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RESEARCH ARTICLE

A comparative study of multiple-criteria decision-making methods for selecting the best process parameters for friction stir welded Al 6061 alloy

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ABSTRACT

The selection of welding process parameters is a tedious operation that demands the process evaluation. Multi criteria decision-making strategies for assessing friction stir welding (FSW) process parameters are scanty. Therefore, a comparative study between five different multi-criteria decision-making methods was applied within friction stir welding process to show the deviations in the ranking of the alternatives. The goal is to find the welding parameters (including rotation speed, shoulder diameter, and travel speed) that result in the highest performance scores or rankings for the considered responses, such as ultimate tensile strength, hardness, and surface roughness. In the following, different decision-making strategies (including TOPSIS, GRA, hybrid GRA-TOPSIS, CoCoSo, and MACROS) are applied to calculate the weight of all different decision-making using entropy. The proposed methods in this study are validated by representing the accurate decision maker's preferences and consideration of uncertainty. The decision-makers choose GRA-TOPSIS and TOPSIS as the best approach with higher efficiency. GRA was determined to be more time-consuming and to have the most variety of outcomes, whereas CoCoSo and MACROS were unable to produce a definite best result. The study is highly promising for researchers and machining specialists to produce quality friction stir welds.

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Decision-Making; tOPSIS; gRA; mACROS; CoCoSo; hybrid GRA-TOPSIS

I. Introduction

Friction stir welding (FSW) is a solid-state joining technology that has been successfully employed in several applications for joining metals and thermoplastics. The FSW is operated with a non-consumable rotating tool with a smaller diameter pin attached to a bigger diameter shoulder. The design of the fixture is vital in FSW operation for increasing the effectiveness of the weld. FSW is performed by using a rotating non-consumable tool which is plunged into the mediator of the two workpieces. The movement of the rotating tool through the mediator produces a frictional heat that heats and softens the material. The frictional force and heat generation significantly affect the quality of the weld. Therefore, the movement of the rotating tool mixes the softened material to produce a bond between the two workpieces [1].

The heat is generated on the workpiece *via* the rotational friction between the no consumable tool and workpiece. The material of the pin gets softened, and it starts moving the material from the front of the workpiece towards the backside by revolving the pin. The weld nugget at the centre of the joint, known as the stir zone (SZ), has a size and morphology determined by the tool's size and shape. The FSW technique is currently determined to be more efficient for joining aluminium (Al) alloys in terms of content [2].

Recently, FSW has been used for combining complex aluminium-based products in lots of applications. The parametric process optimization of the FSW operation is necessary to reach

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the higher weldability and mechanical qualities in the joints. One of the main areas of research in the area of welding is to optimize the welding parameters in order to achieve high-quality joints. Several tools comprising statistical approaches and machine learning algorithms are quite familiar for optimizing the process parameters. The influencing parameters in the FSW process are rotational speed, plunge depth, travel speed, shoulder diameter, shoulder geometry, pin diameter, pin geometry, dwell time, tool material whereas the responses required are tensile strength, extension, surface roughness, hardness, distortion, fracture toughness and so on. Several articles are available for the optimization of FSW process parameters; however, articles dealing with the multi criteria decision-making approaches (MCDM) are scanty. Shojaeefard et al. [3] employed Taguchi's method for joining of Al-Mg and CuZn34 *via* FSW to extract the optimal rotational speed, tool tilt angle, and traverse speed of the process and the rotational speed was found to be the most significant factor affecting the joint soundness with the marginal error between the experimental and predicted tensile shear limited to 2.5%. Sahin [4] used a statistical technique to choose welding parameters and develop a tentative prediction paradigm for friction welding (FW) of Al-Cu. The regression coefficients to estimate the product's tensile strength were obtained using Fisher's method ratio. They evaluate the influence of the friction time, friction pressure, and upset pressure on the quality of the final Al-Cu product. Sabry et al. [5–7] employed a statistical method to choose process parameters and construct an experimental predictive paradigm for the FW of Al-Al where linear paradigm with specific coefficients was used to extract the best process parameters of FW. Eslami et al. [8] utilized a partial factorial Taguchi L25 method to increase welding speed with higher tensile strengths and lower electrical resistance. Their approach successfully predicted a traversal speed of 700 (mm/min), greater than the reported value in the previous research. Cardillo et al. [9] used a Taguchi L9 perpendicular order pursue with analysis of variance (ANOVA) to optimize process parameters for friction spot stirring welding (FSSW) of Al-Cu. However, they have followed the full factorial evaluation of the components to determine the optimal parameters for increasing shear strength. Sabry et al. [10] used a hybrid model of Taguchi L27 orthogonal array and ANOVA to optimize the process parameters for the FSW of Al and discovered that the joint's shear strength is affected by the rotational speed and plunge depth interactions. Colmenero et al. [11] optimized the FSSW process of Al-Cu based on the usage of energy *via* the vibration signal. They have employed the response surface method (RSM) to extract the optimal process parameters of the operation. The confirmatory test revealed perfect agreements amidst empirical and mathematics outcomes. Vijayan et al. [14] used L9 orthogonal array-based Taguchi-Grey for optimizing rotational speed, transverse speed and axial force for attaining good tensile strength and minimum power. As the morphology of the FSW for the Al sample is very ganglion, a regression was adopted to forecast the morphology of the interfacial area of the aluminium joint by Krutzlinger et al. [12].

Multi criteria decision-making approaches were found useful for the selection of choices among decision makers. Vinodh et al. [13] used Technique for Order Preference by Similarity to Ideal Solution, TOPSIS approach for selecting a concept among the five concepts proposed for attaining sustainability in the manufacturing processes during product development and design phases and found TOPSIS is an effective approach for finding the best option. Similarly, Prabhu et al. effectively used TOPSIS for the FSW of aluminium metal matrix composites with silicon carbide particles for the optimal solution and suggested using TOPSIS for such problems relevant to FSW [15]. The work of Manohar and Mahadevan [18] agrees with the finding that the TOPSIS is a successful tool for improving the multi-responses of the friction welds and thereby increasing the process efficiency. Sudhagar et al. [19] used MCDM techniques to evaluate several tool shapes and to come up with the best design for producing sound-quality joints. These MCDM techniques are also an alternative approach for evaluating the quality of the welds apart from the statistical and machine learning techniques [16,17].

As previously noted, in the metal joining process, mechanical properties like tensile strength, hardness, fracture toughness, and elongation are used to assess the quality of joints. Therefore, choosing the appropriate process parameter for friction stir welding is required taking into account the variety of quality factors [20]. Only single-objective issues can be optimized using the Taguchi method and Response surface methodology discussed above; multi-objective problems cannot be solved using these methods [34,36]. Therefore, a number of strategies, such Grey Relational Analysis (GRA) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [21,22], are accessible to tackle numerous objective problems. Grey system theory, on which GRA is based, is appropriate for handling issues involving complicated relationships between a number of components and variables. Power distribution, quality improvement, and resource use in industry are a few examples of challenges that can be solved using GRA [23]. By integrating all of the attribute values into a single value, GRA is able to handle multi-attribute problems, which reduces multi-objective problems to single-objective problems. As a result, the GRA technique lessens the complexity of decision-making and boosts system effectiveness [24]. Using the GRA approach, Hsuan-Liang Lin [25] optimized the gas metal arc welding process parameters by simplifying the problem into a single target and the depth-to-width ratio of the weld bead under two different situations was maximized. With the help of GRA, Hsiao et al. [26] were able to resolve the multi-objective problem in plasma arc welding where root penetration, groove width, and undercut are the three parameters that are computed and employed for the Taguchi method's parameter optimization in order to increase the tensile strength and elongation in the FSWed dissimilar aluminium alloy. Kasman [27] evaluated tensile strength and elongation using GRA and found the significance of parameters are in the order of welding speed accounting for roughly 48.7%, followed by tool type and rotating speed. In a different study, Kasman [28] used FSW to join the two dissimilar aluminum alloys AA6082 and AA5754 where the major goal of the study was to determine how welding speed, rotating speed, and shoulder-to-pin diameter ratio affected tensile strength and elongation. Their results show that the shoulder to pin diameter ratio influences grey relational grade by 50.3%, followed by welding speed by 37.68% and rotational speed by 11.89%. The studies in the area of friction stir welding show the abundance of GRA analysis, ANOVA analysis, TOPSIS analysis used. However, the MCDM approaches such as Combined Compromise Solution (COCOSO), and MACROS for friction stir welding applications have to be explored more.

According to the survey, scholars have researched and debated the effects of modifying process parameters on several elements of FSW, but not the impact of changing process parameters. The overall goal of this study is to find the best and most optimum welding parameters for combining two identical metals using FSW. Based on the current studies that were discussed for the selection of the welding parameters by the means of decision-making methods, most of the studies picked up the parameters using well-known models that were proven to be efficient. The researchers, engineers and academicians who used the decision-making techniques focused on the previously used methods. There is little focus on developing new models that could help to determine the optimal welding parameters in an efficient way. As a result, the current research fills the gaps by creating a novel decision-making model based on risk minimization.

The failure to obtain a rational conclusion is defined as a risk in the context of the investigation. The new decision-making method selects the optimal welding parameters from experiments based on four performance criteria: ultimate tensile strength (UTS), hardness (VHN), and surface roughness (SR). The proposed methodology can be classified as multi-criteria decision-making (MCDM) method because the choice is determined based on numerous criteria.

The MCDM models depend on experimental data. This work is composed of two stages the first stage is experimental work, and the second stage determined the weight for all criteria. In the first stage, the unique MCDM model was created and deployed to determine the best welding parameters. The proposed technique is based on the concept of risk minimization. The decision matrix is turned into a relative benefit matrix in the suggested MCDM model, which decreases the risk of not selecting the option with the highest benefit and lowest cost. Shannon's entropy approach [29] is used to calculate the weight of the criterion on which the choice will be made. A sensitivity analysis is performed to assess the given model's stability and the quality of the final products. The result acquired from the MCDM model is validated in the final part of the first phase by comparison to those using the other decision-making approaches. Finally, a confirmatory test is performed to ensure that the suggested hybrid techniques for order preference by similarity to ideal solution (TOPSIS) and grey relational analysis (GRA) model is viable. Here is the summary of the current study novelties as follows:

1. A comparative study between five different multi-criteria decision-making methods was applied within friction stir welding process to show the deviations in the ranking of the alternatives that occur when different methods are used.
2. Novel MCDM Model is introduced for selecting optimal welding parameters in FSW.TOPSIS, GRA, 3- 3- Hybrid GRA-TOPSIS, COCOSO, and MACROS methods are combined as Multiple Methods Integration for comprehensive evaluation.
3. FSW application applies the developed model and methods specifically to FSW of aluminium alloys, addressing unique challenges.

In the next section, the overview of the FSW of Al-alloy with respect to material, methods, and experimental method is detailed. In Section III, the proposed methodology of this study is explained in detail. The results and discussions are mentioned in Section IV. Section V concludes the remark of this study.

II. Overview of friction stir welded aluminium alloy

This section consists of two subsections, including the material and method used in this study and the explanation of the experiment design.

1. Materials and methods

Aluminium 6061 alloy pipes were used in this study as the parent metal. The weight percent of the elements in the alloy was calculated *via* a vacuum spectrometer. The spectrums were obtained by sparking sparks at various locations and estimating their compositions, as shown in Table 1. The parent metal's tensile characteristics and microhardness were tested and reported in Table 2. The parent metal yielded

Table 1. The %wt of the chemical structure of the pipe's component Al 6061.

Al	Si	Fe	Cu	Mn	Mg	Cr	Zn
Bal	0.4	0.70	0.15	0.15	0.9	0.04	0.25

Table 2. Mechanical properties of 6061.

Description	UTS (MPa)	EL%	Hardness (VHD)
6061	175	16	65

85 (MPa), a tensile strength of 175 (MPa), and a 16% elongation.

The parent metal was measured to have 65 (HV) hardness. The production setup of the materials is shown in Figure 1(a). Also, Figure 1(b) shows that the pipes are fastened to the bed by the fixture. Welding is established with a taper tool which consists of a conical pin profile, shoulder diameter =30, 40 and 50 (mm), upper pin diameter = 6 (mm), lower pin diameter = 1 (mm), and pin length = 3 (mm). Figure 1(c) shows the dimension of the conical pin and the conical pin with shoulder diameter of 30 mm is shown in Figure 1(d).

The ultimate tensile strength, percent elongation, and hardness of the welded joint are affected by rotational speed, traverse speed, and shoulder diameter based on the conducted work by El-Kassas et al. [30]. As a result, the current experiment altered rotational speed, traverse speed, and shoulder diameter. Based on preliminary studies, the parameter range was chosen to determine the lowest and upper limits of the process parameters at which defect-free joints could be achieved.

Figure 2 shows one of the produced welded pipes using the explained FSW process. A tensile test was performed on each specimen to measure the considered responses. The tensile test specimens were produced according to ASTM E8M-04, as shown in Figure 3.

2. Design of experiments

Rotation speed (N), shoulder diameter (D), and travel speed were identified as independent process parameters affecting ultimate tensile strength (UTS), hardness (VHN), and surface roughness (SR) based on preliminary testing and earlier investigations. Table 3 shows the parameters of friction stir welding. By altering one parameter at a time, trial runs were undertaken to determine the maximum and lower limits of process parameters for Al 6061 alloy.

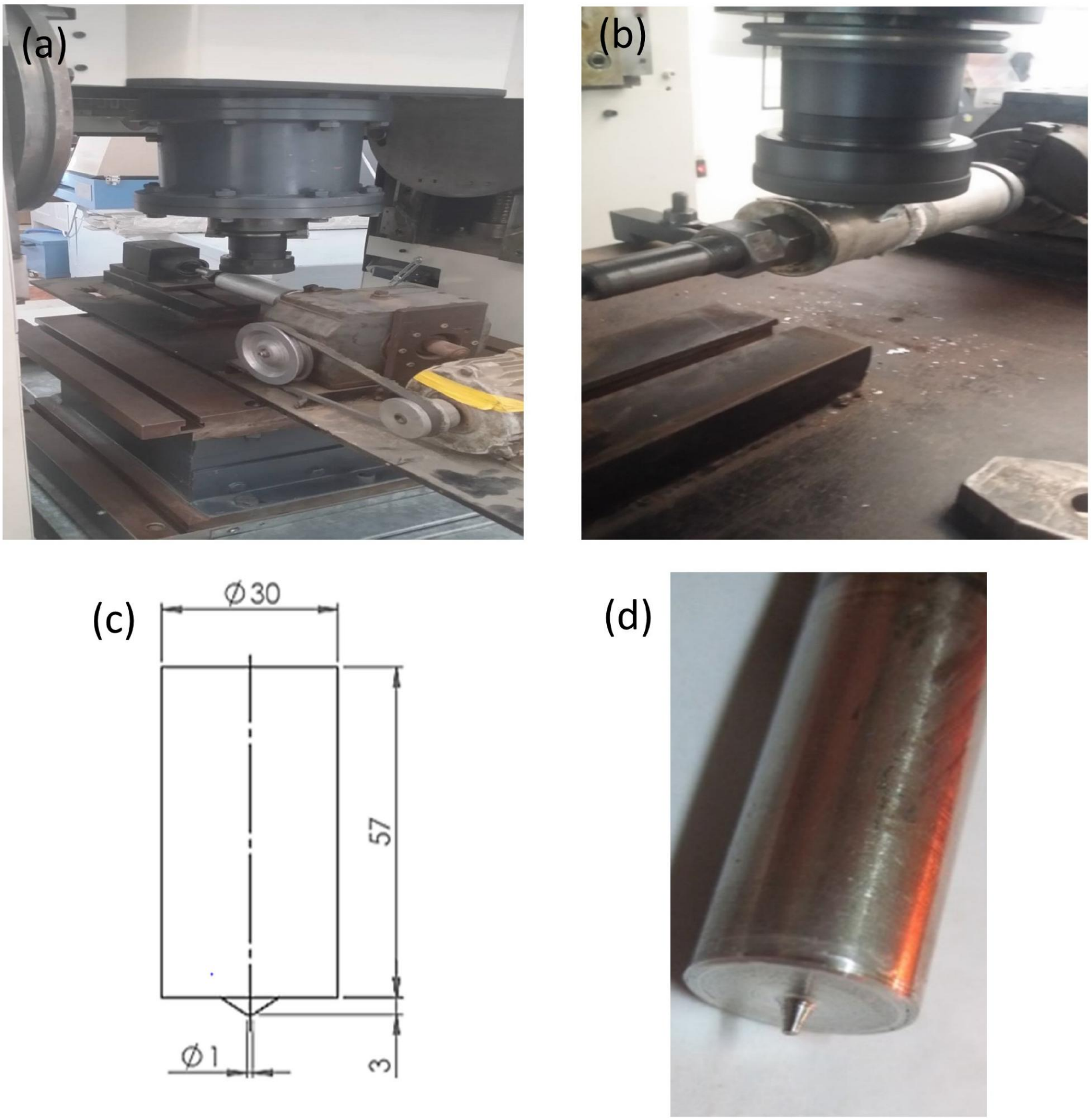

Figure 1. (a): Experimental setup of milling machine, which used in FSW for pipe joint; (b): friction stir welding of pipes (c): the conical pin; (d): the dimension of the FSW's tool.

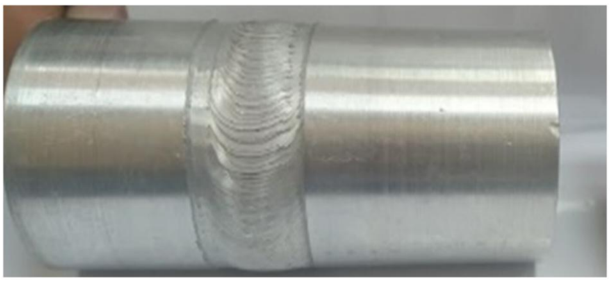

Figure 2. The UWFSW technique produces a welded pipe.

A parameter range was chosen to visually inspect the completed welded junction and revealed no flaws. A factor's upper and lower limits were coded as 1 and 1, respectively. Equation 1 was used to calculate the intermediate coded values [31].

$$X_i = 2X - \frac{X_{\max} + X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X_i, X, $X_{\max}$ and $X_{\min}$ are the required coded value, the variable value, the lower limit of the variable, and the upper limit of the variable [32]. The considered process parameters with their limits, units, and notations are given in Table 3.

Table 4 depicts the design matrix. It's a three-factor, three-level central composite rotatable design with 27 sets of coded conditions, including a full factorial of 24 = 16, six centre points, and five-star points.

Welding responses were assumed to be the UTS, VHN, and SR. Three tensile specimens

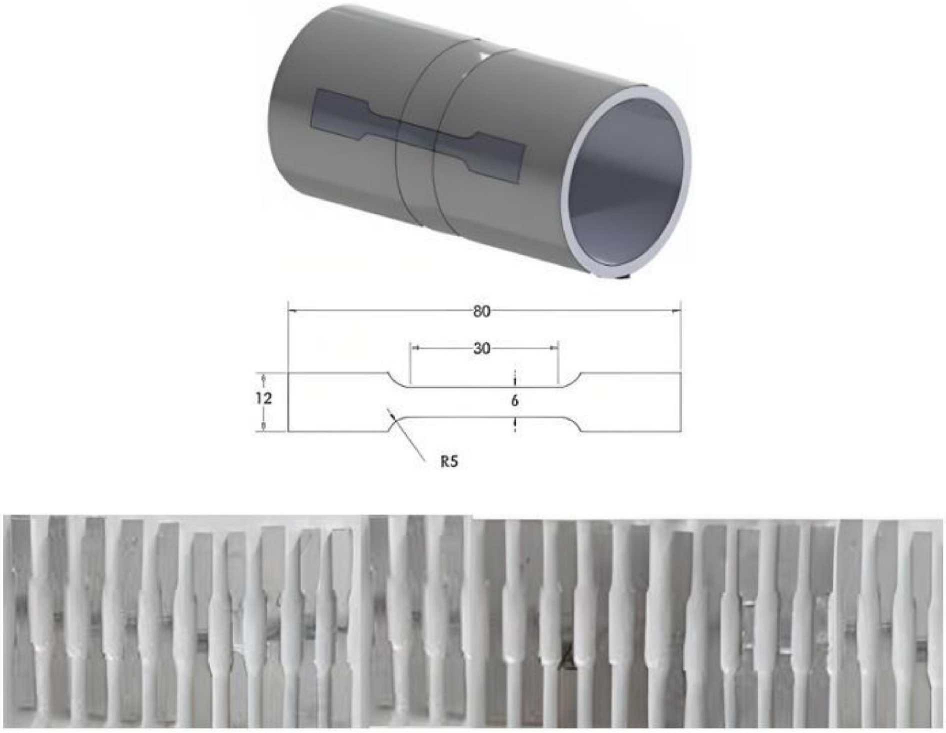

Figure 3. Tensile test sample dimensions and cut samples.

Table 3. Levels of process parameters in FSW.

			Levels		
Process Parameters	Unit	Symbol	−1	0	1
Rotation speed	RPM	N	1000	1400	1800
Travel speed	mm/min	S	10	16	31.5
Shoulder diameter	mm	D	30	40	50

Table 4. Design matrix and experimental value with uts, vhn, and sr projected values.

	FSW process parameters			Responses		
Run	N	D	S	UTS	VHN	SR
1	1800	50	10	162.5	55.30	9.346
2	1400	50	16	151.1	51.20	9.453
3	1000	50	31.5	143.4	48.60	9.879
4	1800	40	10	160.4	47.50	19.32
5	1400	40	16	146.3	45.70	19.64
6	1000	40	31.5	140.1	40.20	19.98
7	1800	30	10	157.8	43.90	20.18
8	1400	30	16	144.6	40.10	20.32
9	1000	30	31.5	135.2	38.30	20.67
10	1800	50	10	147.3	56.30	7.198
11	1400	50	16	141.1	53.20	7.280
12	1000	50	31.5	136.5	49.80	7.340
13	1800	40	10	140.9	53.30	14.67
14	1400	40	16	133.8	50.20	14.84
15	1000	40	31.5	129.4	47.90	14.95
16	1800	30	10	134.0	50.04	15.30
17	1400	30	16	121.0	47.90	15.31
18	1000	30	31.5	119.9	43.98	13.40
19	1800	50	10	122.8	60.30	4.983
20	1400	50	16	114.0	58.70	5.124
21	1000	50	31.5	107.3	56.90	5.299
22	1800	40	10	121.9	59.80	10.01
23	1400	40	16	106.0	55.30	10.23
24	1000	40	31.5	100.9	52.10	10.40
25	1800	30	10	109.0	57.70	11.01
26	1400	30	16	99.98	53.54	11.08
27	1000	30	31.5	89.72	50.09	11.20

were manufactured for each experiment according to the ASTM-E8 standard. In an AGX-V machine, the tensile test was performed at a 0.5 mm/min strain rate. Vickers microhardness measurements were carried out in a microhardness tester by HM-200 system machine at 30 (Kg) force and a dwell period of 10 s along the weld cross-section at an interval of 0.5 (mm) from the weld centerline. Surfaces roughness test was carried out in SJ-210 machine [33].

III. Methodology

Figure 4 shows the flowchart of the proposed method in this study for decision-making in selecting the FSW process parameters. The MCDM strategy picks an action or preference from a collection of homologous possibilities by examining the various views of numerous confounding criteria. There are frequently directed issues in an industrial setting by several opposing elements, which organize the limitations and increase the system's complexity. On the other hand, these elements aid in making a sensible conclusion. Every MCDM approach has a risk associated because of the high integral complexity of the decision-making problem. The risk is defined as a failure to obtain a wise conclusion in decision-making.

This current study proposes a unique MCDM model based on the concept of risk minimization. The mathematical model considers risk management by turning the choice matrix into a relative benefit matrix. The

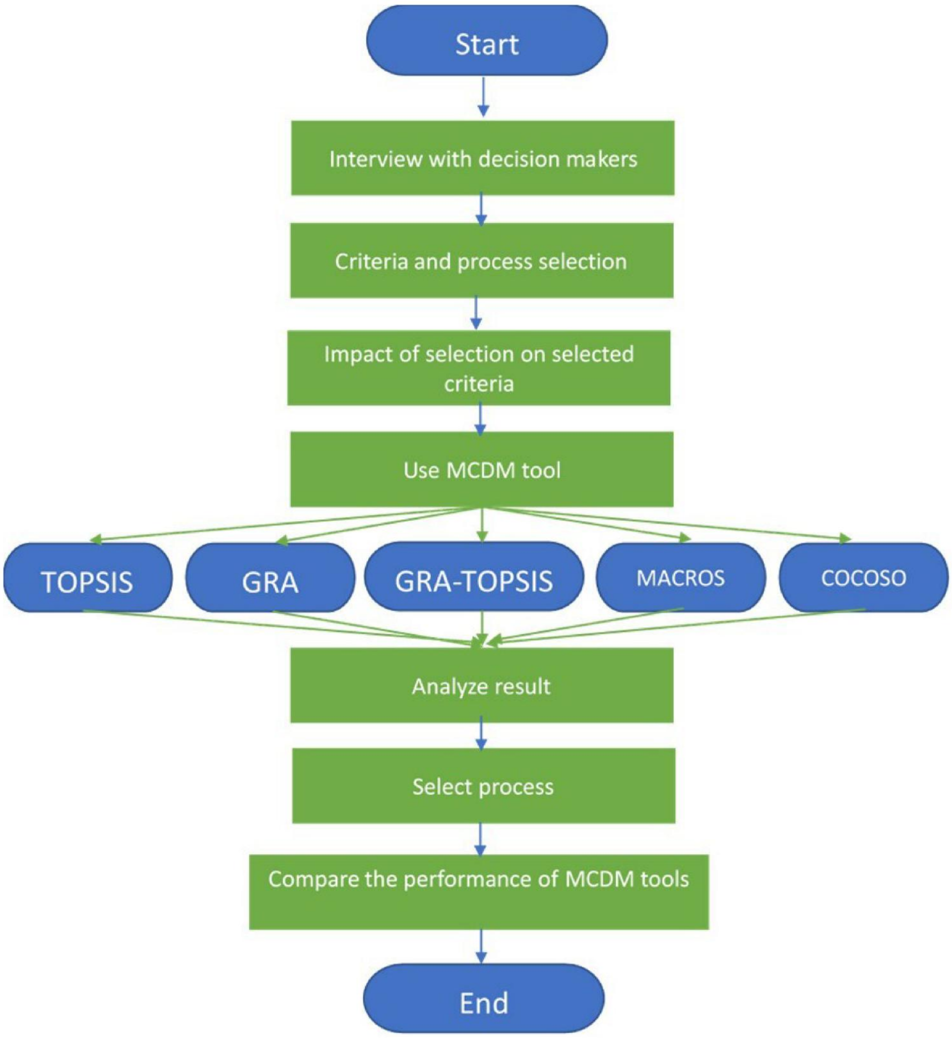

Figure 4. The proposed framework of the proposed method.

proposed framework in Figure 4 consists of four software tools, one for structuring the problem and the other for analysing the problem. The problem-structuring tool is termed a decision set-up. On the other hand, the analysis tools are known by their respective methodological names, including TOPSIS, GRA, hybrid GRA-TOPSIS, combined compromise solution (COCOSO), and ranking according to compromise solution (MACROS).

As shown in Figure 5, the problem structuring tool requires the decision-maker to specify a goal, a set of options, and a set of criteria. The decision set-up puts this data into a single file that any of the three analytic programmers can access. The decision-maker must input criteria weights and decision variables and the reasons for each selection into the analysis tools that produce a decisive result. These parameters can be tweaked to see how sensitive the results are. The analytical tools can aggregate all decision information into a single file or generate a report presenting the results after an accepted decision outcome.

The decision-maker is guided *via* a module of TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS techniques. Figures 6–10 depicts the workflow for this procedure. The decision-maker uses a Decision Set-up file to generate the interface for pairwise criterion comparisons. The user's pairwise preferences are gathered into a reciprocal matrix, then used to generate the principal eigenvectors, which indicate the criteria weights. A consistency check is performed to confirm that the decision-maker has not violated transitivity. Saaty provided the procedure for calculating the principal eigenvectors and checking transitivity [34].

1. Grey relational analysis (GRA)

GRA is one of the more advanced approaches for optimizing process parameters with ambiguous inputs. It is used in fuzzy social surveys to

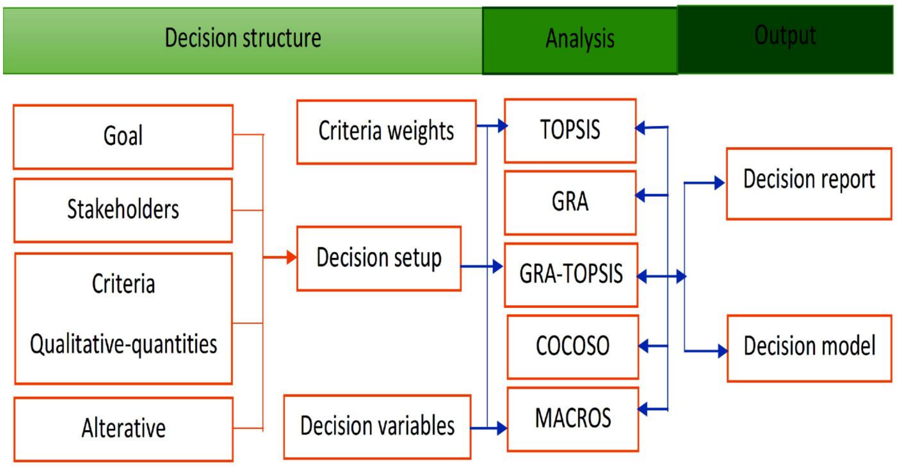

Figure 5. Steps for the application of MCDM tools and their performance evaluation.

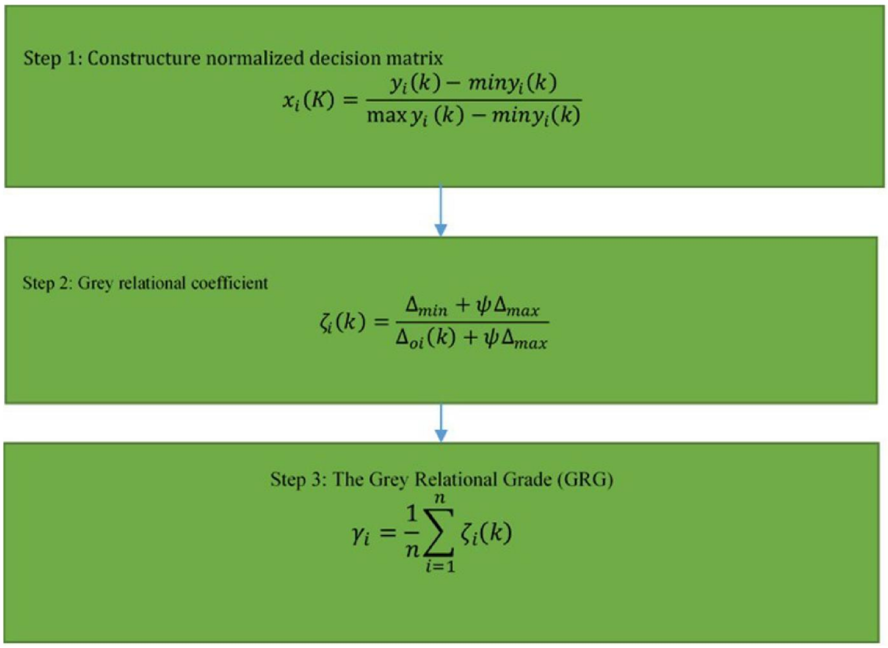

Figure 6. Step-by-Step technique for applying GRA methodology.

change replies from numerous targets to single objectives. The dark test, predicated on the tests' unpredictability, has been moulded into an evaluation tool for obvious structural flaws jammed with fragmented information. This dark examination setup is split into two sections. The white frame contains the completely known relative data, whereas the black frame contains the relatively veiled data. Surface roughness, hardness, and UTS were the quality response targets of the FSW process. FSW characteristics such as rotation speed, travel speed, and shoulder diameter were used to study and optimize the optimal process. The grey analysis was divided into two parts regarding the accompanying advancement. Grey relational information refers to GRA's basic capacity while standardizing the test values between 0-1. The surface roughness, UTS, and VHN were all considered, as shown in Figure 6. Figure 6 shows the flowchart for applying the GRA methodology.

GRA is a method of multi-objective optimization that turns multi-response into a single objective issue. In 1982, Deng created GRA to evaluate the uncertainties of structures, system interactions, etc. [35]. In GRA, for simple interpretation and evaluation, all yield values are standardized between zero and one. These standardized values are then used to calculate each output response's grey relational coefficient. The grey relational grade is then calculated for each experimental test by averaging the grey relational coefficient. Overall experimental trial efficiency relies on grey relational grade. The greater grey relational grade gives ideal solution characteristics. The following steps will be taken in the GRA.

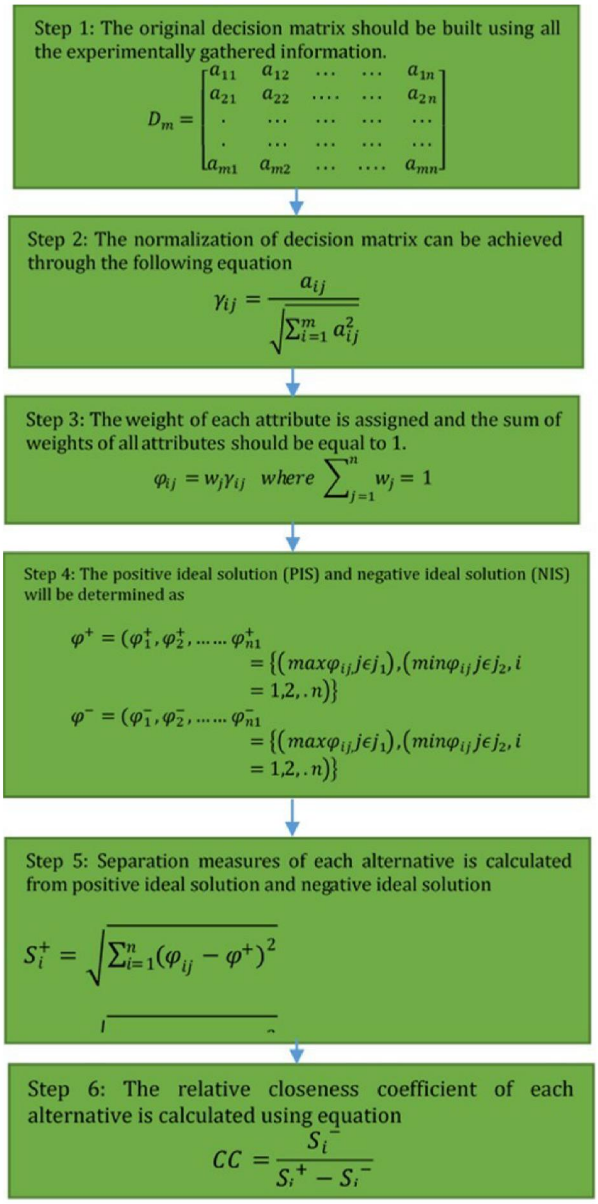

Figure 7. Step-by-Step technique for applying TOPSIS methodology.

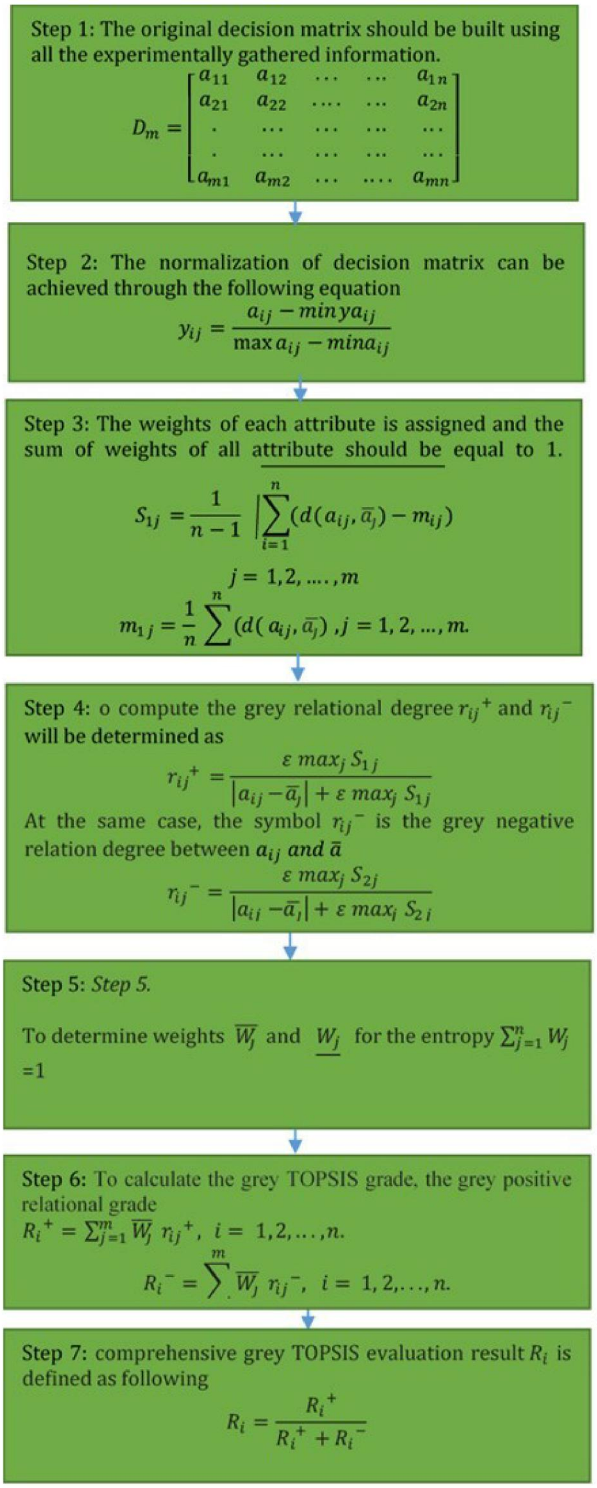

Figure 8. Step-by-Step technique for applying GRA-TOPSIS methodology.

First, Equations (1) and (2) are used to normalize the output response according to the required conditions:

Normalization for larger the better

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{1}$$

Normalization for smaller the better

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{2}$$

where $x_i(K)$ is normalized value of output response, $\min y_i(k)$ is least value of $y_i(k)$ for kth response, $\max y_i(k)$ is highest value of $y_i(k)$ for kth response.

Second, grey relational coefficient $(\zeta_i(k))$ is needed to be generated by Equation (3) to make a relation between the actual normalize value and the ideal one.

$$\zeta_i(k) = \frac{\Delta_{\min} + \psi \Delta_{\max}}{\Delta_{oi}(K) + \psi \Delta_{\max}} \tag{3}$$

where $\Delta_{oi}(k)$ is a set of calculated values where $\Delta_{oi}(k) = |x_0(K) - x_i(K)|$. The minimum and maximum values of the set is taken as $\Delta_{\min}$, $\Delta_{\max}$ respectively.

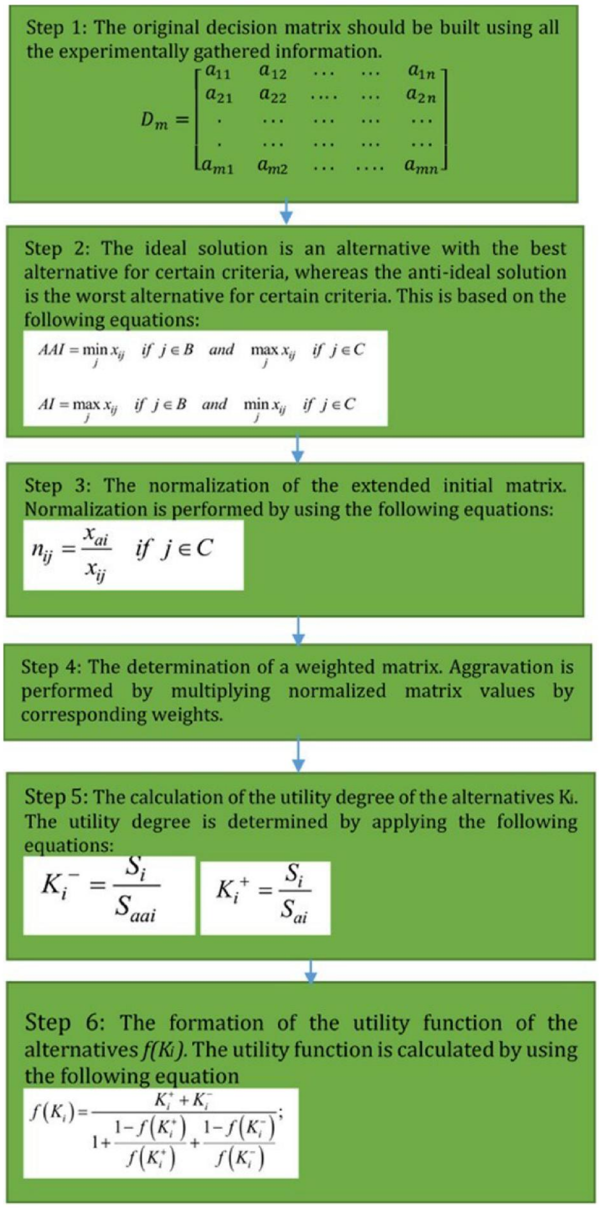

Figure 9. Step-by-step technique for applying CoCoSo methodology.

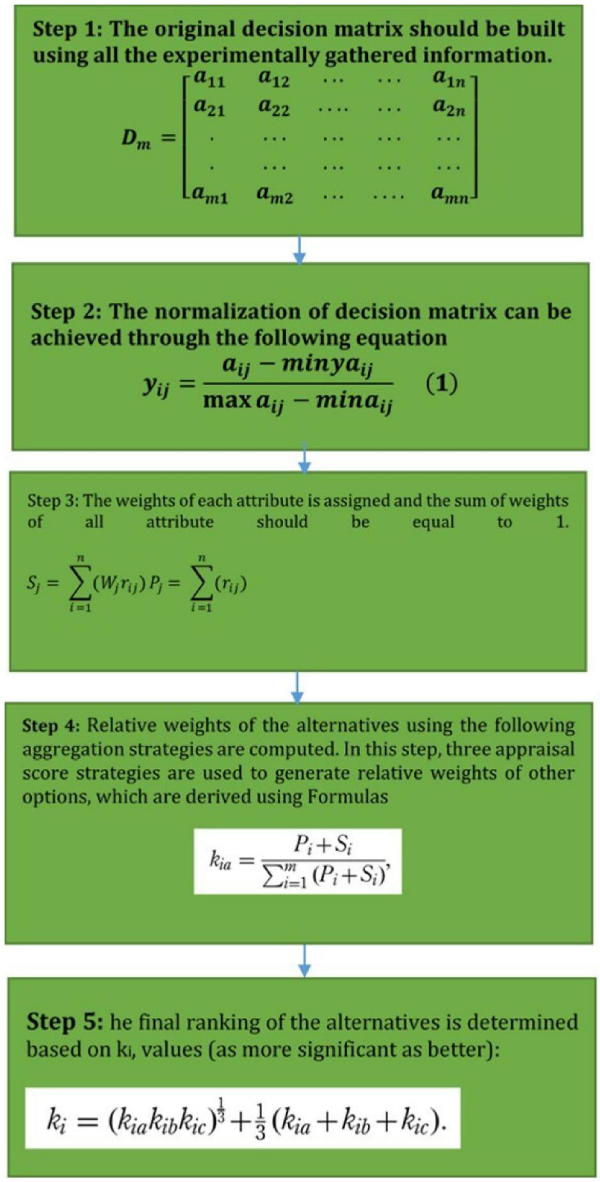

Figure 10. Step-by-step technique for applying MARCOS methodology.

ψ is the distinguishing coefficient where $\psi \in [0, 1]$. Most of the researchers assign a value of 0.5 for the distinguishing coefficient [23].

Third, by Equation (4), the grey relational grade (γ_i) is calculated based on the number of output responses ($\boldsymbol{n}$)

$$\gamma_i = \frac{1}{\boldsymbol{n}} \sum_{i=1}^{\boldsymbol{n}} \zeta_i(\boldsymbol{k}) \tag{4}$$

2. TOPSIS methods

TOPSIS is a simple multi-criteria decision-making technique that aids in the selection of the best answer from several alternatives [36,37]. TOPSIS entails choosing the best option from options with the shortest distance from the ideal positive solution and the greatest distance from the ideal negative solution. In this technique, all responses are classed as advantageous or non-beneficial qualities. The superior attribute is comparable to the less the value, while the user attribute is comparable to the greater. The following steps are shown in Figure 7 when using TOPSIS to make multi-criteria decisions.

TOPSIS is a straightforward multi-criteria decision-making technique that helps to better select the optimum solution among the many alternative solutions. TOPSIS involves determining the optimum solution between alternatives that are the shortest distance from the ideal positive solution and the greatest distance from the ideal negative solution. All answers are categorized as useful or non-beneficial characteristics in this technique. The useful attribute is comparable to the greater the superior attribute is comparable to the less the value. The decision making of multi-criteria through TOPSIS is subject to the following steps:

Step 1: The original decision matrix should be built using all the experimentally gathered information. The matrix of the choice comprises of n characteristics and m option. The output reactions are characteristics in the current issue and experimental studies are alternatives.

$$D_m = \begin{bmatrix} a_{11} & a_{12} & \cdots & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots\cdot & \cdots & a_{2n} \\ . & \cdots & \cdots & \cdots & \cdots \\ . & \cdots & \cdots & \cdots & \cdots \\ a_{m1} & a_{m2} & \cdots & \cdots\cdot & a_{mn} \end{bmatrix} \quad (5)$$

where a_{ij} is the measure of jth attribute to i^{th} alternative.

Step 2: The normalization of decision matrix can be achieved through the following equation

$$\gamma_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \quad (6)$$

where c_{ij} is normalized value for $i = 1, 2, 3, \ldots, m$ and $j = 1, 2, 3, \ldots, n$.

Step 3: The weights of each attribute is assigned and the sum of weights of all attribute should be equal to 1. The weight normalized decision matrix can be calculated by Equation 7.

$$\varphi_{ij} = w_j \gamma_{ij}$$

$$\textbf{where} \quad \sum_{j=1}^{n} w_j = 1 \quad (7)$$

Step 4: The positive ideal solution (PIS) and negative ideal solution (NIS) will be determined as:

$$\varphi^+ = (\varphi_1^+, \varphi_2^+, \ldots, \varphi_n^+) = \{(\max\varphi_{ij} |\ j \in J_1),\ (\min\varphi_{ij} |\ j \in J_2)\} \quad (8)$$

$$\varphi^- = (\varphi_1^-, \varphi_2^-, \ldots, \varphi_n^-) = \{(\min\varphi_{ij} |\ j \in J_1),\ (\max\varphi_{ij} |\ j \in J_2)\} \quad (9)$$

where J_1 is set of beneficial attributes and J_2 is a set of non-beneficial attributes.

Step 5: Separation measures of each alternative is calculated from positive ideal solution and negative ideal solution

$$S_i^+ = \sqrt{\sum_{i=1}^{n} (\varphi_{ij} - \varphi^+)^2} \quad (10)$$

$$S_i^- = \sqrt{\sum_{i=1}^{n} (\varphi_{ij} - \varphi^-)^2} \quad (11)$$

Step 6: The relative closeness coefficient (***CC***) of each alternative is calculated using Equation 12.

$$CC = \frac{S_i^-}{S_i^+ - S_i^-} \quad (12)$$

3. Grey–TOPSIS study

Combining different multi-criteria optimization approaches simplifies data processing and saves time, allowing decision-makers to choose the proper criteria quickly. The TOPSIS is examined for picking the optimal parametric combination [23], and the decision-making model is built to identify the FSW -process parameter and the performance criterion. The TOPSIS and Analytic Hierarchy Process (TOPSIS–AHP) hybrid MCDM technique simplifies calculations and reduces processing effort compared to other standard optimization approaches. As a result, this optimization method can be used to resolve various conflicts in machining settings [38]. The hybrid technique (Entropy-TOPSIS-GRA) was utilized to calculate FSW process parameters in this study. Figure 8 depicts the computational procedure.

A new approach that combines a grey relational analysis and TOPSIS method is proposed in this study. GRA-TOPSIS is most appropriate for solving the decision-making problems while taking into considerations the uncertainty in the measured data. Appendix B shows the proposed model for value chain performance evaluation. The steps of GRA-TOPSIS approach can be illustrated as follows:

Stage 1: The determination of evaluation criteria and alternatives.
Stage 2: Construction of the decision-making matrix (DM) and measuring the importance of criteria.
Stage 3: Convert Linguistic Evaluations into grey numbers.
Stage 4: Normalize the decision-making matrix.
Stage 5: Formulation of weighted normalized decision-making matrix.
Stage 6: Determination of the positive and negative ideal solutions.
Stage 7: Calculation the separation measure and the relative closeness to the ideal solution.

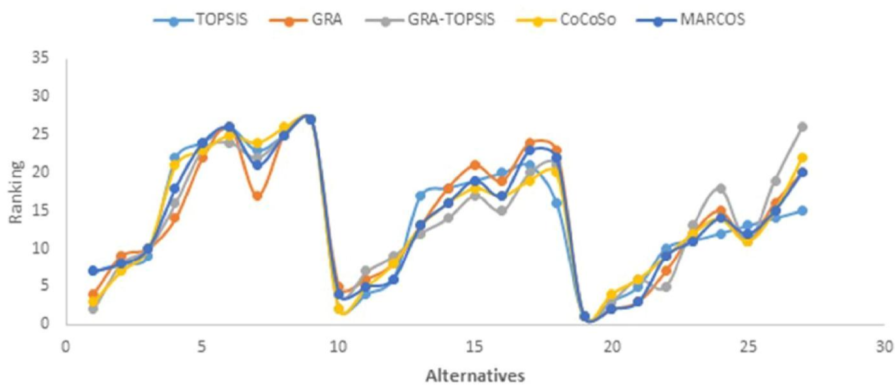

Figure 11. Ranks comparison for TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS.

Table 5. Ranks comparison for TOPSIS, GRA, hybrid GRA-TOPSIS, CoCoSo, and macros.

TOPSIS	GRA	GRA-TOPSIS	CoCoSo	MARCOS
7	4	2	3	7
8	9	8	7	8
9	10	10	10	10
22	14	16	21	18
24	22	23	23	24
26	26	24	25	26
23	17	22	24	21
25	25	25	26	25
27	27	27	27	27
2	5	4	2	4
4	6	7	5	5
6	8	9	8	6
17	13	12	13	13
18	18	14	16	16
19	21	17	18	19
20	19	15	17	17
21	24	20	19	23
16	23	21	20	22
1	1	1	1	1
3	2	3	4	2
5	3	6	6	3
10	7	5	9	9
11	12	13	12	11
12	15	18	14	14
13	11	11	11	12
14	16	19	15	15
15	20	26	22	20

Stage 8: Rank on basis of closeness coefficients of alternatives.

4. CoCoSo study

CoCoSo [39] This type of aggregation is not supported by any MCDM tool's algorithm. Each method would have a ranking score, which a comprehensive ranking index would boost. The procedure is referred to as a combined compromise solution as it is built on a combination of compromise attitudes (CoCoSo). The suggested approach is based on an integrated, simple additive weighting and exponentially weighted product model. It can be a compendium of compromise solutions. The steps of CoCoSo method is shown in Figure 9.

This method is based on two approaches namely, simple additive weighting (SAW) and exponentially weighted product model. This method produces three appraisal scores to measure the alternative's score. Therefore, a final coefficient is determined by combining the three appraisal scores to obtain more robust results. The steps of the CoCoSo method are shown as follows:

Stage 1: The normalization of the decision-making matrix using equations (1) and (2).

Stage 2: The calculation of the comparability sequences using

5. MACROS study

Every business must invest. Such businesses must use project management strategies that enable the smooth implementation of project investments to implement their project investments. A project is a huge endeavour, especially regarding organizational limitations and elements, resources and prices, many people working on it, and other factors that add to its complexity. A project's implementation necessitates particular IT support due to its complexity and relevance to any firm. Developing a comprehensive range of IT software solutions to support the planning, monitoring, and implementation of projects to reach established investment targets has resulted from market demand in this industry. The MARCOS approach is based on establishing a link between alternatives and reference values. Utility functions are used to define decision-making preferences. A utility function defines the position of an alternative to the ideal and anti-ideal solutions. The greatest option is closest to the ideal point while being the furthest away from the anti-ideal point. The MARCOS approach is put into practice, as shown in Figure 10.

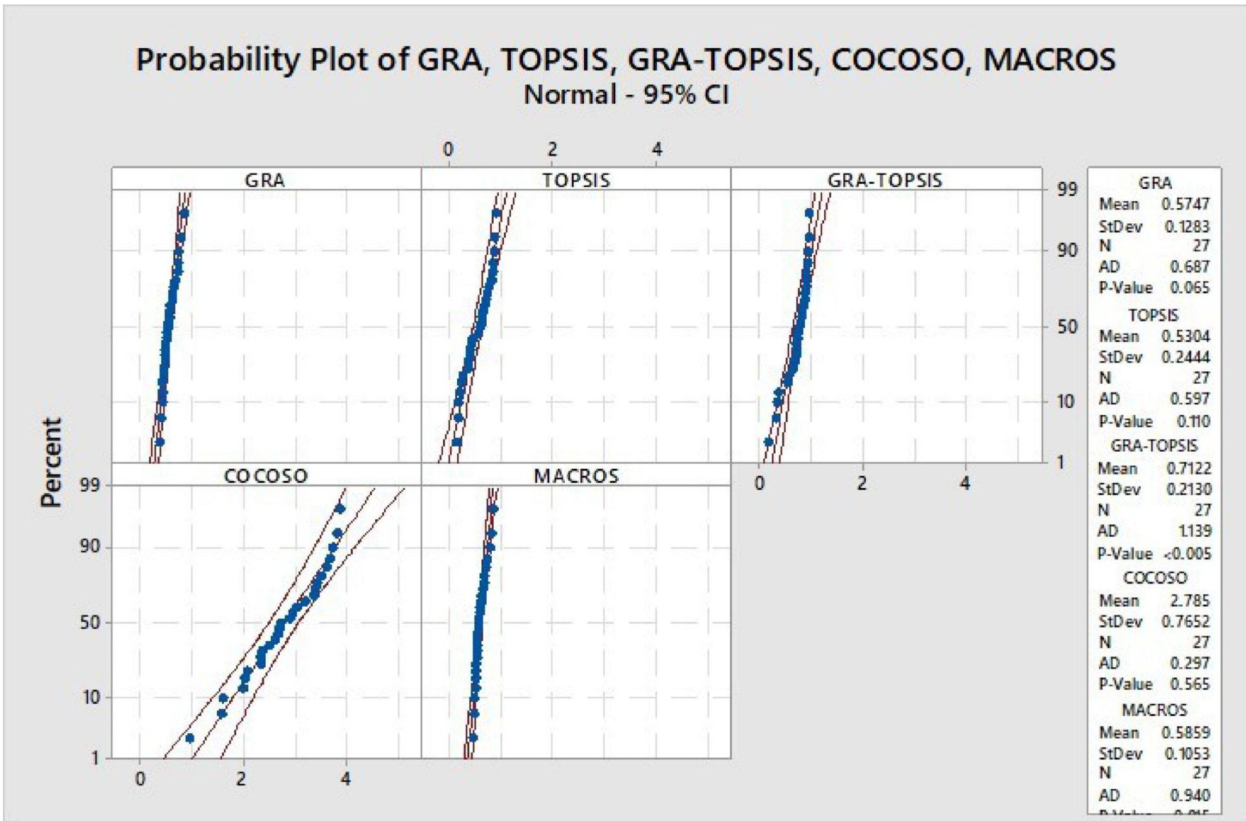

Figure 12. Probability plot comparison for TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS.

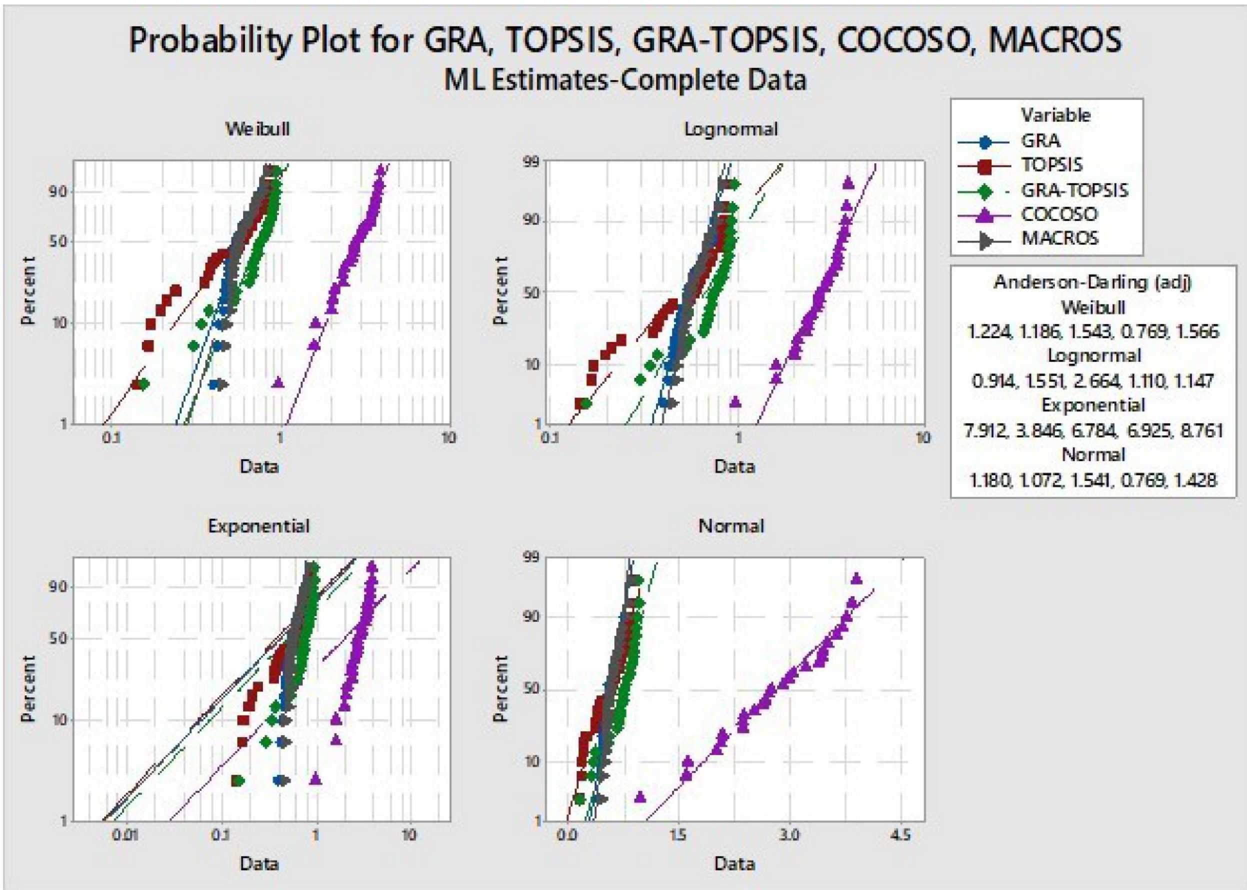

Figure 13. Probability plot of Complete data for TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS.

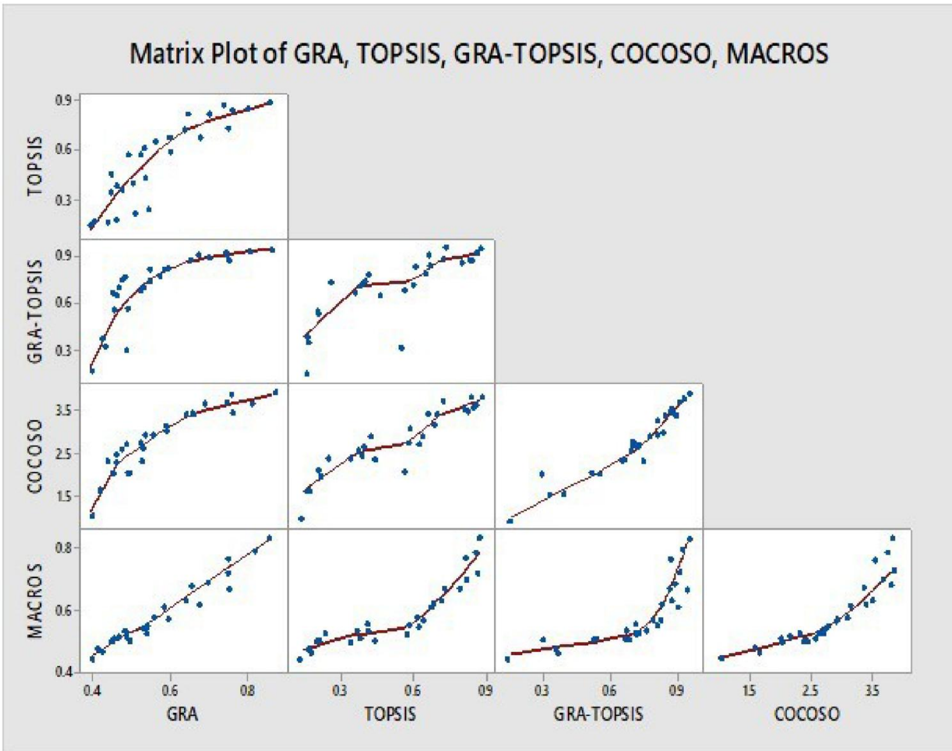

Figure 14. Matrix plot for TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS.

IV. Results and Discussions

This section presents the outcomes of the deterministic application of MCDM approaches. Certain criteria had to be maximized, while others had to be minimized in this application. Only maximization is evaluated here, and if applicable, any minimization criteria are multiplied by one. Most approaches generate absolute scores, which are then used to sort the solutions. Because maximization is considered, the final score should be as high as possible. When a method generates a pairwise answer, the one that outperforms most of the other options is deemed the best. As shown in Figure 11, the techniques produce close to optimum solutions in most cases. TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS results and rankings are summarized in Table 5.

TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS results are shown in Figure 11. Methods combination GRA-TOPSIS and TOPSIS were suggested over MACROS and COCOSO in all five analyses. Table 5 demonstrates, however, that the results are not clearly ordered. The descending rank identified method TOPSIS, GRA as the best alternative, while the ascending rank identified method hybrid GRA-TOPSIS as the best alternative. MACROS and COCOSO were unable to provide a conclusive best result because the ascending rank identified method hybrid GRA-TOPSIS as the best alternative. According to hybrid GRA-TOPSIS, the best alternative was experimental 19, followed by experimental 1 and 20. TOPSIS indicated experimental 19 as the best alternative and revealed that experimental 1 had a significant level of ambiguity. Experimental 20 was the second-best option in terms of most likely value.

The required level of confidence in this inquiry was 95%. The relationship may be deemed adequate if the estimated F value of the constructed model does not exceed the standard tabulated P-value. The standard p-value for a 95% confidence interval is provided. The estimated p-values of the models GRA, TOPSIS, GRA-TOPSIS, COCOSO, and MACROS are 0.065, 0.11, 0.05, 0.565, and 0.015, respectively, for lack-of-fit is smaller than the usual value of 95% confidence level, as shown in Figure 12. As a result, the above hybrid GRA-TOPSIS model is sufficient. Figures 13 and 14 depict the normal probability plot of residuals for wear rate and resistance.

The proposed MCDM technique, as indicated in, can be used to determine the optimal combination of input welding parameters. Step by step, the proposed multi-criteria decision model is followed. The first step is to create the choice matrix, a collection of the performance measures values from the experiments created using the D-optimality method. Table 4 depicts the decision matrix. The weight factors of the performance measurements are computed in the second step.

The entropy approach, as described in, was used to calculate the weight of the criteria. The multi-criteria decision models that have been proposed have been adopted. Using flowchart 1, the decision matrix is first normalized. Table 5 displays the normalized matrix. Flowchart 1 shows how to calculate entropy values, variation factors, and weightage of performance measurements. Table 5 lists the results of the computations. The relative benefit matrix is computed as the following step in the decision-making process. This stage aims to identify the settings that will best optimize the process parameter. The relative benefit matrix's elements are computed. The relative benefit matrix is normalized after that. To get the weighted normalized matrix, multiply the normalized matrix by the weightage of the performance measures. Table 5 shows the elements of the weighted normalized matrix that are assessed. The relative benefit, normalized, and weighted normalized elements are shown in Table 5. The performance scores for the tests are determined using a flowchart 1 to choose the best combination of welding parameters *via* the FSW procedure. With a certain combination of FSW parameters, the experiment with the highest performance score is chosen. The performance scores and the ranks of the experiments are shown in Table 5. From Table 5. It is observed that experiment number 19 has the best combination of welding parameters for welding metals by the FSW process.

V. Conclusion

Friction Stir Welding (FSW) is a solid-state joining technique used to combine aluminium and its alloys. It involves a non-consumable rotating tool that generates frictional heat, softening the material and allowing for the mixing and bonding of the workpieces without melting. FSW has proven to be highly effective in joining aluminium alloys and has even expanded to include thermoplastic materials. There is the lack of focus on developing new models that could efficiently determine the optimal welding parameters. The previous study relied on well-known models and methods that were proven to be efficient, but there was little emphasis on creating novel decision-making models. The current study aims to fill this gap by introducing a new decision-making model based on risk minimization, which is specifically tailored for selecting optimal welding parameters in FSW. The proposed model utilizes multiple criteria, including ultimate tensile strength, hardness, and surface roughness. The study addresses the unique challenges of FSW of aluminium alloys and introduces a new approach to selecting welding parameters. The validation of the proposed model through experiments and comparison with other decision-making approaches, demonstrating its effectiveness in determining the best welding parameters for achieving desired performance criteria such as tensile strength, hardness, and surface roughness. The suggested model's strength is its ability to preserve FSW's performance evaluation of welding parameters. Finally, the proposed MCDM and TOPSIS-GRA models can be used to arrive at a logical conclusion for picking the best and computing the optimal welding parameter for welding two identical metals by FSW. As a future work, the current proposed method can be extended to other welding process to increase to evaluate its applicability and effectiveness in different scenarios. Also, advanced optimization algorithms or machine learning techniques can be employed to further optimize the decision-making process and improve the accuracy of parameter selection.

Authors' contributions

Ibrahim Sabry: Methodology, Visualization, Data curation, Writing - Original draft preparation. Abdel-Hamid Ismail Mourad: Conceptualization, Methodology, Visualization, Data curation, Writing - Original draft preparation, Writing - Reviewing and Editing, Project administration, Supervision, Funding acquisition. Mohammad Alkhedher: Writing - Reviewing and Editing, Visualization. Mohammad Reza Chalak Qazani: Writing - Reviewing and Editing. Ahmed M. El-Araby: Writing - Reviewing and Editing.

Ethics approval

N/A.

Consent to participate

N/A.

Consent for publication

N/A.

Disclosure statement

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Availability of data and material

Datasets are presented inside the paper.

Code availability

On the request of corresponding author.

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