.2	10.8

3. Experimental Work

This section details the sample preparation for welding and the procedure involved for measuring the angular distortions in the welded plate.

3.1. Preparation of the Sample

Sample dimensions of 300×150 mm (length $\times$ width, respectively) structural steel plates (IS2062) were used to prepare the samples required for the experimental work. The samples were formed into the appropriate shapes using an oxy-acetylene gas welding procedure, and edge preparation is performed through a milling machine. The sample has been created with a single “V” groove with 30° included angle, and solid electrode wires made of steel coated with copper of 1.2 mm diameter have been used during the welding process of the samples. The minimal depth of cutting that can be achieved during the grooving operation has been maintained. During machining, cutting fluids were employed to lower residual tensions. The welding sample was moved in opposition to a fixed welding torch with the aid of a servo-motor controlled linear manipulator. This linear manipulator can move the base plate in the X and Y directions at a predetermined welding speed. The experimental sample’s cross section is displayed in Figure 2.

3.2. Experimental Setup

The MIG welding machine of model IWE-MG-TC-400, 2019, manufactured and supplied by M/s Icon welding equipments, Gujarat, India, with a semi-automatic thyristor-control is used for the experimental research. The control panel has meters to show the welding current and arc voltage in addition to adjustable wire feed rates. The automatic MIG welding process used a rectifier power supply and constant potential (flat characteristic) transformer. It had a 415 VAC, 50/60 Hz supply voltage, and could supply currents from 50 to 400 amps. Using a linear manipulator operated by a servo-motor, the welding sample was pushed against a stationary welding torch. The base plate can be moved by

this linear manipulator at a preset welding speed in both the X and Y dimensions. Figure 3 shows the experimental setup.

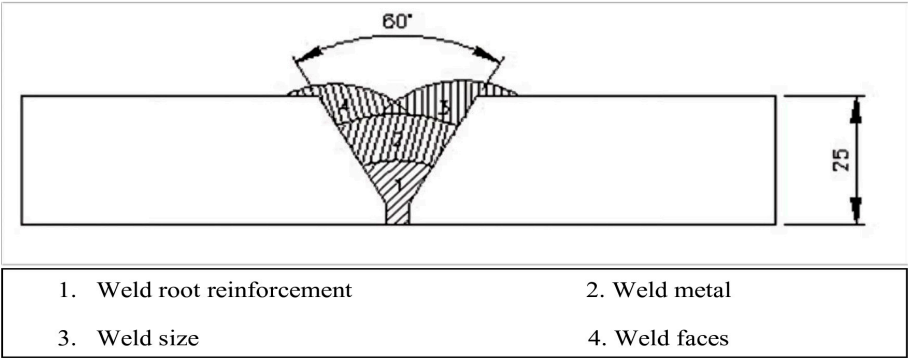
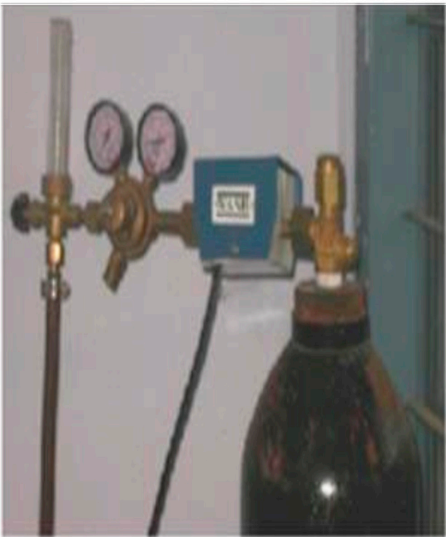


Figure 2. Experimental sample.



Welding power source



Gas supply unit



Linear manipulator



Wire feeding mechanism

Figure 3. GMAW experimental setup.

3.3. Measurement of Angular Distortions

In the current work, the input factor electrode angle with workpiece (θ) has been considered and in addition to that, the measurement of angular distortion at the end of 2nd, 3rd, and 4th welding passes (passes 2, 3, and 4, respectively) has been measured to understand the progression of angular distortion. As the input factor, time gap between passes indicates the duration of time between the ends of the previous pass and the beginning of the next pass, the angular distortion after the first pass is not considered. Through the sine bar concept accompanied by a vernier height gauge, angular distortion (α) has been measured in accordance with ASTM A1030 standard as reference. Figure 4 shows the angular distortion in welded plates.

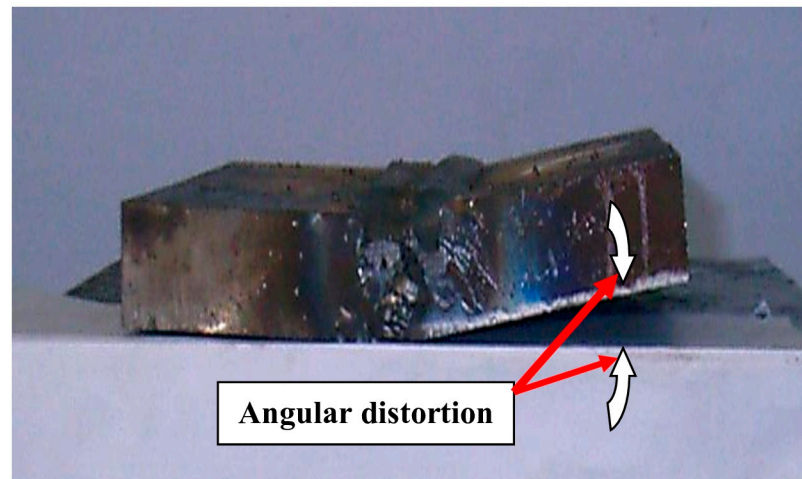


Figure 4. Angular distortion in welded plates.

4. Results and Discussion

The measured values of angular distortion have been analyzed through entropy and principal component analysis techniques to evaluate the weight values of angular distortions. The evaluated weight values have been adopted in TOPSIS method for understanding the variation in the ranking of alternatives. Table 3 shows the measured value of angular distortions at different time passes in a selective manner. Appendix A represents the complete dataset of experimental outcomes for reference.

Table 3. Measured values of angular distortions.

S. No.	θ (°)	T (min)	F (m/min)	S (cm/min)	α_2 (°)	α_3 (°)	α_4 (°)
1	0	0	0	0	1.38	2.32	3.15
2	0	0	−1	2	1.88	2.44	2.81
3	0	0	0	1	1.38	2.22	2.96
4	0	0	1	0	1.34	2.3	3.03
5	0	0	2	−1	1.76	2.68	3.02
6	−1	0	0	2	1.66	1.92	2.42
7	−1	0	−1	1	1.82	2.44	3.09
8	−1	0	0	0	1.4	2.1	2.94
9	−1	0	1	−1	1.44	2.06	2.71
10	−1	0	2	0	2.2	2.94	3.4
11	1	1	0	0	1.05	2.12	2.94
12	1	1	1	−1	1.19	2.26	2.89
13	1	1	2	0	1.53	2.7	3
14	1	2	0	1	0.39	1.15	1.73

Table 3. Cont.

S. No.	θ (°)	T (min)	F (m/min)	S (cm/min)	α_2 (°)	α_3 (°)	α_4 (°)
15	1	2	−1	0	0.71	1.75	2.54
16	2	−1	0	0	2.88	3.36	4.11
17	2	−1	−1	2	3.54	3.85	4.17
18	2	−1	0	1	2.62	3.13	3.82
19	2	−1	1	0	2.16	2.71	3.39
20	2	−1	2	−1	2.16	2.59	2.88
21	2	0	0	2	1.48	1.92	2.33
22	2	0	−1	1	2.66	3.34	3.96
23	2	0	0	0	2	2.76	3.57
24	2	0	1	−1	1.8	2.48	3.1
25	2	0	2	0	1.54	2.46	2.83

The measured values of angular distortion have been observed for variations with respect to the changes in input factors. The values of angular distortion at different stages of the welding process have been tabulated and checked for the variations with a tolerance set of ± 1 mm. In the case of all the three measured angular distortion values, only very few trials have resulted with lower angular distortion with respect to the tolerance set fixed. The maximum deviations observed were very high in comparison to the tolerance set. In all the three cases of angular distortion measurement at various passes, the maximum deviations are positive and they are above the accepted tolerance level value. On the contrary, the minimum deviations at all the three passes are found to be negative.

4.1. Shannon Entropy Method

Shannon developed the entropy approach in 1948. It uses a decision matrix to normalize experimental data and converts it into the appropriate project outcome [21]. The project results that have been assessed are used to calculate the entropy measure and to derive the objective weights that could be used to determine the output replies' weight.

Step 1: Normalization of the arrays of a decision matrix to obtain the project outcomes P_{ij} .

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^m X_{ij}} \quad (1)$$

Step 2: Computation of the entropy measure of project outcomes using the following equation.

$$E_j = -k \sum_{i=1}^m P_{ij} \ln P_{ij}. \quad (2)$$

Step 3: Defining the objective weight based on the entropy concept.

$$W_{ij} = \frac{1 - E_j}{\sum_{j=1}^n (1 - E_j)} \quad (3)$$

Table 4 shows the weight values obtained for the individual angular distortion value. The maximum weightage of 50% has been assigned for angular distortion of the welded workpiece after the first stage of welding and 27% weightage is assigned for angular distortion at the third level, 23% weightage for angular distortion at the fourth level of the welding process. This indicates that the angular distortion happening at the initial stage should be controlled for minimizing the angular distortion at subsequent stages.

Table 4. Weight values of output responses.

α_2 (°)	α_3 (°)	α_4 (°)
0.50	0.27	0.23

4.2. Principal Component Analysis

The current approach makes use of principal component analysis, which computes Eigen values for the principal components; therefore, reducing the dimension of a dataset. When evaluating the response weights, the principal component with the largest contribution is taken into account first, followed by the principal component with the largest contribution after the Eigen vectors have been calculated.

The greatest contribution of the first main component in the current study is found to be 92.0%, while Table 5 displays the contributions of the other principal components. Hence, in the current study, the weight for α_2 is 32%, 35% for α_3 , and 33% for α_4 . Tables 5 and 6 show the Eigen values and Eigen vectors for principal components.

Table 5. Eigen values and proportions for principal components.

Principal Component	Eigen Value	Proportion
First	2.7590	0.920
Second	0.2090	0.070
Third	0.0321	0.011

Table 6. Eigen vectors for principal components and contributions.

Output Response	1st PC	2nd PC	3rd PC	Weight
α_2 (°)	0.566	−0.734	−0.377	0.32
α_3 (°)	0.596	0.048	0.802	0.35
α_4 (°)	0.570	0.678	−0.464	0.33

4.3. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a multi-objective optimization tool which identifies the best alternative having a shorter distance from the positive ideal solution and a longer distance from the negative ideal solution [22]. Ranking of alternatives are ranked based upon the distances from ideal solutions. The current step involves ranking of alternatives through TOPSIS methodology by employing the weights of output responses from both entropy and PCA techniques and the value of closeness coefficient serves as overall or multi-response performance index [23]. Table 7 shows the positive and negative ideal values. Table 8 shows the rankings of alternatives. The current study has considered angular distortion as the minimization problem and the minimum values of angular distortion are considered better to avoid rejection of workpieces after fabrication.

Table 7. Positive and negative ideal values.

S. No.	Output Response	Positive Ideal (v_j^+)	Negative Ideal (v_j^-)
1	α_2 (°)	0.0058	0.0939
2	α_3 (°)	0.0002	0.0432
3	α_4 (°)	0.0002	0.0308

Table 8. Ranking of alternatives through entropy and PCA weighted values.

Trial No.	Entropy Weighted Ranking	PCA Weighted Ranking	Trial No.	Entropy Weighted Ranking	PCA Weighted Ranking
1	58	69	64	37	44
2	97	91	65	95	96
3	49	51	66	30	41
4	41	60	67	36	27
5	90	95	68	27	33
6	63	39	69	65	79
7	113	113	70	107	110
8	70	71	71	9	8
9	26	22	72	17	17
10	57	45	73	22	24
11	49	51	74	76	82
12	98	100	75	116	116
13	49	51	76	80	88
14	41	60	77	115	115
15	84	75	78	80	88
16	30	41	79	18	14
17	66	80	80	59	64
18	30	41	81	108	107
19	35	23	82	123	123
20	105	106	83	92	86
21	23	29	84	62	63
22	21	25	85	69	74
23	9	8	86	80	88
24	61	46	87	101	98
25	116	116	88	64	70
26	68	36	89	40	65
27	94	93	90	86	87
28	44	47	91	7	7
29	48	38	92	47	58
30	109	108	93	24	35
31	33	26	94	28	37
32	88	81	95	77	85
33	16	11	96	4	6
34	20	18	97	11	15
35	79	50	98	8	13
36	44	47	99	13	16
37	67	67	100	19	10
38	44	47	101	110	111
39	87	68	102	122	122
40	112	112	103	38	31
41	60	66	104	29	34
42	78	83	105	73	77
43	83	57	106	120	120
44	104	103	107	124	124
45	121	121	108	118	118
46	89	92	109	106	105
47	75	30	110	103	99
48	93	84	111	38	31
49	114	114	112	119	119
50	125	125	113	102	104
51	49	51	114	91	94
52	98	100	115	73	77
53	49	51	116	12	12
54	41	60	117	96	97
55	84	75	118	56	59
56	70	71	119	15	20

Table 8. Cont.

Trial No.	Entropy Weighted Ranking	PCA Weighted Ranking	Trial No.	Entropy Weighted Ranking	PCA Weighted Ranking
57	111	109	120	6	2
58	70	71	121	2	4
59	25	21	122	14	19
60	55	40	123	2	4
61	49	51	124	1	1
62	98	100	125	5	3
63	34	28			

Step 1: Normalization of the decision matrix.

The normalization formula is given as follows:

$$r_{ij}(x) = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad i = 1, \dots, m; j = 1, \dots, n \quad (4)$$

Step 2: Calculate the weighted normalized decision matrix.

According to the following formula, the normalized matrix is multiplied by the weight of the criteria:

$$v_{ij}(x) = w_j r_{ij}(x) \quad i = 1, \dots, m; j = 1, \dots, n \quad (5)$$

Step 3: Determine the positive ideal and negative ideal solutions.

The aim of the TOPSIS method is to calculate the degree of distance of each alternative from positive and negative ideals. Therefore, in this step, the positive and negative ideal solutions are determined according to the following formulas:

$$A^+ = (v_1^+, v_2^+, \dots, v_n^+) \quad (6)$$

$$A^- = (v_1^-, v_2^-, \dots, v_n^-) \quad (7)$$

So that

$$v_j^+ = \{ (\max v_{ij}(x) | j \in j_1), (\min v_{ij}(x) | j \in j_2) \} \quad i = 1, \dots, m \quad (8)$$

$$v_j^- = \{ (\min v_{ij}(x) | j \in j_1), (\max v_{ij}(x) | j \in j_2) \} \quad i = 1, \dots, m \quad (9)$$

where j_1 and j_2 denote the negative and positive criteria, respectively.

Step 4: Euclidean distance from the positive and negative ideal solutions.

TOPSIS method ranks each alternative based on the relative closeness degree to the positive ideal and distance from the negative ideal. Therefore, in this step, the calculation of the distances between each alternative and the positive and negative ideal solutions is obtained by using the following formulas:

$$d_i^+ = \sqrt{\sum_{j=1}^n [v_{ij}(x) - v_j^+(x)]^2}, \quad i = 1, \dots, m \quad (10)$$

$$d_i^- = \sqrt{\sum_{j=1}^n [v_{ij}(x) - v_j^-(x)]^2}, \quad i = 1, \dots, m \quad (11)$$

Step 5: Calculate the relative closeness degree of alternatives to the ideal solution.

In this step, the relative closeness degree of each alternative to the ideal solution is obtained by the following formula. If the relative closeness degree has a value near 1, it

means that the alternative has a shorter distance from the positive ideal solution and a longer distance from the negative ideal solution.

$$C_i = \frac{d_i^-}{(d_i^+ + d_i^-)}, i = 1, \dots, m \quad (12)$$

Table 8 shows the ranking of alternatives. The ranking of alternatives obtained from both methods are found to have a greater correlation of 96.6%. The best and worst ranked alternatives from both methods are found to be exactly the same (A2B2C1D2). Figure 5 shows the comparison of alternative rankings obtained through the weight values of entropy and PCA techniques applied in TOPSIS alternative ranking.

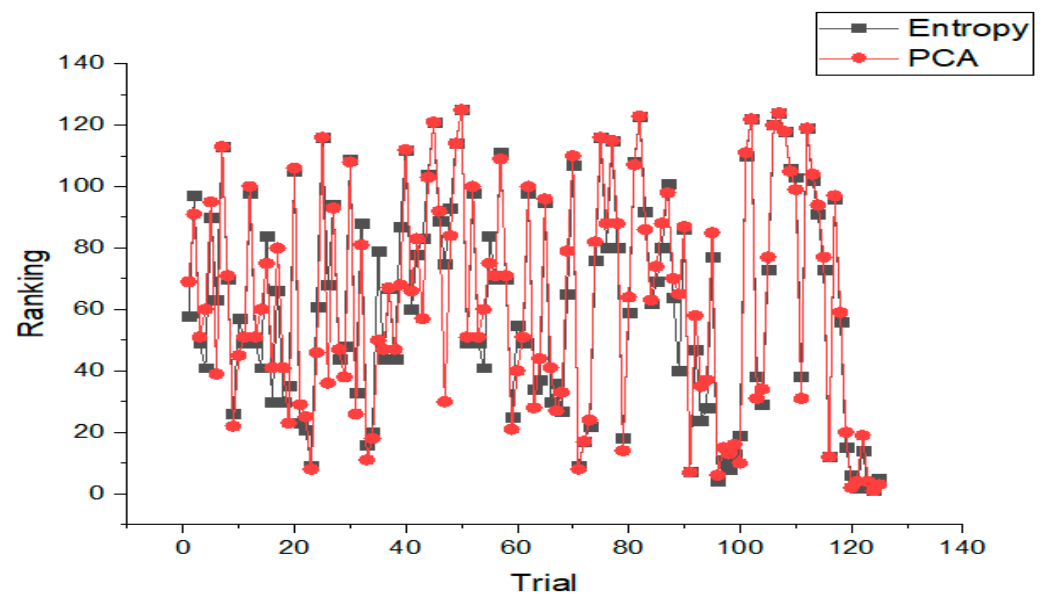


Figure 5. Comparison of alternative rankings.

From the weight values obtained from both entropy and PCA methods, different weight values have been assigned to the angular distortions at different stages of welding. Despite the different weight values of angular distortions from both methods, the alternative ranking is found to have a good correlation of 96.6%, which is a good sign of the methodology employed in the current study.

Confirmation trials have been performed from the optimal combination by measuring the angular distortion by preparing three samples from the same combination. The outcomes of the confirmation trials have been represented in Table 9.

Table 9. Confirmation trial results.

Trial No.	θ (°)	T (min)	F (m/min)	S (cm/min)	α_2 (°)	α_3 (°)	α_4 (°)
1	110	25	5.75	10.8	−0.17	−0.02	−0.02
2					−0.19	−0.02	−0.01
3					−0.17	−0.01	−0.03

The measured values of angular distortions are found to be negative and they are higher at the initial stage and reduce subsequently.

4.4. Statistical Analysis

The closeness coefficient values obtained have been examined through regression to identify the influencing factor and the effect of combined factors. The analysis is carried out by considering 95% confidence interval with p -value less than 0.05. Table 10 shows the regression analysis of closeness coefficient value obtained from the entropy technique.

Table 10. Results of regression examination.

Source	DF	Adj SS	Adj MS	F-Value	p -Value	Contribution %
Regression	10	2.66261	0.26626	56.63	0.000	
θ	1	0.29558	0.29559	62.87	0.000	9.24
T	1	0.1489	0.1489	31.67	0.000	4.66
F	1	0.00361	0.00361	0.77	0.382	0.11
S	1	0.00739	0.00739	1.57	0.213	0.23
θ *T	1	0.97606	0.97606	207.6	0.000	30.52
θ *F	1	0.38742	0.38742	82.4	0.000	12.11
θ *S	1	0.13378	0.13378	28.45	0.000	4.18
T*F	1	0.56394	0.56395	119.95	0.000	17.63
T*S	1	0.00441	0.00441	0.94	0.335	0.14
F*S	1	0.00004	3.7×10^{-5}	0.01	0.929	0.00
Error	114	0.53598	0.0047			16.76
Lack-of-Fit	92	0.53598	0.00583			16.76
Pure Error	22	0.0000	0			0.00
Total	124	3.19858				100.00

Through regression analysis, it is found that the factors angle of electrode to workpiece and time gap between passes are found to be individually significant and the other two input factors such as wire feed rate and welding speed are insignificant over the closeness coefficient values. On the contrary, while observing the combined effects, the interaction between angle of electrode to workpiece $\times$ time gap between passes, angle of electrode to workpiece $\times$ wire feed rate, angle of electrode to workpiece $\times$ welding speed, and time gap between passes $\times$ wire feed rate are found to be significant.

The interaction between angle of electrode to workpiece $\times$ time gap between passes has received the maximum contribution of 30.52% over other combined input factors. Surface plots have been generated for the combined factors which affect the closeness coefficient value to understand their impact [24]. Table 11 shows the model summary of the regression analysis, where R^2 value of 83.24% is a better sign that this regression model can predict the outcomes with a considerable accuracy.

Table 11. Model summary.

S	R-sq	R-sq(adj)	R-sq(pred)
0.0685678	83.24%	81.77%	79.09%

Figures 6–9 show the surface plots developed for combined effects which are significant through regression analysis.

As per regression analysis, surface plots are generated for closeness coefficient values by considering the significant interactions between the control factors. The surface plot between angle of electrode to workpiece with wire feed rate represents the changes in closeness coefficient values. The closeness coefficient value increases when higher levels for both factors have been considered. As per the interaction study between the two factors, their interaction is found to be significant and it has 12.11 contributions over angular distortion. The selection of higher workpiece angle with respect to electrode and faster welding speed increases the closeness coefficient values. Individually, the angle of electrode to workpiece is found to be significant as the p -value is less than 0.05 with a contribution of

9.24%, but on the contrary, the wire feed rate is not individually significant as the p -value is greater than 0.05 and it has poor contribution of 0.11% towards closeness coefficient values.

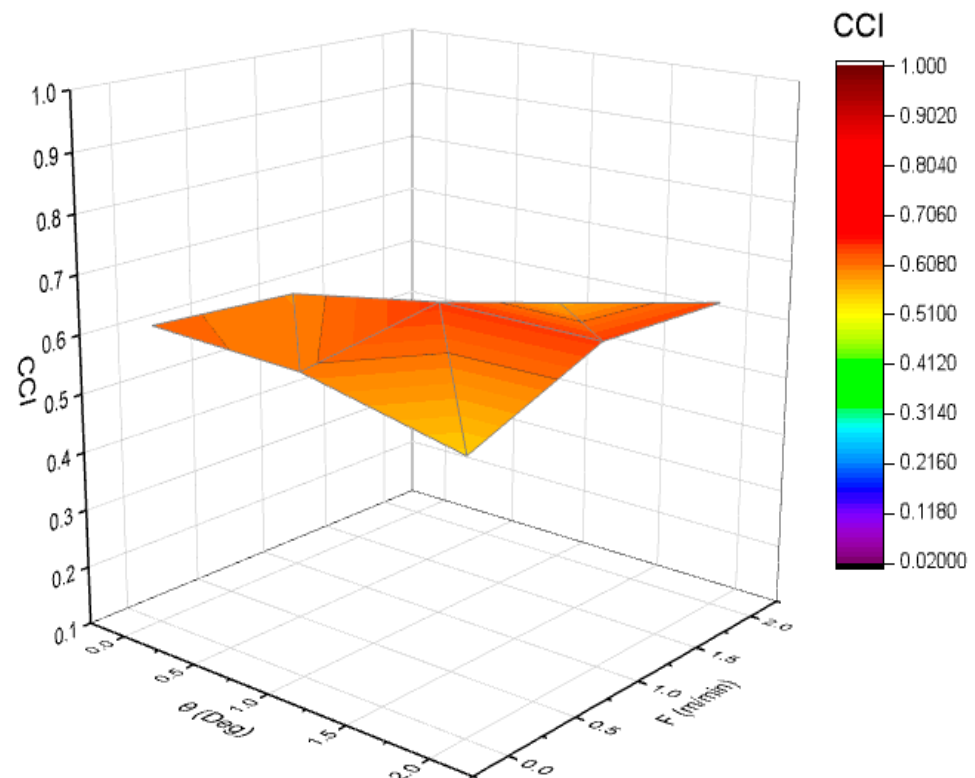


Figure 6. Surface plot for angle of electrode to workpiece $\times$ wire feed rate.

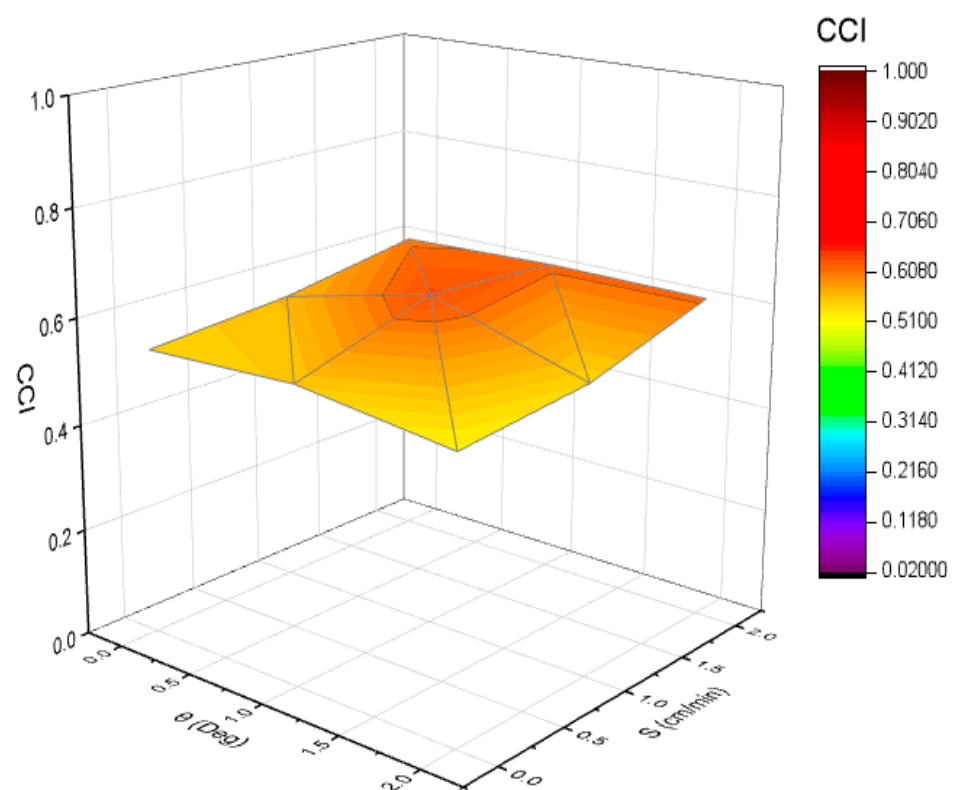


Figure 7. Surface plot for angle of electrode to workpiece $\times$ welding speed.

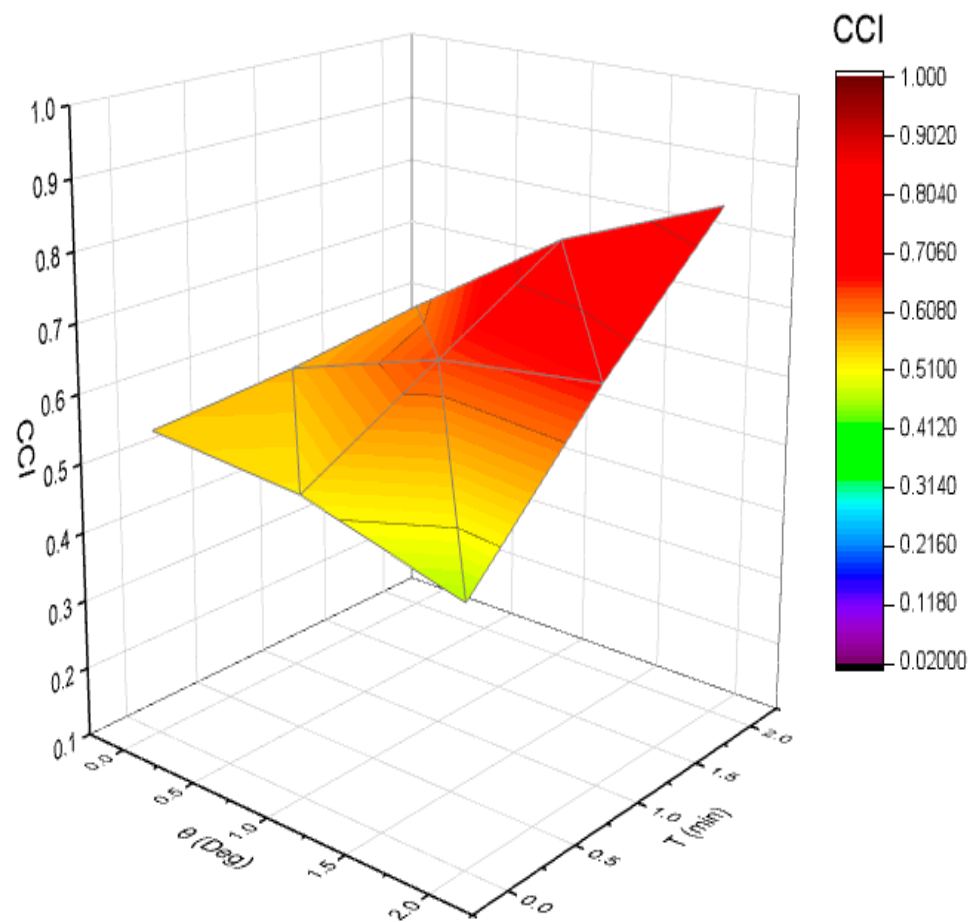


Figure 8. Surface plot for angle of electrode to workpiece $\times$ time gap between passes.

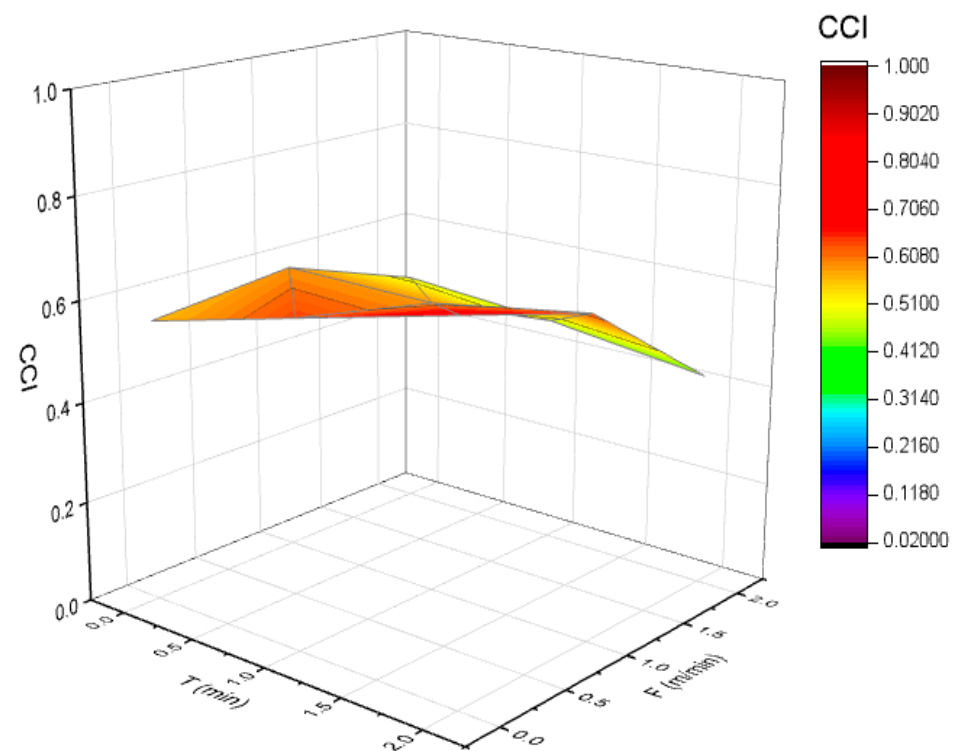


Figure 9. Surface plot for time gap between passes $\times$ wire feed rate.

Figure 7 represents the surface plot between angle of electrode to workpiece with welding speed which has a contribution of 4.18% among other input factor combinations. In the case of increasing the closeness coefficient values, both middle and higher levels have been recommended. In comparison to angle of electrode with workpiece, welding speed has a very low contribution of 0.23% as an individual factor in comparison with 9.24% contribution of welding angle. The surface plot developed indicates that fixing lower levels of above such parameters reduces the closeness coefficient value which may further increase the angular distortion.

As shown in Figure 8, the interaction between angle of electrode to workpiece and time gap between passes is found to be highly significant than any other factor combinations with a maximum contribution of 30.52%. There is a linear increase in closeness coefficient value when the parameter levels are varied from lower to higher. As individual input factors, both the welding electrode angle and the time pass between the passes have significant influence over the closeness coefficient values. Contributions of 9.23 and 4.66% are obtained for welding angle and time gap, which seem to be significant individually and produce combined effects over closeness coefficient values.

The interaction between time gap between passes and wire feed rate contributes 17.63%. As shown in Figure 9 parameter level for time gap should be higher and for wire feed rate should be at the middle level for increasing the closeness coefficient value. A higher time gap allows for better solidification of the welded region and it minimizes the angular distortion. Wire feed rate has no influence over closeness coefficient values and it can be varied to any level by maintaining the time gap between the passes as constant.

As a whole, in the surface plots generated based upon the revelation of input factor interaction through regression analysis, the input factors do not have a linear or sloping relationship with closeness coefficient values. The closeness coefficient values are found to have fluctuation when the levels of significant factors are varied individually or in a combined form from lower to moderate and moderate to higher.

Probability plots have been generated for the closeness coefficient values obtained from both weight assessment techniques. Figure 10 shows the normal probability plot developed for closeness coefficient values for the entropy-based closeness coefficient values for the experimental outcomes obtained for all the 125 experimental trials. The center thin line indicates the normal distribution line and side bars represent the confidence interval percentage. The analyzed data have a mean value of 0.5430 and standard deviation of 0.1606. The closeness coefficient value has been analyzed through Minitab 17.0 to obtain the fit with respect to the normal probability line and the distribution of data. The plot developed indicates that the data have a good fit with normal probability line and only very few points are away from the fitted line.

Similarly, PCA-based closeness coefficient values have been analyzed through probability to check its adequacy in fitting the normal distribution line. The data have a mean of 0.4853 and standard deviation of 0.1493. The plot developed as per Figure 11 indicates that the data analyzed are very good for the normal distribution line. This indicates that the calculated values of closeness values from both entropy and PCA weighted values have a good fit with the normal probability line and follow a normal distribution.

4.5. Regression Machine Learning Techniques

Machine learning (ML) techniques are capable of learning the patterns in a dataset and can perform accurate predictions about the future outcomes. The current study has analyzed the entropy-based closeness coefficient values through regression-based ML algorithms such as random forest, linear regression, and AdaBoost. The performance of the algorithms has been evaluated from the values of mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and R-square. The current study has adopted Orange 3.11.0 data mining software to conduct training on the input dataset. The analysis has been carried out by dividing the entire dataset into a split of training: testing with a ratio of 75:25. Table 11 shows the performance of different regression ML techniques.

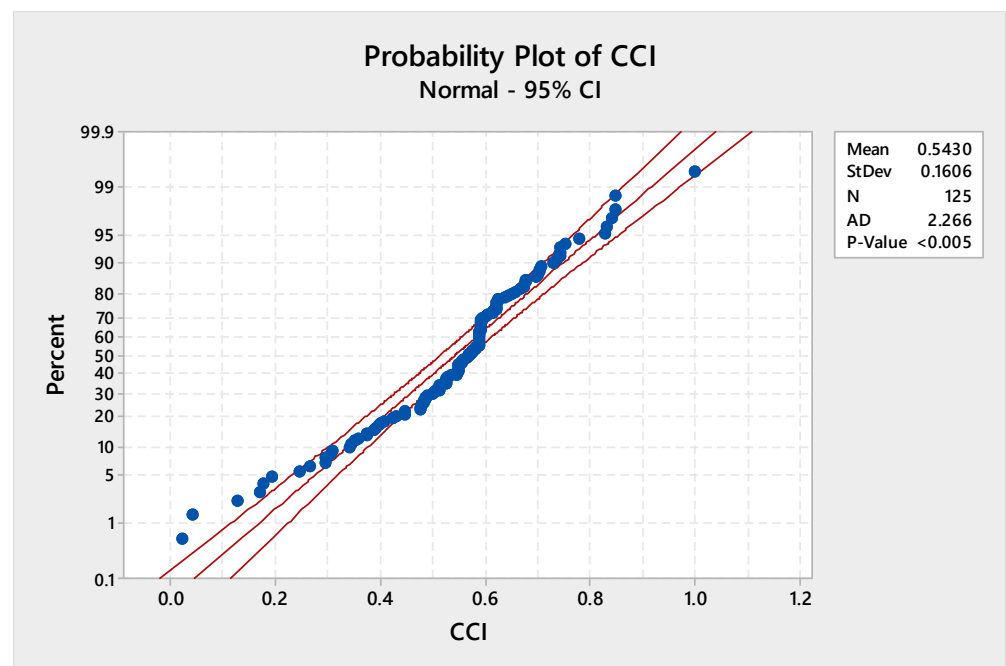


Figure 10. Probability plot for CCI–entropy based.

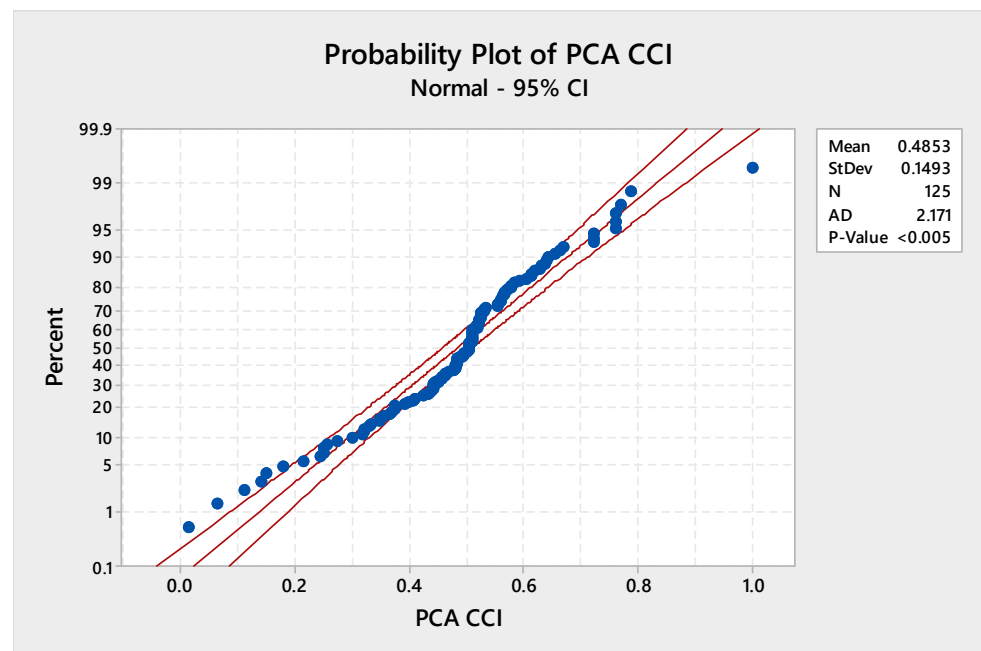


Figure 11. Probability plot for CCI–PCA based.

4.5.1. Random Forest Algorithm

Random forest algorithm is a popular supervised ML technique which can be used for both regression and classification tasks. It consists of a large number of decision trees which can perform predictions over the target variable. It operates on the theory of ensemble learning, in which several teachers collaborate to solve a challenging issue and enhance the functionality of the model.

4.5.2. Linear Regression

A linear relationship between a scalar answer and one or more explanatory variables—also referred to as dependent and independent variables—is estimated using a statistical

model called linear regression. Using linear predictor functions, the unknown model parameters in a linear regression are estimated from the data to represent the relationships.

4.5.3. AdaBoost Algorithm

The AdaBoost method trains a series of weak classifiers repeatedly using various subsets of the training set. It generally focuses on the more difficult cases by giving the incorrectly categorized samples from the previous iteration with more weights throughout each iteration. This procedure enables the later weak classifiers to perform better by giving the previously incorrectly classified data greater attention.

From the results obtained, the performance of Ada Boost algorithm is better than the other two algorithms considered. The R^2 value of 0.99 indicates that the prediction made by this algorithm over the future outcomes will be 99% accurate. The performance of linear regression algorithm is very poor and the random forest algorithm performed in an acceptable manner in terms of evaluation metrics. Figure 12 shows the regression ML workflow and Table 12 represents the evaluation for the regression machine learning algorithms involved.

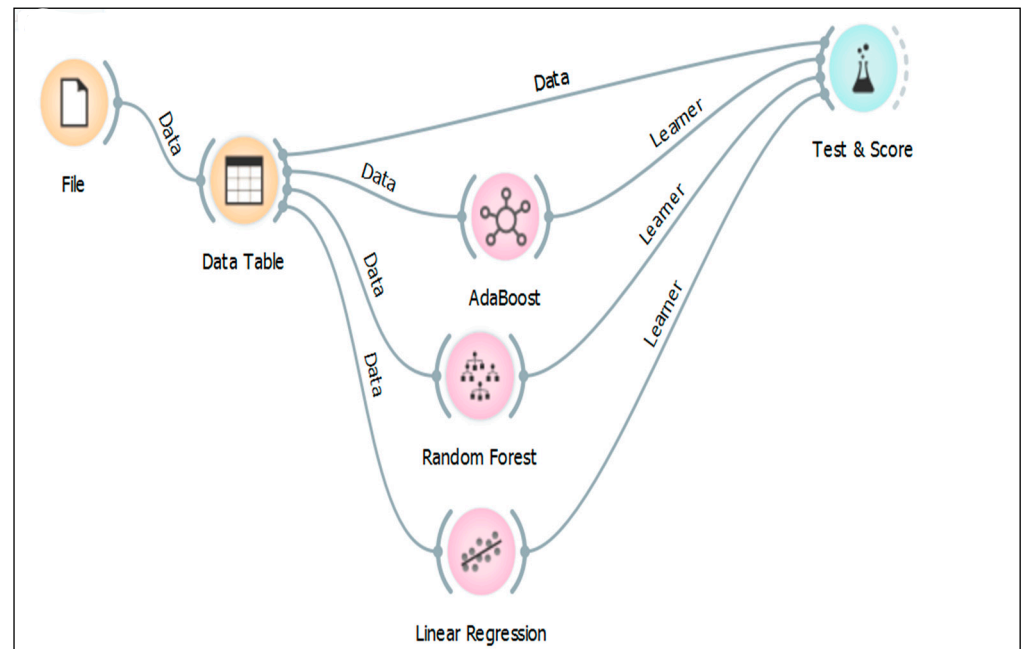


Figure 12. Regression ML workflow.

Table 12. Evaluation metrics for regression ML algorithms.

Method	MSE	RMSE	MAE	R^2
Random Forest	0.003	0.053	0.036	0.890
Linear Regression	0.022	0.148	0.110	0.149
AdaBoost	0.000	0.006	0.001	0.999

5. Microstructure Analysis

The microstructural analysis of the welded joints has been analyzed through an optical microscope and it has been viewed at different magnifications to understand the effect of varying input parameters. The evolution of microstructure at different zones such as melted zone, heat affected zone (HAZ), and substrate can be visually understood through the microstructural images. The weld intersect area has been viewed at $200\times$ at different scales such as $10\text{ }\mu\text{m}$ and $100\text{ }\mu\text{m}$. Figures 13–15 show the microstructure of weld intersect, weld zone, and heat affected zone. The microstructure of the welded plates at different sections such as 40 mm, 80 mm and 120 mm have been at $200\times$ magnification in both zones.

Both the weld and heat affected zones have a coarser microstructure due to the passage of more current during welding and at higher welding speed.

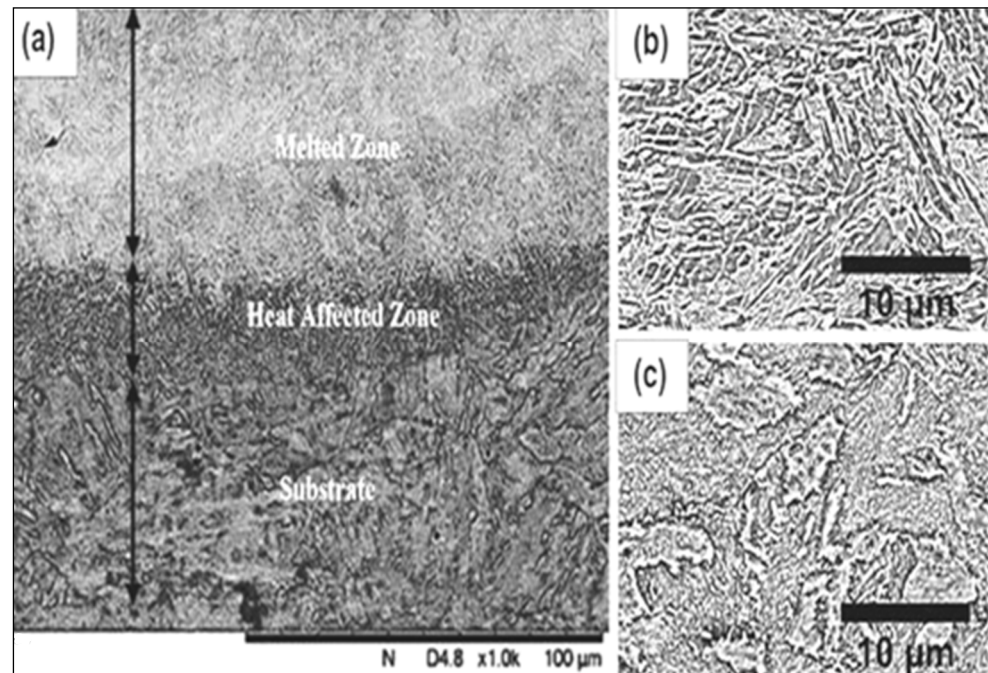


Figure 13. Microstructure at the weld intersect area (a–c).

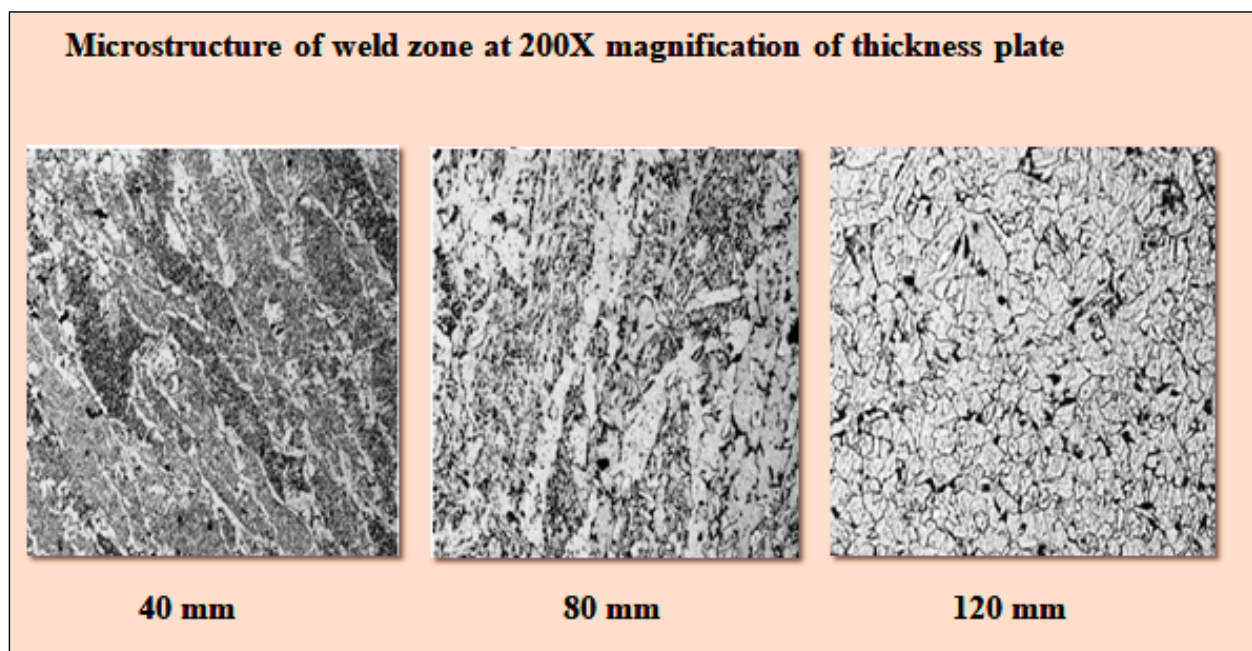


Figure 14. Microstructure of weld zone at 200 $\times$.

Figure 13a distinguishes the melted zone, heat affected zone, and substrate material through SEM analysis. The extended analysis of the microstructure at different zones of the sample indicates the presence and formation of ferrite as shown in Figure 13b. Moreover, the structure should comprise some pure ferrite with aligned carbides, and pearlite + ferrite structures were validated by the examination of areas beyond the welding bead. The ferrite grains become coarser in the outside areas of the welding seam. The changes in grain diameter were due to the temperature changes as a result of the fast and slow cooling rate.

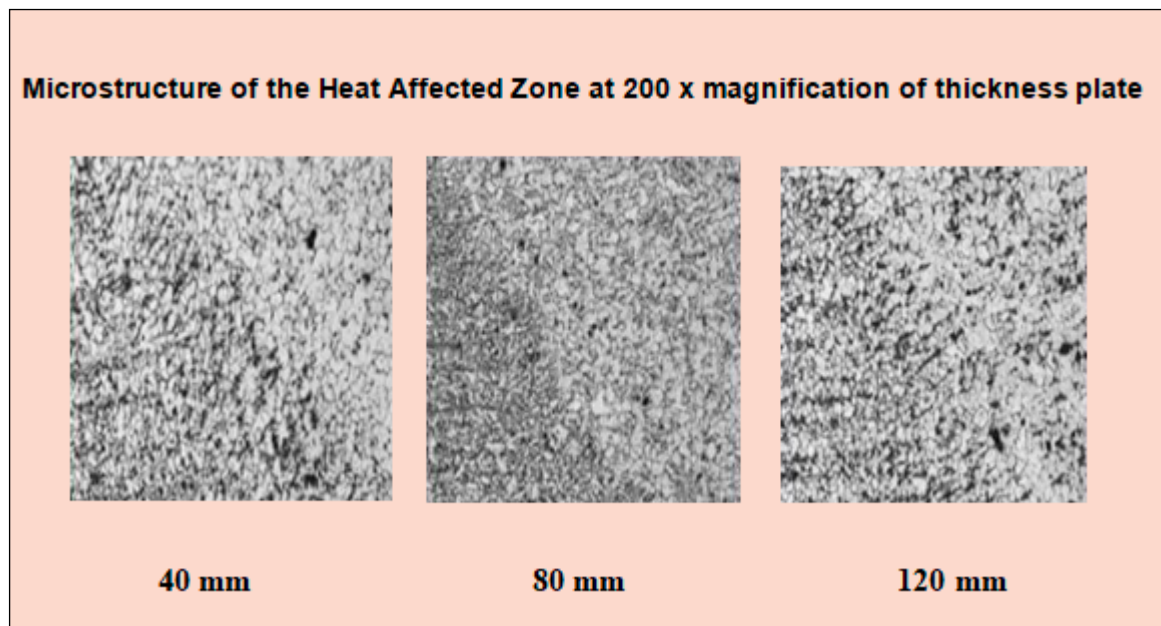


Figure 15. Microstructure of HAZ at 200 $\times$.

As shown in Figure 13b, at a scale of 10 μm , the transformation of parent metal microstructure such as ferrite and small amount of ferrite gets transformed into acicular ferrite. Similarly from Figure 13a the presence of retained austenite and martensite can be viewed at a scale of 10 μm through SEM analysis.

As shown in Figures 14 and 15, on the contrary, the grains formed in the weld zone and heat affected zone were found to have austenite formation due to the impact of temperature and higher welding speed, where the time for solidification is low. Similarly, higher welding angles result in the formation of coarse microstructure.

6. Conclusions

The current study has focused on optimizing the GMAW process parameters towards minimizing the angular distortion through MCDM techniques and ML algorithms. The concluding remarks of the study are mentioned herewith:

- The experimental trials have been conducted as per response surface methodology and the value of angular distortion of the welded plates has been measured after every pass.
- The measured values of angular distortion are above the tolerance limit and they have been analyzed through entropy and principal component analysis methods for weight evaluation.
- The entropy method has assigned 50% weightage for angular distortion at initial stage, 27% and 23% for the subsequent stages of angular distortions. On the contrary, the PCA method has given almost closer weightage to all three stages of angular distortion such as 32%, 35%, and 33%, respectively.
- The combination comprising 110 degrees of electrode to workpiece angle, 25 min time gap, 5.75 mm/min wire feed rate, and 10.8 cm/min welding speed (A2B2C1D2) is found to be the optimal parameter combination for reducing angular distortions and the ranking of alternatives obtained from both methods are found to have 96.6% correlation.
- Through statistical analysis of closeness coefficient values, the parameters angle of electrode to workpiece and time gap between passes are found to be individually significant with p -value less than 0.05.
- The interaction between electrode angle to workpiece $\times$ time gap between passes, electrode angle to workpiece $\times$ wire feed rate, electrode angle to workpiece $\times$ welding

- speed, and time gap between passes $\times$ wire feed rate are found to be significant with contributions of 30.52%, 12.11%, 4.18%, and 17.63%, respectively.
- The analysis of closeness coefficient value through AdaBoost algorithm has received superior performance with R^2 value equal to 0.99.
 - The study ensures the possibility of reducing angular distortion in GMAW welded steel plates through optimized parameter combinations.
 - The proposed hybridized methodology PCA-Entropy-TOPSIS can be utilized as an effective tool for identifying the optimal parameter conditions from a set of available alternatives. The methodology can be employed in a variety of industrial scenarios, where conflicting demands are arising in product development and optimal solutions can be arrived with less complexity.
 - Evaluating the mechanical properties such as tensile strength, hardness, and other properties has been considered as the future scope of the current research to unveil the associated industrial applications of the GMAW welded joints.

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Abbreviations

ANN	Artificial Neural Network
ARAS	Additive Ratio Assessment
ASTM	American Society for Testing of Materials
CCI	Closeness Coefficient Value
COPRAS	Complex Proportional Assessment
FE	Finite Element
GMAW	Gas Metal Arc Welding
HAZ	Heat Affected Zone
MAE	Mean Absolute Error
MCDM	Multi-Criteria Decision Making
MIG	Metal Inert Gas
ML	Machine Learning
MOORA	Multi-Objective Optimization Ratio Analysis
MSE	Mean Square Error
PCA	Principal Component Analysis
TIG	Tungsten Inert Gas
TOPSIS	Technique Order Preference Similar to Ideal Solution
Θ	Angle of the electrode with workpiece, degrees
T	Time gap between passes, min
F	Wire feed rate, mm/min
S	Welding speed, cm/min

Appendix A

Table A1. The complete dataset of experimental outcomes.

S. No.	θ (°)	T (min)	F (m/min)	S (cm/min)	α_2 (°)	α_3 (°)	α_4 (°)
1	0	0	0	0	1.38	2.32	3.15
2	0	0	−1	2	1.88	2.44	2.81
3	0	0	0	1	1.38	2.22	2.96
4	0	0	1	0	1.34	2.3	3.03
5	0	0	2	−1	1.76	2.68	3.02
6	0	−1	0	2	1.56	2.02	2.57
7	0	−1	−1	1	2.32	3	3.62
8	0	−1	0	0	1.56	2.24	3.05
9	0	−1	1	−1	1.26	1.78	2.4
10	0	−1	2	0	1.42	2.2	2.71
11	0	0	0	1	1.38	2.22	2.96
12	0	0	−1	0	1.88	2.84	3.57
13	0	0	0	−1	1.38	2.22	2.96
14	0	0	1	0	1.34	2.3	3.03
15	0	0	2	2	1.76	2.38	2.45
16	0	1	0	0	1.2	2.24	3.05
17	0	1	−1	−1	1.44	2.5	3.22
18	0	1	0	0	1.2	2.24	3.05
19	0	1	1	2	1.42	1.89	2.09
20	0	1	2	1	2.1	3.01	3.18
21	0	2	0	−1	1.02	2.08	2.84
22	0	2	−1	0	1	2.02	2.77
23	0	2	0	2	1.02	1.24	1.43
24	0	2	1	1	1.5	2.2	2.56
25	0	2	2	0	2.44	3.46	3.61
26	−1	0	0	2	1.66	1.92	2.42
27	−1	0	−1	1	1.82	2.44	3.09
28	−1	0	0	0	1.4	2.1	2.94
29	−1	0	1	−1	1.44	2.06	2.71
30	−1	0	2	0	2.2	2.94	3.4
31	−1	−1	0	1	1.36	1.78	2.59
32	−1	−1	−1	0	1.78	2.26	2.94
33	−1	−1	0	−1	1.1	1.38	2.07
34	−1	−1	1	0	1.14	1.6	2.4
35	−1	−1	2	2	1.77	2.02	2.34
36	−1	0	0	0	1.4	2.1	2.94
37	−1	0	−1	−1	1.56	2.22	2.85
38	−1	0	0	0	1.4	2.1	2.94
39	−1	0	1	2	1.83	2.09	2.5
40	−1	0	2	1	2.33	2.95	3.33
41	−1	1	0	−1	1.44	2.24	2.99
42	−1	1	−1	0	1.6	2.44	3.18
43	−1	1	0	2	1.83	2	2.36
44	−1	1	1	1	2.13	2.7	3.23
45	−1	1	2	0	2.89	3.7	4.02
46	−1	2	0	0	1.74	2.46	3.18
47	−1	2	−1	2	1.77	1.75	1.92
48	−1	2	0	1	1.87	2.29	2.83
49	−1	2	1	0	2.43	3.13	3.66
50	−1	2	2	−1	3.45	4.27	4.41
51	0	0	0	1	1.38	2.22	2.96
52	0	0	−1	0	1.88	2.84	3.57
53	0	0	0	−1	1.38	2.22	2.96
54	0	0	1	0	1.34	2.3	3.03

Table A1. Cont.

S. No.	θ (°)	T (min)	F (m/min)	S (cm/min)	α_2 (°)	α_3 (°)	α_4 (°)
55	0	0	2	2	1.76	2.38	2.45
56	0	−1	0	0	1.56	2.24	3.05
57	0	−1	−1	−1	2.32	2.82	3.34
58	0	−1	0	0	1.56	2.24	3.05
59	0	−1	1	2	1.26	1.75	2.25
60	0	−1	2	1	1.42	2.19	2.66
61	0	0	0	−1	1.38	2.22	2.96
62	0	0	−1	0	1.88	2.84	3.57
63	0	0	0	2	1.38	1.92	2.39
64	0	0	1	1	1.34	2.2	2.84
65	0	0	2	0	1.76	2.78	3.21
66	0	1	0	0	1.2	2.24	3.05
67	0	1	−1	2	1.44	1.93	2.23
68	0	1	0	1	1.2	2.05	2.72
69	0	1	1	0	1.42	2.47	3.13
70	0	1	2	−1	2.1	3.19	3.46
71	0	2	0	2	1.02	1.24	1.43
72	0	2	−1	1	1	1.74	2.3
73	0	2	0	0	1.02	2	2.75
74	0	2	1	−1	1.5	2.56	3.12
75	0	2	2	0	2.44	3.46	3.61
76	1	0	0	0	1.58	2.54	3.36
77	1	0	−1	−1	2.42	3.26	3.91
78	1	0	0	0	1.58	2.54	3.36
79	1	0	1	2	1.07	1.71	2.04
80	1	0	2	1	1.41	2.41	2.71
81	1	−1	0	−1	2.24	2.72	3.37
82	1	−1	−1	0	3.08	3.76	4.4
83	1	−1	0	2	1.85	2.36	2.86
84	1	−1	1	1	1.47	2.22	2.89
85	1	−1	2	0	1.55	2.38	2.84
86	1	0	0	0	1.58	2.54	3.36
87	1	0	−1	2	2.03	2.63	2.98
88	1	0	0	1	1.45	2.33	3.05
89	1	0	1	0	1.33	2.33	3.04
90	1	0	2	−1	1.67	2.63	2.95
91	1	1	0	2	0.79	1.32	1.66
92	1	1	−1	1	1.37	2.28	2.91
93	1	1	0	0	1.05	2.12	2.94
94	1	1	1	−1	1.19	2.26	2.89
95	1	1	2	0	1.53	2.7	3
96	1	2	0	1	0.39	1.15	1.73
97	1	2	−1	0	0.71	1.75	2.54
98	1	2	0	−1	0.65	1.73	2.53
99	1	2	1	0	0.79	1.83	2.4
100	1	2	2	2	1.26	1.64	1.22
101	2	0	0	−1	2.26	2.88	3.62
102	2	0	−1	0	2.92	3.66	4.39
103	2	0	0	2	1.48	1.92	2.33
104	2	0	1	1	1.28	2.04	2.62
105	2	0	2	0	1.54	2.46	2.83
106	2	−1	0	0	2.88	3.36	4.11
107	2	−1	−1	2	3.54	3.85	4.17
108	2	−1	0	1	2.62	3.13	3.82
109	2	−1	1	0	2.16	2.71	3.39
110	2	−1	2	−1	2.16	2.59	2.88

Table A1. Cont.

S. No.	θ (°)	T (min)	F (m/min)	S (cm/min)	α_2 (°)	α_3 (°)	α_4 (°)
111	2	0	0	2	1.48	1.92	2.33
112	2	0	−1	1	2.66	3.34	3.96
113	2	0	0	0	2	2.76	3.57
114	2	0	1	−1	1.8	2.48	3.1
115	2	0	2	0	1.54	2.46	2.83
116	2	1	0	1	0.86	1.59	2.26
117	2	1	−1	0	1.78	2.65	3.45
118	2	1	0	−1	1.38	2.21	3.02
119	2	1	1	0	0.92	1.85	2.51
120	2	1	2	2	0.66	1.18	0.97
121	2	2	0	0	0.24	1.08	1.89
122	2	2	−1	−1	0.9	1.78	2.64
123	2	2	0	0	0.24	1.08	1.89
124	2	2	1	2	−0.22	−0.02	−0.03
125	2	2	2	1	0.56	1.28	1.24
		Minimum			−0.22	−0.02	−0.03
		Maximum			3.54	4.27	4.41
		Average			1.58	2.31	2.87

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