Materials selection method using improved TOPSIS without rank reversal based on linear max-min normalization with absolute maximum and minimum values

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Abstract

Technique for order preference by similarity to ideal solution (TOPSIS) is a well-known multi attribute decision making (MADM) method and it has been widely used in materials selection. However, the main drawback of the traditional TOPSIS is that it has a rank reversal phenomenon. To overcome this drawback, we propose an improved TOPSIS without rank reversal based on linear max-min normalization with absolute maximum and minimum values by modifying normalization formula and ideal solutions. Moreover, to study the impacts of changing attribute weights on relative closeness values of alternatives, we propose a sensitivity analysis method to attribute weights on the relative closeness values of the alternatives. We applied the proposed method to select best absorbent layer material for thin film solar cells (TFSCs). As a result, copper indium gallium diselenide was selected as the best one and the next cadmium telluride from among five materials. When the alternative is added to or removed from the set of original alternatives, the elements of the normalized decision-matrix, PIS, NIS and the relative closeness values don’t change at all, they are always coincide with the corresponding elements of the original ones. The relative closeness values are absolute values irrelevant to the composition of the alternatives in the improved TOPSIS, while the relative closeness values are relative values relevant to the composition of the alternatives in the traditional TOPSIS. Therefore, the proposed TOPSIS overcomes the rank reversal phenomenon, perfectly. It could be actively applied to practical problems for materials selection.

1. Introduction

Technique for order preference by similarity to ideal solution (TOPSIS) evaluates the overall performances of alternatives by the similarity to the positive and negative ideal solutions. It is based on the principle that the best alternative must have the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS) [1, 2]. The TOPSIS has been widely used in multi attribute decision making (MADM) problems such as materials selection [2–7]. Won-Chol Yang et al proposed the materials selection method using TOPSIS with some popular normalization method and applied it to select the optimal boron based tribological coating material with high wear resistance and adhesion among a set of available coating materials [2]. Won-Chol Yang et al also proposed the materials selection method combined with different MADM methods such as TOPSIS and applied it to select optimal magnesium alloy material for automobile wheels [3]. K Thirumavalavan et al applied the TOPSIS and Taguchi analysis to analyze the influence of process parameters of severe surface mechanical treatment process on the surface properties of AA7075 T651 [4]. M D Sameer et al applied the TOPSIS and grey relational analysis to optimize and characterize the dissimilar friction stir welded DP600 dual phase steel and AA6082-T6 aluminium alloy sheets [5]. R A Ramnath et al reviewed the MADM techniques such as TOPSIS for optimizing the machining parameters of composites [6]. Many studies have been carried out to apply other intelligent methods such as fuzzy set theory to the MADM methods.
including the TOPSIS [8–11]. G R Jahanshahlooa et al considered the extension of the TOPSIS with fuzzy data in decision making problems [8]. J Ali et al proposed the TOPSIS model for probabilistic interval-valued hesitant fuzzy sets [9]. M G Malik et al considered the probabilistic hesitant intuitionistic linguistic term sets in multi-attribute group decision making [10]. Z Bashir et al proposed a novel multi-attribute group decision-making approach in the framework of proportional dual hesitant fuzzy sets [11].

However, the TOPSIS has a non-negligible drawback: rank reversal phenomenon. It refers to the ranks of the alternatives change when one alternative is removed from or added to the list of alternatives [12, 13]. Commonly, the stability and consistency of solution is very important characteristics of numerical analysis methods. The quality and reliability of the MADM method depends on the stability and consistency of the results of decision-making. Although the composition of alternatives is changed, the corresponding overall performance scores and ranks of the existing alternatives should be unchangeable and the evaluation results should be consistent. Since the rank reversal violates the invariance principle of utility theory, the validity of the TOPSIS could be debatable [14]. Belton and Gear first pointed out the rank reversal in analytic hierarchy process (AHP) method [15]. Wang and Luo described that the rank reversal may arise in simple additive weighting (SAW) and TOPSIS too [16].

Many scholars have carried out the studies to overcome the rank reversal phenomenon and find effective solutions in the TOPSIS. Ren et al proposed M-TOPSIS to overcome the rank reversal [17]. Kong mentioned that the vector normalization as the reason of the rank reversal and the normalization must be independent of the alternatives [18]. They proposed the most satisfactory and the most unsatisfactory attribute values to overcome the rank reversal. García-Cascales and Lamata indicated the normalization and the selection of the ideal solutions as the reason of the rank reversal in the TOPSIS [14]. They proposed a new normalization method and two fictitious alternatives with the best and the worst values of each attribute. Lahby et al proposed an enhanced TOPSIS to overcome the rank reversal [19]. Senouci et al proposed some normalization methods to eliminate the rank reversal phenomenon in the TOPSIS [20]. Mousavi-Nasab and Sotoudeh-Anvari provided a comparative analysis about the rank reversal problem in complex proportional assessment (COPRAS), TOPSIS and Vise Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) methods [21]. They proposed a new MADM-based method to overcome the rank reversal and exemplified their reasoning with thirteen cases. Aires and Ferreira reviewed the literature on the rank reversal in different MADM methods such as AHP, TOPSIS, elimination and et choice translating reality (ELECTRE), preference ranking organization method for enrichment evaluations (PROMETHEE) based on 130 related articles in the international journals [13]. Aires and Ferreira proposed R-TOPSIS with domain parameters and demonstrated its effectiveness from the statistical viewpoint [22].

Although many works have been conducted, the MADM methods such as TOPSIS still suffer from the rank reversal, and it is need to give further study to overcome the rank reversal phenomenon perfectly. So we propose an improved TOPSIS without rank reversal and apply it to materials selection.

In the following section, we describe the traditional TOPSIS and a new materials selection method using an improved TOPSIS without rank reversal based on linear max-min normalization with absolute maximum and minimum values, and the sensitivity analysis method to attribute weights on relative closeness values. In the further section, we apply the methods to select the absorbent layer material for thin film solar cells (TFSCs) and verified the effectiveness of the proposed method.

2. Methods

2.1. Traditional TOPSIS and cause of the rank reversal

There are \( n \) alternatives and \( p \) attributes (\( n, p \geq 2 \)). The alternatives are evaluated according to each attribute and the values construct a decision-matrix \( X = (x_{ik})_{n \times p} \), where \( x_{ik} \) is the measured value for \( k \)th attribute of \( i \)th alternative.

The main steps of the traditional TOPSIS are as follows [1, 2, 23–25]:

**Step 1.** Construct the normalized decision-matrix \( Z = (z_{ik})_{n \times p} \) from the decision-matrix \( X = (x_{ik})_{n \times p} \).

Commonly, the following vector normalization formula is used:

\[
z_{ik} = x_{ik} / \sqrt{\sum_{i=1}^{n} x_{ik}^2},
\]

The normalization of decision matrix is necessary to convert all the criteria values into non-dimensional form in the TOPSIS [26]. The normalization transforms different scales and units among various criteria into
common measurable units to allow comparisons across the criteria [27]. The normalization is required to transform the performance rating with different data measurement unit into a compatible unit [28].

**Step 2.** Construct the weighted normalized decision-matrix $V = (v_{ik})_{n \times p}$, where $v_{ik}$ is as follows:

$$v_{ik} = w_k \times z_{ik}; \quad i = \Gamma, \ n, \quad k = \Gamma, \ p,$$

where $w_k$ is the weight of $k$th attribute ($w_k > 0, w_1 + \ldots + w_k + \ldots + w_p = 1$).

**Step 3.** Decide the PIS $V^+ = (v^+_1, \ldots, v^+_p)$ and the NIS $V^- = (v^-_1, \ldots, v^-_p)$ as follows:

$$v^+_k = \begin{cases} \max_{1 \leq i \leq n} v_{ik}; & k \in K^+ \\ \min_{1 \leq i \leq n} v_{ik}; & k \in K^- \end{cases}$$

$$v^-_k = \begin{cases} \min_{1 \leq i \leq n} v_{ik}; & k \in K^+ \\ \max_{1 \leq i \leq n} v_{ik}; & k \in K^- \end{cases}$$

where $K^+$ and $K^-$ are respectively the index sets for the benefit and cost attributes.

**Step 4.** Calculate the distances $D_i^+$ and $D_i^-$ from the alternatives to the positive and negative ideal solutions as follows: ($i = \Gamma, \ n$)

$$D_i^+ = \sqrt{\sum_{k=1}^{p} (v^+_k - v_{ik})^2}, \quad D_i^- = \sqrt{\sum_{k=1}^{p} (v^-_k - v_{ik})^2}.$$ 

**Step 5.** Calculate the relative closeness values of the alternatives as follows:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}; \quad C_i \in [0, \ 1]; \quad i = \Gamma, \ n.$$

$C_i$ is used to order the alternatives; the greater the proximity the value of $C_i$ is to 1, the greater is its relative closeness value to the PIS, and therefore, it has a higher priority.

**Step 6.** Rank the alternatives in the descending order based on the values of $C_1, \ldots, C_n$, and decide the alternative with the maximum value as the best one.

The denominator of the vector normalization formula (equation (1)) is calculated with the attribute values of the alternatives. When the composition of the alternatives is changed, the value of the denominator is changed and the normalized values are also changed, and therefore the normalized decision-matrix is changed. The PIS and the NIS are determined from the maximum or minimum value among the attribute values of the present alternatives. When the alternative with maximum or minimum value is removed or added, the PIS and the NIS are changed. Hence the distances from the alternatives to the PIS and the NIS are changed, and the relative closeness values are also changed, and therefore, the rank reversal phenomenon may be generated.

To overcome the rank reversal, the normalization method and determination method of the PIS and the NIS should be not irrelevant to the composition of alternatives. Therefore, it is need to improve the normalization method in Step 2 and the determination method of the PIS and NIS in Step 3. From this viewpoint, we propose a new materials selection method using an improved TOPSIS without rank reversal.

2.2. Materials selection method using an improved TOPSIS without rank reversal based on linear max-min normalization with absolute maximum and minimum values

In this subsection, we propose materials selection using improved TOPSIS without rank reversal based on linear max-min normalization with absolute maximum and minimum values.

The main steps are as follows:

**Step 1.** Construct the normalized decision-matrix $Z = (z_{ik})_{n \times p}$ from the matrix $X = (x_{ik})_{n \times p}$ using the following linear max-min normalization method with absolute maximum and minimum values

$$z_{ik} = \begin{cases} (x_{ik} - L_k) / (U_k - L_k); & k \in K^+ \\ (U_k - x_{ik}) / (U_k - L_k); & k \in K^- \end{cases}$$

where $U_k$ and $L_k$ are respectively absolute maximum and minimum values of $k$th materials attribute.
Ideally, $U_k$ and $L_k$ should be least upper bound (supremum) and greatest lower bound (infimum) of $k$th attribute. In practical, these values could be determined based on knowledge and experience of materials designers and literature survey. Commonly, $U_k = \max \{ x_{ik} \}$ and $L_k = \min \{ x_{ik} \}$.

It is obviously true that the normalized values corresponding to $U_k$ and $L_k$ are as follows:

$$z_{kU} = 1, z_{kL} = 0; i = 1, n, k = 1, p.$$  

**Step 2.** Construct the weighted normalized decision-matrix $V = (v_{ik})_{n \times p}$, where $v_{ik}$ is calculated as follows:

$$v_{ik} = w_j \times z_{ik}; i = 1, n, k = 1, p.$$  

**Step 3.** Calculate the distances from the alternative materials to the PIS and the NIS ($V^+$ and $V^-$).

It is obviously true that

$$V^+ = (w_1, \ldots, w_k, \ldots, w_p), \quad V^- = (0, \ldots, 0, \ldots, 0).$$  

It is because

$$v_{k}^+ = w_k z_{kU} = w_k, \quad v_{k}^- = w_k z_{kL} = 0; \quad k = 1, p.$$  

The distances are calculated as follows:

$$D_i^+ = \sqrt{\sum_{k=1}^{p} (w_k - v_{ik})^2},$$  

$$D_i^- = \sqrt{\sum_{k=1}^{p} (0 - v_{ik})^2} = \sqrt{\sum_{k=1}^{p} v_{ik}^2}.$$  

**Step 4.** Calculate the relative closeness values of the alternative materials as follows:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad C_i \in [0, 1], \quad i = 1, n.$$  

**Step 5.** Arrange the alternative materials with the descending order based on the relative closeness values, and decide the material with the maximum value as the best one.

In Step 2, the attribute weights can be determined by the AHP or entropy weighting method [2, 29–32]. The entropy weighting formula is as follow:

$$w_k = \frac{1 - e_k}{\sum_{m=1}^{p} (1 - e_m)}, \quad k = 1, p,$$

where

$$e_k = -\frac{1}{\ln n} \sum_{i=1}^{n} \frac{p_{ik}}{\ln p_{ik}}, \quad k = 1, p,$$

$$p_{ik} = x_{ik} / \sum_{i=1}^{n} x_{ik}^i; \quad i = 1, n, k = 1, p.$$  

As shown in subsection 2.1, in the traditional TOPSIS, the following vector normalization formula is used to normalize the decision-matrix:

$$z_{ik} = x_{ik} / \sqrt{\sum_{j=1}^{n} x_{jk}^2},$$

where the denominator is relative value relevant to the composition of alternatives.
The traditional linear max-min normalization formula is as follows [2]:

\[
Z_{ik} = \frac{x_{ik} - x_{k_{\min}}}{(x_{k_{\max}} - x_{k_{\min}})}; \quad k \in K^+
\]

where \(x_{k_{\max}} = \max_{1 \leq i \leq n} \{x_{ik}\}\) and \(x_{k_{\min}} = \min_{1 \leq i \leq n} \{x_{ik}\}\) are also relative values relevant to the composition of alternatives.

In the improved TOPSIS, the following linear max-min normalization with absolute maximum and minimum values is used to normalize the decision-matrix:

\[
Z_{ik} = \begin{cases} 
\frac{(x_{ik} - L_k)}{(U_k - L_k)}; & k \in K^+ \\
\frac{(U_k - x_{ik})}{(U_k - L_k)}; & k \in K^- 
\end{cases}
\]

where \(U_k\) and \(L_k\) are unconditional values irrelevant to the composition of alternatives.

On the other hand, as shown in subsection 2.1, in the traditional TOPSIS, the PIS and NIS are relative values relevant to the alternatives. In the improved TOPSIS, the PIS \(V^+ = (w_1, \cdots, w_k, \cdots, w_p)\) and the NIS \(V^- = (0, \cdots, 0, \cdots, 0)\) are always fixed-values irrelevant to the composition of alternatives.

Accordingly, it is sure that the causes of rank reversal are eliminated, and therefore the rank reversal phenomenon does not occur in the improved TOPSIS.

Figure 1 shows the diagram of the traditional TOPSIS and improved TOPSIS.
2.3. Sensitive analysis method to attribute weights in the improved TOPSIS

To study the impacts of changing the attribute weights on the relative closeness values of the alternatives, we propose a sensitivity analysis method to attribute weights on the relative closeness.

Derive the partial derivative of the relative closeness $C_i$ of $i$th alternative with respect to $k$th attribute weight $w_k$, using the similar method in [32].

In the improved TOPSIS, since $C_i = D_i^-/(D_i^+ + D_i^-)$, $D_i^+ = \sqrt{\sum_{j=1}^{p} w_j^2 (1 - z_{ij})^2}$ and $D_i^- = \sqrt{\sum_{j=1}^{p} w_j^2 z_{ij}^2}$, we have

$$\frac{\partial C_i}{\partial w_k} = \frac{\partial C_i}{\partial D_i^+} \cdot \frac{\partial D_i^+}{\partial w_k} + \frac{\partial C_i}{\partial D_i^-} \cdot \frac{\partial D_i^-}{\partial w_k}. \tag{16}$$

In this equation,

$$\frac{\partial C_i}{\partial D_i^+} = \frac{1}{D_i^+ + D_i^-} \cdot \frac{\partial}{\partial w_k} \left[ \sum_{j=1}^{p} w_j^2 (1 - z_{ij})^2 \right], \tag{17}$$

$$\frac{\partial D_i^+}{\partial w_k} = \frac{1}{2 \sqrt{\sum_{j=1}^{p} w_j^2 (1 - z_{ij})^2}} \cdot \frac{\partial}{\partial w_k} \left[ \sum_{j=1}^{p} w_j^2 (1 - z_{ij})^2 \right] = \frac{1}{2 \sqrt{\sum_{j=1}^{p} w_j^2 (1 - z_{ij})^2}} \cdot 2 w_k^2 (1 - z_{ik})^2. \tag{19}$$

Therefore,

$$\frac{\partial D_i^-}{\partial w_k} = \frac{1}{2 \sqrt{\sum_{j=1}^{p} w_j^2 z_{ij}^2}} \cdot \frac{\partial}{\partial w_k} \left[ \sum_{j=1}^{p} w_j^2 z_{ij}^2 \right] = \frac{1}{2 \sqrt{\sum_{j=1}^{p} w_j^2 z_{ij}^2}} \cdot 2 w_k z_{ik}^2. \tag{20}$$

Therefore,

$$\frac{\partial C_i}{\partial w_k} = \frac{\partial C_i}{\partial D_i^+} \cdot \frac{\partial D_i^+}{\partial w_k} + \frac{\partial C_i}{\partial D_i^-} \cdot \frac{\partial D_i^-}{\partial w_k} = \frac{D_i^-}{(D_i^+ + D_i^-)^2} \cdot \frac{w_k(1 - z_{ik})^2}{\sqrt{\sum_{j=1}^{p} w_j^2 (1 - z_{ij})^2}} + \frac{1}{(D_i^+ + D_i^-)^2} \cdot \frac{w_k z_{ik}^2}{\sqrt{\sum_{j=1}^{p} w_j^2 z_{ij}^2}}.$$

Conclusively,

$$\frac{\partial C_i}{\partial w_k} = \frac{w_k}{\sqrt{\sum_{j=1}^{p} w_j^2 (1 - z_{ij})^2} + \sqrt{\sum_{j=1}^{p} w_j^2 z_{ij}^2}} \cdot \frac{z_{ik}^2 \sqrt{\sum_{j=1}^{p} w_j^2 (1 - z_{ij})^2} - (1 - z_{ik})^2 \sqrt{\sum_{j=1}^{p} w_j^2 z_{ij}^2}}{\sqrt{\sum_{j=1}^{p} w_j^2 (1 - z_{ij})^2} + \sqrt{\sum_{j=1}^{p} w_j^2 z_{ij}^2}}.$$

This formula becomes the analytic expression for the sensitivity analysis to attribute weights.
Table 1. Attribute values for five alternative materials [33].

| Alternative materials          | Band gap (eV) (C1) | Absorption coefficient ($\times 10^5$/s) (C2) | Diffusion length (µm) (C3) | Thermodynamic stability (eV) (C4) | Recombination velocity (cm s$^{-1}$) (C5) |
|--------------------------------|-------------------|---------------------------------------------|-----------------------------|----------------------------------|------------------------------------------|
| Copper Indium Gallium Diselenide (M1) | 1.2               | 3                                           | 0.30                        | 3.7                              | 710                                      |
| Amorphous Silicon (M2)          | 1.1               | 0.8                                         | 0.75                        | 4.3                              | 410                                      |
| Copper Indium Disulphide (M3)   | 1.53              | 1.2                                         | 0.34                        | 2.6                              | 370                                      |
| Cadmium Telluride (M4)          | 1.5               | 2                                           | 0.56                        | 5.75                             | 250                                      |
| Perylene diamine (M5)           | 0.8               | 0.5                                         | 0.78                        | 3.13                             | 140                                      |
The equation (21) can be rewritten as follows:

$$\frac{\partial C_i}{\partial w_k} = \frac{w_k}{D_i^+ + D_i^−} \left[ z_{ik}^2 (D_i^−)^2 - (1 - z_{ik})^2 (D_i^+)^2 \right].$$  \hspace{1cm} (22)

The value of $s_{ik} = \frac{\partial C_i}{\partial w_k}$ shows the degree of sensitivity to $k$th attribute weight on the overall performance score (relative closeness value) of $i$th alternative. In case of $s_{ik} > 0$, when the weight of $k$th attribute increases (decreases), the relative closeness value of $i$th alternative also increases (decreases). In case of $s_{ik} < 0$, when the weight of $k$th attribute increases (decreases), the relative closeness value of $i$th alternative decreases (increases). The absolute magnitude of $s_{ik}$ reflects the velocity of increase or decrease of the relative closeness value of $i$th alternative according to the change of $k$th attribute weight, that is, the impact of $k$th attribute weight on the relative closeness value of $i$th alternative. The value of $S_k = \frac{1}{n} \sum_{i=1}^{n} |s_{ik}|$ shows the sensitivity degree to $k$th attribute weight on the relative closeness values of all the alternatives. The larger the value of $S_k$ is, the higher the impact of $k$th attribute weight is. The attribute with largest value of $S_k$ is the most sensitive attribute.

### 3. Results and discussion

In this section, we apply the improved TOPSIS without rank reversal to select the best absorbent layer material for thin film solar cells (TFSCs).

There are some alternative materials for the TFSC absorbent layer. To improve the performance of the TFSCs, it should be selected the best material from among the possible alternative materials. The materials selection attributes are as follows: band gap, absorption coefficient, diffusion length, thermodynamic compatibility and recombination velocity [33, 34]. These are benefit attributes. Table 1 shows the attributes of five alternative materials for the absorbent layer.

We calculate the attribute weights using the entropy weighting method. Table 2 shows the values of $p_{ik}$ calculated by using equation (15) ($i = 1, 5, k = 1, 5$).

The values of $e_k$ calculated by using equation (14) are as follows: ($k = 1, p$).

0.9843, 0.889 42, 0.956 81, 0.976 57, 0.920 51.
Therefore, the attribute weights calculated by using equation (13) are as follows:

0.057 651, 0.405 95, 0.158 56, 0.086 026, 0.291 82.

### 3.1. In case of the traditional TOPSIS

In this subsection, we apply the traditional TOPSIS to select the best absorbent layer material for the TFSCs. Tables 3 and 4 show the normalized decision-matrix, the weighted normalized decision-matrix, the PIS and NIS. Table 5 shows the distances from the alternatives to the PIS and NIS, the relative closeness values and their ranks. As can be seen in table 5, the ranks of the absorbent layer materials are respectively 1, 3, 4, 2 and 5. The material M1 (copper indium gallium diselinide) was selected as the best absorbent layer material.

Next, we survey the rank reversal when the worst material M5 is removed. When the worst material M5 is removed, the normalized decision-matrix is shown in table 6.

Table 7 shows the weighted normalized decision-matrix, PIS and NIS. Table 8 shows the distances from the alternative absorbent layer materials to the PIS and NIS, the relative closeness values and their ranks. Table 8 demonstrates that the traditional TOPSIS has the rank reversal.

Figure 2 shows the relative closeness values of the alternatives using the traditional TOPSIS when the worst material M5 is removed.

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**Table 5.** Distances to the PIS and NIS, the relative closeness values and their ranks (Traditional TOPSIS).

| Alternative materials | $D^+$  | $D^-$  | $C$    | Rank |
|------------------------|--------|--------|--------|------|
| M1                     | 0.062 075 | 0.3137 | 0.834 81 | 1    |
| M2                     | 0.2468 | 0.106 04 | 0.300 54 | 4    |
| M3                     | 0.222 83 | 0.102 81 | 0.315 73 | 3    |
| M4                     | 0.178 01 | 0.165 69 | 0.482 07 | 2    |
| M5                     | 0.314 77 | 0.058 759 | 0.157 31 | 5    |

**Table 6.** Normalized decision-matrix when the worst material M5 is removed (Traditional TOPSIS).

| Alternative materials | C1    | C2    | C3    | C4    | C5    |
|------------------------|-------|-------|-------|-------|-------|
| M1                     | 0.445 95 | 0.772 54 | 0.288 45 | 0.436 04 | 0.7605 |
| M2                     | 0.408 79 | 0.206 01 | 0.721 12 | 0.506 75 | 0.439 16 |
| M3                     | 0.568 58 | 0.309 02 | 0.326 91 | 0.306 41 | 0.396 32 |
| M4                     | 0.557 44 | 0.515 03 | 0.538 44 | 0.677 63 | 0.267 78 |

**Table 7.** Weighted normalized decision-matrix, PIS and NIS when the worst material M5 is removed (Traditional TOPSIS).

| Alternative materials | C1    | C2    | C3    | C4    | C5    |
|------------------------|-------|-------|-------|-------|-------|
| M1                     | 0.025 709 | 0.313 61 | 0.045 735 | 0.037 511 | 0.221 93 |
| M2                     | 0.023 567 | 0.083 63 | 0.114 34 | 0.043 594 | 0.128 15 |
| M3                     | 0.032 78 | 0.125 45 | 0.051 833 | 0.026 359 | 0.115 65 |
| M4                     | 0.032 137 | 0.299 08 | 0.085 372 | 0.058 294 | 0.078 143 |
| PIS                     | 0.032 78 | 0.313 61 | 0.114 34 | 0.058 294 | 0.221 93 |
| NIS                     | 0.023 567 | 0.083 63 | 0.045 735 | 0.026 359 | 0.078 143 |

**Table 8.** Distances to the PIS and NIS, the relative closeness values and their ranks when the worst material M5 is removed (Traditional TOPSIS).

| Alternative materials | $D^+$  | $D^-$  | $C$    | Rank |
|------------------------|--------|--------|--------|------|
| M1                     | 0.072 03 | 0.271 47 | 0.790 31 | 1    |
| M2                     | 0.248 97 | 0.086 629 | 0.258 13 | 3    |
| M3                     | 0.227 22 | 0.057 249 | 0.201 25 | 4    |
| M4                     | 0.180 11 | 0.135 65 | 0.429 59 | 2    |
As can be seen in tables 3–8, the normalized and weighted normalized decision matrices, the PIS and NIS, the distances to the PIS and NIS, the relative closeness values and their ranks are changed when the worst material M5 is removed.

### 3.2. In case of the improved TOPSIS without rank reversal

In this subsection, we apply the improved TOPSIS without rank reversal to select the best absorbent layer material for the TFSCs.

We introduce the absolute maximum and minimum values of each attribute according to knowledge and experience of materials designers and engineers.

The absolute minimum values of each attribute are as follows:

**Table 9. Normalized decision-matrix (Improved TOPSIS).**

| Alternative materials | C1     | C2     | C3     | C4     | C5     |
|-----------------------|--------|--------|--------|--------|--------|
| M1                    | 0.466  | 0.722  | 0.125  | 0.425  | 0.871  |
| M2                    | 0.4    | 0.111  | 0.6875 | 0.575  | 0.442  |
| M3                    | 0.686  | 0.222  | 0.175  | 0.15   | 0.385  |
| M4                    | 0.666  | 0.444  | 0.45   | 0.9375 | 0.214  |
| M5                    | 0.2    | 0.027  | 0.725  | 0.2825 | 0.057  |

**Table 10. Weighted normalized decision-matrix (Improved TOPSIS).**

| Alternative materials | C1     | C2     | C3     | C4     | C5     |
|-----------------------|--------|--------|--------|--------|--------|
| M1                    | 0.026  | 0.293  | 0.019  | 0.036  | 0.254  |
| M2                    | 0.023  | 0.045  | 0.109  | 0.049  | 0.129  |
| M3                    | 0.039  | 0.090  | 0.027  | 0.012  | 0.112  |
| M4                    | 0.038  | 0.180  | 0.071  | 0.080  | 0.062  |
| M5                    | 0.011  | 0.011  | 0.114  | 0.024  | 0.016  |

**Table 11. Distances to the PIS and NIS, the relative closeness values and their ranks (Improved TOPSIS).**

| Alternative materials | $D^+$  | $D^-$  | C      | Rank |
|-----------------------|--------|--------|--------|------|
| M1                    | 0.191  | 0.391  | 0.671  | 1    |
| M2                    | 0.402  | 0.183  | 0.313  | 3    |
| M3                    | 0.393  | 0.0152 | 0.279  | 4    |
| M4                    | 0.333  | 0.0222 | 0.400  | 2    |
| M5                    | 0.489  | 0.119  | 0.196  | 5    |

As can be seen in tables 3–8, the normalized and weighted normalized decision matrices, the PIS and NIS, the distances to the PIS and NIS, the relative closeness values and their ranks are changed when the worst material M5 is removed.
The absolute maximum values of each attribute are as follows: 2, 4, 1, 6, 800.

Since the PIS and the NIS are always \( V^+ = (w_1, \cdots, w_k, \cdots, w_p) \) and \( V^- = (0, \cdots, 0, \cdots, 0) \) in the proposed method, we have \( V^+ = (0.057 651, 0.405 95, 0.158 56, 0.086 026, 0.291 82) \) and \( V^- = (0, 0, 0, 0, 0) \). Table 9 shows the normalized decision-matrix.

Table 10 shows the weighted normalized decision-matrix. Table 11 shows the distances from the alternative absorbent layer materials to the PIS and the NIS, the relative closeness values and their ranks. As can be seen in table 11, the ranks of the absorbent layer materials are respectively 1, 3, 4, 2 and 5. The material M1 is selected as the best absorbent layer material.

Next, we survey the rank reversal when each absorbent layer material is removed.

Table 12 shows the normalized decision-matrix when the worst material M5 is removed. Table 13 shows the distances to the PIS and NIS, the relative closeness values and the ranks of the remaining materials when the worst material M5 is removed.

Figure 3 shows the relative closeness values of the alternatives using the improved TOPSIS when the worst material M5 is removed.

As can be seen in tables 9, 11–13, the normalized decision-matrix, the distances to the PIS and NIS, the relative closeness values and the ranks of the alternative materials don’t changed at all when the worst material M5 is removed. It is because that the normalized decision-matrix, the PIS and NIS don’t changed when the worst material M5 is removed. They are still \( V^+ = (0.057 651, 0.405 95, 0.158 56, 0.086 026, 0.291 82) \) and \( V^- = (0, 0, 0, 0, 0) \).
Table 14 shows the ranks of the absorbent layer materials when each alternative material is removed (Improved TOPSIS).

| Removed material | M1 | M2 | M3 | M4 | M5 |
|------------------|----|----|----|----|----|
| —                | 1  | 3  | 4  | 2  | 5  |
| M1               | 2  | 3  | 1  | 4  |    |
| M2               | 1  | 3  | 2  | 4  |    |
| M3               | 1  | 3  | 2  | 4  |    |
| M4               | 1  | 2  | 3  | 4  |    |
| M5               | 1  | 3  | 4  | 2  |    |

Table 15 demonstrates that there is no rank reversal when each alternative material is removed. Above results demonstrate that the improved TOPSIS overcomes the rank reversal perfectly. In all cases, M1 was evaluated as the best material and the next was M4. M5 was evaluated as the worst material.

3.3. Sensitivity analysis result to attribute weights

In this subsection, we conduct the sensitive analysis to attribute weights on the relative closeness values of the alternatives.

Table 15 shows the sensitivity matrix to attribute weights on the relative closeness value of the alternatives and the values of $S_k; k = 1, 2, \ldots, 5$ at the attribute weights $w_1 = 0.057651, w_2 = 0.40595, w_3 = 0.15856, w_4 = 0.086026$ and $w_5 = 0.29182$.

| Alternatives | C1     | C2     | C3     | C4     | C5     |
|--------------|--------|--------|--------|--------|--------|
| M1           | −0.046844 | 0.068356 | −0.42282 | −0.086491 | 0.16939 |
| M2           | 0.0184  | −0.23106 | 0.26877  | 0.094478 | 0.14391 |
| M3           | 0.1242  | −0.080104 | −0.053855 | −0.035079 | 0.1265 |
| M4           | 0.061397 | 0.06603  | 0.029081 | 0.20342  | −0.17975 |
| M5           | 0.00063484 | −0.15216 | 0.55421  | 0.028247 | −0.097902 |
| $S_k$        | 0.050299 | 0.11954  | 0.26575  | 0.089543 | 0.14349 |

| Rank | 5 | 3 | 1 | 4 | 2 |

Table 16. Ranks of sensitivity to the attribute weights on the relative closeness values of each alternatives at the attribute weights $w_1 = 0.057651, w_2 = 0.40595, w_3 = 0.15856, w_4 = 0.086026$ and $w_5 = 0.29182$.

| Alternatives | C1 | C2 | C3 | C4 | C5 |
|--------------|----|----|----|----|----|
| M1           | 5  | 4  | 1  | 3  | 2  |
| M2           | 5  | 2  | 1  | 4  | 3  |
| M3           | 2  | 3  | 4  | 5  | 1  |
| M4           | 4  | 3  | 5  | 1  | 2  |
| M5           | 5  | 2  | 1  | 4  | 3  |

Table 14 shows the ranks of the alternative materials when each alternative material is removed. Table 14 demonstrates that there is no rank reversal when each alternative material is removed. Above results demonstrate that the improved TOPSIS overcomes the rank reversal perfectly. In all cases, M1 was evaluated as the best material and the next was M4. M5 was evaluated as the worst material.

3.3. Sensitivity analysis result to attribute weights

In this subsection, we conduct the sensitive analysis to attribute weights on the relative closeness values of the alternatives.

Table 15 shows the sensitivity matrix to attribute weights on the relative closeness value of the alternatives and the values of $S_k; k = 1, 2, \ldots, 5$ at the attribute weights $w_1 = 0.057651, w_2 = 0.40595, w_3 = 0.15856, w_4 = 0.086026$ and $w_5 = 0.29182$ (from the entropy weighting method).

In Table 15, the values of $S_k; k = 1, 2, \ldots, 5$ shows that the weight of the third attribute C3 (diffusion length) has the highest sensitivity on the relative closeness values of all the alternatives ($S_3 = 0.26575$), and the next are the fifth attribute C5 (recombination velocity), the second attribute C2 (absorption coefficient), etc. Meanwhile, the weight of the first attribute C1 (band gap) has the lowest sensitivity. The rank of sensitivity of the attribute weights on the relative closeness values of all the alternatives is as follows:

C3 (diffusion length) > C5 (recombination velocity) > C2 (absorption coefficient) > C4 (thermodynamic stability) > C1 (band gap).

When the weight of the third attribute increases/decreases, the relative closeness values of M1 and M3 will decrease/increase, and the relative closeness values of M5, M2 and M4 will increase/decrease. When its weight is

---

| Alternatives | C1 | C2 | C3 | C4 | C5 |
|--------------|----|----|----|----|----|
| M1           | 5  | 4  | 1  | 3  | 2  |
| M2           | 5  | 2  | 1  | 4  | 3  |
| M3           | 2  | 3  | 4  | 5  | 1  |
| M4           | 4  | 3  | 5  | 1  | 2  |
| M5           | 5  | 2  | 1  | 4  | 3  |
The proposed method overcomes the rank reversal phenomenon, perfectly. Applying it to select the best absorbent layer material for TFSCs. We proposed the materials selection method using an improved TOPSIS without rank reversal based on linear max-min normalization with absolute maximum and minimum values and demonstrated its effectiveness by applying it to select the best absorbent layer material for TFSCs.

### 4. Conclusions

We proposed the materials selection method using an improved TOPSIS without rank reversal based on linear max-min normalization with absolute maximum and minimum values and demonstrated its effectiveness by applying it to select the best absorbent layer material for TFSCs.

Conclusively, the following conclusions are drawn:

- The proposed method overcomes the rank reversal phenomenon, perfectly.

| Alternatives | C1     | C2     | C3     | C4     | C5     |
|--------------|--------|--------|--------|--------|--------|
| M1           | −0.040488 | 0.16046 | −0.32046 | −0.073938 | 0.27443 |
| M2           | −0.041904 | −0.26387 | 0.20641 | 0.10599 | −0.006623 |
| M3           | 0.33843  | −0.096783 | −0.12794 | −0.14346 | 0.029765 |
| M4           | 0.10436  | −0.073139 | −0.069568 | 0.30588 | −0.26853 |
| M5           | −0.081258 | −0.16955 | 0.433143 | −0.024891 | −0.15735 |
| Sk_k         | 0.12129  | 0.15276  | 0.23128 | 0.13083 | 0.14733  |
| Rank         | 5       | 2       | 1      | 4      | 3       |

| Alternatives | C1     | C2     | C3     | C4     | C5     |
|--------------|--------|--------|--------|--------|--------|
| M1           | 5       | 3       | 1      | 4      | 2       |
| M2           | 4       | 1       | 2      | 3      | 5       |
| M3           | 1       | 4       | 3      | 2      | 5       |
| M4           | 3       | 4       | 5      | 1      | 2       |
| M5           | 4       | 2       | 1      | 5      | 3       |

When the weight of the fifth attribute increases/decreases, the relative closeness values of M1, M2 and M3 will increase/decrease, and the relative closeness values of M4 and M5 will decrease/increase. When its weight is changed, the relative closeness values of M4, M1, M2 and M4 have similar amount of change and the relative closeness value of M3 has the smallest amount of change.

The similar analysis could be conducted for other attributes.

Table 16 shows the ranks of sensitivity to the attribute weights on the overall performances of each alternatives at the attribute weights $w_1 = 0.057651, w_2 = 0.40595, w_3 = 0.15856, w_4 = 0.086026$ and $w_5 = 0.29182$. As shown in table 16, the weight of C3 has the highest sensitivity on the relative closeness values of the alternatives M1, M2 and M5, the weight of C4 has the highest sensitivity on the relative closeness value of the alternative M4, and the weight of C5 has the highest sensitivity on the relative closeness value of the alternative M3.

Table 17 shows the sensitivity matrix to attribute weights on the relative closeness values of the alternatives and the values of $S_k; k = 1, 2, \ldots, 5$ at the attribute weights $w_1 = w_2 = w_3 = w_4 = w_5 = 1/5$ (equal weights).

Tables 15 and 17 demonstrate that the sensitivity values to attribute weights are changed according to the current weights of the attributes.

At the attribute weights $w_1 = w_2 = w_3 = w_4 = w_5 = 1/5$, the rank of sensitivity of the attribute weights on the relative closeness values of all the alternatives is as follows:

- C3 (diffusion length) > C2 (absorption coefficient) > C5 (recombination velocity) > C4 (thermodynamic stability) > C1 (band gap).

Table 18 shows the ranks of sensitivity to the attribute weights on the relative closeness values of each alternatives at the attribute weights $w_1 = w_2 = w_3 = w_4 = w_5 = 1/5$.

In the same way, we can evaluate the impacts of changing the attribute weights on the relative closeness values of the alternatives.

### Table 17. Sensitivity to attribute weights on the relative closeness values of the alternatives at the attribute weights $w_1 = w_2 = w_3 = w_4 = w_5 = 1/5$.  

| Alternatives | C1     | C2     | C3     | C4     | C5     |
|--------------|--------|--------|--------|--------|--------|
| M1           | −0.040488 | 0.16046 | −0.32046 | −0.073938 | 0.27443 |
| M2           | −0.041904 | −0.26387 | 0.20641 | 0.10599 | −0.006623 |
| M3           | 0.33843  | −0.096783 | −0.12794 | −0.14346 | 0.029765 |
| M4           | 0.10436  | −0.073139 | −0.069568 | 0.30588 | −0.26853 |
| M5           | −0.081258 | −0.16955 | 0.433143 | −0.024891 | −0.15735 |
| $S_k$        | 0.12129  | 0.15276  | 0.23128 | 0.13083 | 0.14733  |
| Rank         | 5       | 2       | 1      | 4      | 3       |

### Table 18. Ranks of sensitivity to the attribute weights on the relative closeness values of each alternatives at the attribute weights $w_1 = w_2 = w_3 = w_4 = w_5 = 1/5$.  

| Alternatives | C1     | C2     | C3     | C4     | C5     |
|--------------|--------|--------|--------|--------|--------|
| M1           | 5       | 3       | 1      | 4      | 2       |
| M2           | 4       | 1       | 2      | 3      | 5       |
| M3           | 1       | 4       | 3      | 2      | 5       |
| M4           | 3       | 4       | 5      | 1      | 2       |
| M5           | 4       | 2       | 1      | 5      | 3       |
The relative closeness values are absolute values irrelevant to the composition of the alternatives in the proposed TOPSIS, while the values are relative values relevant in the traditional TOPSIS.

Its computation is simpler than the traditional TOPSIS. Since the PIS is always equal to attribute weight vector and the NIS is always equal to zero vector, it is not necessary to determine the PIS and NIS. Moreover, the distance calculation from the alternatives to the PIS and NIS is simpler than the traditional TOPSIS.

It is enable to evaluate the superiority or inferiority of each attribute for each alternative from the normalized decision matrix. The greater the normalized value is, the more superior the corresponding attribute of the alternative is, and the smaller it is, the more inferior the corresponding attribute of the alternative is.

In the best absorbent layer material selection for TFSCs, copper indium gallium diselinide was selected as the best material and the next cadmium telluride from among five absorbent layer materials for the TFSCs by using the improved TOPSIS.

The method to derive the analytic expression for sensitivity analysis and the sensitive analysis method could be also applied to the other MADM methods.

The proposed method could be applied to many real materials selection problems in practice, actively and effectively.

In this work, the rational method to determine the absolute maximum and minimum values of the attributes was not considered. And the work to overcome the rank reversal in the other well-known MADM methods was not considered owing to limited space and time. Future work needs to deal these problems.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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Appendix. MATLAB code for improved TOPSIS method

```matlab
clc; clear all; close all;

%% Improved TOPSIS without rank reversal
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X = [1.2 3 0.30 3.7 710 1.1 0.8 0.75 4.3 410]
```

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1.53 1.2 0.34 2.6 370
1.5 2.0 5.56 5.75 250
0.8 0.5 0.78 3.13 140

Cate = [2 2 2 2]; % Attribute type: 1-cost, 2-benefit
L = [0.5, 0.4, 0.2, 2, 100]; % Absolute minimum values
U = [2, 4, 1, 6, 800]; % Absolute maximum values
disp(’%SENSITIVITY TO ATTRIBUTE WEIGHT %’)
[N,P] = size(X);
for i = 1:N
for j = 1:P
p(i,j) = X(i,j)/sum(X(:,j));
if p(i,j) == 0
p(i,j) = 0.000 000 000 01;
end
end
end
for j = 1:P
e(j) = -1/log(N)*sum(p(:,j).*log(p(:,j)));
end
g = 1−e;
W = g./sum(g)
disp(’%IMPROVED TOPSIS %’)
for j = 1:P
if (Cate(j) == 1)
Z(:,j) = (U(j)−X(:,j))/(U(j)−L(j));
elseif (Cate(j) == 2)
Z(:,j) = (X(:,j)−L(j))/(U(j)−L(j));
end
end
for j = 1:P
V(:,j) = W(j)*Z(:,j);
end
Vp = W;Vm = zeros(size(W));
Z,V,Vp,Vm
for i = 1:N
Dp(i) = norm(Vp−V(i,:));
Dm(i) = norm(Vm−V(i,:));
end
C = Dm./(Dm+Dp);
Cr = N + 1-tiedrank(C);
o_Dp_Dm_C_Rank = [1:N]’ Dp’ Dm’ C’ Cr’
disp(’%SENSITIVITY TO ATTRIBUTE WEIGHT %’)
for i = 1:N
for k = 1:P
S(i,k) = W(k)/(Dp(i)+Dm(i))’((Z(i,k)^2*Dp(i)^2 2 ... -(1−Z(i,k))^2*Dm(i)^2)/(Dp(i)^2*Dm(i)));
end
end
S
S_Sum = mean(abs(S))
S_Sum_Rank = P + 1-tiedrank(S_Sum)
S_Rank = (P + 1-tiedrank(abs(S)))’

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