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A Comparative Study of Multiple-Criteria Decision-Making Methods for selecting the best process parameters for friction stir welded Al alloy

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Abstract

The selection of welding process parameters is a difficult operation that proves the need for process evaluation. Several decision-making strategies have been presented for assessing friction stirring welding (FSW) process parameter selection difficulties considering the process up and down. It should be noted that few comparative studies have been conducted on the FSW problem without consideration of decision-making strategies. This article compares three multi-attribute decision-making strategies to select the parameters of the FSW process. The aim of this work applied different decision-making strategies TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS, using entropy for the calculated weight for all different decision-making. 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.

Keywords: Decision-Making, TOPSIS, GRA, MACROS, COCOSO, hybrid GRA-TOPSIS.

I. INTRODUCTION

Friction stirring welding (FSW) is a solid-state joining technology that has been successfully utilized in combining aluminum and its alloys [1–4]. FSW is operated with a non-consumable rotating tool with a smaller diameter pin attached to a bigger diameter shoulder. Designing the fixture is vital in FSW operation to increase the effectiveness of the weld via regeneration of the substantial forces [5].

FSW works by using a non-consumable tool, which is rotated and plunged into the interface of two workpieces. The tool is then moved through the interface and the frictional heat causes the material to heat and soften. The rotating tool then mechanically mixes the softened material to produce a solid-state bond. 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. This procedure was patented as a solid-state connecting technology because no melting occurred. The weld nugget at the center 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 aluminum alloys in terms of content [6–9]. Friction stir welding has advanced to be adaptable for thermoplastic materials [10,11].

Recently, FSW has been used for combining complex aluminum-based products in lots of applications . The parametric process optimization of the FSW operation is necessary to reach the higher weldability and mechanical qualities in the joints. The main goal of this study is to research optimization process parameters for FSW. The optimal parameter combinations have better tensile strength with the combining decision model. As a result, many researchers use statistical tools such as MCDM, RSM, and mathematical models and analyze them to find the optimum process parameters that maximize the values of responses. Shojaeefard et al. [12] employed Taguchi's method in lab joining of Al-Mg and CuZn34 via FSW to extract the optimal rotational speed, tool tilt angle, and traverse speed the process. Based on their work [12], the rotational speed has the most significant contribution in deciding the joint soundness. The margin error between the experimental and predicted tensile shear is 2.5%, extracted by the verification test. Sahin [13] 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. [14–16] employed a statistical method to choose process parameters and construct an experimental predictive paradigm for the FW of Al-Al. A simple linear paradigm with specific coefficients was used to extract the best process parameters of FW. Eslami et al. [17] 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. [18] 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. [19] used a hybrid model of Taguchi L27 orthogonal array and ANOVA to optimize the process parameters for the FSW of Al. They discovered that the joint's shear strength is affected by the rotational speed and plunge depth interactions. Colmenero et al. [20] 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. 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 aluminum joint by Krutzlinger et al.[21].

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. According to the current state of the art on the selection of welding parameters by the decision-making process, most studies select the parameters based on already created or well-known models. Even though many engineers, researchers, and academicians have used decision-making techniques, there has been very

little focus on developing new decision-making models that could be used to determine the ideal welding parameters. 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. This work is a combination of equally-weighted experimental and computational research.

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 [22] 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.

In the next section, the overview of the FSW of Al-alloy is explained. It consists of explaining the material, methods, and experimental method. 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 ALUMINUM 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 85 (MPa), a tensile strength of 112 (MPa), and a 16 percent elongation.

The parent metal was measured to have 62 (HV) hardness. The production setup of the materials is shown in Fig. 1a. Also, Fig. 1a 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 =10 (mm), upper pin diameter=6 (mm), lower pin diameter=1 (mm), and pin length=5 (mm). Fig. 1b shows the conical pin of the FSW process. Also, the dimension of the conical pin is shown in Fig. 1c.

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. [7]. 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.

Fig. 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 Fig. 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 [23]. 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. 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. Eq. 1 was used to calculate the intermediate coded values [24].

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

where $\boldsymbol{X_i}$, $\boldsymbol{X}$, $\boldsymbol{X_{max}}$ and $\boldsymbol{X_{min}}$ are the required coded value, the variable value, the lower limit of the variable, and the upper limit of the variable [25]. 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 center points, and five-star points.

Welding responses were assumed to be the UTS, VHN, and SR. Three tensile specimens 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 [26].

III. METHODOLOGY

Fig. 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 proposed framework in Fig. 4 consists of four software tools, one for structuring the problem and the other for analyzing the problem. The problem structuring tool is termed a decision setup. 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 Fig. 5, the problem structuring tool requires the decision-maker to specify a goal, a set of options, and a set of criteria. The decision setup 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. Fig. 6-10 depicts the workflow for this procedure. The decision-maker uses a Decision Setup 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 [27].

1.Grey Relational Analysis (GRA)

GRA is one of the more advanced approaches for optimizing process parameters with ambiguous inputs [28]. It is used in fuzzy social surveys to change replies from numerous targets to single objectives. The dark test, predicated on the tests' unpredictability, has been molded 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 Fig. 6. Fig. 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. [29]. In GRA, for simple interpretation and evaluation, all yield values are standardized between zero and one. These standardized values are 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.

First, Eq. (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 Eq. (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 Δ_{min}, Δ_{max} respectively.

ψ is distinctive coefficient, whose rule is to determine the grey relational coefficient's range. It is usually in the range [0-1]. But it doesn't affect the rank of the coefficient. The suggested value of ψ is "0.5" [30].

Third, by Eq. (4), the grey relational grade (γ_i) is calculated based on the number of output responses (n)

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

2.TOPSIS Methods

TOPSIS is a simple multi-criteria decision-making technique that aids in the selection of the best answer from several alternatives [31,32]. 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 Fig. 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.

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

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

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

$$\boldsymbol{\gamma_{ij}} = \frac{\boldsymbol{a_{ij}}}{\sqrt{\sum_{i=1}^{m} \boldsymbol{a_{ij}^2}}} \tag{6}$$

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

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.

$$\varphi_{ij} = w_j \gamma_{ij} \tag{7}$$

$$\boldsymbol{where} \sum_{j=1}^{n} \boldsymbol{w_j} = \boldsymbol{1}$$

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

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

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

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

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

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

Step 6: The relative closeness coefficient ($\boldsymbol{CC}$) of each alternative is calculated using Equation 12.

$$\boldsymbol{CC} = \frac{\boldsymbol{S_i}^-}{\boldsymbol{S_i}^+ - \boldsymbol{S_i}^-} \tag{12}$$

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 [33], 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 [34]. The hybrid technique (Entropy-TOPSIS-GRA) was utilized to calculate FSW process parameters in this study. Fig. 8 depicts the computational procedure.

A new approach that integrates a grey-based theory and TOPSIS is proposed for ordering the choice of action in evaluating value chain performance. Grey-TOPSIS is most appropriate for solving the group decision-making problems under the environment of uncertainty. Appendix B shows the proposed model for value chain performance evaluation . In this paper, the criteria weights and ratings of performance dimensions are considered as linguistic variables. The linguistic variables are presented in grey numbers by scales that are accepted by decision makers. The process of determining the preference option is summarized as follows:

Stage 1: Form a committee of decision makers and determine the evaluation scales

Stage 2: Determine decision matrix and Obtain criteria importance weights.

Step 2.1: Determine decision matrix

Step 2.2: Obtain criteria importance weights.

Stage 3: Convert Linguistic Evaluations into grey numbers.

Stage 4: Degrey the decision matrix data and Criteria Importance Weights

Stage 5: Normalize the decision matrix and criteria importance weights

Stage 6: Form weighted decision matrix

Stage 7: Determination of the positive ideal solution and negative ideal solution

Stage 8: Calculation the separation measure and the relative closeness to the ideal solution

Stage 9: Rank the preference order

4.CoCoSo Study

CoCoSo [35] 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 if 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. To solve a CoCoSo decision problem, shown in Fig. 9.

This method was developed recently. which is based on two common approaches namely weighted sum model (WSM) and exponentially weighted product model. This method develops three different appraisal scores to evaluate the alternatives. Thus, a final coefficient combining these scores is calculated 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 endeavor, 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 [36] 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 Fig. 10.

Relatively new CoCoSo method (Combined Compromise Solution), is based on the integration of simple additive weighting (SAW) and the exponentially weighted product model (MEP). The essence of this method lies in combining compromise perspectives, which ultimately reconciles the evaluation criteria, which are often conflicting. The CoCoSo method provides an overview of possible compromise solutions available to the decision maker.

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 Fig. 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 Fig. 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 Fig. 12. As a result, the above hybrid GRA-TOPSIS model is sufficient. Figs. 13 and14 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

The optimal welding parameters for connecting aluminum by FSW are selected using a novel MCDM model provided in this work. The study's findings are summarised in the following:

- The proposed MCDM model is approximately 82.31% accurate according to the sensitivity analysis. According to Fig. 8 and Table 5, the suggested MCDM model is very stable and resilient and may be used for decision-making.
- The suggested MCDM model's computed result is compared to experimental results. The rank comparison graph is shown in Figure 10. The rank for welding parameters of experiment 1(rotational speed = 1800 rpm, traverse speed = 10 mm/s, and shoulder diameter 50 mm) is the best overall.

- 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.

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Fig. 1. (a): Experimental setup of milling machine, which used in FSW for pipe joint; (b): The conical pin; (c): The dimension of the FSW's tool.

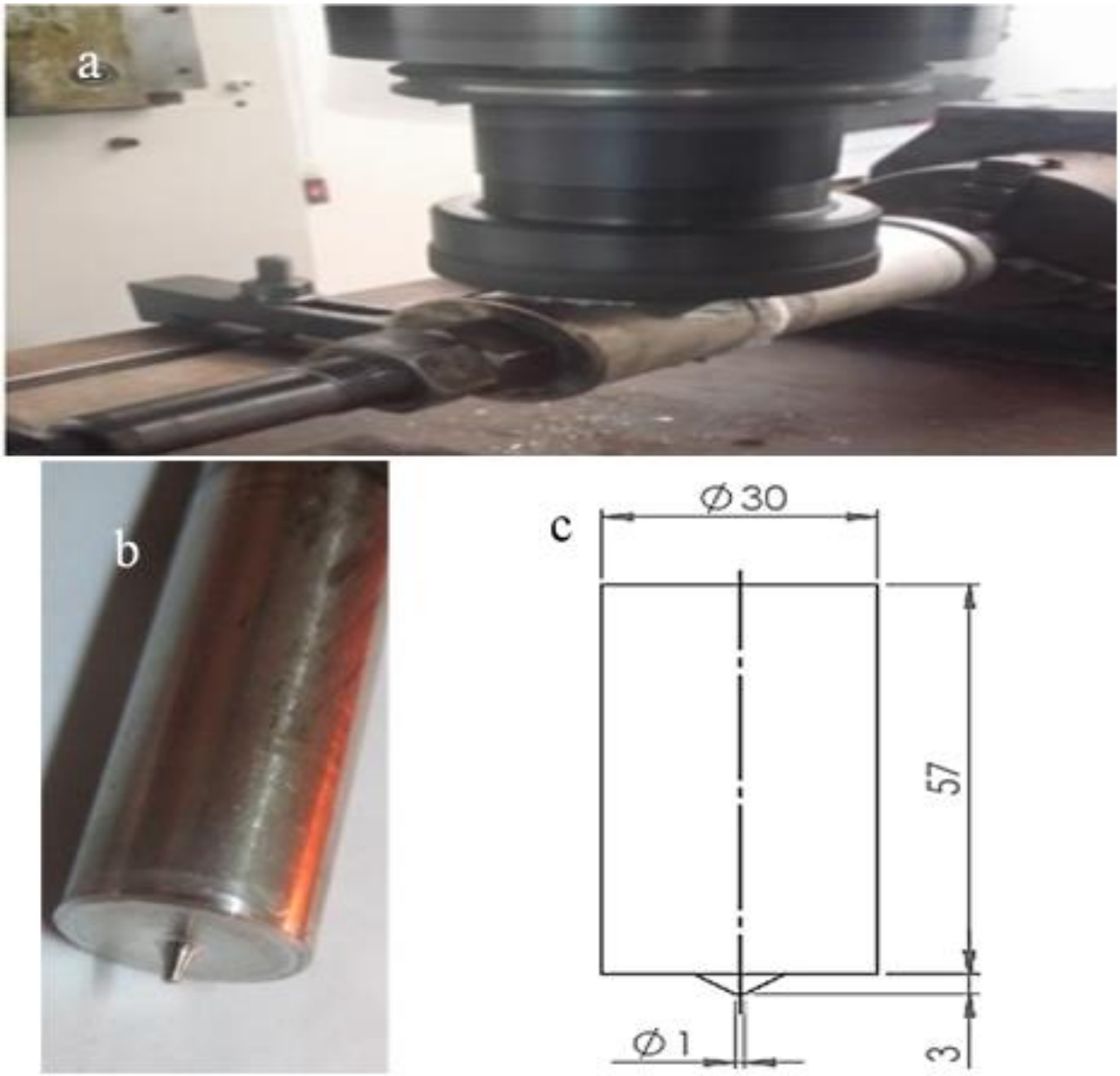

Fig. 2. The UWFSW technique produces a welded pipe.

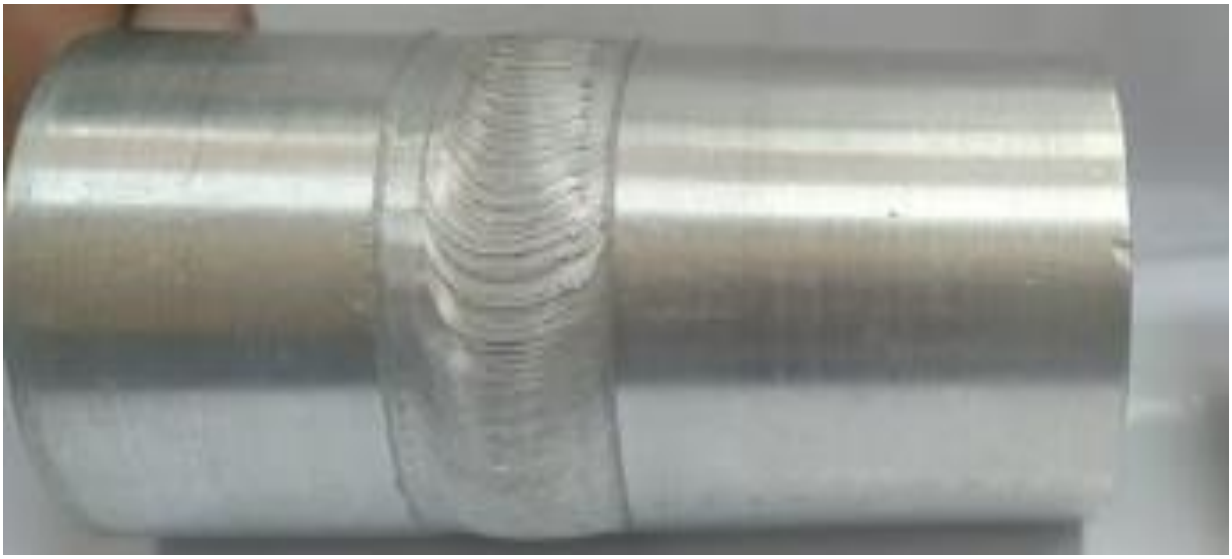

Fig. 3. A tensile test sample.

Fig. 4. The proposed framework of the proposed method.

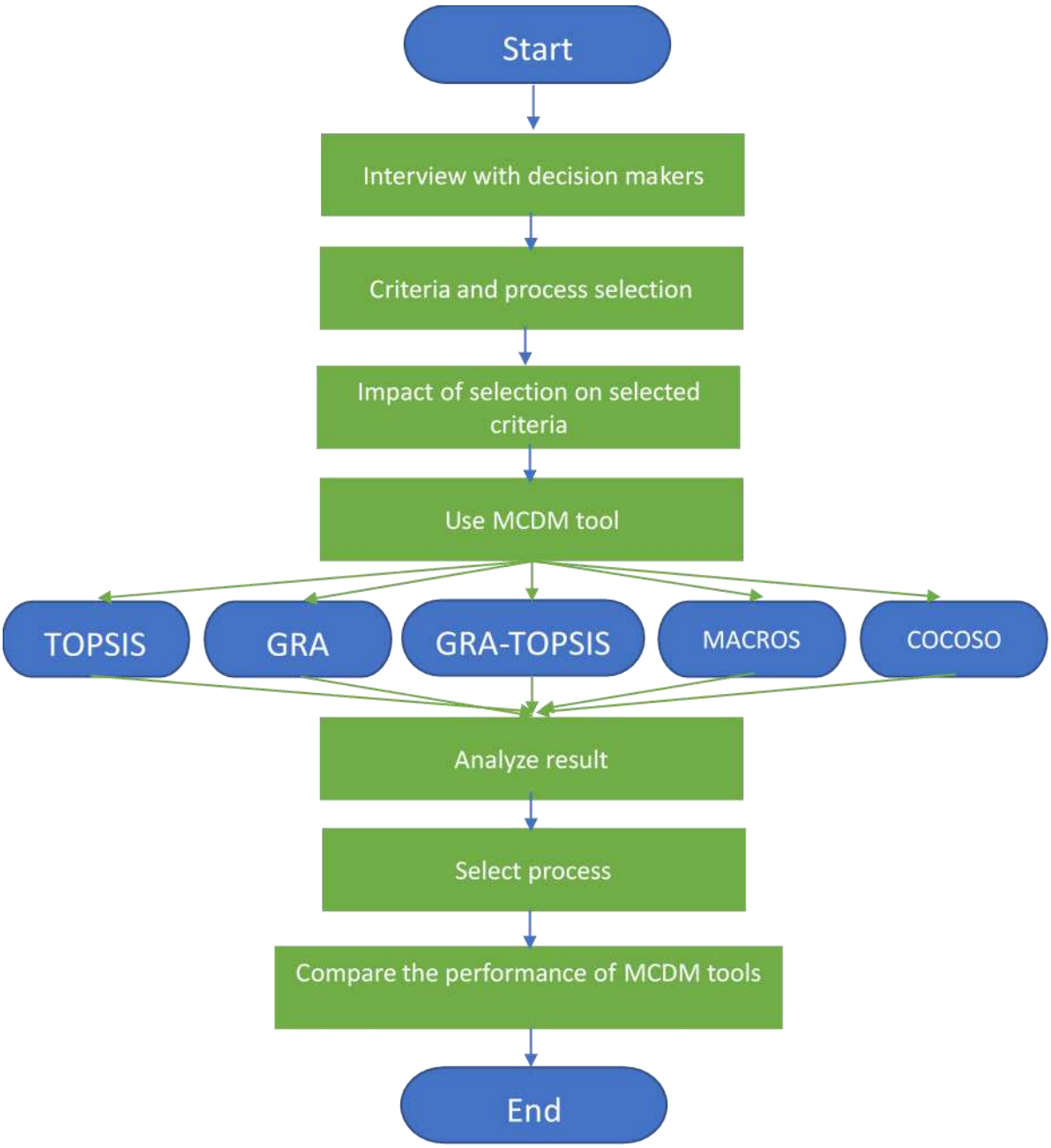

Fig. 5. Steps for the application of MCDM tools and their performance evaluation.

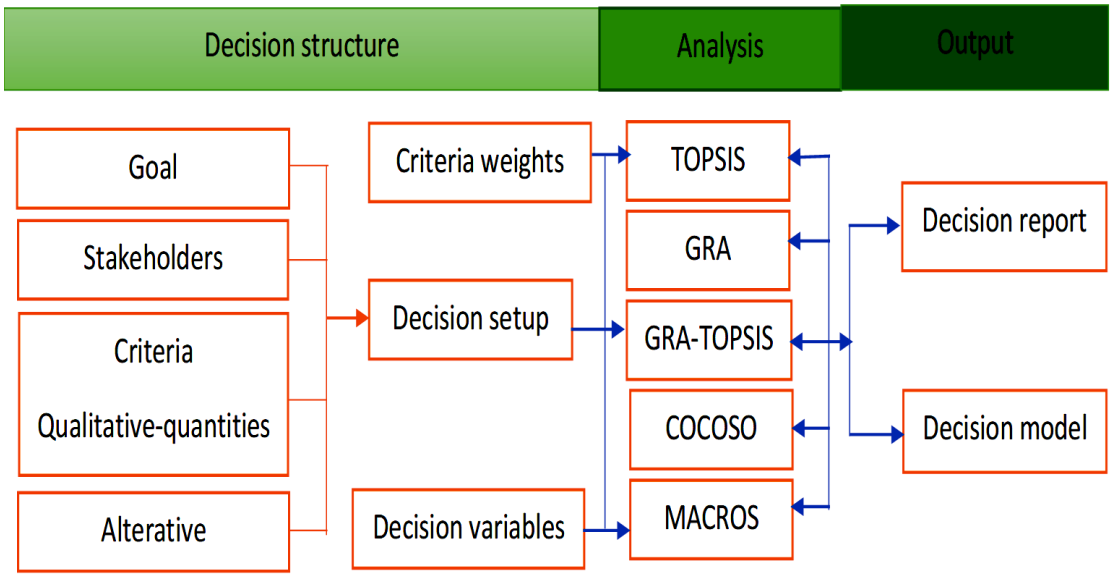

Fig. 6. Step-by-step technique for applying GRA methodology.

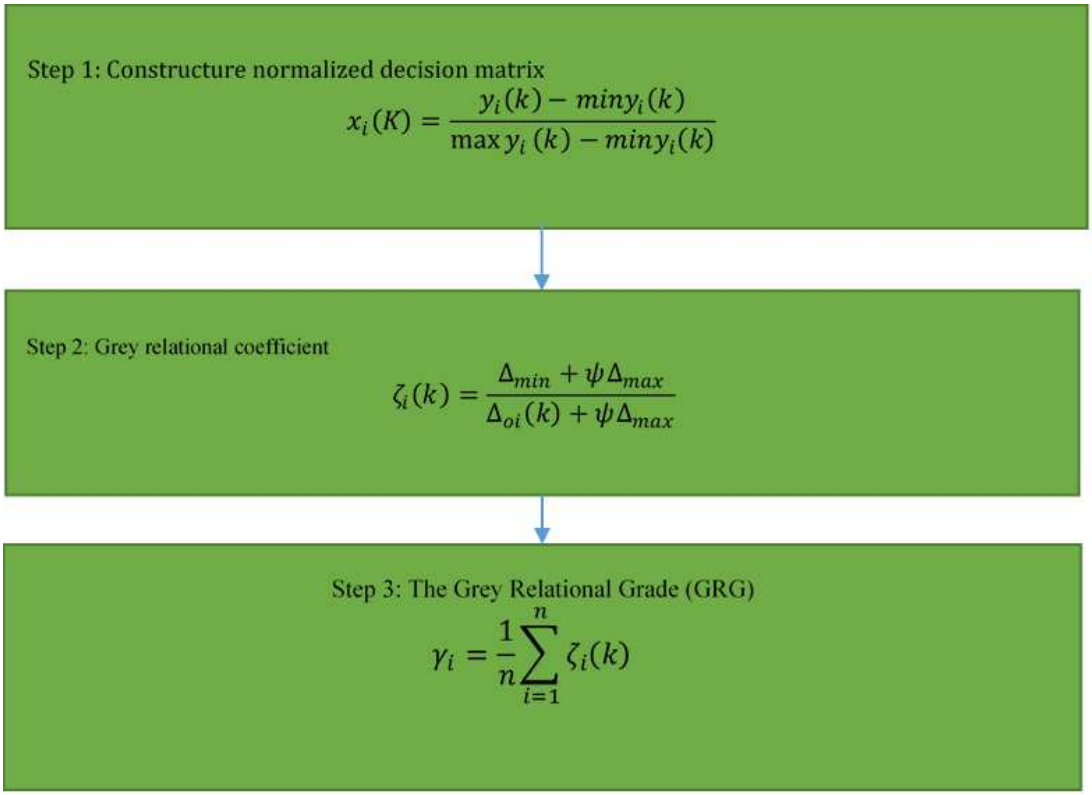

Fig. 7. Step-by-step technique for applying TOPSIS methodology.

Step 1: The original decision matrix should be built using all the experimentally gathered information.

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

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

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

Step 3: The weight of each attribute is assigned and the sum of weights of all attributes should be equal to 1.

$$\varphi_{ij} = w_j \gamma_{ij} \quad where \sum_{j=1}^{n} w_j = 1$$

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

$$\varphi^+ = (\varphi_1^+, \varphi_2^+, \ldots\ldots \varphi_{n1}^+ = \{(max\varphi_{ij} j\epsilon j_1), (min\varphi_{ij} j\epsilon j_2, i = 1,2,.n)\}$$

$$\varphi^- = (\varphi_1^-, \varphi_2^-, \ldots\ldots \varphi_{n1}^- = \{(max\varphi_{ij} j\epsilon j_1), (min\varphi_{ij} j\epsilon j_2, i = 1,2,.n)\}$$

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

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

Step 6: The relative closeness coefficient of each alternative is calculated using equation

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

Fig. 8. Step-by-step technique for applying GRA-TOPSIS methodology.

Step 1: The original decision matrix should be built using all the experimentally gathered information.

$$D_m = \begin{bmatrix} a_{11} & a_{12} & \dots & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & \dots & a_{2n} \\ . & \dots & \dots & \dots & \dots \\ . & \dots & \dots & \dots & \dots \\ a_{m1} & a_{m2} & \dots & \dots & a_{mn} \end{bmatrix}$$

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

$$y_{ij} = \frac{a_{ij} - min y a_{ij}}{\max a_{ij} - min a_{ij}}$$

Step 3: The weights of each attribute is assigned and the sum of weights of all attribute should be equal to 1.

$$S_{1j} = \frac{1}{n-1} \left| \sum_{i=1}^{n} (d(a_{ij}, \bar{a}_j) - m_{ij}) \right.$$

$$j = 1, 2, \dots, m$$

$$m_{1j} = \frac{1}{n} \sum^{n} (d(a_{ij}, \bar{a}_j), j = 1, 2, \dots, m.$$

Step 4: o compute the grey relational degree $r_{ij}{}^{+}$ and $r_{ij}{}^{-}$ will be determined as

$$r_{ij}{}^{+} = \frac{\varepsilon \, max_j \, S_{1j}}{|a_{ij} - \bar{a}_j| + \varepsilon \, max_j \, S_{1j}}$$

At the same case, the symbol $r_{ij}{}^{-}$ is the grey negative relation degree between a_{ij} *and* $\bar{a}$

$$r_{ij}{}^{-} = \frac{\varepsilon \, max_j \, S_{2j}}{|a_{ij} - \bar{a}_j| + \varepsilon \, max_j \, S_{2j}}$$

Step 5: *Step 5.*

To determine weights $\overline{W_j}$ and $\underline{W_j}$ for the entropy $\sum_{j=1}^{n} W_j$ =1

Step 6: To calculate the grey TOPSIS grade, the grey positive relational grade

$R_i{}^{+} = \sum_{j=1}^{m} \overline{W_j} \, r_{ij}{}^{+}, \; i = 1, 2, \dots, n.$

$$R_i{}^{-} = \sum^{m} \overline{W_j} \, r_{ij}{}^{-}, \; i = 1, 2, \dots, n.$$

Step 7: comprehensive grey TOPSIS evaluation result R_i is defined as following

$$R_i = \frac{R_i{}^{+}}{R_i{}^{+} + R_i{}^{-}}$$

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

Step 1: The original decision matrix should be built using all the experimentally gathered information.

$$D_m = \begin{bmatrix} a_{11} & a_{12} & \dots & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & \dots & a_{2n} \\ . & \dots & \dots & \dots & \dots \\ . & \dots & \dots & \dots & \dots \\ a_{m1} & a_{m2} & \dots & \dots & a_{mn} \end{bmatrix}$$

Step 2: The ideal solution is an alternative with the best alternative for certain criteria, whereas the anti-ideal solution is the worst alternative for certain criteria. This is based on the following equations:

$$AAI = \min_j x_{ij} \quad if \ j \in B \quad and \quad \max_j x_{ij} \quad if \ j \in C$$

$$AI = \max_j x_{ij} \quad if \ j \in B \quad and \quad \min_j x_{ij} \quad if \ j \in C$$

Step 3: The normalization of the extended initial matrix. Normalization is performed by using the following equations:

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \quad if \ j \in C$$

Step 4: The determination of a weighted matrix. Aggravation is performed by multiplying normalized matrix values by corresponding weights.

Step 5: The calculation of the utility degree of the alternatives K_i. The utility degree is determined by applying the following equations:

$$K_i^- = \frac{S_i}{S_{aai}} \qquad K_i^+ = \frac{S_i}{S_{ai}}$$

Step 6: The formation of the utility function of the alternatives *f(Ki)*. The utility function is calculated by using the following equation

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}};$$

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

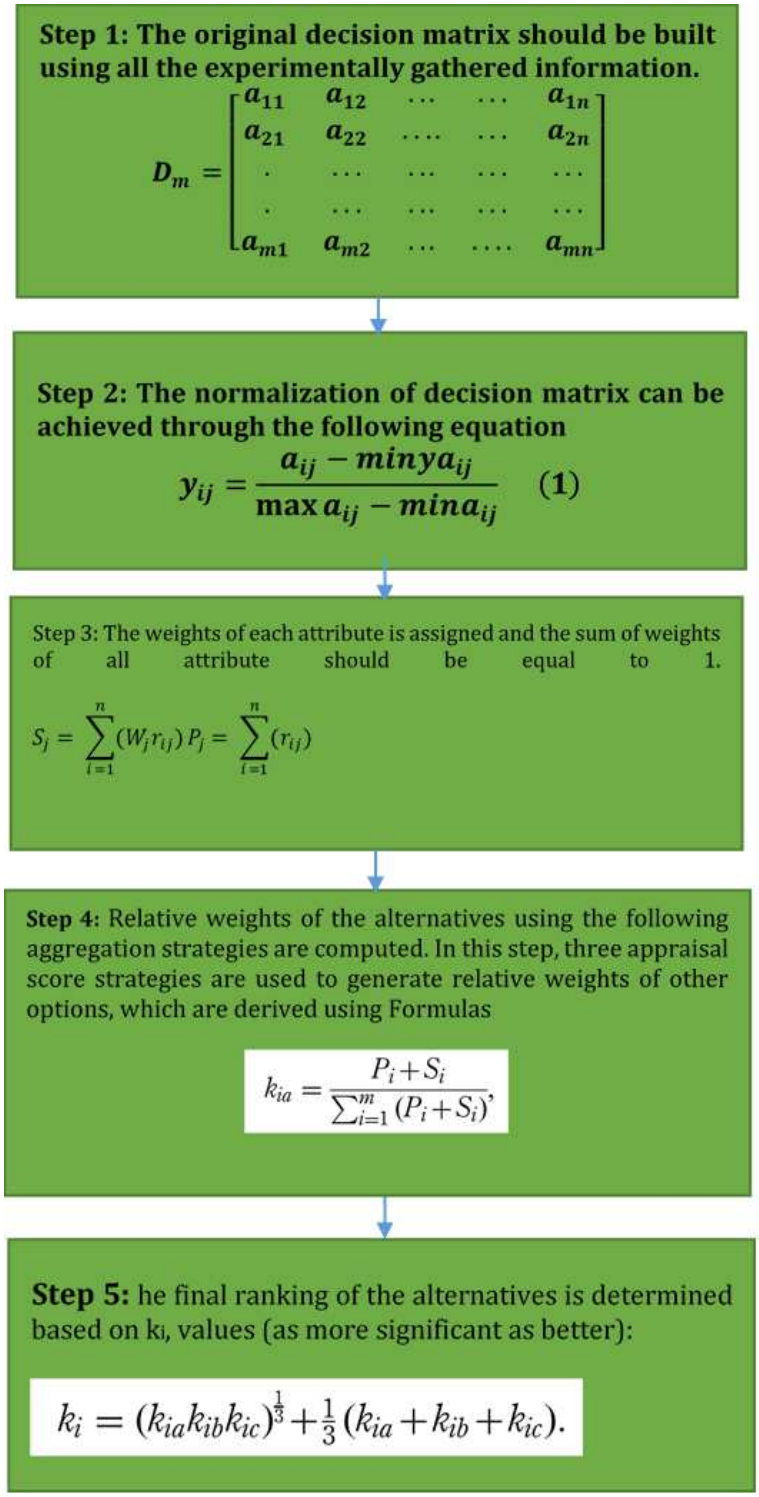

Fig. 11. Ranks comparison for TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS.

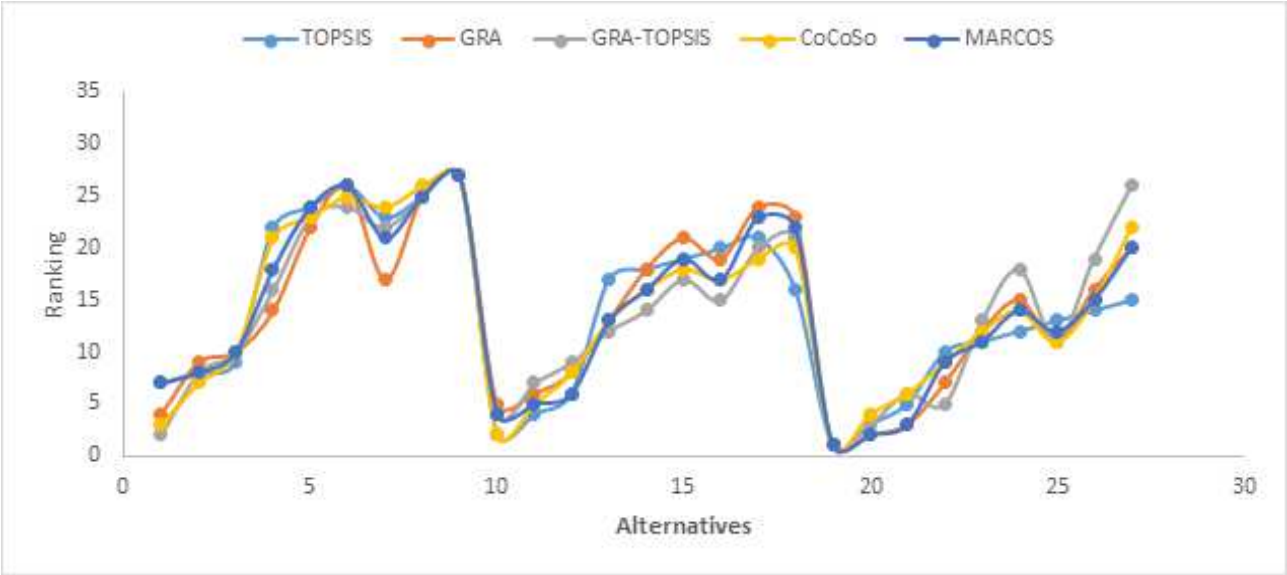

Fig. 12. Probability plot comparison for TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS.

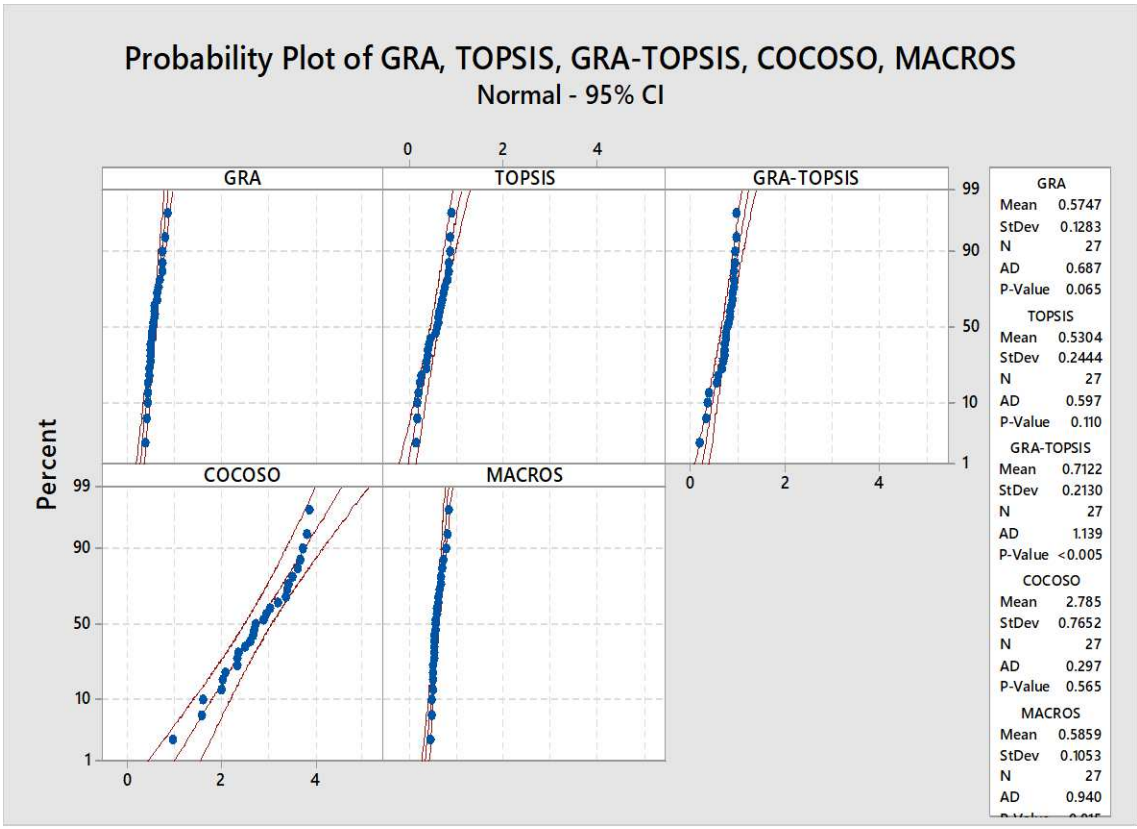

Fig. 13. Probability plot of complete data for TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS.

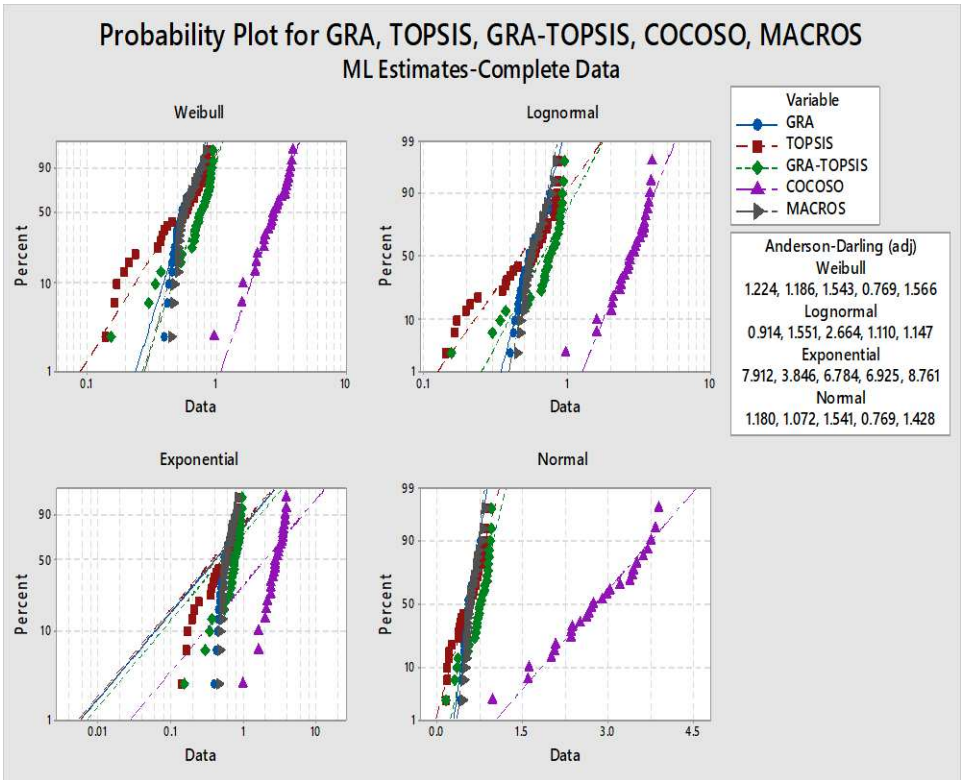

Fig. 14. Matrix plot for TOPSIS, GRA, hybrid GRA-TOPSIS, COCOSO, and MACROS.

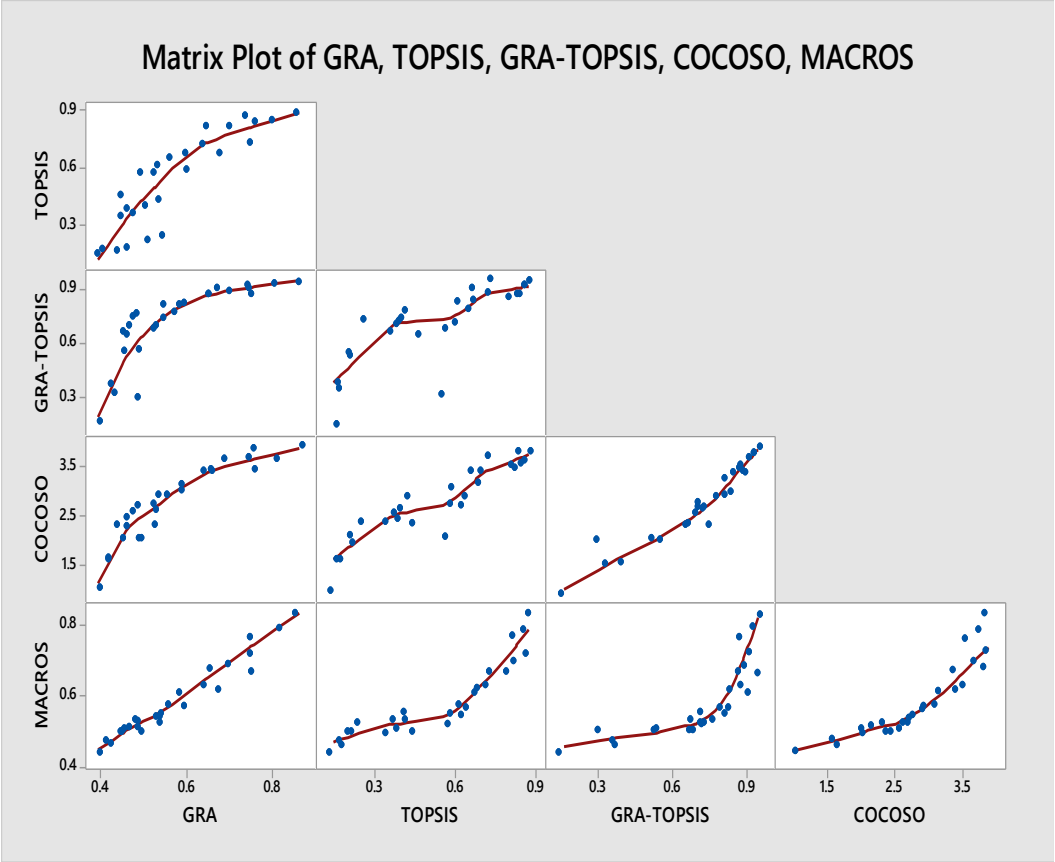

TABLE 1
The percentage of the chemical structure of the pipe's component AL 6060.

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	252.690	8	86

TABLE 3
LEVELS OF PROCESS PARAMETERS IN FSW.

Process Parameters	Unit	Symbol	Levels		
			-1	0	1
Rotation speed	RPM	N	710	1120	1400
Travel speed	mm/min	S	16	20	31.5
Shoulder diameter	mm	D	30	40	50

TABLE 4
DESIGN MATRIX AND EXPERIMENTAL VALUE WITH UTS, VHN, AND SR PROJECTED VALUES.

Run	FSW process parameters			Responses		
	N	D	S	UTS	VHN	SR
1	1800	50	10	162.5	55.30	9.346
2	1400	50	10	151.1	51.20	9.453
3	1000	50	10	143.4	48.60	9.879
4	1800	40	10	160.4	47.50	19.32
5	1400	40	10	146.3	45.70	19.64
6	1000	40	10	140.1	40.20	19.98
7	1800	30	10	157.8	43.90	20.18
8	1400	30	10	144.6	40.10	20.32
9	1000	30	10	135.2	38.30	20.67
10	1800	50	16	147.3	56.30	7.198
11	1400	50	16	141.1	53.20	7.280
12	1000	50	16	136.5	49.80	7.340
13	1800	40	16	140.9	53.30	14.67
14	1400	40	16	133.8	50.20	14.84
15	1000	40	16	129.4	47.90	14.95
16	1800	30	16	134.0	50.04	15.30
17	1400	30	16	121.0	47.90	15.31
18	1000	30	16	119.9	43.98	13.40
19	1800	50	31.5	122.8	60.30	4.983
20	1400	50	31.5	114.0	58.70	5.124

21	1000	50	31.5	107.3	56.90	5.299
22	1800	40	31.5	121.9	59.80	10.01
23	1400	40	31.5	106.0	55.30	10.23
24	1000	40	31.5	100.9	52.10	10.40
25	1800	30	31.5	109.0	57.70	11.01
26	1400	30	31.5	99.98	53.54	11.08
27	1000	30	31.5	89.72	50.09	11.20

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