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Aggregating and Ranking Method for the Evaluation of Product Design Materials

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ABSTRACT

A new MCDM model based on a triangular intuitionistic fuzzy (TIF) aggregating and ranking model is proposed for the evaluation of adhesive materials used in joining fibre-reinforced plastic. The new model which uses the triangular intuitionistic fuzzy numbers (TIFN), TIF aggregating operators and the TIF ranking functions provides a more accurate method for assessing uncertain or imprecise information in the decision-making process. The model addresses the MCDM problem in which the available information cannot be assessed with exact numbers and requires the use of a more holistic approach which is a drawback in the existing MCDM methods used in the evaluation of design materials in literature. The result from the evaluation shows that the alternative T3 (Polyurethane) has the best chances of been used in joining the FRP with respect to the fracture mechanics-based criteria. With the ranking result presented, the study can conclude that the procedure used for the evaluation of the adhesive material has led to the selection of the best adhesive material for joining the FRP elements.

KEYWORDS

Adhesive materials, Fibre Reinforced Plastic (FRP), MCDM model, TIFN ranking functions, Triangular intuitionistic fuzzy (TIF) aggregating operators, Triangular Intuitionistic Fuzzy Number (TIFN)

INTRODUCTION

In the development of new products, from the design concept stage through to the development of the detailed design all involve a progressive assessment and culling of a large number of material choices (Mouritz, 2012). The process of material selection during these stages is not always the same for all products. For product and structures whose performances are not solely based on physical scientific parameters, but on aesthetic, tactile, sensual and cultural factors, such products like clothes, building interiors, pens, mug etc. which are mainly designed by members of the arts community, don't follow the typical engineering process of material selection (Laughlin & Howes, 2014).

However, the process of selecting materials for the design of mechanical components and systems involves a three main process stage which starts with; material translation which deals with the examination of the functions and objectives of material for the design, material screening, which is about the elimination of materials whose properties do not meet the design constraints and finally material ranking, which involves the actual selection of the materials that surpass the design constraint limits.

Materials selection which pays a significant role in the engineering design process is one of the most critical tasks for product designers. Designers are expected to identify material(s) with specific functionalities and properties for their design concepts (Chatterjee & Chakraborty, 2012). There are several engineering materials with diverse properties available to the designers, to satisfy

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and meet specific design constraint limits. With a large number of materials available and their diverse properties as well as the interrelationship, interconnectivity, and interaction between the selections criteria, the material selection process can be regarded as a complex, challenging and a time-consuming process. It is referred to as multi-criteria decision making (MCDM) problem since multiple criteria are considered when trying to deal with or meet with the design constraints. Design constraints which are required conditions in engineering design, need to be dealt with for the design project to be successful, also they help in forcing the designers to evaluate and narrow their material choice to the best material alternative.

Although, there are several articles that have employed MCDM methods for the selection of design material in literature. Some of which includes; Gul et al. (2017), who presents a fuzzy logic based PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) method for the selection of materials used in the design of automotive instrument panel. Girubha & Vinodh, (2012), employed the VIKOR method as MCDM tool to determine the most appropriate material for the instrument used in the design of electric panels. Chatterjee & Chakraborty, (2012) present a four-preference ranking based MCDM methods for resolving material selection problem. Rahman, et al., (2012) proposed a knowledge-based decision support system for selecting material for the design of a building roof. The decision support system utilized a TOPSIS-based method to facilitate the selection process. Liu, et al., (2013) developed a methodology that employs MCDM method with interval 2-tuple linguistic information which uses subjective and objective weights in solving material selection problem in a two-case study in the automotive industry.

Anajkumar, et al., (2014) uses four (4) different MCDM methods (i.e. the fuzzy analytic hierarchy process (FAHP) and technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), FAHP and VIKOR method, FAHP and ELECTRE method and finally, FAHP and PROMTHEE method) for the selection of materials used in pipes design in the sugar industry, by taking into account different alternatives and evaluation criteria. Liu, et al., (2014) integrated decision-making trial and evaluation laboratory (DEMATEL) based analytic network process (ANP) and VIKOR method for resolving bush material selection problem which consists of many interdependent criteria.

Others include Liao, (2015) who presents an interval type 2 fuzzy multi-attribute decision making for material selection. The method is illustrated in an engineering application of material selection in a jet fuel system. Govindan, et al., (2016) constructed a model to select the most appropriate construction material by utilizing DEMATEL, ANP and TOPSIS. Zhao, et al., (2016) present an integrated grey relational analysis (GRA) with an analytic hierarchy process (AHP) for the selection of commercially available materials in the context of a sustainable design. Kumar et al. (2014) used an entropy-based TOPSIS method for the evaluation of optimum material used in exhaust manifold design, where cost is taken as the main criterion and. Caliskan et al. (2013), who apply different MCDM methods for the selection of materials used in tool holding working under a hard-milling condition.

In all, these existing techniques, all fail to deal with the MCDM problem where the available material selection information cannot be assessed with exact numbers and requires the use of a more holistic approach like the Triangular Intuitionistic Fuzzy Number (TIFN) to assess the uncertainty or imprecise information in the decision-making process. TIFN is a generalized and holistic platform for communicating imprecise and incompleteness in the information used in the decision-making process otherwise called uncertainty (Aikhuele & Odofin, 2017; Wan, Lin, & Dong, 2016). The TIFN has the advantage of being more accurate in representing and accounting for uncertainty than the traditional Intuitionistic Fuzzy Number (IFN) (Aikhuele, 2018a; M. J. Zhang & Nan, 2013).

To this end, this paper attempts to bridge the gap by defining and presenting a new MCDM model which is based on a triangular intuitionistic fuzzy aggregating and ranking model. The new model consists of data that are presented in TIFN, triangular intuitionistic fuzzy (TIF) aggregating operators, which are used for aggregating the decision-making information and the preference judgments of the experts associated with the material selection process and. Finally, a TIFN ranking functions for ranking the design materials. In applying the TIF aggregating operators, the study has been able to account for and deal with the MCDM issues resulting from unbalanced expertise in the decision-making process is still a drawback in most of the existing decision models.

To do this, first, the concept of the TIFN, the ranking functions as well as some Triangular Intuitionistic Fuzzy aggregating operators are introduced in Section two (2). This is followed by the algorithm of the proposed triangular intuitionistic fuzzy aggregating and ranking method in Section three (3). The new proposed model is then applied for the selection of design materials which is presented in Section 4. Finally, some concluding remarks are presented in the last Section.

TIFN CONCEPT, RANKING FUNCTIONS, AND THE TIF AGGREGATING OPERATORS.

The TIFN is an extension of the IFN originally proposed by Atanassov, (1986), and IFN was extended from the traditional fuzzy set introduced by Zadeh (1965). TIFN which can be denoted as $\acute{\delta} = \left(\left[l, m, n\right]; \mu_{\delta}, v_{\delta}\right)$ for convenience (Aikhuele, 2018b; Li, 2010), has the characteristic membership $\mu_{\delta}\left(x\right)$ and non-membership functions $v_{\delta}\left(x\right)$ which are given as;

$$\mu_{\delta}\left(x\right) = \begin{cases} \dfrac{\left(x-l\right)\mu_{\delta}}{\left(m-l\right)} & \left(\&l \leq x < m\right) \\ \mu_{\alpha} & \left(x = m\right) \\ \dfrac{\left(n-x\right)\mu_{\delta}}{n-m} & \left(m < x \leq n\right) \\ 0 & \text{otherwise} \end{cases} \quad \text{and} \tag{1}$$

$$v_{\delta}\left(x\right) = \begin{cases} \dfrac{\left(m-x+v_{\delta}\left(x-l'\right)\right)}{\left(m-l\right)} & \left(\&l' \leq x < m\right) \\ v_{\alpha} & \left(x = m\right) \\ \dfrac{\left(x-m+v_{\delta}\left(n'-x\right)\right)}{n'-m} & \left(m < x \leq n'\right) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where $0 \leq \mu_{\delta} \leq 1; 0 \leq v_{\delta} \leq 1; 0 \leq \mu_{\delta} + v_{\delta} \leq 1, l, m, n, \acute{l}, \acute{n} \in \mathbb{R}$.

In the application of the TIFN, several operational rules (i.e. Equation 3-5), crisp conversion functions (i.e. Equation 6-10) and aggregation methods (i.e. Equation 11-12) have been proposed. However, for convenience, the study will focus on the most relevant ones required for the development and formation of the new MCDM model. Some of the operational rules otherwise called TIFN properties, conversion functions and aggregation methods are given in the definitions below.

Definition 1 (Liang, Zhao, & Zhang, 2014; Zhang & Liu, 2010)

If the following $\tilde{\delta}_1 = \left(\left[l_1, m_1, n_1\right]; \mu_{\delta_1}, v_{\delta_1}\right)$ and $\tilde{\delta}_2 = \left(\left[l_2, m_2, n_2\right]; \mu_{\delta_2}, v_{\delta_2}\right)$ are two TIFN, then we have;

$$\left.\begin{aligned} \tilde{\delta}_1 + \tilde{\delta}_2 &= \left(\left[l_1 + l_2, m_1 + m_2, n_1 + n_2\right]; \mu_{\delta_1} + \mu_{\delta_2} - \mu_{\alpha_1}\mu_{\delta_2}, v_{\delta_1} v_{\delta_2}\right) \\ \tilde{\delta}_1 \tilde{\delta}_2 &= \left(\left[l_1 l_2, m_1 m_2, n_1 n_2\right]; \mu_{\alpha_1}\mu_{\delta_2}, v_{\delta_1} + v_{\delta_2} - v_{\delta_1} v_{\delta_2}\right) \end{aligned}\right\} \tag{3}$$

If » ≤ 0 , then;

$$\left.\begin{aligned} \lambda \tilde{\delta} &= \left(\left[\lambda l, \lambda m, \lambda n\right]; 1 - (1 - \mu_\delta)^\lambda, \left(v_\delta\right)\right) \ \ and \\ \tilde{\delta}^\lambda &= \left(\left[l^\lambda, m^\lambda, n^\lambda\right]; (\mu_\delta)^\lambda, 1 - (1 - v_\delta)^\lambda\right) \end{aligned}\right\} \tag{4}$$

The results of the operational rules above are summarized in the TIFN theorem.

$$\left.\begin{aligned} \tilde{\delta}_1 + \tilde{\delta}_2 &= \tilde{\delta}_2 + \tilde{\delta}_1 \\ \tilde{\delta}_1 \otimes \tilde{\delta}_2 &= \tilde{\delta}_2 \otimes \tilde{\delta}_1 \\ \lambda(\tilde{\delta}_1 + \tilde{\delta}_2) &= \lambda \tilde{\delta}_1 + \text{»} \tilde{\delta}_2, \lambda \geq 0 \\ \lambda_1 \tilde{\delta} + \lambda_2 \tilde{\delta} &= (\lambda_1 + \lambda_2) \tilde{\delta} \ \lambda_1 \ \lambda_2 \geq 0 \\ \tilde{\delta}^{\lambda_1} \otimes \tilde{\delta}^{\lambda_2} &= \tilde{\delta}^{\lambda_1 + \lambda_2} \ \ \lambda_1 \ \lambda_2 \geq 0 \\ \tilde{\delta}_1^{\lambda} \otimes \tilde{\delta}_2^{\lambda} &= \left(\tilde{\delta}_1 \otimes \tilde{\delta}_2\right)^\lambda \ \lambda \geq 0 \end{aligned}\right\} \tag{5}$$

In formulating the ranking function, the score and accuracy function original proposed by Li, (2010) for converting TIFN to a crisp is integrated into the MCDM model for ranking of the design materials. The score and accuracy functions are defined as follows;

Definition 2 (Li, 2010)

If the TIFN is denoted as $\tilde{\delta} = \left(\left[l, m, n\right]; \mu_\delta, v_\delta\right)$, and the characteristic membership and non-membership functions in the TIFN are present in the score function $CSF\left(\tilde{\delta}\right)$ and accuracy function $CAF\left(\tilde{\delta}\right)$ respectively, then the functions are defined as follows;

$$CSF\left(\acute{\delta}\right) = \frac{\left(l + 2m + n\right)\mu_{\delta}}{4} \tag{6}$$

$$CAF\left(\acute{\delta}\right) = \frac{\left(l + 2m + n\right)(1 - v_{\delta})}{4} \tag{7}$$

The results of the score function $CSF\left(\acute{\delta}\right)$ and accuracy function $CAF\left(\acute{\delta}\right)$ above are summarized in the TIFN ranking theorem.

$$\left.\begin{array}{r} \text{If } CSF\left(\acute{\delta}_1\right) < CSF\left(\acute{\delta}_2\right) \text{ then } \acute{\delta}_1 < \acute{\delta}_2 \\ \text{If } CSF\left(\acute{\delta}_1\right) = CSF\left(\acute{\delta}_2\right) \text{ and } CAF\left(\acute{\delta}_1\right) = CAF\left(\acute{\delta}_2\right), \text{ then } \acute{\delta}_1 = \acute{\delta}_2 \\ \text{If } CSF\left(\acute{\delta}_1\right) = CSF\left(\acute{\delta}_2\right) \text{ and } CAF\left(\acute{\delta}_1\right) < CAF\left(\acute{\delta}_2\right), \text{ then } \acute{\delta}_1 < \acute{\delta}_2 \end{array}\right\} \tag{8}$$

In aggregating data represented in TIFN, the following Triangular Intuitionistic fuzzy aggregating operators have been defined and presented for the formation of the MCDM model.

Definition 4 (Liang et al., 2014)

If a collection of TIFNs are denoted as $\acute{\delta}_i = \left(\left[l_i, m_i, n_i\right]; \mu_{\acute{\delta}_i}, v_{\acute{\delta}_i}\right)$, where $i = 1, 2, 3, \ldots, n$. Then the triangular intuitionistic fuzzy ordered weighted geometric (TIFOWG) operator of dimension *n* is a mapping of TIFOWG: $©^n \rightarrow ©$, which has a weighting vector $\omega = \left(\omega_1, \omega_2, \omega_3, \ldots, \omega_n\right)^v$, such that $\omega_i \in \left[0, 1\right]$, and $\sum_{i=1}^{n} \omega_i = 1$. Hence, the TIFOWG operator is given as;

$$\text{TIFOW}G_{\omega}\left(\delta_1, \delta_2, \delta_3, \ldots, \delta_n\right) = \omega_1\left(\delta_1\right) \otimes \omega_2\left(\delta_2\right) \otimes \omega_3\left(\delta_3\right) \ldots \otimes \omega_n\left(\delta_n\right)$$

$$= \left(\left[\prod_{i=1}^{n}(l_i)^{\omega_i}, \prod_{i=1}^{n}(m_i)^{\omega_i}, \prod_{i=1}^{n}(n_i)^{\omega_i}\right]; \prod_{i=1}^{n}\left(\mu_{\acute{\delta}_i}\right)^{\omega_i}, 1 - \prod_{i=1}^{n}\left(1 - v_{\acute{\delta}_i}\right)^{\omega_i}\right) \tag{11}$$

where l_i is the *i*th largest of the of the TIFN $\left(\delta_i\right)$. When, $\omega = \left(\frac{1}{n}, \frac{1}{n}, ,,,1/n\right)^v$, the TIFOWG operator is reduced into the Intuitionistic Fuzzy Order Weighted Geometric (IFOWG) operator.

The TIFOWG operator, which is able to weights the intuitionistic fuzzy values, however, are not effective when weighing the induced ordering positions of the intuitionistic fuzzy values. In handling this issue and limitation the induced triangular intuitionistic fuzzy ordered weighted geometric (I-TIFOWG) operator is introduced as shown in the definition below;

Definition 5 (Aikhuele & Odofin, 2017)

If a collection of TIFNs are denoted as $\acute{\delta}_i = \left(\left[l_i, m_i, n_i\right]; \mu_{\acute{\delta}_i}, v_{\acute{\delta}_i}\right)$, where $i = 1,2,3,\ldots,n$. Then the dimension *n* of an *I*-TIFOWG operator which have the advantage of weighting and inducing the ordering positions of the intuitionistic fuzzy values is given as a mapping of I-TIFOWG: $©^n \rightarrow ©$. The I-TIFOWG operator has a weighting vector of $w = (w_1, w_2, w_3, \ldots, w_n)^v$, such that $w_i \in \left[0,1\right]$, and $\sum_{i=1}^{n} w_i = 1$. And a weighting vector $\omega = \left(\omega_1, \omega_2, \omega_3, \ldots, \omega_n\right)^v$ that is associated with the I-TIFOWG operator such that $\omega_i \in \left[0,1\right]$, $\sum_{i=1}^{n} \omega_i = 1$. Hence, the I-TIFOWG operator is given as;

$$I - \text{TIFOW}G_{\omega,W}\left(x_1, \delta_1, x_2, \delta_2, x_3, \delta_3, \ldots, x_n, \delta_n\right) = \omega_1\left(\delta_1\right) \otimes \omega_2\left(\delta_2\right) \otimes \omega_3\left(\delta_3\right) \ldots \otimes \omega_n\left(\delta_n\right)$$

$$= \left(\left[\prod_{i=1}^{n}(l_i)^{\omega_i}, \prod_{i=1}^{n}(m_i)^{\omega_i}, \prod_{i=1}^{n}(n_i)^{\omega_i}\right]; \prod_{i=1}^{n}\left(\mu_{\delta_i}\right)^{\omega_i}, 1 - \prod_{i=1}^{n}\left(1 - v_{\delta_i}\right)^{\omega_i}\right) \tag{11}$$

where the TIFOWG pair x_i, δ_i is the order inducing variable and δ_i is the triangular intuitionistic fuzzy argument variable.

THE ALGORITHM OF THE PROPOSED MCDM MODEL

In formulating the MCDM model, the following main parameters are taken into consideration, that is; the TIFN concept, the ranking functions, and the TIF aggregating operators.

Let a typical MCDM problem be given by the set of alternatives in the form $T = \left\{T_1, T_2, T_3, \ldots, T_m\right\}$. If they are evaluated based on some multiple criteria which can be represented as $MC = \left\{MC_1, MC_2, MC_3, \ldots, MC_m\right\}$. Then the best alternative(s) can be determined when the weight of the criteria are known, and with special consideration of the uncertainty in the decision-making process. The proposed algorithm of the model which is aimed at addressing the MCDM problem where the available information cannot be assessed with exact numbers and requires the use of a more holistic approach to assess uncertain or imprecise information in the selection process is given in the following steps;

1: Invite a group of experts otherwise called the board of decision-makers (E_i), to give their preference judgment and rating on the set of alternatives $T = \left\{T_1, T_2, T_3, \ldots, T_m\right\}$ $\left(i = 1,2,\ldots,m\right)$, with respect to a set of multiple criteria $MC = \left\{MC_1, MC_2, MC_3, \ldots, MC_m\right\}$ $\left(j = 1,2,\ldots,n\right)$. The preference judgment of each of the DM are given in the intuitionistic fuzzy decision matrix $Z = (S_{ij})_{mxn}$ below. The preference judgment and rating are given using the TIF linguistic scale in Table 1.

$$Z = \begin{bmatrix} \left(\left[l_{11}, m_{11}, n_{11}\right]; \mu_{11}, v_{11}\right) & \cdots & \cdots & \left(\left[l_{1n}, m_{1n}, n_{1n}\right]; \mu_{1n}, v_{1n}\right) \\ \left(\left[l_{21}, m_{21}, n_{21}\right]; \mu_{21}, v_{21}\right) & \cdots & \cdots & \left(\left[l_{2n}, m_{2n}, n_{2n}\right]; \mu_{2n}, v_{2n}\right) \\ \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \ddots & \cdots \\ \left(\left[l_{m1}, m_{m1}, n_{m1}\right]; \mu_{m1}, v_{m1}\right) & \cdots & \cdots & \left(\left[l_{mn}, m_{mn}, n_{mn}\right]; \mu_{mn}, v_{mn}\right) \end{bmatrix}$$

2: The decision information given by the different board of Decision-makers in the intuitionistic fuzzy decision matrix $Z = (S_{ij})_{mxn}$ are aggregated using the I-TIFOWG operator, to obtain the overall preference values, which is referred here as the preference value and information (P_i) $\left(i = 1, 2, 3, \ldots, K\right)$ of different alternatives T_i.

$$P_i = \left(\left[l^{cp}{}_i, m^{cp}{}_i, n^{cp}{}_i\right]; \mu_{\delta^{cp}{}_i}, v_{\delta^{cp}{}_i}\right) = I - TIFOWG_w\left(x_1, \alpha_1, x_2, \alpha_2, \ldots, x_n, \alpha_n\right)$$
$$= \left(\left[\prod_{i=1}^{n} (l^{cp}{}_i)^{w_i}, \prod_{i=1}^{n} (m^{cp}{}_i)^{w_i}, \prod_{i=1}^{n} (l^{cp}{}_i)^{w_i}\right]; \prod_{i=1}^{n} \left(\mu_{\delta^{cp}{}_i}\right)^{w_i}, 1 - \prod_{i=1}^{n} \left(1 - v_{\delta^{cp}{}_i}\right)^{w_i}\right)$$

where $w = \left(w_1, w_2, w_3, \ldots, w_n\right)^v$ is the weighting vector of the invited board of decision-makers (E_i).

3: Used the TIFOWG operator to integrate the preference value and information of the different alternatives T_i. into a comprehensive preference value and information (CP_i) for the different alternatives T_i.

$$\text{TIFOW}G_\omega\left(\delta_1, \delta_2, \delta_3, \ldots, \delta_n\right) = \omega_1\left(\delta_1\right) \otimes \omega_2\left(\delta_2\right) \otimes \omega_3\left(\delta_3\right) \ldots \otimes \omega_n\left(\delta_n\right)$$
$$= \left(\left[\prod_{i=1}^{n} (l_i)^{\omega_i}, \prod_{i=1}^{n} (m_i)^{\omega_i}, \prod_{i=1}^{n} (n_i)^{\omega_i}\right]; \prod_{i=1}^{n} \left(\mu_{\delta_i}\right)^{\omega_i}, 1 - \prod_{i=1}^{n} \left(1 - v_{\delta_i}\right)^{\omega_i}\right)$$

where $\omega = (\omega_1, \omega_2, \omega_3, \ldots, \omega_n)^v$ is the weighting vector of the multiple criteria, which is obtained by asking the invited board of decision-makers (E_i) to rate the importance of the multiple criteria to the evaluation of the alternatives T_i.

Table 1. TIF linguistic scale

Linguistic terms	Fuzzy Numbers
Very low (SL)	([0.1, 0.25, 0.3]; 06,0.4)
Low (LW)	([0.2, 0.3, 0.55];06;0.5)
Good (GD)	([0.3, 0.45, 0.6];0.6,0.6)
High (HH)	([0.5, 0.6, 0.7];0.6,0.8)
Excellent (EX)	([0.6, 0.75, 0.9];0.6,0.8)

4: Compute the scores function $CSF\left(cp_i\right)\left(i = 1,2,\ldots,n\right)$ and accuracy function $CAF\left(cp_i\right)\left(i = 1,2,\ldots,n\right)$ for the membership and non-membership functions of the TIFN.

$$CSF\left(\acute{\delta}\right) = \frac{\left(l + 2m + n\right) * \mu_{\delta})}{4}$$

$$CAF\left(\acute{\delta}\right) = \frac{\left(l + 2m + n\right)(1 - v_{\delta})}{4}$$

4: Rank the alternatives using the value from $CSF\left(\acute{\delta}\right)$ and $CAF\left(\acute{\delta}\right)$ based on Equation 8.

5: End.

DESIGN MATERIAL SELECTION EXAMPLE AND ITS ANALYSIS

Due to the attractive physical and mechanical properties of Fibre Reinforced Plastic (FRP), particularly its high strength, stiffness and its lightweight characteristic (Mohammed et al., 2015). The next generation of the Boeing 787 Dreamliner is expected to have 50% of its structural element made of FRP; basically to reduce the weight of the aircraft and minimize its fuel consumption and corresponding engine emissions (Milberg, 2015; Nicolais et al., 2011).

Adhesives bonds which are used extensively in the joining of FRP elements are considered a strong potential to replace the bolted joints found in commercial aircraft. With adhesive bonds in commercial aircraft, it is estimated that about 50% of the joint weight in the structure is bound to reduce (Halliwell, 2012). There are several families of adhesive materials (See Table 2) available for this purpose. In this Section, the propose MCDM model is applied for the selection of the best adhesive material(s) for joining the FRP elements with respect to the following fracture mechanics-based criteria (fracture toughness C_1, crack-resistance C_2, yield strength C_3, and fatigue threshold C_4).

In implementing the model, a three-man board panel was set up, which includes; Two Adhesive bond experts (E_1 and E_2) and a Mechanical Engineering Professor (E_3). The board members who were assigned the following weight vectors 0.2, 0.3 and 0.35, respectively, based on their years of experience were asked to give their preference judgment and assessment, for the adhesive materials with respect to the fracture mechanics-based criteria using the TIF linguistic scale (intuitionistic fuzzy decision matrix $Z = \left(\left(S_{ij}\right)_{mxn}\right)$.

This is followed by asking them to rate also the fracture mechanics-based criteria, using the same TIF linguistic scale to determine the level of importance of the different criteria in the assessment of the adhesive materials. Their preference judgments and assessment, as well as the rating of the criteria, are presented in Table 3.

By following the algorithm of the model in Section 3 above, the preference values and information P_i of different alternatives T_i given by the different board members (intuitionistic fuzzy decision matrix $Z = (S_{ij})_{mxn}$) are aggregated using the I-TIFOWG operator. This is followed by the aggregation of the preference rating of the multiple fracture mechanics-based criteria. The results of the aggregations are given in Table 4.

Furthermore, the preference values and information for the different alternatives are integrated into the comprehensive preference values CP_i using the TIFOWG operator. The result of the integration is shown in Table 5. This is followed by the computation of the scores function

Table 2. List of adhesive materials

Adhesive Materials	Code
Rubber adhesive	T_1
Acrylic	T_2
Polyurethane	T_3
Anaerobic	T_4
Solvent-based adhesive	T_5
Hot-melt adhesive	T_6
Amino or urea-based adhesive	T_7
Phenolics and resorcinolic adhesive	T_8
Epoxy	T_9
Polyimides and bismaleimides adhesive	T_{10}
PVA adhesive and related emulsion systems	T_{11}
Plastisols and elastosols adhesive	T_{12}
Cyanoacrylate	T_{13}
Silicone	T_{14}

Table 3. Ratings of the of the adhesive materials (intuitionistic fuzzy decision matrix)

C_i	E_1	E_2	E_3	E_1	E_2	E_3	E_1	E_2	E_3	E_1	E_2	E_3
	MC_1			MC_2			MC_3			MC_4		
T_1	LW	GD	SL	HH	LW	HH	SL	HH	GD	GD	LW	SL
T_2	HH	HH	SL	EX	GD	EX	LW	EX	HH	SL	GD	LW
T_3	EX	EX	LW	SL	HH	HH	GD	HH	EX	LW	HH	GD
T_4	HH	HH	GD	LW	GD	GD	LW	LW	SL	GD	LW	SL
T_5	HH	GD	LW	GD	HH	GD	HH	GD	LW	LW	GD	LW
T_6	SL	GD	HH	H	EX	HH	EX	LW	SL	GD	HH	GD
T_7	LW	HH	SL	EX	HH	HH	LW	GD	LW	HH	GD	HH
T_8	HH	EX	LW	SL	EX	EX	GD	HH	GD	GD	HH	LW
T_9	SL	HH	HH	SL	HH	HH	SL	GD	SL	GD	SL	GD
T_{10}	LW	SL	EX	LW	EX	EX	LW	LW	LW	HH	LW	HH
T_{11}	GD	LW	HH	SL	HH	HH	GD	GD	GD	EX	GD	HH
T_{12}	SL	HH	GD	HH	HH	GD	SL	HH	HH	LW	EX	GD
T_{13}	LW	SL	EX	SL	SL	SL	SL	SL	HH	GD	HH	HH
T_{14}	HH	LW	HH	GD	LW	GD	GD	LW	HH	LW	EX	GD
Criteria Rating	MC_1			MC_2			MC_3			MC_4		
	E_1	E_2	E_3	E_1	E_2	E_3	E_1	E_2	E_3	E_1	E_2	E_3
	HH	EX	LW	SL	EX	EX	GD	HH	GD	GD	HH	LW

Table 4. The preference values and information for alternatives and the criteria weight vector

	MC_1	MC_2	MC_3	MC_4
T_1	([0.23, 0.38, 0.50]; 0.65, 0.45)	([0.42, 0.53, 0.69]; 0.65, 0.66)	([0.34, 0.49, 0.59]; 0.65, 0.60)	([0.22, 0.37, 0.50]; 0.65, 0.43)
T_2	([0.32, 0.48, 0.55]; 0.65, 0.63)	([0.53, 0.67, 0.81]; 0.65, 0.69)	([0.49, 0.60, 0.76]; 0.65, 0.69)	([0.25, 0.39, 0.55]; 0.65, 0.46)
T_3	([0.44, 0.57, 0.77, 0.65, 0.65)	([0.40, 0.54, 0.62]; 0.65, 0.68)	([0.53, 0.66, 0.78]; 0.65, 0.71)	([0.39, 0.51, 0.67]; 0.65, 0.61)
T_4	([0.46, 0.59, 0.70]; 0.65, 0.68)	([0.33, 0.47, 0.64]; 0.65, 0.52)	([0.20, 0.34, 0.49]; 0.65, 0.41)	([0.22, 0.37, 0.50]; 0.65, 0.43)
T_5	([0.35, 0.47, 0.65]; 0.65, 0.57)	([0.42, 0.55, 0.68]; 0.65, 0.63)	([0.35, 0.47, 0.65]; 0.65, 0.57)	([0.29, 0.41, 0.62]; 0.65, 0.48)
T_6	([0.34, 0.50, 0.60]; 0.65, 0.61)	([0.59, 0.69, 0.80]; 0.65, 0.75)	([0.25, 0.40, 0.54]; 0.65, 0.51)	([0.42, 0.55, 0.68]; 0.65, 0.63)
T_7	([0.26, 0.42, 0.52]; 0.65, 0.55)	([0.58, 0.68, 0.78]; 0.65, 0.75)	([0.29, 0.41, 0.62]; 0.65, 0.48)	([0.48, 0.59, 0.71]; 0.65, 0.69)
T_8	([0.43, 0.54, 0.73]; 0.65, 0.65)	([0.45, 0.63, 0.73]; 0.65, 0.68)	([0.42, 0.55, 0.68]; 0.65, 0.63)	([0.36, 0.48, 0.66]; 0.65, 0.60)
T_9	([0.40, 0.54, 0.62]; 0.65, 0.65)	([0.40, 0.54, 0.62]; 0.65, 0.68)	([0.20, 0.37, 0.44]; 0.65, 0.43)	([0.26, 0.43, 0.53}; 0.65, 0.48)
T_{10}	([0.30, 0.47, 0.60]; 0.65, 0.57)	([0.52, 0.65, 0.83]; 0.65, 0.69)	([0.25, 0.36, 0.60]; 0.65, 0.45)	([0.42, 0.53, 0.69]; 0.65, 0.66)
T_{11}	([0.38, 0.50, 0.67]; 0.65, 0.61)	([0.43, 0.59, 0.68]; 0.65, 0.68)	(]0.36, 0.51, 0.65]; 0.65, 0.54)	([0.49, 0.62, 0.74]; 0.65, 0.69)
T_{12}	([0.34, 0.49, 0.59]; 0.65, 0.60)	([0.46, 0.59, 0.70]; 0.65, 0.68)	([0.40, 0.54, 0.62]; 0.65, 0.68)	([0.41, 0.55, 0.72]; 0.65, 0.61)
T_{13}	([0.30, 0.47, 0.60]; 0.65, 0.57)	([0.14, 0.31, 0.36]; 0.65, 0.35)	([0.25, 0.42, 0.48]; 0.65, 0.56)	([0.50, 0.61, 0.72]; 0.65, 0.71)
T_{14}	([0.42, 0.53, 0.69]; 0.65, 0.66)	([0.32, 0.45, 0.63]; 0.65, 0.51)	([0.38, 0.50, 0.67]; 0.65, 0.61)	([0.41, 0.55, 0.72]; 0.65, 0.61)
	Weighting Vector for MC_1	Weighting Vector for MC_2	Weighting Vector for MC_3	Weighting Vector for MC_4
	([0.43, 0.54, 0.73]; 0.65, 0.65)	([0.45, 0.63, 0.73]; 0.65, 0.68)	([0.42, 0.55, 0.68]; 0.65, 0.63)	([0.36, 0.48, 0.66]; 0.65, 0.60)

$CSF\left(cp_i\right)\left(i = 1,2,\ldots,n\right)$ and accuracy function $CAF\left(cp_i\right)\left(i = 1,2,\ldots,n\right)$ for the membership and non-membership functions in the comprehensive preference values $\left(CP_i\right)$. Finally, the results are ranked based on Equation 8 as shown in Table 5.

With the ranking result presented in Table 5, the study can conclude that the procedure used for the evaluation of the adhesive material has led to the selection of the best adhesive material for joining the FRP elements to be used for the replacement of the bolted joints in commercial aircraft. Also, it has revealed the suitability of using the proposed model for ranking alternatives with respect to conflicting criteria like the ones used in this study.

Finally, to prove the rationality and feasibility of the MCDM model which is based on a triangular intuitionistic fuzzy aggregating and ranking model, the result presented in Table 5 are compared with similar computational model in literature including the traditional fuzzy TOPSIS model and

Table 5. Ranking result for the adhesive materials

T_i	CP_i	CSF	CAF	Ranking
T_1	([0.130, 0.165, 0.201]; 0.323, 0.870)	0.041	0.002	12
T_2	([0.205, 0.252, 0.308]; 0.323, 0.922)	0.050	0.002	5
T_3	([0.255, 0.289, 0.379]; 0.323, 0.939)	0.055	0.002	1
T_4	([0.128, 0.157, 0.214]; 0.323, 0.851)	0.041	0.002	13
T_5	([0.175, 0.194, 0.297]; 0.323, 0.882)	0.046	0.003	10
T_6	([0.203, 0.249, 0.294]; 0.323, 0.924)	0.050	0.002	6
T_7	([0.199, 0.231, 0.296]; 0.323, 0.923)	0.049	0.002	8
T_8	([0.234, 0.272, 0.370]; 0.323, 0.928)	0.053	0.002	2
T_9	([0.139, 0.187, 0.189]; 0.323, 0.890)	0.042	0.002	11
T_{10}	([0.184, 0.212, 0.330]; 0.323, 0.908)	0.048	0.002	9
T_{11}	([0.227, 0.269, 0.343]; 0.323, 0.925)	0.052	0.002	3
T_{12}	([0.219, 0.260, 0.306]; 0.323, 0.929)	0.051	0.002	4
T_{13}	([0.108, 0.155, 0.159]; 0.323, 0.878)	0.039	0.002	14
T_{14}	([0.199, 0.217, 0.331]; 0.323, 0.906)	0.049	0.002	7

the distance to the ideal alternative (DiA) algorithm (Tran & Boukhatem, 2008) under the same condition. The comparison result which focuses on the ranking of the adhesive material shows total agreement with the proposed method. The results are shown in Table 6.

CONCLUSION

In this paper, a new MCDM model which is based on a triangular intuitionistic fuzzy aggregating and ranking model is proposed for the evaluation of adhesive material used in joining FRP. The new model which consists of data that are presented in TIFN, triangular intuitionistic fuzzy (TIF) aggregating operators and a TIFN ranking functions provides a more accurate method for assessing uncertain or imprecise information in the decision-making process. The model addresses the MCDM problem in which the available information cannot be assessed with exact numbers and requires the use of a more holistic approach which is a drawback in the existing MCDM methods used in the evaluation of design materials in literature. In applying the TIF aggregating operators, the study has also been able to account for and deal with the MCDM issues resulting from unbalanced expertise in the decision-making process, as the aggregation operators are able to aggregate the different information from the experts irrespective of their expertise using numerical figures assigned to them according to their years of experience and expertise.

To prove the rationality and feasibility of the new MCDM model, the result from the study have been compared with a similar computational model in literature including the traditional fuzzy TOPSIS model and the distance to the ideal alternative (DiA) algorithm (Tran & Boukhatem, 2008) under the same condition. Hence, the study can conclude that the procedure used for the evaluation of the adhesive material has led to the selection of the best adhesive material for joining the FRP elements. Also, it has revealed the suitability of using the proposed model for ranking alternatives with respect to conflicting criteria like the ones used in this study.

Table 6. Comparison of the proposed model with similar computational models

Alternatives	The Proposed Model		Rank	(Tran & Boukhatem, 2008)	Rank	Traditional Fuzzy TOPSIS	Ranking
	CSF	CAF					
T_1	0.041	0.002	12	0.376	12	0.404	12
T_2	0.050	0.002	5	0.093	3	0.503	3
T_3	0.055	0.002	1	0.000	1	0.534	1
T_4	0.041	0.002	13	0.384	13	0.403	13
T_5	0.046	0.003	10	0.249	10	0.448	10
T_6	0.050	0.002	6	0.094	4	0.502	4
T_7	0.049	0.002	8	0.135	7	0.489	7
T_8	0.053	0.002	2	0.036	2	0.522	2
T_9	0.042	0.002	11	0.351	11	0.413	11
T_{10}	0.048	0.002	9	0.186	9	0.471	9
T_{11}	0.052	0.002	3	0.110	5	0.496	5
T_{12}	0.051	0.002	4	0.127	6	0.490	6
T_{13}	0.039	0.002	14	0.391	14	0.401	14
T_{14}	0.049	0.002	7	0.180	8	0.472	8

REFERENCES

Aikhuele, D. O. (2018a). Intuitionistic Fuzzy Model for Reliability Management in Wind Turbine System. *Applied Computing and Informatics*.

Aikhuele, D. O. (2018b). Reliability evaluation using MAGDM based on triangular intuitionistic attitudinal ranking and aggregating model. *Journal of Modern Technology & Engineering*, *3*(2), 165–178.

Aikhuele, D. O., & Odofin, S. (2017). A Generalized Triangular Intuitionistic Fuzzy Geometric Averaging Operator for Decision-Making in Engineering and Management. *Information*, *8*(3), 1–17. doi:10.3390/info8030078

Anajkumar, L., Ilangkumaran, M., & Sasirekha, V. (2014). Comparative analysis of MCDM methods for pipe material selection in sugar industry. *Expert Systems with Applications*, *41*(6), 2964–2980. doi:10.1016/j.eswa.2013.10.028

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *20*(1), 87–96. doi:10.1016/S0165-0114(86)80034-3

Caliskan, H., Kursuncu, B., Kurbanoglu, C., & Guven, S. Y. (2013). Material Selection for the Tool Holder Working under Hard Milling Conditions Using Different Multi-Criteria Decision Making Methods. *Materials & Design*, *45*, 473–479. doi:10.1016/j.matdes.2012.09.042

Chatterjee, P., & Chakraborty, S. (2012). Material selection using preferential ranking methods. *Materials & Design*, *35*, 384–393. doi:10.1016/j.matdes.2011.09.027

Girubha, R. J., & Vinodh, S. (2012). Application of fuzzy VIKOR and environmental impact analysis for material selection of an automotive component. *Materials & Design*, *37*, 478–486. doi:10.1016/j.matdes.2012.01.022

Govindan, K., Shankar, K. M., & Kannan, D. (2016). Sustainable material selection for construction industry – A hybrid multicriteria decision-making approach. *Renewable & Sustainable Energy Reviews*, *55*, 1274–1288. doi:10.1016/j.rser.2015.07.100

Gul, M., Celik, E., Gumus, A. T., & Guneri, A. F. (2017). A fuzzy logic based PROMETHEE method for material selection problems. *Beni-Suef University Journal of Basic and Applied Sciences*, *7*(1), 68–79. doi:10.1016/j.bjbas.2017.07.002

Halliwell, S. (2012). *Repair of fiber reinforced polymer (FRP) structures*. NetComposites.

Kumar, R., Jagadish, A., & Ray, A. (2014). Selection of Material for Optimal Design Using Multi-Criteria Decision Making. *Procedia Mater. Sci.*, *6*, 590–596. doi:10.1016/j.mspro.2014.07.073

Laughlin, Z., & Howes, P. (2014). The Sound and Taste of Materials. *Materials Experience: Fundamentals of Materials and Design,* 39-49.

Li, D.-F. (2010). A ratio ranking method of triangular intuitionistic fuzzy numbers and its application to MADM problems. *Computers & Mathematics with Applications (Oxford, England)*, *60*(6), 1557–1570. doi:10.1016/j.camwa.2010.06.039

Liang, C., Zhao, S., & Zhang, J. (2014). Aggregation operators on triangular intuitionistic fuzzy numbers and its application to multi-criteria decision making problems. *Foundations of Computing and Decision Sciences*, *3*(2), 321–326. doi:10.2478/fcds-2014-00

Liao, T. W. (2015). Two interval type 2 fuzzy TOPSIS material selection methods. *Materials & Design*, *88*, 1088–1099. doi:10.1016/j.matdes.2015.09.113

Liu, H. C., Liu, L., & Wu, J. (2013). Material selection using an interval 2-tuple linguistic VIKOR method considering subjective and objective weights. *Materials & Design*, *52*, 158–167. doi:10.1016/j.matdes.2013.05.054

Liu, H. C., Yu, J. X., Zhen, L., & Fan, X. J. (2014). A novel hybrid multiple criteria decision-making model for material selection with target-based criteria. *Materials & Design*, *60*, 380–390. doi:10.1016/j.matdes.2014.03.071

Milberg, E. (2015). Boeing Completes Detailed Design for 787-10 Dreamliner. *Composites Manufacturing Magazine*.

Mohammed, L., Ansari, M. N. M., Pua, G., Jawaid, M., & Islam, M. S. (2015). A Review on Natural Fiber Reinforced Polymer Composite and Its Applications. *International Journal of Polymer Science*, *2015*, 1–15. doi:10.1155/2015/243947

Mouritz, A. P. (2012). Materials selection for aerospace. In *Introduction to Aerospace Materials* (pp. 569–600).

Nicolais, L., Meo, M., & Milella, E. (2011). *Composite materials: a vision for the future*. Springer. doi:10.1007/978-0-85729-166-0

Rahman, S., Odeyinka, H., Perera, S., & Bi, Y. (2012). A product-cost modeling approach for the development of a decision support system for optimal roofing material selection. *Expert Systems with Applications*, *39*(8), 6857–6871. doi:10.1016/j.eswa.2012.01.010

Tran, P. N., & Boukhatem, N. (2008). The distance to the ideal alternative (DiA) algorithm for interface selection in heterogeneous wireless networks. In *Proceedings of the 6th ACM International Symposium on Mobility Management and Wireless Access - MobiWac '08*. ACM. doi:10.1145/1454659.1454671

Wan, S., Lin, L.-L., & Dong, J. (2016). MAGDM based on triangular Atanassov's intuitionistic fuzzy information aggregation. *Neural Computing & Applications*, (February). doi:10.1007/s00521-016-2196-9

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353. doi:10.1016/S0019-9958(65)90241-X

Zhang, M. J., & Nan, J. X. (2013). A compromise ratio ranking method of triangular intuitionistic fuzzy numbers and its application to MADM problems. *Iranian Journal of Fuzzy Systems*, *10*(6), 21–37. doi:10.1016/j.camwa.2010.06.039

Zhang, X., & Liu, P. (2010). Method for aggregating triangular fuzzy intuitionistic fuzzy information and its application to decision making. *Technological and Economic Development of Economy*, *16*(2), 280–290. doi:10.3846/tede.2010.18

Zhao, R., Su, H., Chen, X., & Yu, Y. (2016). Commercially available materials selection in sustainable design: An integrated multi-attribute decision making approach. *Sustainability*, *8*(79), 1–15. doi:10.3390/su8010079

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