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Research Article

Selection of Semiconductor Packaging Materials by Combined Fuzzy AHP-Entropy and Proximity Index Value Method

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The residue of no-clean flux (NCF) on the printed circuit board assembly has been one of the major reasons for corrosion reliability failure of electronic devices. The source of aggressive contamination is the carboxylic acid activator as the main cleaning agent for soldering surfaces. Selecting the suitable activator has always been one of the concerns due to its conflicting properties, for example, suberic acid has a lower boiling point that will help in minimizing the residue; however, its dissociation constant is low which will increase the aggressive residue. The selection of a suitable activator based on the conflicting criteria is a multicriteria decision-making (MCDM) problem. In this study, thirty-one carboxylic acids (mono, di, tri, and hydroxyl) were ranked based on the six different criteria, i.e., melting point, molecular weight, boiling point, acid dissociation constant (pK_a value), solubility, and number of carboxylic acids using combined fuzzy AHP-entropy and the proximity index value method. Weight of the criterion was calculated using combined fuzzy AHP-entropy; whereas, ranking of the alternative carboxylic acid was done by the proximity index value method. First, the ranking was done based on the overall carboxylic acid; consequently, the groupwise ranking was also evaluated. As a result of this study, margaric acid occupied rank 1 out of all the thirty-one carboxylic acids and monocarboxylic acids; whereas, malonic acid acquired the lowest rank. In addition, out of 9 dicarboxylic acids, sebacic acid was the most suitable alternative. In the case of tricarboxylic acids, trimesic acid was a suitable alternative. Sensitivity analysis was performed to verify the reliability and consistency of the result obtained through applied MCDM.

1. Introduction

Solder flux market was valued ~USD 240 million in 2019 and the growth rate was expected to increase by ~5.7% from 2019 to 2026 [1]. NCF includes the WOA activators that are various mono, di, tri, and hydroxyl carboxylic acids reacting with the metal oxide on the solder surface and metal pad surface on the substrate and remove oxide with the help of metal oxide and acid reaction [2]. In recent years, the interest on WOA-based NCF is increasing as it gives the lowest residue compared to other fluxes and residues of WOA-based NCF that are compatible with the underfill. The packaging of the semiconductors using the NCF and cleanable fluxes is significantly different. For example, in flip-chip manufacturing using water soluble flux, the total number of production steps from the wafer cutting until package goes for reliability is 12. This process takes approximately 170 minutes for manufacturing one pallet. However, the flip-chip manufacturing using the NCF eliminates a flux cleaning step as it is one of the major time-consuming stages. This elimination reduces the production time to 125 minutes for the same one pallet which is a huge reduction of production time for the semiconductor industry, leading to good business opportunities. However, ionic residue is the major concern for WOA-based NCF which decreases the reliability of PCBA. Also, an incompatible residue decreases the properties of underfill such as glass transition temperature and elastic modulus [3–6]. Therefore, selection of a suitable activator is significantly important.

The selection of acid activator based on several attributes resembles a multicriteria decision-making (MCDM) problem. Several techniques have been developed and employed to solve MCDM problems pertaining to different knowledge

domains. For example, Yang et al. [7] tried to expand MCDM methods to solve a phase change material (PCM) selection problem. The methodology used for selection of PCM consists of initially determining subjective and objective weights of the criteria using an analytic hierarchy process (AHP) and information entropy method, respectively. Subsequently, the weights are combined and used with a technique for order of preference by similarity to ideal solution (TOPSIS) method to rank pre-screened PCMs. Patnaik et al. [8] demonstrated the use of the AHP-TOPSIS method for material selection in a structural/mechanical design process. A hybrid MCDM approach composed of AHP and gray correlation technique for order performance by similarity to ideal solution (GC-TOPSIS) has been effectively used for green decoration material selection [9]. Mousavi-Nisab and Sotoudeh-Anvari [10] used complex proportional assessment of alternatives (COPRAS) and TOPSIS method to tackle a material selection problem. However, in this work, authors also examined the use of DEA to solve material selection problem and found that MCDM methods are well again to solve this kind of problems. Further, Zhou et al. [11] applied fuzzy hybrid DEMATEL-AEW-FVIKOR to select sustainable recycling partner in small-medium enterprises. The VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method is used to rank the alternative machine tools [12]. A comparative analysis between FAHP-TOPSIS, FAHP-VIKOR, FAHP-ELECTRE, and FAHP-PROMTHEE was performed by Anojkumar et al. [12] for pipe material selection in sugar industry. It has been found in the literature that the TOPSIS method is extensively used for solving MCDM problems. However, a novel MCDM method identified as proximity index value (PIV) method has been developed recently with an advantage over the TOPSIS method in terms of rank reversal [13]. Amiri and Emamat [14] proposed goal programming-based models for BWM (GPBWM), which result in a unique solution. The GPBWM had fewer constraints in comparison with the previous BWM-based models. Wakeel et al. [15, 16] applied the linear GPBWM and PIV to an automotive material selection problem. Amiri et al. [17] extended BWM based on the possibilistic distribution. This study showed the possibility approach presents more robust results in comparison with other approaches.

Among different MCDM methods to compute weights of the attributes, the weights obtained using combined objective and subjective methods are more consistent [18–20]. Therefore, this work considers use of the fuzzy-AHP method to compute subjective weights of the attributes and entropy method for objective weight calculations. The combined weights are used with the proximity index value (PIV) method to select an appropriate acid activator. To the best of author's knowledge, no work has been done to apply a mathematical modeling for obtaining suitable activator selection as a primary stage before proceeding to development of new NCF which will minimize the production time and cost of semiconductor industry. In this study, the selection of most suitable and ranking of thirty-one WOA acid activators was done based on the six different conflicting criteria by employing the fuzzy-AHP-PIV method. As a result of this study, the most suitable carboxylic acid was obtained and ranking for each section of carboxylic acid (mono, di, and tri) was done.

The rest of structure of this article is as follows: Section 2 includes the step-by-step methodology adopted in this study which includes fuzzy AHP, entropy, and PIV methods. Section 3 presents the results obtained in this research. Discussion and sensitivity analysis are explained in Section 4. The contribution of this research is demonstrated in Section 5. Finally, conclusion, limitation of research, and future directions are given in Section 6 of this study.

2. Research Methodology

The methodology used in this work for the selection of acid activator is an integrated method consists of the fuzzy analytical hierarchy process (F-AHP), entropy, and proximity index value (PIV) methods. The research framework used in this work is represented in the form of a flowchart in Figure 1.

F-AHP and entropy methods are used to derive weights of the attributes, whereas the PIV method is employed to provide ranks to the acids. The weights which reflect importance are affected by the quality of the attributes as well as the subjective judgment of the experts. The entropy method is one method that derives weights based on the quality of the attributes regarded as objective weights [18]. On the other hand, weights that are determined on the basis expert's opinion are identified as subjective weights [19]. AHP is an efficient and widely accepted method to compute subjective weights of the attributes. However, to incorporate the inconsistency and vagueness in the data, the use of the fuzzy-AHP method for subjective weight calculation is highly recommended in the literature [18–20]. Therefore, in this work, weights of the attributes are computed using the entropy and F-AHP methods which are combined to determine the final weights of the attributes. Finally, the PIV method which is an efficient and newly developed method for comparison of the alternatives is used to find out an appropriate acid activator.

2.1. Identification of Criteria. As per the literature, three beneficial and three nonbeneficial criteria, i.e., molecular weight, melting point, boiling point, acid dissociation constant, solubility, and the number of carboxyl functional groups of weak organic acids are used to select the suitable alternative as follows.

2.1.1. Molecular Weight. Molecular weight of acid will determine solubility, melting point, and boiling point of WOA. Bigger molecules will have larger number of bonds, and therefore, higher number of forces will be required to break the bond; thus, higher molecular weight will have a higher melting point. However, it also effects the boiling point, but major dominant factors for boiling points are molecular shape, size, and polarizability [21]. Higher number of carbons means higher hydrophobic nature, thus lower solubility in water also means a higher molecular size solute will

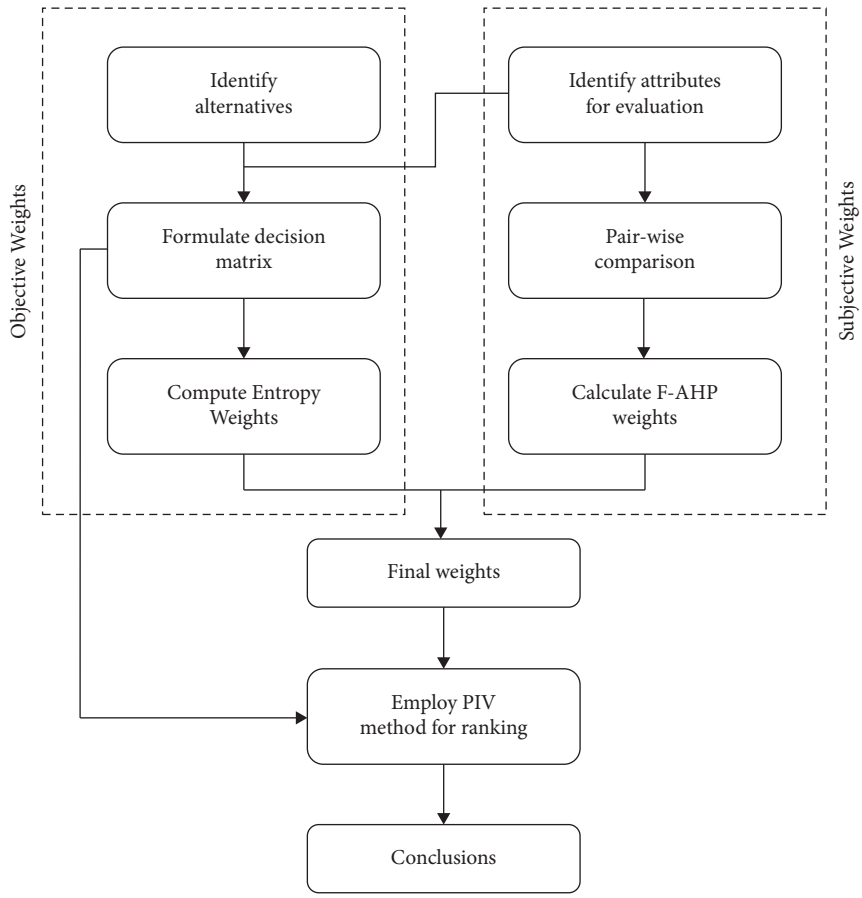

Figure 1: Research framework for activator selection.

have difficulty to be surrounded by solvent, thereby possessing lower solubility. Therefore, the molecular weight of WOA should be minimized.

2.1.2. Melting Point of WOA. Melting point of acid is defined by its molecular structure and it has been observed that an odd number of carbon atoms in acid has lower melting point compared to even number of carbon atoms acid [22]. In a lower melting point WOA, molecules arrange themselves in a manner that is easier to break, thereby increasing the solubility in the water [21]. The melting point of the WOA also determines the residue aggressiveness which depends on the structure of WOA, number of methyl groups, and molecular arrangements. Lower melting point carboxylic acid will increase the dissolution, thereby having easier water interaction or increasing solubility at lower temperature thus increasing the aggressiveness of residue. Therefore, a higher melting point WOA is the preferable choice.

2.1.3. Boiling Point. Boiling point of WOA determines the decomposition of WOA near soldering temperature. Evaporation rate of WOA determines the extent of residue on PCB. A lower boiling point WOA will be active at lower temperature and thus can leave minimal residue. Also, the activator will have a longer activity time to remove the oxide. Therefore, the boiling point of WOA should be minimized.

2.1.4. Acid Dissociation Constant (pK_a). Ionization of the residue is defined by dissociation of acidic ions which is termed as a pK_a value. pK_a represents the strength of an acid or its tendency of ionization/dissociation in a solution which is indirectly related to the pH value. Lower pK_a will increase the higher dissociation of acidic ions which will leave a more ionic/aggressive residue. Thus, it is preferable that WOA strength (pK_a) should be as higher as it can be in order to minimize the aggressiveness or leakage current [23].

2.1.5. Solubility. Solubility will define the interaction of WOA with the solvent/water or affinity with the water. Higher solubility means higher dissociation of ions with water increasing conductivity, thereby reducing the SIR of surface. Therefore, solubility of WOA should be low.

2.1.6. Number of Carboxylic Functional Groups. Increasing the number of carboxylic groups will increase the affinity with the water, thereby increasing the conductive water layer thickness thus increasing the leakage current. Therefore, the number of carboxylic functional group should be minimal.

2.2. Fuzzy Set Theory. Bellman and Zadeh [24] proposed the fuzzy set theory to deal with situations having ambiguity and elusiveness of data. In the fuzzy set theory, fuzzy numbers are used which are well-organized to deal with the interpretation that is approximate rather than exact [25]. Several kinds of fuzzy numbers viz. triangular fuzzy number (TFNs), trapezoidal fuzzy number (TrFNs), and pentagonal fuzzy numbers (PFNs) have been discussed in the literature [26]. However, the most commonly used shape of fuzzy numbers is triangular fuzzy numbers (TFNs). A TFN is characterized by a set of three real numbers of the form (a_0, a_1, a_2) with a membership function as defined by equation (1).

$$\mu_L(x) = \left\{ \begin{array}{ll} \dfrac{(x-a_0)}{(a_1-a_0)}; & a_0 \le x \le a_1 \\ \dfrac{(a_2-x)}{(a_2-a_1)}; & a_1 \le x \le a_2 \\ 0; & \text{otherwise} \end{array} \right\}. \tag{1}$$

A membership function is used to define the degree of fuzziness of the data. The value of the membership function lies in the interval [0, 1]. If two fuzzy number $\widetilde{P}$ and $\widetilde{Q}$ are defined as $\widetilde{P} = (p_0, p_1, p_2)$ and $\widetilde{Q} = (q_0, q_1, q_2)$, then the addition is defined as $\widetilde{P} + \widetilde{Q} = (p_0 + q_0, p_1 + q_1, p_2 + q_2)$, subtraction as $\widetilde{P} - \widetilde{Q} = (p_0 - q_2, p_1 - q_1, p_2 - q_0)$, multiplication as $\widetilde{P} \times \widetilde{Q} = (p_0 \times q_0, p_1 \times q_1, p_2 \times q_2)$, and division as $\widetilde{P}/\widetilde{Q} = (p_0/q_2, p_1/q_1, p_2/q_0)$ [9]. Further, the summation operator and inverse operator is defined as $\sum_{i=1}^{n} \widetilde{P}_i = (\sum_{i=1}^{n} (p_0)_i, \sum_{i=1}^{n} (p_1)_i, \sum_{i=1}^{n} (p_2)_i)$ and $(\widetilde{P})^{-1} = (1/p_2, 1/p_1, 1/p_0)$, respectively. Subsequently, the principle for the comparison of fuzzy number is defined which is as follows [27]: If two fuzzy numbers $\widetilde{P}$ and $\widetilde{Q}$ are defined as $\widetilde{P} = (p_0, p_1, p_2)$ and $\widetilde{Q} = (q_0, q_1, q_2)$, then the degree of possibility (d) of P is greater than Q is defined by equation (2).

$$d(\widetilde{P} \ge \widetilde{Q}) = \left\{ \begin{array}{ll} 1 & \text{if } p_1 \ge q_1 \\ 0 & \text{if } q_0 \ge p_2 \\ \dfrac{q_0 - p_2}{(p_1 - p_2) - (q_1 - q_0)} & \text{otherwise} \end{array} \right\}. \tag{2}$$

However, to compute the degree of possibility of a fuzzy number $\widetilde{P}$ to be greater than other n fuzzy numbers say $\widetilde{Q}_1, \widetilde{Q}_2, \ldots\ldots\ldots, \widetilde{Q}_n$, equation (3) is used.

$$d\left(\widetilde{P} \ge \widetilde{Q}_1, \widetilde{Q}_2, \ldots\ldots\ldots, \widetilde{Q}_n\right) = \min\left\{d\left(\widetilde{P} \ge \widetilde{Q}_1\right), d\left(\widetilde{P} \ge \widetilde{Q}_2\right), \ldots\ldots\ldots, d\left(\widetilde{P} \ge \widetilde{Q}_n\right)\right\}. \tag{3}$$

2.3. Fuzzy Analytical Hierarchy Process (F-AHP). Analytical hierarchy process (AHP) is a powerful decision-making tool that was developed in 1980 [28]. It includes managerial judgment for comparison and assigning weights to the attributes. The managerial judgment in classical AHP is considered to be definite which does not take account of human's interchangeable thoughts [29]. Therefore, researchers have integrated a fuzzy set theory with AHP to overcome the imprecision and discrepancy of the data and proposed fuzzy analytical hierarchy process (F-AHP) method [30]. In literature, among the different forms of F-AHP methods, the extent analysis method of F-AHP is widely accepted and most fascinated [27, 31]. Therefore, this work exploits the F-AHP method based on extent analysis to compute the subjective weights of the attributes. The step-by-step procedure for which is explained as follows [32–35]:

Step 1: Formulate fuzzy pairwise comparison matrix (FPCM)

A fuzzy pairwise comparison matrix is obtained by comparing attributes in a pairwise manner. The judgment from experts/decision-makers is entered in linguistic terms which are transformed into fuzzy numbers as given in equation (4).

$$\text{FPCM} = \begin{bmatrix} \widetilde{u}_{1,1} & \cdots & \widetilde{u}_{1,b} & \cdots & \widetilde{u}_{1,J} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \widetilde{u}_{a,1} & \cdots & \widetilde{u}_{a,b} & \cdots & \widetilde{u}_{a,J} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \widetilde{u}_{J,1} & \cdots & \widetilde{u}_{J,b} & \cdots & \widetilde{u}_{J,J} \end{bmatrix}, \tag{4}$$

where $\widetilde{u}_{a,b}$ represents the fuzzy number when criterion a is compared with criterion b. J represents the total number of attributes. a and b vary from 1 to J. It must be noted that the elements of FPCM satisfy the following property:

$$\widetilde{u}_{a,a} = (1, 1, 1) \text{ and } \widetilde{u}_{b,a} = \frac{1}{\widetilde{u}_{a,b}}. \tag{5}$$

Step 2: Calculate fuzzy synthetic degree value ($\widetilde{\text{SD}}$)

The extent analysis method considers the satisfied extent of an attribute to define weights. The satisfied extent is the degree of an object to be satisfied for the goal which is defined in terms of synthetic degree value as defined by equation (6).

$$\widetilde{\text{SD}}_i = \left(\sum_{b=1}^{J} \widetilde{u}_{a,b}\right) \times \left(\sum_{a=1}^{J} \sum_{b=1}^{J} \widetilde{u}_{a,b}\right)^{-1}. \tag{6}$$

Step 3: Compute weight vector.

It has been suggested in extent analysis that an attribute having the highest synthetic degree will be given more weight compared to others. Therefore, a comparison of the SD values of each attribute with others is required to determine the weight vector. The SD values of attributes are fuzzy numbers; hence, the principle for the comparison of fuzzy number as defined in section 1.1 is used which results in weight vector as shown in equation (7).

$$W = \left(\mathrm{zA}_1, \mathrm{zA}_2, \mathrm{zA}_3, \ldots\ldots\ldots, \mathrm{zA}_J\right), \tag{7}$$

where $\mathrm{zA}_i = d\left(\mathrm{SD}_i \geq \mathrm{SD}_1, \mathrm{SD}_2, \ldots\ldots, \mathrm{SD}_J\right)$.

The weight vector so obtained is normalized to obtain the final weight of the criteria using (8).

$$w_b^A = \frac{\mathrm{zA}_b}{\sum_{b=1}^{J} \mathrm{zA}_b}. \tag{8}$$

2.4. Entropy Method. The entropy method, which was proposed by Shannon in 1985, is an objective method for computing attribute weights. Shannon employs the concept of entropy in the field of information theory to obtain information essence and useful information of a given dataset [36]. According to entropy theory, the information entropy of a criterion is small if the difference in the criterion value among the considered alternatives is large. A criterion with small information entropy will provide more useful information about the given dataset and vice versa [37]. Hence, weights to the criteria should be provided in the inverse order of the information entropy, i.e., a criterion with small information entropy should have high weight and vice versa. The step-by-step procedure to implement this method is as follows [37–40]:

Step 1: Arrange different alternatives and their attribute values in rows and columns identified as the decision matrix (D) is as given by equation (9).

$$D = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1b} \\ v_{21} & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ v_{a1} & \cdots & \cdots & v_{a,b} \end{bmatrix}_{I \times J}, \tag{9}$$

where the value for attribute b of alternative a is represented by va, b. I and J are the total number of alternatives and attributes, respectively.

Step 2: Normalize the decision matrix using equation (10).

$$v_{a,b}^n = \begin{Bmatrix} \dfrac{v_{a,b} - \min\limits_a \left(v_{a,b}\right)}{\max\limits_a \left(v_{a,b}\right) - \min\limits_a \left(v_{a,b}\right)} & \text{for beneficial criteria} \\ \dfrac{\max\limits_a \left(v_{a,b}\right) - v_{a,b}}{\max\limits_a \left(v_{a,b}\right) - \min\limits_a \left(v_{a,b}\right)} & \text{for cost criteria} \end{Bmatrix}. \tag{10}$$

Step 3: Determine the information entropy of the attributes using equation (11).

$$E_b = -\frac{1}{J} \times \sum_{a=1}^{J} r_{a,b} \ln\left(r_{a,b}\right), \tag{11}$$

where $r_{a,b} = v_{a,b}^n / \sum_{a=1}^{J} v_{a,b}^n$.

Step 3: Compute entropy weights in the inverse proportion of the entropy values as defined by equation (12).

$$w_b^E = \frac{1 - E_b}{\sum_{b=1}^{J} \left(1 - E_b\right)}. \tag{12}$$

2.5. Proximity Index Value (PIV) Method. The proximity index value (PIV) method is an efficient and recently developed MCDM method with an advantage of minimizing the rank reversal phenomenon over the TOPSIS method [13]. Due to this advantage, it has been widely accepted and fascinated among researchers in different knowledge domains [41, 42]. This method compares alternatives based on a proximity value which represents the deviation from the best alternative. The computation step of this method is as follows [13, 43]:

Step 1. Formulate decision matrix (D) as defined in equation (9)

Step 2. Normalize the decision matrix using equation (13)

$$v_{a,b}^n = \frac{v_{a,b}}{\sqrt{\sum_{a=1}^{I} v_{a,b}^2}}. \tag{13}$$

Step 3. Computed weighted normalized values using equation (14)

$$v_{a,b}^{wn} = w_b \times v_{a,b}^n \tag{14}$$

where w_b is the weight of the b^{th} attribute.

Step 4. Calculate absolute dispersion (AD_a) from the best alternative using equation (15)

$$\mathrm{AD}_{a,b} = \begin{Bmatrix} v_{\max}^{wn} - v_{a,b}^{wn}; & \text{for beneficial criteria} \\ v_{a,b}^{wn} - v_{\min}^{wn}; & \text{for cost criteria} \end{Bmatrix}. \tag{15}$$

Step 5. Compute proximity value which is the algebraic sum of absolute dispersion, PV_a, using equation (16)

$$\mathrm{PV}_a = \sum_{b=1}^{J} \mathrm{AD}_{a,b}. \tag{16}$$

The PV_a represents the minimum deviation from the best and it is used to rank the alternatives. The alternative having the minimum PVi value is ranked first and the ranking of the alternatives decreases with increasing PVi value.

Table 1: Pairwise comparison of attributes in linguistic terms.

	Molecular weight (MW)	Melting point (MP)	Boiling point (BP)	Solubility (S)	pK_a	Number of carboxylic acid (NC)
MW	("E", ""E", "E", "E", "E")	("VS", "AS", "SS", "SS", "FS")	("SS", "FS", "E", "E", "SS")	("SS", "FS", "FS", "E", "FS")	("FS", "SS", "SS", "SS", "SS")	("AS", "VS", "AS", "VS", "AS")
MP	("VW","AW", "SW", "SW", "FW")	("E", "E", "E", "E", "E")	("FW", "SW", "VW", "FW", "FW")	("FW", "E", "SW", "E", "SS")	("VW", "SW", "SW", "SW", "SW")	("FS", "SS", "SS", "FS", "SS")
BP	("SW", "FW", "E", "E", "SW")	("FS", "SS", "VS", "FS", "FS")	("E", "E", "E", "E", "E")	("VS", "VS", "FS", "VS", "SS")	("E", "SS", "VS", "SS", "SS")	("AS", "FS", "AS", "VS", "VS")
S	("SW", "FW", "FW", "E", "FW")	("FS", "E", "SS", "E", "SW")	("VW", "VW", "FW", "VW", "SW")	("E", "E", "E", "E", "E")	("SW", "E", "E", "E", "SW")	("FS", "VS", "SW", "SS", "SS")
PK	("FW", "SW", "SW", "SW", "SW")	("VS", "SS", "SS", "SS", "SS")	("E", "SW", "VW", "SW", "SW")	("SS", "E", "E", "E", "SS")	("E", "E", "E", "E", "E")	("VS", "VS", "SS", "SS", "FS")
NC	("AW", "VW", "AW", "VW", "AW")	("FW", "SW", "SW", "FW", "SW")	("AW", "FW", "AW", "VW", "VW")	("FW", "VW", "SS", "SW", "SW")	("VW", "VW", "SW", "SW", "FW")	("E", "E", "E", "E", "E")

Table 2: Fuzzy pairwise comparison matrix.

	MW	MP	BP	S	PK	NC
MW	(1.0, 1.0, 1.0)	(1.3, 1.6, 2.1)	(1.0, 1.1, 1.4)	(1.0, 1.3, 1.7)	(1.0, 1.1, 1.6)	(1.8, 2.3, 2.8)
MP	(0.513, 0.713, 0.833)	(1.0, 1.0, 1.0)	(0.513, 0.7, 0.933)	(0.833, 0.933, 1.1)	(0.614, 0.9, 0.933)	(1.0, 1.2, 1.7)
BP	(0.767, 0.933, 1.0)	(1.1, 1.5, 2.0)	(1.0, 1.0, 1.0)	(1.3, 1.7, 2.2)	(1.1, 1.2, 1.6)	(1.6, 2.1, 2.6)
S	(0.633, 0.8, 1.0)	(0.933, 1.1, 1.3)	(0.473, 0.633, 0.8)	(1.0, 1.0, 1.0)	(0.867, 1.0, 1.0)	(1.033, 1.3, 1.7)
PK	(0.634, 0.933, 1.0)	(1.1, 1.2, 1.7)	(0.68, 0.9, 0.933)	(1.0, 1.0, 1.2)	(1.0, 1.0, 1.0)	(1.2, 1.5, 2.0)
NC	(0.36, 0.44, 0.567)	(0.6, 0.867, 1.0)	(0.393, 0.493, 0.667)	(0.647, 0.833, 1.033)	(0.527, 0.733, 0.867)	(1.0, 1.0, 1.0)

Table 3: Weights obtained using the F-AHP method.

Attribute	MW	MP	BP	S	PK	NC
w^A	0.277	0.111	0.278	0.132	0.182	0.02

3. Results

The linguistic terms such as absolutely strong (AS), very strong (VS), fairly strong (FS), slightly, strong (SS), equal (E), slightly weak (SW), fairly weak (FW), very weak (VW), and absolutely weak (AW) are used for pairwise comparison of the attributes. The TFNs used to describe these linguistic terms are as follows [33]: (2, 2.5, 3) for AS, (1.5, 2, 2.5) for VS, (1, 1.5, 2) for FS, (1, 1, 1.5) for SS, (1, 1, 1) for E, (0.667, 1, 1) for SW, (0.5, 0.667, 1) for FW, (0.4, 0.5, 0.667) for VW, and (0.333, 0.4, 0.5) for AW. A decision-making panel comprising of seven experts from two NCF industries and four different universities individually assessed the importance of attributes in pairwise form using linguistic terms and the results are shown in Table 1.

It must be noted that in Table 1, the pairwise judgment of five experts when attribute MW is compared with MP is depicted as "VS", "AS", "SS", "SS", and "FS", respectively. The linguistic terms are transformed into fuzzy numbers for further analysis. In this study, more than one decision-maker is involved; therefore, the aggregated value of transformed fuzzy numbers is determined by simply averaging the values given by all the decision makers. The aggregated fuzzy pairwise comparison matrix so obtained is depicted in Table 2.

The fuzzy pairwise comparison matrix is used to compute the fuzzy synthetic degree value of each attribute using (2). The fuzzy synthetic value of each attribute is compared with others to determine the weight vector. It must be noted that the synthetic values of each attribute are a fuzzy number; therefore, the principle of comparison of fuzzy number is used to determine the degree of possibility of the synthetic value of one attribute to be greater than other. Finally, the weight vector is normalized to compute the weights of the attributes and is shown in Table 3.

The weights obtained using the F-AHP method are based on the subjective opinion of experts and are regarded as subjective weights. The quality of the attribute values also has a significant impact on the selection of the best acid activator. Hence, thirty carboxylic acids with different characteristics are compared in this study and the quality of these acids is included by computing weights using the entropy method. The first step in the entropy method is to formulate the decision matrix. A decision matrix is an arrangement of alternatives and their attribute values in rows and columns is as shown in Table 4.

It can be observed from Table 4 that the attribute values are defined on a different scale and have a different range. Therefore, the decision matrix is normalized to convert these values into a similar scale using equation (10). The normalized values are used to compute the information entropy of attributes as defined by equation (11) which assists in

Table 4: Decision matrix [44–49].

Acid activator	Molecular weight (MW)	Melting point (MP)	Boiling point (BP)	Solubility (S) (gm/100 ml)	pK_a	Number of carboxylic acid (NC)
Valeric	102	−34.5	186	4.97	4.82	1
S-lactic	90	16.8	122	10	3.86	1
Caproic	116.15	−3	205.8	1.08	4.88	1
Enanthic	130.18	−7.5	223	0.24	4.8	1
Benzoic	122.12	122.3	249.2	0.29	4.2	1
Caprylic	144.21	16.7	237	0.06	4.89	1
Phenylacetic	136.15	78	265	1.5	4.31	1
Pelargonic	158.23	12.5	254	0.03	4.96	1
Sorbic	112.13	134.5	228	0.16	4.75	1
Capric	172.26	31.6	269	0.015	4.9	1
Lauric	200.31	43.2	298.9	0.048	5.3	1
Myristic	228.37	54.4	250.5	0.24	4.95	1
Palmitic	256.43	62.9	351	0.007	4.78	1
Margaric	275.45	61.3	227	$1.5E-05$	4.95	1
Stearic	284.48	69.3	361	0.0059	4.75	1
Cinnamic	148.15	133	300	5.11	4.46	1
Adipic	146.16	152.1	337.5	1.9	4.41	2
Pimelic	160.17	105	353.7	511.2	4.71	2
Suberic	174.2	144	230	0.24	4.52	2
Sebacic	202.25	134	294.4	0.025	4.72	2
Fumaric	116.07	287	290	0.63	3.03	2
Succinic	118.09	184	235	8.32	4.21	2
Benzilic	228.24	151	180	14.1	3.03	1
Gallic	170.12	260	500	1.19	4.5	1
Vanillic	168.14	213	353	15	4.51	1
Salicylic	138.12	158.6	211	0.248	2.79	1
Glutaric	147.13	98	200	63.9	4.32	2
Malic	134.08	134.09	306.4	5920	3.4	2
Malonic	104.06	135	386.8	6230	2.85	2
Trimesic	210	375	561	0.26	3.12	3
Citric	192.12	153	310	180.9	3.1	3

Table 5: Weights obtained using the entropy method.

Attribute	MW	MP	BP	S	PK	NC
E_b	0.932	0.944	0.979	0.988	0.95	0.967
w^E	0.283	0.233	0.088	0.05	0.208	0.138

Table 6: Aggregated weights of the attributes.

Attribute	w^A	w^E	W
MW	0.277	0.283	0.4456
MP	0.111	0.233	0.1470
BP	0.278	0.088	0.1391
S	0.132	0.050	0.0375
PK	0.182	0.208	0.2152
NC	0.020	0.138	0.0157

determining the weights of the attributes using equation (12). The information entropy and weights of the attributes so obtained using the entropy method is depicted in Table 5.

The entropy weights and the AHP weights are aggregated to determine the global weights of the attributes. The idea behind aggregating these weights is to combine the subjective and objective behavior of the attributes. The mathematical formula used to compute the global weights of the attributes is shown in equation (17) [50].

$$w_b = \frac{w_b^A \times w_b^E}{\sum_{b=1}^{J} w_b^A \times w_b^E}. \tag{17}$$

The weights of the attributes so obtained are depicted in Table 6.

The weight so obtained is used to compare the different acid activators. Thirty acid activators are considered for comparison and the attribute values of these acids are

Table 7: Proximity value and ranks of the acid activators.

Acid	Proximity index value	Rank
Valeric	0.170213	29
S-lactic	0.169535	28
Caproic	0.158928	27
Enanthic	0.155369	26
Benzoic	0.142765	23
Caprylic	0.144745	25
Phenylacetic	0.144737	24
Pelargonic	0.139788	22
Sorbic	0.138499	21
Capric	0.131523	15
Lauric	0.115263	11
Myristic	0.099153	6
Palmitic	0.094472	4
Margaric	0.073944	1
Stearic	0.08132	2
Cinnamic	0.130638	13
Adipic	0.133462	17
Pimelic	0.136515	19
Suberic	0.111839	9
Sebacic	0.10424	7
Fumaric	0.130921	14
Succinic	0.133856	18
Benzilic	0.092627	3
Gallic	0.113465	10
Vanillic	0.11064	8
Salicylic	0.137944	20
Glutaric	0.132468	16
Malic	0.174551	30
Malonic	0.201396	31
Trimesic	0.094742	5
Citric	0.123803	12

Table 8: Ranking of monocarboxylic acids.

Monocarboxylic acid	Proximity index value	Rank
Valeric	0.170213	21
S-lactic	0.169535	20
Caproic	0.158928	19
Enanthic	0.155369	18
Benzoic	0.142765	15
Caprylic	0.144745	17
Phenylacetic	0.144737	16
Pelargonic	0.139788	14
Sorbic	0.138499	13
Capric	0.131523	11
Lauric	0.115263	9
Myristic	0.099153	5
Palmitic	0.094472	4
Margaric	0.073944	1
Stearic	0.08132	2
Cinnamic	0.130638	10
Benzilic	0.092627	3
Gallic	0.113465	8
Vanillic	0.11064	7
Salicylic	0.137944	12

depicted in Table 4. An efficient and widely accepted MCDM method identified as the proximity index value (PIV) method is employed to rank these acid activators. The attribute values of the acid activators are normalized by the PIV method using equation (13). The aggregated weights of the attributes are multiplied with the normalized value to develop a weighted normalized decision matrix as discussed in equation (14). Further, the absolute dispersion of each acid activator from the best one is determined by employing equation (15), which is identified is the weighted proximity index value. Subsequently, a proximity value which is the algebraic sum of the weighted proximity index value is computed. It has been suggested in the PIV method that proximity value depicts the deviation of an alternative from the best alternative. Therefore, an alternative with least proximity value will be very much close to the best one and is ranked first. Rests of the alternative are ranked in ascending order of the proximity values. The proximity values and ranks of the alternatives so obtained are shown in Table 7.

Table 7 lists the ranking of all the acid activator which clearly shows that margaric acid is the most suitable acid for the formulation of NCF based on the criteria requirement. From Table 4, it is clearly observed that boiling point/decomposition temperature of the margaric acid (~227°C) which will evaporate easily and leave the minimal residue as compared to other WOA-NCF [5]. Further, higher solubility will lead to the higher dissolution of ions in the water that will increase the conductivity of the board. However, the solubility of the margaric acid is minimal than other acid that will decrease the chances ionic residue thereby minimal leakage current. pK_a of the margaric acid as discussed will minimize the ionic dissociation of the acid thereby minimizing the water interaction. The number of carboxylic functional group in the margaric acid will decrease the affinity with the polar solvent/water. Besides, a higher number of carbon atoms (higher molecular weight) will increase the hydrophobic nature, thereby decreasing the solubility of the acid. Therefore, based on the suitable criteria as illustrated above, margaric acid is the most suitable acid for NCF activator.

Total 21 monocarboxylic acids are candidates for the activator as per the literature survey and their ranking is listed in Table 8. It can be clearly observed that margaric acid acquired the first rank due to a lower boiling point, lower solubility, higher pK_a value as compared to other acids.

Table 9: Ranking of dicarboxylic acids.

Mono carboxylic acid	Proximity index value	Rank
Pimelic	0.136515	6
Suberic	0.111839	2
Sebacic	0.10424	1
Fumaric	0.130921	3
Succinic	0.133856	5
Glutaric	0.132468	4
Malic	0.174551	7
Malonic	0.201396	8

4. Discussion

Out of all the 8 dicarboxylic acids, sebacic acid occupied the first rank followed by suberic, fumaric, and other acids as presented in Table 9. All the dicarboxylic acids have 2

Table 10: Weights of the attributes during sensitivity analysis.

	Original	$r-0.1$	$r-0.2$	$r-0.3$	$r-0.4$	$r-0.5$	$r-0.6$	$r-0.7$	$r-0.8$	$r-0.9$
MW	0.4456	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
MP	0.147	0.239	0.212	0.186	0.159	0.133	0.106	0.08	0.053	0.027
BP	0.1391	0.226	0.201	0.176	0.151	0.125	0.1	0.075	0.05	0.025
S	0.0375	0.061	0.054	0.047	0.041	0.034	0.027	0.02	0.014	0.007
PK	0.2152	0.349	0.311	0.272	0.233	0.194	0.155	0.116	0.078	0.039
NC	0.0157	0.025	0.023	0.02	0.017	0.014	0.011	0.008	0.006	0.003

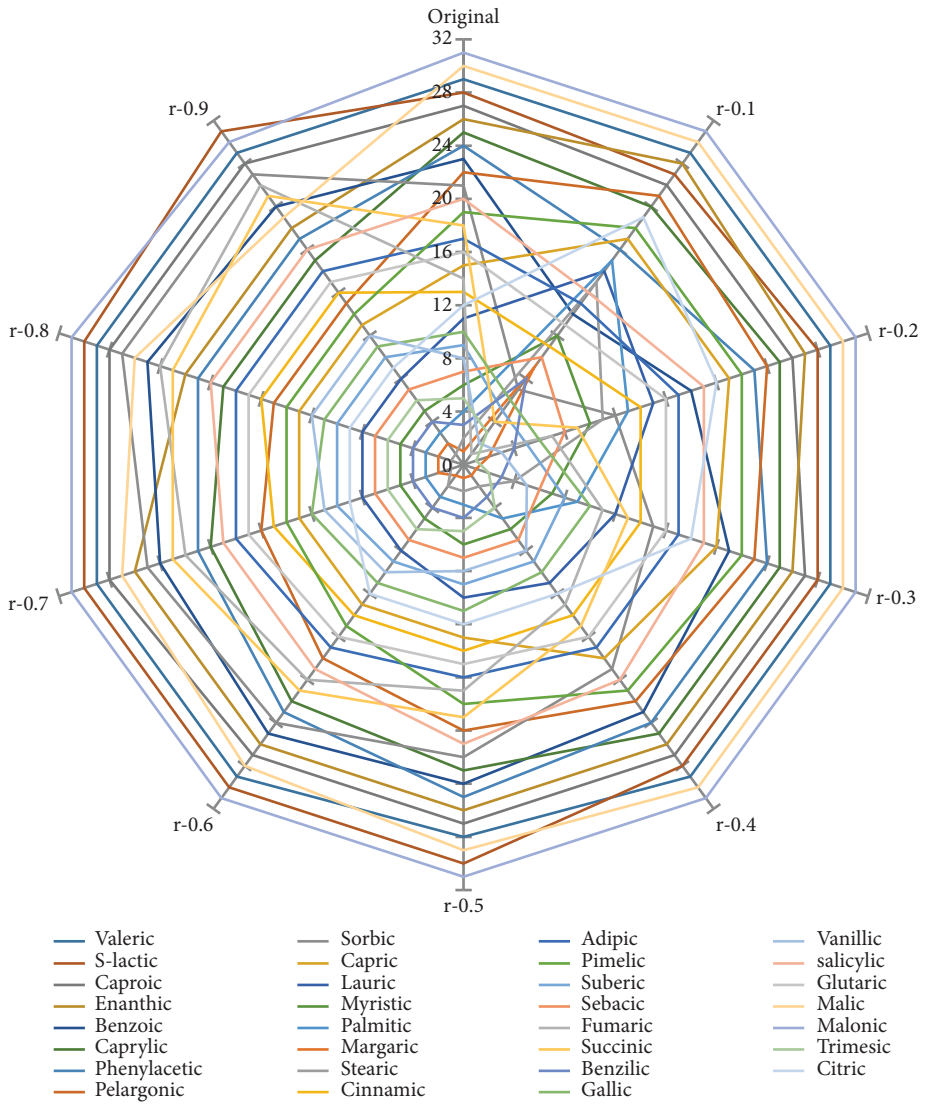

Figure 2: Sensitivity analysis results.

carboxylic functional groups; however, the solubility of sebacic acid is lower than other acids which decreases the water interaction of acid. Various works have been reported on the succinic, glutaric, and pimelic acids; however, it has been found that they leave a lot of residue because of the higher decomposition temperature. In addition, higher solubility is another concern with these acids. Therefore, based on the expert opinion and ranking model sebacic acid occupied the first rank followed by others. Furthermore, as per the literature only few tricarboxylic acids have been proposed due to their higher boiling point as listed in Table 4. However, in terms of their selection, trimesic acid acquired the first rank followed by citric acid due to their lower solubility and higher dissociation constant.

4.1. Sensitivity Analysis. The ranking of the acid activators achieved using the PIV method relies on the attribute weights. It is likely that minute change in these weights may alter the rank so obtained. Therefore, it is imperative to

examine the robustness of the derived rank for which sensitivity analysis is performed in this work. Among the several methods available in literature to perform sensitivity analysis, the method employed in this work is based on the method given by the authors of reference [51]. According to this method, the weight of the most important attribute, i.e., the attribute having the highest weight varies from 0.1 to 0.9. Correspondingly, the weight of other attributes is changed in proportion with the highest weight attribute. Subsequently, changes in ranks of different alternatives due to change in the weights of the attributes are examined and if the ranks of alternatives do not alter, it is concluded that the ranks so obtained are robust. In this view, the weights of the attributes considered in this work are varied in proportion with the highest weighted attribute and the weights so obtained are depicted in Table 10.

Further, the ranking of the acid activator using PIV method is done. Figure 2 shows the ranks of different acid activators obtained in the sensitivity analysis in the form of the radar chart. It is evident from Figure 2 that the discrepancy of ranks so obtained is very small. Hence, it can be concluded that the combined MCDM methods used in this paper are able to produce robust ranks of the acid activators.

5. Contribution of This Research

Semiconductor material and packaging industries are facing a lot of challenges for selecting the most suitable alternative materials to enhance the performance of packaging. These materials may include fluxes, underfills, solders, wire bonds, bond pads, wafer, etc. Thus, combined fuzzy-AHP and PIV method will solve these material selection issues which will lead to extensive business opportunities for semiconductor industries.

6. Conclusion

Combined fuzzy-AHP and proximity value method have been successfully employed for the selection of suitable activator for NCF based on the six conflicting criteria. Based on the above discussion, following major conclusion are made.

(1) Among thirty carboxylic acid activator candidates, margaric acid is the most suitable activator for the efficient NCF formulation followed by sebacic and trimesic acid in the di- and tricarboxylic group, respectively.

(2) Based on the various industrial and academic experts, molecular weight and acid dissociation constant are the two most important criteria for selecting the suitable WOA activator.

(3) Sensitivity analysis results showed that proposed method fuzzy-AHP-PIV is reliable and consistent.

(4) Sensitivity analysis clearly represented that ranking obtained by combined fuzzy-AHP and proximity value method is consistent and reliable.

(5) The modeling used in this study can be extended to select other packaging materials such as solders, underfills, solder masks, bond pads, wafers, etc.

7. The Limitations of This Study and Future Directions

This study used fuzzy AHP-PIV methods to solve the material selection issue. However, other methods such as GPBWM can be applied and compared with the existing method. This study was limited to selection of components of flux; however, in future selection of other packaging materials such as solders, underfills and bond pads can be studied thoroughly.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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