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A hybrid-fuzzy model with reliability-based criteria for selecting consumables used in welding dissimilar aluminum alloys joint

Daniel O. Aikhuele*

College of Engineering, Bells University of Technology, Ota, Nigeria

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Abstract

This study proposes a new MCDM model for the selection of the consumables (filler alloys) used in the welding of dissimilar aluminum alloy joints. The model is based on the triangular intuitionistic fuzzy hamming distance (TIFHD) and the induced triangular intuitionistic fuzzy ordered weighted geometric (I-TIFOWG) operator. It uses a value-index method to rank filler alloy alternatives and for determining the degree of flexibility in the decision-making process. The model has the following advantages: (1) the ability to capture fuzziness in the decision-making process, (2) it accounts for a degree of flexibility in the decision-making process, and, finally, (3) the method helps in reducing uncertainty in the evaluation process using the Triangular Intuitionistic Fuzzy Number(s). This allows for a more holistic and better tool for representing vague or imprecise information. In demonstrating the feasibility of the proposed model, a comparison analysis was performed. From the result of this analysis, it was observed that the model is feasible, flexible and accounts for the fuzziness in the decision-making process, as well as selecting the best filler alloy for a dissimilar aluminum weld.

Keywords: Triangular intuitionistic fuzzy hamming distance, Induced triangular intuitionistic fuzzy ordered weighted geometric operator, Filler alloys, Dissimilar aluminum alloy joints

1. Introduction

Dissimilar welds of aluminum alloy joints of 5083-O and 606-T651 have found several applications in the design of load bearing structures, such as rooftops of commercial and industrial buildings, pressure vessels, oil cargo tanks and marine cranes [1]. Welded joints are expected to withstand direct mechanical loadings and impacts, stresses caused by thermal cycling and gradients, tensile and compressive stresses, torsional and bending stresses [2]. In some cases, welded joints are subjected to chemical and biological interactions [3]. In the event that a welded joint fails, the implications, which are most likely disastrous, can lead to losses of economic assets, damage to the environment, and sometimes loss of human lives [4]. However, to increase the service life of a dissimilar welded joint, the joint needs to be improved by carefully considering the mechanical and chemical properties of the materials used in preparing the joint. This can be achieved by selecting the best filler alloy materials, welding electrode and proper shielding gas from the numerous alternatives available in the market (consumables) [5]. Also, a welded joint can be improved by selecting the correct welding process parameters [6-7].

Traditionally, when consumables are used for some welding purposes, welding experts and practitioners often use intuition to select the best alternatives. This approach is not only time consuming, but also it is expensive when a welded joint fails [8]. Recently, Multi-criteria Decision-Making (MCDM) methods have been used to address this problem. For example, Baghel and Nagesh [5] proposed an integrated analytical hierarchy process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (AHP-TOPSIS). Their model was used to screen and select the best filler alloy, electrode, and shielding gas for TIG welding. Singh and Rao [9] applied a Multiple Attribute Decision-making approach to select a welding processes and welding consumables for a system. Achebo [10] used a TOPSIS method to find the best way to improve weld deposit and quality in a material. Sánchez-Lozano et al. [11] used a combined TOPSIS-AHP Methods and Fuzzy logic to evaluate Arc welding processes.

Although, the MCDM methods presented in the literature have been able to handle and determine the best consumable alternatives for welded joints, the methods presented are not holistic, flexible and are unable to fully account for the uncertainties. They cannot provide any flexibility in the decision-making process. Previous studies used limited mechanical properties to select welding consumables. This approach cannot fully guarantee the reliability of the final weld.

In the current study, a new MCDM model is proposed for the selection of the consumables that are to be used to

*Corresponding author.
Email address: danbishop_22@yahoo.co.uk
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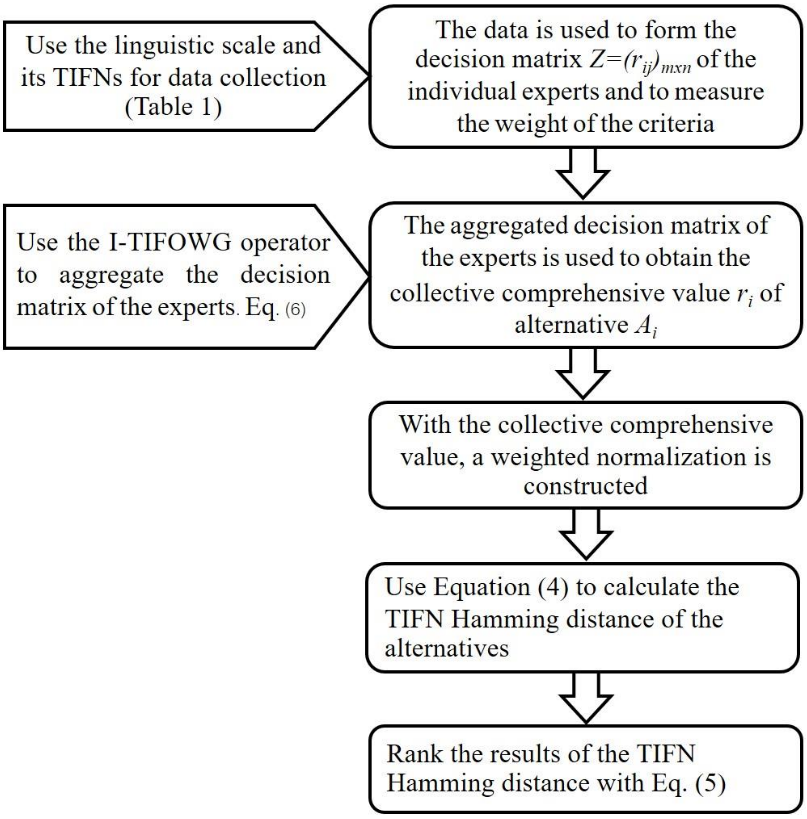

Figure 1 Flow chart of the method

weld dissimilar aluminum alloy joints. The model is based on the triangular intuitionistic fuzzy hamming distance (TIFHD) method and the induced triangular intuitionistic fuzzy ordered weighted geometric (I-TIFOWG) operator [12]. It uses a value-index ranking method to rank the filler alloys (alternatives) and to determine the degree of flexibility in the decision-making process. The evaluation criteria used in the selection process are based on the mechanical and micro-structural characteristics of the consumables. This ensures weld reliability.

The proposed model has the following advantages: (1) the ability to capture fuzziness and hesitation in the decision-making process, and (2) the ability to account for a degree of flexibility in the decision-making process. Additionally, the proposed model will help to reduce uncertainty in the evaluation process using triangular intuitionistic fuzzy number(s) (TIFNs), which is considered a more holistic and better tool for representing vague or imprecise information [13].

2. Methodology

In this section, the methodology used to investigate the research problem and the rationale for its application is presented (Figure 1). The methodology is based on a new MCDM method. The method uses a triangular intuitionistic fuzzy hamming distance (TIFHD) method and an induced triangular intuitionistic fuzzy ordered weighted geometric (I-TIFOWG) operator [12] to evaluate reliability-based criteria and consumables for welding dissimilar aluminum alloys. Furthermore, the methodology addresses the following issue:

Data collection and data generation

Data analysis

2.1 TIFN and the triangular intuitionistic fuzzy hamming distance (TIFHD) method

In addressing the fuzziness and hesitation of decision-making in the real world, Atanassov [14] introduced an intuitionistic fuzzy set (IFS) as an extension of the traditional fuzzy set (FS) originally proposed by Zadeh [15]. The concepts of an intuitionistic fuzzy set (IFS) and a triangular intuitionistic fuzzy set from which the TIFN is derived are presented as follows:

Definition 1: [14]

Let an intuitionistic fuzzy set A in the universe of discourse $X = \{x\}$ be defined as Equation (1).

$$A = \{\langle x, \mu_A(x), v_A(x)\rangle | x \in X\} \quad (1)$$

where μ_A and v_A are membership and non-membership functions, respectively, and they are bounded by the condition $0 \leq \mu_A(x) + v_A(x) \leq 1, \mu_A(x), v_A(x) \in [0,1], \forall x \in X$.

The index of the element x in the intuitionistic fuzzy set A can then be computed using a hesitation function (Equation 2).

$$\pi_A(x) = 1 - (\mu_A(x) + v_A(x)) \quad (2)$$

To improve the efficiency of IFSs to capture and express fuzzy information, the IFS is extended into a triangular intuitionistic fuzzy set (TIFS). It is represented as $\acute{\alpha} = \langle([a,b,c];\mu_\alpha),([a,b,c];v_\alpha)\rangle$. [16-17].

where μ_α and v_α are membership and non-membership functions, respectively. For convenience, the TIFN can be define as $\acute{\alpha} = ([a\ , b, c]; \mu_\alpha, v_\alpha)$.

Definition 2: [18-19]

If $\alpha_1 = ([a_1, b_1, c_1]; \mu_{\alpha_1}, v_{\alpha_1})$ and $\alpha_2 = ([a_2, b_2, c_2]; \mu_{\alpha_2}, v_{\alpha_2})$ are two TIFNs, when $\lambda \leq 0$, the operational properties of TIFNs can be expressed as Equation (3).

$$\left.\begin{array}{c} \alpha_1 + \alpha_2 = \alpha_2 + \alpha_1 \\ \alpha_1 \otimes \alpha_2 = \alpha_2 \otimes \alpha_1 \\ \lambda(\alpha_1 + \alpha_2) = \lambda\alpha_1 + \lambda\alpha_2 \lambda \geq 0, \\ \lambda_1\alpha + \lambda_2\alpha = (\lambda_1 + \lambda_2)\alpha \ \ \lambda_1\lambda_2 \geq 0 \\ \alpha^{\lambda_1} \otimes \alpha^{\lambda_2} = \alpha^{\lambda_1+\lambda_2} \lambda_1\lambda_2 \geq 0 \\ {\alpha_1}^{\lambda} \otimes {\alpha_2}^{\lambda} = (\alpha_1 \otimes \alpha_2)^{\lambda} \lambda \geq 0 \end{array}\right\} \quad (3)$$

Definition 3: [20]

If $\alpha_1 = ([a_1, b_1, c_1]; \mu_{\alpha_1}, v_{\alpha_1})$ and $\alpha_2 = ([a_2, b_2, c_2]; \mu_{\alpha_2}, v_{\alpha_2})$ are TIFNs, then the Hamming distance between α_1 and α_2 is given as follows:

$$d(\alpha_1, \alpha_2) = \frac{1}{6}\begin{bmatrix} |(1 + \mu_{\alpha_1} - v_{\alpha_1})a_1 - (1 + \mu_{\alpha_2} - v_{\alpha_2})a_2| \\ +|(1 + \mu_{\alpha_1} - v_{\alpha_1})b_1 - (1 + \mu_{\alpha_2} - v_{\alpha_2})b_2| \\ +|(1 + \mu_{\alpha_1} - v_{\alpha_1})c_1 - (1 + \mu_{\alpha_2} - v_{\alpha_2})c_2| \end{bmatrix} \quad (4)$$

The above Hamming distance is effective in determining the distance measured between TIFNs. Several authors used it with a relative closeness co-efficient to rank alternatives. However, it is ineffective when flexibility is required in the decision-making process. Hence, this study introduces a new ranking method.

Definition 4:

The overall preferences and degree of flexibility can be calculated using a value-index ranking method, which is given as Equation (5).

$$R = \beta d({\alpha_i}^{+}, \alpha_i) + (1 - \beta\ d({\alpha_i}^{-}, \alpha_i) \quad (5)$$

where β denote the degree of flexibility which is in range $\beta \in [0.1; 1.0]$.

2.2 Aggregation operators for flexible raking of TIFNs

Based on the need to account for fuzziness, hesitation, mean confidence level and flexibility of the experts when using TIFNs, the induced TIFOWG (I-TIFOWG) operator is presented as follows:

Definition 5: [12]

Let the I-TIFOWG operator be defined as Equation (6)

$$I - \text{TIFOW}G_{\omega,W}(\langle x_1, \alpha_1\rangle, \langle x_2, \alpha_2\rangle, \langle x_3, \alpha_3\rangle, \dots, \langle x_n, \alpha_n\rangle) = \omega_1(\alpha_{\sigma 1}) \otimes \omega_2(\alpha_{\sigma 2}) \otimes \omega_3(\alpha_{\sigma 3}) \dots \otimes \omega_n(\alpha_{\sigma n})$$

$$= \left(\left[\prod_{i=1}^{n}(a_{\sigma i})^{\omega_i}, \prod_{i=1}^{n}(b_{\sigma i})^{\omega_i}, \prod_{i=1}^{n}(c_{\sigma i})^{\omega_i}\right]; \prod_{i=1}^{n}(\mu_{\alpha_{\sigma i}})^{\omega_i}, 1 - \prod_{i=1}^{n}(1 - v_{\alpha_{\sigma i}})^{\omega_i}\right) \quad (6)$$

where $a_{\sigma i}$ is the weighted intuitionistic fuzzy value of the TIFOWG pair $\langle x_1, \alpha_1\rangle$ having the i^{th} largest $x_i (x_i \in [0, 1])$, x_i in $\langle x_i, \alpha_i\rangle$ is the order inducing variable, α_i denotes an intuitionistic fuzzy argument variable and $\omega = (\omega_1, \omega_2, \omega_3, \dots, \omega_n)^T$ is a weighting vector which can also be defined in the form $\omega_i \in [0, 1]$, where $\sum_{i=1}^{n} w_i = 1$, $i = 1,2,3, \dots, n,$.

3. The MCDM algorithm of the TIFHD-ITFOWG model

Given that a MCDM problem consists of a set of alternatives $ER = \{ER_1, ER_2, ER_3, \dots, ER_m\}$ that can be expressed in TIFNs to be evaluated using a set of criteria or attributes - $CR = \{CR_1, CR_2, CR_3, \dots, CR_m)$ with a known weight, then the fuzziness and degree of hesitancy of the alternatives with respect to the criteria can be captured. This process is solved using the proposed TIFHD-ITFOWG model. The model's computational steps are given as follows:

Step 1: Select a number of experts (*E*) with suitable expertise in the subject.

Step 2: Allow them to access and evaluate the alternatives with linguistic terms (Table 1) with respect to the criteria. Then use their responses to form a decision matrix $Z = (r_{ij})_{mxn}$ as shown below:

$$Z = \begin{bmatrix} ([a_{11}, b_{11}, c_{11}]; \mu_{11}, v_{11}) & \dots & \cdots & ([a_{1n}, b_{1n}, c_{1n}]; \mu_{1n}, v_{1n}) \\ ([a_{21}, b_{21}, c_{21}]; \mu_{21}, v_{21}) & \dots & \cdots & ([a_{2n}, b_{2n}, c_{2n}]; \mu_{2n}, v_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ ([a_{m1}, b_{m1}, c_{m1}]; \mu_{m1}, v_{m1}) & \dots & \cdots & ([a_{mn}, b_{mn}, c_{mn}]; \mu_{mn}, v_{mn}) \end{bmatrix}$$

Table 1 Linguistic scale and its TIFNs for data collection

Linguistic terms	**TIFNs**
Bad (BD)	**([0.10, 080, 0.2]; 0.4, 0.4)**
Unimportant (UT)	**([0.20, 0.70, 0.2]; 0.4, 0.2)**
Important (IT)	**([0.30, 0.60, 0.1]; 0.5, 0.3)**
Vital (VT)	**([0.50, 0.50, 0.1]; 0.6, 0.2)**
Extremely Vital (HT)	**([0.80, 0.10, 0.1]; 0.6, 0.1)**

Step 3: Aggregate the DMs results and express the results in matrix form:$Z = (r_{ij})_{mxn}$, and use the I-TIFOWG operator to obtain a collective comprehensive value r_i of alternative A_i. The collective comprehensive value x_i of alternative $A_i$is given as follows:

$$x_i = ([{x^k}_i, {x^k}_i, {x^k}_i]; \mu_{{x^k}_i}, v_{{x^k}_i}) = I - TIFOWG_w(\langle x_1, \alpha_1\rangle, \langle x_2, \alpha_2\rangle, \dots, \langle x_n, \alpha_n\rangle) = \left(\left[\prod_{i=1}^{n}({x^k}_i)^{w_i}, \prod_{i=1}^{n}({x^k}_i)^{w_i}, \prod_{i=1}^{n}({x^k}_i)^{w_i}\right]; \prod_{i=1}^{n}(\mu_{{x^k}_i})^{w_i}, 1 - \prod_{i=1}^{n}(1 - v_{{x^k}_i})^{w_i}\right)$$

where $w = (w_1, w_2, w_3, \dots, w_n)^T$ is the weighting vector of the attributes.

Step 4: Define the criteria weight in linguistic and crisp terms.

Step 5: Construct a weighted normalization for the aggregate results.

Table 2 Composition of the filler alloys alternatives

ER 5356	ER 5556	ER 5183	ER 5654
High strength	High strength	--	--
Maximum Ductility	--	--	Ductility
Best Color Match After Anodizing	Best Color Match After Anodizing	Best Color Match After Anodizing	Best Color Match After Anodizing
Maximum Salt Water Corrosion resistance	Maximum Salt Water Corrosion resistance	Maximum Salt Water Corrosion resistance	--
Least cracking tendency	--	--	--

Table 3 Linguistic results of the evaluated filler alloys by the experts

Linguistic evaluations of the filler alloys by Expert 1					
ER_i	**CR_1**	**CR_2**	**CR_3**	**CR_4**	**CR_5**
ER_1	**IT**	**HT**	**HT**	**VT**	**IT**
ER_2	**UT**	**BD**	**HT**	**UT**	**BD**
ER_3	**IT**	**HT**	**UT**	**IT**	**VT**
ER_4	**HT**	**UT**	**UT**	**UT**	**HT**
Linguistic evaluations of the filler alloys by Expert 2					
ER_i	**CR_1**	**CR_2**	**CR_3**	**CR_4**	**CR_5**
ER_1	**IT**	**IT**	**IT**	**HT**	**IT**
ER_2	**UT**	**HT**	**UT**	**IT**	**UT**
ER_3	**IT**	**HT**	**HT**	**HT**	**IT**
ER_4	**UT**	**BD**	**BD**	**VT**	**UT**
Linguistic evaluations of the filler alloys by Expert 3					
ER_i	**CR_1**	**CR_2**	**CR_3**	**CR_4**	**CR_5**
ER_1	**IT**	**HT**	**HT**	**VT**	**IT**
ER_2	**UT**	**BD**	**HT**	**BD**	**UT**
ER_3	**IT**	**IT**	**HT**	**HT**	**VT**
ER_4	**VT**	**UT**	**VT**	**IT**	**IT**

Step 6: Use Equation (4) to calculate the TIFN Hamming distance of the alternatives. This step will generate positive and negative ideal solutions $d(\alpha_i{}^+, \alpha_i)$ *and* $d(\alpha_i{}^-, \alpha_i)$ $(i = 1,2,\ldots,n)$ for each alternative.

$$A^+ = \{\langle C_j, [\max a, max\ b, \max c]\rangle | C_j \in C\}\ j = 1,2,3,\ldots,n$$

$$A^- = \{\langle C_j, [\min a\ min\ b, \min c]\rangle | C_j \in C\}\ j = 1,2,3,\ldots,n$$

$$d(\alpha_1, \alpha_2) = \frac{1}{6}\begin{bmatrix} |(1+\mu_{\alpha_1} - v_{\alpha_1})a_1 - (1+\mu_{\alpha_2} - v_{\alpha_2})a_2| + \\ |(1+\mu_{\alpha_1} - v_{\alpha_1})b_1 - (1+\mu_{\alpha_2} - v_{\alpha_2})b_2| \\ +|(1+\mu_{\alpha_1} - v_{\alpha_1})c_1 - (1+\mu_{\alpha_2} - v_{\alpha_2})c_2| \end{bmatrix}$$

Step 7: Using the value-index ranking method, calculate the overall preferences of the experts and the degree of flexibility.

$$R = \beta d(\alpha_i{}^+, \alpha_i) + (1 - \beta\ d(\alpha_i{}^-, \alpha_i)$$

where $\beta \in [0.1; 0.9]$ denotes a flexibility function.

Step 8: Rank the alternatives using the non-increasing order of TIFNs. Finally, use the flexibility function to perform a sensitivity analysis.

4. Numerical illustration

In this section, the proposed TIFHD-ITFOWG Model is used to select consumables (filler alloys) for the welding of dissimilar aluminum alloy joints. This alloy plays an important role in the arc-welding of dissimilar aluminum alloys so that they are appropriate and match the base alloy chemical composition. However, matching the filler alloys used in the welding process depends mainly on the joint type and loading conditions. Hence, most of the defects involve solidification cracking in the fusion welding process, porosity that occurs as a result of the selection, and use of improper filler alloy materials. The filler alloys are selected based on their mechanical and microstructural properties. These properties are used as evaluation criteria to select the best filler alloy for a particular welding process. They include strength (CR_1), toughness (CR_2), corrosion resistance (CR_3), sensitivity to cracking (CR_4), and low temperature service capability (CR_5). The filler alloy alternatives to be ranked are ER 5356(ER_4), ER 5556(ER_2), ER 5183(ER_3) and ER 5654(ER_4). Their composition is given in Table 2.

Using the proposed algorithm in Section 3, three experts with significant expertise in welding and non-destructive testing were invited to analyze and contribute their expertise in the selection of a filler alloy. The experts were drawn from academia - *(E_1)* and industry - (E_2) and (E_3); their weighting vector $is = (0.20, 0.30, 0.30)^T$. Using the linguistic scale in Table 1, an intuitionistic fuzzy decision matrix $Z = (r_{ij})_{mxn}$was constructed (Table 3). These linguistic terms were converted to TIFNs. Using the proposed TIFHD-ITFOWG model, the intuitionistic fuzzy decision matrix $Z = (r_{ij})_{mxn}$ with the TIFNs of each of the experts was aggregated using the I-TIFOWG operator. This process generated a collective comprehensive value r_i of the alternatives W_i (Table 4).

Steps 4 & 5: The fuzzy weight of the criteria was converted to the crisp values shown in Table 5. The values were then used to construct a weighted normalization matrix (Table 5).

Using Equation (4), the positive and negative ideal solution of TIFN Hamming distance method was calculated

Table 4 The aggregated result of the intuitionistic fuzzy decision matrixes

	CR_1	CR_2	CR_3	CR_4	CR_5
ER_1	([0.38, 0.66, 0.16];0.57, 0.25)	([0.62, 0.27, 0.16];0.63, 0.15)	([0.62, 0.27, 0.16];0.63, 0.15)	([0.66, 0.35, 0.16];0.66, 0.13)	([0.38, 0.66, 0.16];0.57, 0.25)
ER_2	([0.28, 0.75, 0.28];0.48, 0.16)	([0.30, 0.45, 0.22];0.54, 0.25)	([0.55, 0.28, 0.20];0.59, 0.11)	([0.25, 0.75, 0.22];0.51, 0.26)	([0.24, 0.77, 0.28];0.48, 0.22)
ER_3	([0.38, 0.66, 0.16];0.57, 0.25)	([0.62, 0.27, 0.16];0.63, 0.15)	([0.63, 0.23, 0.18];0.61, 0.10)	([0.69, 0.23, 0.16];0.64, 0.13)	([0.49, 0.61, 0.16];0.63, 0.20)
ER_4	([0.48, 0.46, 0.20];0.59, 0.14)	([0.22, 0.78, 0.28];0.48, 0.23)	([0.30, 0.71, 0.22];0.54, 0.23)	([0.41, 0.65, 0.81];0.58, 0.20)	([0.41, 0.49, 0.20];0.56, 0.18)

Table 5 The weight of the criteria and the weighted normalized aggregate results

	CR_1	CR_2	CR_3	CR_4	CR_5
Criteria weight	([0.28,0.66,0.45]; 0.70,0.60)	([0.70,0.65,0.20];0.50,0.60)	([0.70,0.62,0.65];0.60,0.70)	([0.59,0.80,1.00]; 0.60,0.30)	([0.20,0.76,0.65]; 0.40,0.70)
	0.41875	0.4125	0.48625	0.51125	0.43375
Weighted normalization of the aggregate results					
ER_1	([0.16, 0.28, 0.07];0.24, 0.10)	([0.26, 0.11, 0.07];0.26, 0.06)	([0.30, 0.13, 0.08];0.31, 0.07)	([0.34, 0.18, 0.08];0.34, 0.07)	([0.17, 0.29, 0.07];0.25, 0.11)
ER_2	([0.12, 0.31, 0.12];0.20, 0.07)	([0.12, 0.18, 0.09];0.22, 0.10)	([0.27, 0.14, 0.09];0.29, 0.05)	([0.13, 0.38, 0.11];0.26, 0.13)	([0.10, 0.33, 0.12];0.21, 0.09)
ER_3	([0.16, 0.28, 0.07];0.24, 0.10)	([0.26, 0.11, 0.07];0.26, 0.06)	([0.31, 0.11, 0.09];0.30, 0.05)	([0.35, 0.12, 0.08];0.33, 0.06)	([0.21, 0.26, 0.07];0.27, 0.09)
ER_4	([0.20, 0.19, 0.08];0.25, 0.06)	([0.09, 0.32, 0.11];0.20, 0.10)	([0.14, 0.34, 0.11];0.26, 0.11)	([0.21, 0.33, 0.09];0.30, 0.10)	([0.18, 0.21, 0.08];0.24, 0.08)

Table 6 TIFN Hamming distance

	$d(\alpha_i^+, \alpha_i)$	$d(\alpha_i^-, \alpha_i)$
ER_1	0.5315	0.1110
ER_2	0.4558	0.1004
ER_3	0.5223	0.1076
ER_4	0.5272	0.1188

Table 7 The overall result using the proposed method with a flexibility function

β	ER_1	ER_2	ER_3	ER_4	Ranking order	Best result
0.1	0.1530	0.1360	0.1491	0.1597	$ER_4 > ER_1 > ER_3 > ER_2$	ER_4
0.2	0.1951	0.1715	0.1906	0.2005	$ER_4 > ER_1 > ER_3 > ER_2$	ER_4
0.3	0.2371	0.2071	0.2320	0.2414	$ER_4 > ER_1 > ER_3 > ER_2$	ER_4
0.5	0.3212	0.2781	0.3150	0.3230	$ER_4 > ER_1 > ER_3 > ER_2$	ER_4
0.7	0.4053	0.3492	0.3979	0.4047	$ER_1 > ER_4 > ER_3 > ER_2$	ER_1
0.8	0.4474	0.3848	0.4394	0.4455	$ER_1 > ER_4 > ER_3 > ER_2$	ER_1
0.9	0.4895	0.4203	0.4808	0.4864	$ER_1 > ER_4 > ER_3 > ER_2$	ER_1

for each of the filler alloys. The results are presented in Table 6. The proposed method, with a flexibility function, was used to generate the overall results for the ranking process (Table 7).

From the result presented in Table 7, the ranking orders of the alternatives are different. This implies that the ranking process depends on the coefficients of the flexibility function. For example, when the flexibility function is $\beta = 0.7$, the consensus result for the filler alloys is in the following ranked order: $ER_1 > ER_4 > ER_3 > ER_2$, and filler alloy ER_1 is consider the best alternative. When $\beta = 0.2$, the ranked order is $ER_4 > ER_1 > ER_3 > ER_2$, and then ER_4 is the best alternative. The main advantage of this function is that it gives flexibility and allows a welder to choose different coefficients according to his subjective preference.

4.1 Comparison analysis of the result obtained using the TIFHD-ITFOWG model

In this sub-section, the results from the proposed model are compared with a modified TOPSIS model [21] and an intuitionistic fuzzy method [19]. From the results in Table 8, the proposed model performance is consistent with the performance of the models in [19] and [21].

5. Conclusions

Traditionally, when consumables (filler alloys) are used for welding purposes, welding experts and practitioners often use their experience to test each of the various materials when selecting the best alternative for a specific welding process. This approach is sometime time consuming and expensive. Apart from this problem, the use of intuition to address this kind of selection problem is neither holistic, nor flexible. It cannot fully account for the uncertainty in the decision-making process. When decision-makers use this approach, they will be able to evaluate few mechanical properties that cannot fully guarantee the reliability of the

Table 8 Comparison Analysis of the result obtained using the proposed Model

β	ER_1	ER_2	ER_3	ER_4	Ranking order	Best result
The result of the proposed model with the flexibility function						
0.1	0.1530	0.1360	0.1491	0.1597	$ER_4 > ER_1 > ER_3 > ER_2$	
0.2	0.1951	0.1715	0.1906	0.2005	$ER_4 > ER_1 > ER_3 > ER_2$	ER_4
0.5	0.3212	0.2781	0.3150	0.3230	$ER_4 > ER_1 > ER_3 > ER_2$	
Relative closeness to the ideal solutions method[21]						
	0.1727	0.1806	0.1709	0.1839	$ER_4 > ER_1 > ER_2 > ER_3$	ER_4
Score and the accuracy function of triangular intuitionistic fuzzy method [19]						
SF	0.0421	0.0366	0.0393	0.0498	$ER_4 > ER_1 > ER_3 > ER_2$	$\boldsymbol{ER_4}$
AF	0.0798	0.0962	0.0782	0.1171		

final weld. Multi-criteria decision-making (MCDM) methods can be used to address this problem.

This study, therefore, proposes a new MCDM model for the selection of the consumables to be used during the welding of dissimilar aluminum alloy joints. The model is based on the triangular intuitionistic fuzzy hamming distance (TIFHD) method and an induced triangular intuitionistic fuzzy ordered weighted geometric (I-TIFOWG) operator [12]. It uses a value-index ranking method to rank filler alloy alternatives and to determine the degree of flexibility in the decision-making process. This model has the following advantages: (1) the ability to capture fuzziness and hesitation in the decision-making process, (2) the ability to account for the degree of flexibility in the decision-making process, and, (3) it helps in reducing uncertainty in the evaluation process using triangular intuitionistic fuzzy number(s) (TIFNs). This is considered a more holistic and better tool for representing vague or imprecise information [13].

During the selection process, mechanical properties and micro-structural characteristics of welding consumables were considered. In analyzing fillers, four filler alloys (alternatives) and five criteria were considered. The results that were obtained showed that when the flexibility function is $\beta = 0.7$,the ranked order was $ER_1 > ER_4 > ER_3 > ER_2$, indicating that filler alloy ER_1 was the best choice. When $\beta = 0.2$, the ranked order was $ER_4 > ER_1 > ER_3 > ER_2$, ER_4 was the best filler alloy. The results from the proposed model were compared with a modified TOPSIS model[21] and an intuitionistic fuzzy method [19]. The proposed model's performance is consistent with the performance of the models in [19] and [21]. Thus, these results show the advantage of flexibility. The model allows experts to choose different coefficients according to their subjective preferences. In the future, the model will be applied in other domains.

6. References

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