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Optimization of Submerged arc Welding Setting Parameters Using Taguchi-Based MCDM Methods: A Comparative Case Study

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ABSTRACT

The process parameters' right choice is a major problem for researchers. The sectors' decision-makers must consider a large diversity of attributes based on a group of contradicting criteria. Multi-criteria decision-making (MCDM) techniques are applied to enhance the selection of these parameters. This paper examines using the VIKOR, MOORA, and TOPSIS methodologies to determine the optimal arrangement of processing factors in submerged arc welding (SAW). Consideration is given to one case study on optimization. This case study depends on the experimental work conducted on the SAW of Cr–Mo–V steel. Significant parameters of the input process are wire feed, welding current, voltage, and speed. The influence of these factors on different responses about weld penetration, bead width, tensile strength, weld reinforcement, and weld hardness is investigated. Comparing the TOPSIS, VIKOR, and MOORA procedures demonstrate that all three techniques have shown similar results and are interchangeable. The Taguchi analysis-based TOPSIS technique is compared to the QO-Jaya algorithm, Jaya algorithm, and (TLBO) teaching learning-based optimization.

***Keywords**: Taguchi, MOORA, TOPSIS, VIKOR, Submerged arc welding*

1. INTRODUCTION

SAW operation is vastly utilized in the heavy-duty welding sector to construct mines, pipelines, gas cylinders, shipbuilding, and mineral processing equipment, among other applications. In the case of the SAW process, selecting the setting parameters to achieve the highest performance is a challenge shared by all manufacturers. Multiple setting parameters, such as arc traversal speed, electrode stick out, voltage, wire feed rate, contact tip-to-plate distance, welding current, etc., characterize the SAW process. These factors affect the reactions, such as tensile strength, hardness, impact value, weld penetration, weld shape, deposition rate, etc., in a significant manner.

Conventionally, manufacturers determine the operation parameter setting via a trial-and-error technique of the time-consuming, depending on the findings of machine operators, or by consulting the machine's manual. Nevertheless, the operation parameter setting calculated in this method is typically not optimal. To attain more optimal values of output characteristics, researchers have turned to optimization techniques for selecting SAW setting parameters. Researchers have made numerous attempts to enhance the SAW process for quality.Using (TLBO) Teaching-learning-based optimization, Rao and Kalyankar [1] built and implemented mathematical models to optimize the SAW process.

Olabi and Benyounis [2] performed a detailed analysis of the statistical methods, evolutional algorithms, and computer networks utilized by past research to optimize SAW setting parameters. Evaluation of the relevant literature reveals that researchers have typically developed a SAW process regression model and used them as objective functions for heuristic optimization algorithms to identify the parameters combination of optimal settings to improve the performance of the SAW process. Ghaderi et al. [3] applied the (ICA) Imperialist competitive algorithm and (GA) Genetic algorithm. Moradpour et al. [4] applied an (NSGA) non-dominated sorting genetic algorithm. Kumanan [5] created mathematical models and utilized the (PSO) particle swarm optimization approach to decrease the width of the weld. Dhira P. Rai and R.Venkata Rao [6] employed the Jaya algorithm to solve optimization problems of the SAW process. Also, the QO-Jaya algorithm is suggested to improve the Jaya algorithm's performance. According to researchers, the optimality method algorithms used in the aforementioned tactics are complex.

(DoE) Design of Experiments based optimization strategies are dependable and use minimal data to foresee the optimal input factors or parameters. MCDM approaches are gaining favor in the manufacturing industry to address multipart real-time issues. An MCDM technique rates the options and suggests the one with the highest ranking to the decision-maker. Several scholars employ the mutual approach of DoE and MCDM methodologies. The Taguchi method is one of the most popular and trustworthy strategies for optimization due to its low DoE and computational simplicity. However, the separate Taguchi approach cannot accommodate several objectives simultaneously. This needs hybridization with other MCDM approaches that turn numerous objectives into a single objective, which Taguchi can readily manage. Various MCDM techniques, such as Grey Relational Analysis (GRA), Response Surface Methodology (RSM), Complex Proportional Assessment (COPRAS), Technique for Order of Preference by Similarity to Ideal Solutions(TOPSIS), etc., can be used in conjunction with the Taguchi method to make decisions in the multiple conflicting criteria existence. A quick overview of several noteworthy research papers has been presented in this regard. Numerous machining procedures have utilized the TOPSIS technique., such as grinding by Stephen et al. [7], electrical discharge machining by Huu-Quang Nguyen et al. [8], and Zeng. et al. [9]. The Multi-Objective Optimization depends on Ratio Analysis (MOORA) technology has been successfully employed to improve various manufacturing processes, including the milling in Ladakh. [10]. The MOORA methodology has been successfully utilized in many non-traditional processes by Khan et al. [11]. GRA is integrated with PCA, RSM's desirability method, and other soft computing-based optimization algorithms to improve the GFRP inclined laser drilling process by Yadvendra et al. [12]. Nafisa et al. [13] used TOPSIS, COPRAS, and GRA-based optimization to improve the factors of the hardened steel turning process. Rajeev Ranjan1 [14] used MOORA and TOPSIS to select the best processing parameter combination for the GTAC process... Chakraborty and Zavadskas [15] attempted to demonstrate the efficiency of the WASPAS technique for selecting arc welding processes. Applying grey-based Taguchi techniques, Tarng, Y. S. et al. Using the Taguchi approach and fuzzy logic, [17] optimized the SAW process with numerous performance criteria. A. Sing et al.[18] optimized the parameters of SAW bead shape using a fuzzy-based desirability function technique. Datta et al. [19] optimized the SAW process using the Taguchi approach. To improve the SAW process, Narang et al. [20] employed (RSM) response surface methodology to construct the empirical models for certain responses. Roy et al. [21] optimized the mechanical characteristics of SA welded joints using a fuzzy-based multi-objective threshold acceptance method. Lee and Song [22] employed the Taguchi approach and fuzzy logic to improve the SAW process parameters. Singh et al. [23] optimized SA welded joints using a desired function technique. Sarkar et al. [24] optimized the SAW process using the grey-fuzzy Taguchi approach. Laudan et al. [25] constructed empirical models for certain responses in the SAW process, which are then enhanced using the desire function technique. Aghakhani et al. [26] utilized fuzzy logic to enhance the SAW process's weld bead penetration. Using the response surface concept, Kazemi et al. [27] improved the penetration depth in the SAW process.

According to the study of relevant literature given above, Multi-Objective Optimization (MOO) of contemporary machining processes has made substantial use of MCDM techniques. Few studies have been conducted on MCDM for SAW process optimization. The application of TOPSIS, VIKOR, which stands for a compromise solution and multi-criteria optimization, and MOORA to the MOO of SAM has not been investigated. This paper summarizes the conclusions of a SAW-based MCDM study. According to the literature review, there is no comparison work comparing hybrid Taguchi techniques such as TOPSIS, VIKOR, and MOORA in the SAW process.

Three methods, VIKOR, including TOPSIS, and MOORA, are utilized for MCDM and the entropy method to evaluate the weights for each criterion. Evaluation and condensing of the outputs of treating the MCDM problem using different ways are carried out. In addition, the ideal approach for concurrently attaining the smallest bead width, weld hardness, greatest weld penetration, and tensile strength is described. The Taguchi analysis-based TOPSIS technique is compared to the Jaya algorithm, QO-Jaya algorithm, and teaching learning-based optimization (TLBO)

2. MCDM METHODS

In this section, certain fundamental MCDM ideas, definitions, notations, properties, and approaches that will be required to address MCDM issues in subsequent sections are explained and briefly reviewed.

2.1. Calculation of Criteria Weight in MCDM Problems,

Because attribute weights can influence analytical outcomes, such as ordering alternatives, the procedure for evaluating appropriate attribute weights is crucial. There are various objective weight assignment methods in the literature. The entropy method is the most typical approach to obtaining objective weights. The entropy approach will be used in this study to allocate weights equitably. Following are the processes involved in applying the entropy weight approach to solve a decision-making problem: (Rao RV [28])

With m choices and n criteria, decision-makers suggest a decision matrix that depicts the link between alternatives and criteria. The matrix of decision-making can be extracted as follows:

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_n \end{array} \left| \begin{array}{ccccc} C_1 & C_2 & C_3 & \cdots & C_n \\ X_{11} & X_{12} & X_{13} & \cdots & X_{1n} \\ X_{21} & X_{22} & X_{23} & \cdots & X_{2n} \\ X_{31} & X_{32} & X_{33} & \cdots & X_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & X_{m3} & \cdots & X_{mn} \end{array} \right| \quad (1)$$

where A_i (i= 1,2.... m) signifies the possible alternatives, C_j (j= 1,2....... n) represents the attributes relating to alternative performance, and x_{ij} is the performance of Ai concerning attribute C_j

The next procedures calculate the weight of each criterion using the entropy weight approach.

Step 1. Determine the normalized decision matrix (p_{ij}) using Equation (1):

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} p_{ij} \quad (2)$$

Where j= 1, 2, …, n and i= 1, 2, …, m

Step 2. Determine the entropy value for each criterion (E_j) using Equation (2) :

$$E_j = -h \sum_{i=1}^{m} p_{ij} \ln(p_{ij}) \quad (3)$$

where $h = \frac{1}{\ln(m)}$ is constant and $0 \le E_j \le 1$

Step 3. For each criterion, the weight W_{j_j} is computed as:

$$W_j = \frac{d_j}{\sum_i^n (dj)} \quad (4)$$

Where d_j is the degree to which the average intrinsic information of each criterion deviates from one another and computed as: $d_j = 1 - E_j$

Compute the weight (Wj) representing the importance of criteria as:

$$\sum_{j=1}^{n} W_j \quad = 1, j = 1, \dots, n. \quad (5)$$

The computational details of the MCDM methods used in this paper are presented here-in-under

2.2. TOPSIS Method

This technique depends on the premise that the best choice selected should have the smallest Euclidean distance from the best solution and the largest distance from the worst solution. Below, Saha and Mondal [29] outline the key phases of the TOPSIS methodology.:

Step 1. Constructing the decision matrix by assigning each possibility a priority score for each condition.

Step 2. Calculating (Wj) the weight expressing the significance of each criterion

Step 3. Calculating $(r_{ij})$the normalized decision matrix.:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} (x_{ij})^2}}, i = 1, \dots, m; j = 1, \dots, n. \quad (6)$$

Step 4. Computing the weighted normalized decision matrix:

Multiply the columns r_{ij} by the corresponding weights (WJ) as:

$$v_{ij} = W_j \, * r_{ij}, \quad (7)$$

where W_j is the weight of its attribute

Step 5. Using the following formulae, get the best and worst solutions:

$$A^+ = \{v_1^+, v_2^+, \dots, v_m^+\}$$
$$\{(max_i v_{ij}/j \in B), min_i v_{ij}/j \in C)\}$$
$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\}$$
$$= \{(min_i v_{ij}/j \in B), max_i v_{ij}/j \in C)\} \quad (8)$$

where B and C correspond, respectively, to the benefit and cost criterion sets.

Step 6. Using the Euclidean distance, calculate the separation measures Si+ and Si of each choice from the PIS and NIS as follows:

$$S_i^+ = \sqrt{\sum_{i=1}^{m} (V_{ij} - V_j^+)^2},$$

$$S_i^- = \sqrt{\sum_{i=1}^{m} (V_{ij} - V_j^-)^2}, \quad (9)$$

Step 7: Determine the optimal choices using the relative closeness coefficient (RCCi) as:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}, i = 1, 2, \dots, m; 0 \le RC_i \le 1 \quad (10)$$

Step 8. Rank the alternatives based on their relative proximity coefficient RCCi to the ideal alternatives: the higher the RCCi value, the better the alternative Ai.

2.3. VIKOR M\ethod for MCDM

The following section investigates the methodological basis of VIKOR to be applied in this work by Prasenjit [30]. VIKOR method begins with a decision matrix, as expressed previously. The algorithm VIKOR has the following steps.

Step 1 : Determine the best and the worst values of all the criteria using Equation (8).

Step 2 : Determine the average *Sj* and the worst group score *Rj* as defined by Equations (11) and (12):

$$S_i = \sum_{j=1}^{m} (W_j * \frac{X_i^+ - X_{ij}}{X_i^+ - X_i^-}) \quad (11)$$

$$R_i = Max_j (W_j * \frac{X_i^+ - X_{ij}}{X_i^+ - X_i^-}) \quad (12)$$

Step 3 : Determine the overall ranking index for each alternative (Qi) using the following formula:

$$Q_i = v * \left(\frac{S_i - S^*}{S^- - S^*}\right) + (1 - v) * \left(\frac{R_i - R^*}{R^- - R^*}\right) \quad (13)$$

where: $S^* = Min_i S_i$, $S^- = Max_i S_i$.$R^* = Min_i R_i$, $R^- = Max_i R_i$, and v is the indication of the strategy of criteria (objectives) majority whose value is usually set to be 0.5.

2.4. MOORA Method

The following section investigates the methodological fundamentals of MOORA to be applied in this work. The steps of the MOORA method are investigated as follows (Chakraborty [31]:

The MOORA approach begins with a decision matrix, as previously described. Herein is outlined the technique for utilizing MOORA to rate options.

Step 1: First, compute the normalized decision matrix using the vector approach as specified in Equation. (14):

$$X'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} (x_{ij})^2}} \tag{14}$$

Step 2: Calculate the composite score as given in Equation (15):

$$Z_i = \sum_{j=1}^{b} X'_{ij} - \sum_{j=b+1}^{n} X'_{ij} \tag{15}$$

Where $\sum_{j=1}^{b} X'_{ij}$ and $\sum_{j=b+1}^{n} X'_{ij}$ are, respectively, the benefit and non-benefit (cost) criteria. If certain traits are more significant than others, the composite score is calculated as follows: (16):

$$Z_i = \sum_{j=1}^{b} W_j \quad X'_{ij} - \sum_{j=b+1}^{n} W_j \quad X'_{ij},$$

$$i = 1, \ldots, m \tag{16}$$

Where W_j is the weight of j^{th} the criterion.

Step 3: The Zi value may be positive or negative based on the sums of the options' maxima (benefit attributes) and minima (non-benefit attributes) in the decision matrix. The ultimate preference is determined by an ordinal ranking of Zi, with the best option having the greatest Zi value and the worst option having the lowest.

3. MULTI OPTIMIZATION OF SUBMERGED ARC WELDING SETTING PARAMETERS

3.1. Illustrative Case Study

To show and evaluate the efficacy of the TOPSIS, VIKOR, and MOORA approaches for solving MOO issues, the author has considered Rao and Kalyankar's [1] experimental work on the submerged arc welding of Cr–Mo–V steel. For simplicity and to avoid lengthy explanations, the whole experimental work is described in the same reference. Included in the SAW setting parameters are welding current "I" (Amp), welding speed "S" (cm/min), voltage "V" (volts), and wire feed "F" (cm/min). In the testing, Cr–Mo–V steel has been employed. Using Taguchi's L9 orthogonal array, nine tests are conducted in total. Output variables include bead width 'BW' (mm), weld penetration 'P' (cm/min), weld reinforcement 'R' (mm), weld hardness 'H' (Rc), and tensile strength 'TS' (MPa). The experimental plan is implemented as-is. Table (1) presents the experimental design and acquired findings. The numerous reactions studied in this study are contradictory; weld reinforcement and weld bead width must be decreased, while the remaining responses must be increased.

Table 1 –Design of Experiments and Average Value for each Response

	Setting Parameters				Responses				
Exp. No.	I	V	S	F	BW	R	P	TS	H
١	350	28	4	190	26.168	4.45	6.27	671	36
٢	350	30	12	250	30.969	4.567	11	815	34
٣	350	32	20	310	29.33	3.876	6.65	771	36
٤	400	28	12	310	31.354	9.46	8.69	783	31
٥	400	30	20	190	18.502	0.256	11	744	28
٦	400	32	4	250	22.025	1.543	8.03	866	31
٧	450	28	20	250	19.216	1.263	9.2	855	34
٨	450	30	4	310	26.259	3.054	11	842	33
٩	450	32	12	190	29.505	5.001	9.94	854	34

4. RESULTS AND DISCUSSION

4.1. Weight Determination Using Entropy Method

Each performance metric's relative weights are evaluated using the Entropy Method according to Equations (1 - 5). Following Entropy Method, the weightage for each criterion is listed in Table (2)

Table 2 –The Weightage for all Criteria

	BW	R	P	TS	H
Ej	0.9924	0.8884	0.9914	0.9986	0.9987
1-Ej	0.0079	0.1115	0.0085	0.0013	0.0012
Wj	0.0583	0.8562	0.0653	0.0103	0.0098

4.2. TOPSIS Approach

The procedure for using the TOPSIS method is presented previously and will be applied hereunder: According to Equation (6), the normalized value of each alternative may be computed. Applying Eq. (7) to the normalized decision matrix yields the appropriate weighted normalized decision matrix. Now, utilizing Equation (8), the best and worst solutions for each criterion are calculated and reported in Table (3)

Table 3–The Best and the Worst Solutions for all Criteria

	BW	R	P	T	H
A+	0.0136	0.0161	0.0258	0.0037	0.0035
A-	0.0231	0.5978	0.0147	0.0028	0.0027

The separation measures of each option from the best and the worst solutions (Si(+) and Si(-)) are then computed by applying Equation (9). Using Equation (10), the relative closeness values RCCi and the rank of each experiment are calculated, and the outcomes are displayed in Table (4)

Table 4–The Separation Measures, the Relative Closeness Value of each Alternative, and the Rank of all the Criteria

Exp. No.	Si(+)	Si(-)	Si(+)+ Si(-)	RCCi	Rank
A1	0.2653	0.3166	0.5820	0.5440	6
A2	0.2726	0.3094	0.5820	0.5316	7
A3	0.2291	0.3529	0.5820	0.6063	5
A4	0.5818	0.0057	0.5875	0.0097	9
A5	0.0009	0.5818	0.5828	0.9983	1
A6	0.0816	0.5004	0.5821	0.8596	3
A7	0.0637	0.5181	0.5819	0.8903	2
A8	0.1769	0.4050	0.5819	0.6959	4
A9	0.3000	0.2819	0.5819	0.4844	8

It is found that alternative A5 is the top alternative among the given options

4.3. VIKOR Approach

The approach for employing the VIKOR method has been described earlier and will be implemented below:
Each criterion's best and worst values are determined using Equation (8). Using equations (11) and (12), the values of group utility Si and individual regret for each choice may be calculated (12).It is also possible to determine the values of $S^- = \max_i S_i$, $S^* = \min_i S_i$, $R^- = \max_i R_i$, and $R^* = \min_i R_i$. Then, using equation (13), the compromise value for each alternative can be calculated, and the rank of each experiment may be established. The outcomes are displayed in Table (5)

Table 5–The Value of Group Utility Si and the Individual Regret Value R_i, the Compromise Value Q_i, and the rank for each alternative

Exp. No	S_i	R_i	Q_i	RANK
A1	0.5006	0.3902	-0.0179	7
A2	0.4628	0.4011	-0.0316	6
A3	0.4510	0.3368	-0.0758	5
A4	0.9570	0.8563	0.5000	9
A5	0.0162	0.0098	-0.5000	1
A6	0.1829	0.1197	-0.3465	3
A7	0.1248	0.0937	-0.3927	2
A8	0.3004	0.2603	-0.2010	4
A9	0.5091	0.4414	0.0169	8

It is found that alternative A5 is the top alternative among the given options

4.4. MOORA Approach

The procedure for using the MOORA method is presented previously and will be applied hereunder:
Step1: A normalized value of each alternative has been calculated according to Eq. (14).
Step2: Weighted normalized matrix has been developed utilizing Eq. (15).
Step 3: The composite score for all criteria can be calculated as expressed in Equation (16). The results of the composite score for all criteria with their resulting rank of each alternative are shown in Table (6).

Table 6 –Composite Score with Their Resulting Rank

EXP. NO	sum of Benefit	sum of Cost	Zi	Rank
A1	0.0176	0.3005	-0.2829	7
A2	0.0293	0.3114	-0.2821	6
A3	0.0189	0.2666	-0.2476	5
A4	0.0238	0.6210	-0.5972	9
A5	0.0290	0.0298	-0.0007	1
A6	0.0226	0.1137	-0.0911	3
A7	0.0253	0.0940	-0.0686	2
A8	0.0295	0.2123	-0.1828	4
A9	0.0270	0.3378	-0.3107	8

It is found that alternative A5 is the top alternative among the given options

5. COMPARATIVE ANALYSIS

5.1. Comparison of Results Obtained using MCDM Methods

The comparison of some MCDM methods is presented in many published papers. One of the most important questions is, 'Which is the best method for a given problem?'.

Whether all MCDM approaches provide identical outcomes is likewise significant and pertinent. Consequently, a comparative study of the acquired findings from the three MCDM approaches employed in this work is one of the primary goals envisioned as a result of this effort. Table (7) and Figure (1) illustrate a comparison of the possibilities ranked by the three algorithms TOPSIS, VIKOR, and MOORA.

It is found that alternative A5 is the top alternative among the given options

Table 7–Ranking of Alternatives by the Three Different Methods

Exp. No	TOPSIS	VIKOR	MOORA
A1	6	7	7
A2	7	6	6
A3	5	5	5
A4	9	9	9
A5	1	1	1
A6	3	3	3
A7	2	2	2
A8	4	4	4
A9	8	8	8

From Table (7) and Figure (1), the following observations are proposed:

1. The ranking order of choices differs across the three approaches.
2. It is quite interesting to note that for all three methods, the positions of the top five alternatives (A5 > A7 > A6 > A8 > A3) remain unchanged. In contrast, minor changes in the rankings of the remaining alternatives may be attributable to differences in the mathematical procedures of the adopted methodologies affecting the welding conditions selection problem. This indicates that determining the best option depends on the decision-making approach employed.
3. Comparing findings acquired using MCDM approaches, the VIKOR, MOORA, and TOPSIS methods have up to 7/9 choices graded the same, indicating that these three methods have yielded relatively similar results and may be utilized interchangeably.
4. Using the VIKOR and MOORA techniques, equivalent options are assessed.
5. To simultaneously attain "minimum" (W and R) and "maximum" (P, T, and H), the optimal process parameters offered include the following values: I = 400 Amps, V = 30 Volts, S = 20 cm/min, and F = 190 cm/min. Experiment 5 in Table (1)

6. MULTI-RESPONSE OPTIMIZATION USING TAGUCHI ANALYSIS BASED TOPSIS METHOD

TOPSIS aims to transform numerous replies into a comparable responses. The proximity coefficient value of each option (RCCi) is shown in Table 4 and may be regarded as a multi-performance characteristic index of each welding combination (TOPSIS -index). Minitab19 is used to design and examine the impact of SAW process parameters (I, V, S, and F) on the TOPSIS index.

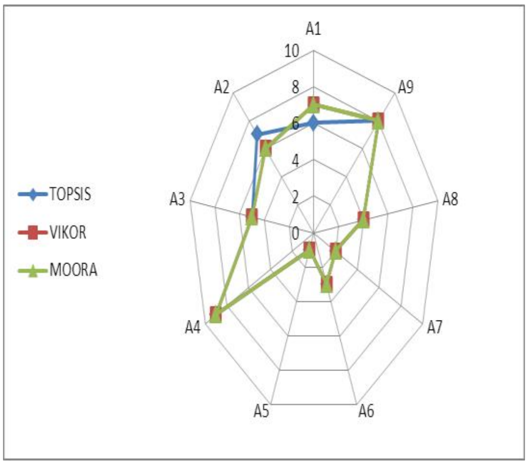

Fig. 1–A Graph for Comparing the Results of MCDM by Using Different Methods.

To assess the influence of each process parameter on the TOPSIS index, the response table and main effect plot for raw data are calculated. Table (8) provides the response table for TOPSIS -index, whereas Figure (2) illustrates the influence of factors on the TOPSIS -index. The evaluated delta (the difference between the highest and minimum value) for the process parameters is displayed in Table 8. The greatest effect on the TOPSIS - index is attributed to S, followed by F, V, and I. The study of Table (8) reveals that S (40.7%), F (26.86%), V (21.66%), and I (10.77%) represent the relative contributions of the control variables to the TOPSIS index. Table (8) also indicates that the values of the variables (I = 450(Amp), V =30 volts, S= 20 cm/min, and F= 250 cm/min) are the highest levels for maximal TOPSIS –index. As seen in Fig. (2), the TOPSIS –index continues to rise as the welding current increases, with the maximum recorded TOPSIS –index occurring at the highest welding current value. The voltage's TOPSIS index varies, beginning with a low index at low voltage levels, growing abruptly, then decreasing as the voltage continues to rise. As the welding speed increases to 12 cm/min, the TOPSIS index decreases abruptly from 0.7 to 0.35 as the welding speed increases from 0 to 12 cm/min. As the welding speed increases, the TOPSIS index rises once again. Wire feed has exhibited the same fluctuation as voltage in the TOPSIS index, beginning with less at the low wire feed rate, increasing abruptly, then decreasing as the wire feed rate rises.

Table 8 –Response Table for Means of TOPSIS-index

Level	I	V	S	F
1	0.5607	0.4814	0.6999	0.6756
2	0.6226	0.7420	0.3420	0.7606
3	0.6903	0.6502	0.8317	0.4373
Delta	0.1296	0.2606	0.4897	0.3232
Rank	4	3	1	2
Contribution	10.77%	21,66	40.7%	26.86%

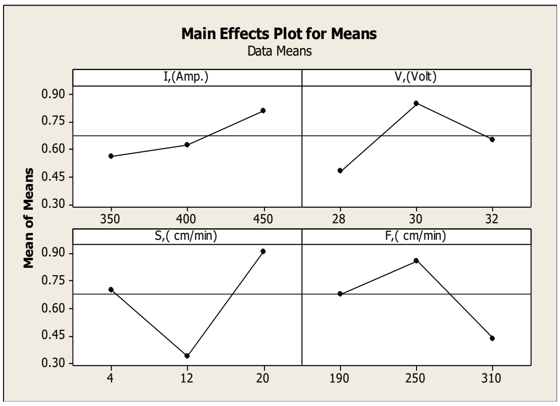

Fig. 2–Main Effects Plot for Means of TOPSIS-index

Because these combined factors are selected from the response table as a result of Taguchi analysis, and these combined factors are not present in the orthogonal array (Table 1), the predicted (calculated) TOPSIS -index utilizing the optimum level setting variables can be calculated using Minitab 19 or the following equation., Roos [32].

$$\eta\text{pred} = \eta\text{m} + \sum_{i=1}^{n}(\eta\text{i} - \eta\text{m}) \quad (17)$$

Where ηm is the total mean of the raw data, $\Sigma(\eta i{-}\eta m)$ is the all improvement (contribution) from all, ηi is the mean for factors at designated optimal levels, and n is the number of the main factors that affect the quality characteristics. The predicted value of the TOPSIS – index and each response's predicted (calculated) value using the optimum level setting variables can be determined from Minitab 19 and equation (17). The predicted (calculated) value of each response are W=18.88 mm , R= 0.05 mm , P=12.15 mm , T= 885.6 MPa and H=32 Rc

6.1. Comparison of Results Obtained Using Taguchi Analysis-Based MCDM Methods, TLBO, Jaya, and QO-Jaya Algorithms

Rao and Kalyankar [1] applied response surface modeling to an identical case study. Also established is a combined objective function that may be utilized to get the common parameter setting that concurrently meets all objectives for all answers. An optimized parameter setting is produced using the teaching–learning-based optimization (TLBO) approach. R. Venkata Rao and Dhiraj P. Rai [6] solved the optimization issue for the same case study using the Jaya and QO-Jaya algorithms. In their study, they formulated the objective function using the empirical models produced by Rao and Kalyyankar [1]. The results comparison performed by using MCDM methods revealed that the VIKOR, MOORA, and TOPSIS methods have up to 7/9 alternatives rated the same, and the VIKOR and MOORA methods have, alternatives rated the same, demonstrating that these three methods have produced quite comparable results and can be used interchangeably.

To illustrate the efficacy of Taguchi analysis-based MCDM approaches in solving the optimization issues of the SAW process, the results of the Taguchi analysis-based TOPSIS method are compared with those of other algorithms. For comparison of results, a solution obtained by the TLBO, Jaya, and QO-Jaya algorithms is reproduced from Rao and Kalyankar [1] and R. Venkata Rao and Dhiraj P. Rai [6] in Table (9).

Table 9- Comparison of Results Obtained Using Taguchi Analysis based TOPSIS Method, TLBO, Jaya, and QO-Jaya Algorithms

Method	Setting parameter				Responses				
	I	V	S	F	BW	R	P	T	H
TOPSIS	400	30	20	190	26.2	0.45	6.27	671	**36**
Taguchi analysis Based TOPSIS	450	30	20	250	18.88	0.05	**12.15**	**885.6**	3
TLBO [1]	445	32	7	193	27	0.8	9.3	845	33.4
Jaya [6]	423	29.8	4	267	20.89	0.015	11.19	856.7	29.7
QO-Jaya [6]	382.4	29.4	20	190	**17.5**	**0.006**	10.4	718	29

The values in bold represent an algorithm's superior performance relative to other algorithms.

The penetration and tensile strength values obtained by the Taguchi analysis-based TOPSIS approach are greater than those obtained by the TLBO, Jaya, and QO-Jaya algorithms, as shown in Table. This is mostly because the QO-Jaya algorithm sacrificed penetration and tensile strength to enhance weld bead width and reinforcement, and the TOPSIS approach sacrificed penetration and tensile strength to improve weld hardness. The weld quality values obtained by the TLBO and Jaya algorithms are lower than those obtained by the other techniques. However, Taguchi analysis-based MCDM approaches take less computing time than other methods. Taguchi-based MCDM approaches for selecting setting parameters will greatly benefit industrial applications. These methods are straightforward and devoid of algorithm-specific parameters. These are efficient, dependable, and practical approaches for handling the welding process and other machining process optimization issues

7. CONCLUSIONS

Using Taguchi analysis-based MCDM approaches, this study solves the SAW process optimization problem. Three MCDM approaches are evaluated independently, and the results obtained are compared to those achieved by well-known optimization algorithms such as TLBO, Jaya, and QO-Jaya.

The following conclusions are taken from the findings of the research.

1. This is the first time the Taguchi-based TOPSIS, VIKOR, and MOORA algorithms have been employed for the MCDM of a SAW. process
2. Each of the three approaches identified the same optimal solution. However, the Taguchi analysis-based MOORA approach requires less computing time than the Taguchi analysis-based TOPSIS and VIKOR methods.
3. The solution supplied by MCDM approaches is typically a discrete combination of specified levels of process parameters; hence, the provided solution may not be optimal (near optimum).
4. Based on Taguchi's analysis methods for optimizing the submerged arc welding process and other machining processes using MCDM are rapid, resilient, simple, and devoid of algorithm-specific parameters. In addition, these techniques are useful for optimizing submerged arc welding and other machining operations.
5. However, applying meta-heuristic algorithms for optimization problems needs mathematical models of the process that can map the relationship between input and output parameters to define the objective function.

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