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# Note on the Application of Intuitionistic Fuzzy TOPSIS Model for Dealing With Dependent Attributes

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## ABSTRACT

In this article, the effectiveness of the intuitionistic fuzzy TOPSIS model (IF-TOPSIS$_{EF}$) is tested for addressing, capturing, and resolving the effect of correlation between attributes, otherwise called the dependency of attributes. This was achieved by using several normalization methods in the implementation of the IF-TOPSIS$_{EF}$ model. Furthermore, the result of the computation is compared with the one obtained when the normalization methods are implemented using a traditional TOPSIS model. The study contributes and extends the state of the art in TOPSIS method study, by addressing, capturing and resolving the effect of correlation between attributes otherwise called dependency of attributes.

## KEYWORDS

Dependency of Attributes, IF-TOPSISEF, Intuitionistic Fuzzy TOPSIS Model, Traditional TOPSIS Model

## 1. INTRODUCTION

TOPSIS is one of the most widely used decision-making techniques (Aikhuele & Turan, 2017). It was developed by Hwang and Yoon in 1981, and is based on the concept that the most appropriate alternative in a set of alternatives should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. Where the positive ideal solution tends to maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Behzadian et al., 2012). The method has a compensatory aggregation, that compares sets of alternatives by

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identifying the weights for each criterion, and the normalize the scores for the criterion and calculating the geometric distance between each of the alternative and the ideal alternative, which is regarded as the best score in each of the criterion. The rating and assigning of weight are done by a group of decision makers hence the process is said to be imprecise, since human judgments are vague and cannot be estimated with exact numeric values. However, to resolve the ambiguity arising from the rating scale and vague human judgments, Chen (2000) presented an extension of the TOPSIS model to the fuzzy environment, giving numerical example of a system analysis engineer selection for a software company.

Ever since, several other authors have contributed and extended the TOPSIS model in the fuzzy environment, some of which include, Awasthi et al (2011) who presented a fuzzy TOPSIS model for the evaluation and selection of the best location for siting an urban distribution centre, the model used the fuzzy set-based theory for quantifying the criteria values under uncertainty. Chen and Tsao (2008) proposes an extension of the TOPSIS method based on interval-valued fuzzy sets in decision analysis, using a comprehensive experimental analysis to observe the interval-valued fuzzy TOPSIS results yielded by different distance measures. Chu (2002) applied the fuzzy TOPSIS model for the selection of plant location, where the ratings and weights assigned by decision makers are averaged and normalized into a comparable scale. Tsaura et al. (2002) applies the fuzzy set theory for the evaluation of service quality of an airline company. Ding (2011) uses the fuzzy TOPSIS model for improving the quality of decision making and for ranking alternatives, the fuzzy TOPSIS model also accounts for the classification of criteria by integrating the weight of criteria and that of the sub-criteria.

Yong-tao et al. (2010) applies the Fuzzy TOPSIS approach in assisting contractors in selecting appropriate projects for bidding, the model which considered multiple attributes, integrates the opinions of a group experts. Linguistic terms were used in gathering the expert's opinion and was later converted to the triangular fuzzy numbers for onward ratings of alternatives. Aguarón-Joven (2015), discuss the assumption in TOPSIS methodology that all contemplated attributes are independent in nature, they further suggest the need to extend the state of the art to address the dependency issue of attributes since TOPSIS model measures distances in the Euclidean norm. The majority of published literature on the TOPSIS methodology has always assume the independency of attributes. In this paper however, some examples have are presented to show the effectiveness of the Intuitionistic fuzzy TOPSIS model which is based on exponential-related function (IF-$\text{TOPSIS}_{\text{EF}}$) originally proposed in (Aikhuele & Turan, 2017; Aikhuele & Turan, 2016) for dealing with attributes dependency issues. This is achieved by implementing the traditional TOPSIS model originally proposed by Hwang & Yoon (2000) using several normalization methods and then compared the results with the ones from the IF-$\text{TOPSIS}_{\text{EF}}$ under the same condition. The study contributes and have extend the state of the art in the study of TOPSIS methodology by addressing, capturing and resolving the effect of correlation between attributes otherwise called dependency of attributes.

The rest of the paper is organized as follows; in the proceeding Section, the computational steps of the traditional TOPSIS model and that of the IF-TOPSIS$_{EF}$ model are presented. In section 3, a numerical case study is presented to demonstrate the effectiveness of the model, while some concluding remarks on resolving the dependency issues of Attributes and a theoretical comparison of proposed method with the traditional fuzzy TOPSIS method are given in section 4.

## 2. PRELIMINARIES

In this section, the implementation steps of the traditional TOPSIS model as described (Cables et al., 2012; Afsordegan, 2015; Aikhuele & Turan, 2016) are presented as shown in Table 1, while the proposed computational algorithm of the IF-TOPSIS$_{EF}$ is given in the subsection.

### 2.1. The Proposed IF-TOPSIS$_{EF}$ Model

Let consider an MAGDM problem where a set of alternatives $A = \left\{A_1, A_2, A_3, \ldots, A_m\right\}$, are assessed with respect to the attributes denoted by $C = \left\{C_1, C_2, C_3, \ldots, C_m\right\}$. The characteristics of the alternative $A_i$ with respect to an attribute $C_j$ are defined first with linguistic variable and then converted to an Intuitionistic Fuzzy Set (IFS) value $a_{ij} = \left(\mu_{ij}, v_{ij}\right)$ $\left(i = 1, 2, \ldots, m, j = 1, 2, \ldots, n\right)$, which represents the membership, non-membership and hesitancy degree of the alternative $A_i \in A$ with respect to the attribute $C_j \in C$ for the intuitionistic fuzzy concept. As compared to the traditional TOPSIS algorithm, the proposed IF-TOPSIS$_{EF}$ model offers a general view of TOPSIS with group preference aggregation. The computation algorithm of the IF-TOPSIS$_{EF}$ is given in the following steps:

**Step 1:** Set up a group of Decision-makers (DMs) and aggregate all their individual assessment matrices $D^k \left(k = 1, 2, 3, \ldots, l\right)$ into one comprehensive group assessment matrix $R_{mxn}(a_{ij})$ using the intuitionistic fuzzy weighted geometric (IFWG) operator (Li, 2014) (see Equation 2):

**Table 1. The main implementation steps**

| | Computational Steps of the Traditional Fuzzy TOPSIS Method |
|---|---|
| 1 | The construction of Decision matrix |
| 2 | The Normalization of the decision matrix |
| 3 | The weighted normalization of the decision matrix |
| 4 | Determination of the Positive Ideal Solution (PIS) and the Negative Ideal Solutions (NIS) |
| 5 | Calculation of the distances of each alternative to the positive and negative ideal solutions |
| 6 | Calculation of the Closeness Coefficient (CC) of all the alternatives and finally |
| 7 | Ranking of the alternatives |

$$R_{mxn}\left(a_{ij}\right)=\begin{bmatrix}\left(\mu_{11},v_{11}\right) & \left(\mu_{12},v_{12}\right) & \cdots & \left(\mu_{1n},v_{1n}\right)\\ \left(\mu_{21},v_{21}\right) & \left(\mu_{22},v_{22}\right) & \cdots & \left(\mu_{2n},v_{2n}\right)\\ \vdots & \vdots & \ddots & \vdots\\ \vdots & \vdots & \ddots & \vdots\\ \left(\mu_{m1},v_{m1}\right) & \left(\mu_{m2},v_{m2}\right) & \cdots & \left(\mu_{mn},v_{mn}\right)\end{bmatrix} \tag{1}$$

$$IFWG\left(d_1 d_2 d_3,\ldots,d_n\right)=\left(\prod_{\mathrm{i}=1}^{\mathrm{n}}\left(\mu_{ij}\right)^{\gamma_j},1-\prod_{i=1}^{n}\left(1-v_{ij}\right)^{\gamma_j}\right) \tag{2}$$

where $\mu_{ij}$ is the membership function, $v_{ij}$ the non-membership while $\gamma_j$ is the weight vector of the DMs.

**Remark:** If the data show clear dependents the comprehensive group assessment matrix should be normalized.

**Step 2:** Construct the exponential-related matrix.

Using the exponential-related function (*ER)*, the intuitionistic fuzzy decision matrix $R_{mxn}\left(a_{ij}\right)$ is converted into the exponential related matrix $ERM_{mxn}\left(ER_{ij}\left(a_{ij}\right)\right)$ which represents the aggregated effect of the positive and negative evaluations in the performance ratings of the alternatives based on the intuitionistic fuzzy set (IFS) data:

$$ER\left(A\right)=\ e^{\left(\frac{1-\left(\mu^2-v^2\right)}{3}\right)},\text{where } E\quad R\left(A\right)\in\left[1/e,\ e\right] \tag{3}$$

where $\mu$ the membership function, while *v* is the non-membership function of the IFS:

$$ERM_{mxn}\left(E_{ij}\left(a_{ij}\right)\right)=\begin{bmatrix}ER_{11}\left(x_{11}\right) & ER_{12}\left(x_{12}\right) & \ldots & ER_{1n}\left(x_{1n}\right)\\ ER_{22}\left(x_{22}\right) & ER_{22}\left(x_{22}\right) & \ldots & ER_{2n}\left(x_{2n}\right)\\ \vdots & \vdots & \ddots & \vdots\\ \vdots & \vdots & \ddots & \vdots\\ ER_{m1}\left(x_{m1}\right) & ER_{m2}\left(x_{m2}\right) & \ldots & ER_{mn}\left(x_{mn}\right)\end{bmatrix} \tag{4}$$

**Step 3:** Determine the weight of the attributes using the intuitionistic fuzzy entropy (IFE) method.

Following the operations of the IFS and based on the generalization of fuzzy information entropy, the intuitionistic fuzzy entropy method which is based on subjective and objective approach is defined.

**Definition 4.2 (Liu & Ren, 2014):** See below.

Let us consider an intuitionistic fuzzy set $A$ in the universe of discourse. .The intuitionistic fuzzy set $A$ can be transformed into a fuzzy set to structure an entropy measure of the intuitionistic fuzzy set by means of $\mu_{\bar{A}}\left(x_i\right)=\left(\mu_A\left(x_i\right)+1-v_A\left(x_i\right)\right)/2$. Based on the definition of fuzzy information entropy, Liu & Ren (2014) proposes the intuitionistic fuzzy entropy method for the computation of attribute weights when the weight information is completely unknown. By describing the entropy measures of the intuitionistic fuzzy set $A$ as a trigonometric function:

$$E\left(A\right)=\frac{1}{n}\sum_{i=1}^{n}\mathrm{Cot}\left(\frac{\pi}{4}+\frac{\left|\mu^2{}_A\left(x_i\right)-v^2{}_A\left(x_i\right)\right|}{4}\pi\right) \tag{5}$$

while the attribute weight is defined as:

$$\omega_j=\frac{1-H_j}{n-\sum_{j=0}^{n}H_j}$$

where $\omega_j\in\left[0,1\right]$, $\sum_{j=1}^{n}\omega_j=1$, $H_j=\frac{1}{m}E\left(A_j\right)$ and $0\leq H_j\leq 1$ for $\left(j=1,2,3,\ldots,n\right)$.

**Step 4:** Define the intuitionistic fuzzy positive and negative ideal solution.

The intuitionistic fuzzy positive ideal solution (IFPIS) $A^+=\left(\mu_j,v_j\right)$ and the intuitionistic fuzzy negative ideal solution (IFNIS) $A^-=\left(\mu_j,v_j\right)$, for the IF-TOPSIS$_{\mathrm{EF}}$ model applied in this thesis is predetermined for the computation of the exponential related function-based distance method as shown below:

$$A^+=\left\{C_j,\left[1,1\right]\left|C_j\in C\right.\right\},\quad j=1,2,3,\ldots,n \tag{6}$$

$$A^-=\left\{C_j,\left[0,0\right]\left|C_j\in C\right.\right\},\quad j=1,2,3,\ldots,n \tag{7}$$

**Step 5:** Compute the exponential related function-based separation measures.

Using the exponential related matrix $ERM_{mxn}\left(ER_{ij}\left(a_{ij}\right)\right)$ and the attribute weights, under an intuitionistic fuzzy environment the exponential related function-based separation measures $(d^+{}_i(A^+,\ A_i)$ and $\left(d^-{}_i\left(A^-,A_i\right)\right)$ for each alternative from the IFPIS and IFNIS is calculated:

$$d^+_i\left(A^+, A_i\right) = \sqrt{\sum_{i=1}^{n}\left[\omega_j\left(1-\left(ERM_{nxm}\left(a_{ij}\right)\right)\right)\right]^2} \tag{8}$$

$$d^+_i\left(A^+, A_i\right) = \sqrt{\sum_{i=1}^{n}\left[\omega_j\left(ERM_{nxm}\left(a_{ij}\right)\right)\right]^2} \tag{9}$$

where $\omega_j$ is the weight of the criteria.

**Step 6:** Calculate the relative closeness coefficient of each alternative to the IFPIS.

Compute the relative closeness coefficient, $\left(CC_i\right)$, which is defined to rank all possible alternatives with respect to the IFPIS $A^+$. The general formula is given as:

$$CC_i = \frac{d^-_i\left(A^-, A_i\right)}{d^-_i\left(A^-, A_i\right) + d^+_i\left(A^+, A_i\right)} \tag{10}$$

where $CC_i\left(i = 1,2, ..n\right)$ is the relative closeness coefficient of $A_i$ with respect to the positive ideal solution $A^+$ and $0 \le CC_i \le 1$.

**Step 7:** Rank the alternatives in the descending order.

## 3. ILLUSTRATIVE EXAMPLES

To prove the effectiveness of the models in addressing, capturing and resolving the effect of correlation between attributes otherwise called dependency of attributes, two illustrative examples from literature are presented.

**Example 1:** Let us consider a practical MADM problem originally reported by Hung & Chen (2009) to demonstrate the effect of dependent attributes on the final ranking result. Careful observation of the decision matrix as given in Table 2 shows some few dependencies of the criteria on each other, as it relates to data having the

**Table 2. Decision matrix**

| | $C_1$ | $C_2$ | $C_3$ |
|---|---|---|---|
| $A_1$ | (0.70, 0.20) | (0.85, 0.10) | (0.30, 0.50) |
| $A_2$ | (0.90, 0.05) | (0.70, 0.25) | (0.40, 0.50) |
| $A_3$ | (0.80, 0.10) | (0.85, 0.10) | (0.30, 0.60) |
| $A_4$ | (0.90, 0.00) | (0.80, 0.10) | (0.20, 0.70) |
| $A_5$ | (0.80,0.15) | (0.75, 0.20) | (0.50, 0.40) |

same values. We determine the best alternative with respect to the criteria using the TOPSIS methodology and then the IF-TOPSIS$_{EF}$ model with the following normalization modes; Ideal normalization (IN) method, Distributive normalization (DN) method and Linear Max-Min normalization (LMM) method.

**Ideal normalization (IN) method:** The ideal normalization method requires dividing each element in column by the highest value or lowest value depending if the criteria were to be maximized or minimized i.e.:

$$r_{ai} = \frac{x_{ai}}{u_a^{+}},\ for\ \ a = 1,\ldots,n\ \ and\ \ i = 1,2,\ldots m$$

where:

$$u_a^{+} = \max\left(x_{ai}\right) for\ \ all\ \ a = 1,\ldots,n$$

Similarly:

$$r_{ai} = \frac{x_{ai}}{u_a^{-}},\ for\ \ a = 1,\ldots,n\ \ and\ \ i = 1,2,\ldots m$$

where:

$$u_a^{-} = \max\left(x_{ai}\right) for\ \ all\ \ a = 1,\ldots,n$$

**Distributive normalization (DN) method:** The distributive normalization (DN) method requires the element are divided by the square root of the sum of each squared element in a column i.e.:

$$r_{ai} = \frac{x_{ai}}{\sqrt{\sum_{a=1}^{n} x_{ia}^{\ 2}}},\ for\ \ a = 1,\ldots,n\ \ and\ \ i = 1,2,\ldots m$$

**Linear Max-Min normalization (LMM) method:** The Linear Max-Min Normalization technique can represent in the following general form:

$$r_{ai} = \frac{x_{ij-x_j^{min}}}{x_j^{max} - x_j^{min}},\ \ i = 1,\ldots,m\ \ and\ \ j = 1,2,\ldots n$$

In using the implementation steps given in Table 1 and in Section 2.1 for the TOPSIS methodology and that of the IF-TOPSIS$_{EF}$ model respectively, the dependencies issues in the illustrated example above can be solved using the different normalization methods. The result of the traditional TOPSIS methodology using different normalization methods is showed in Table 3. In comparing the three normalization methods for the TOPSIS methodology, it is not hard to see that there is a clear difference in the ranking results, which proves that the traditional TOPSIS methodology is unable to accurately address, capture and resolve the effect of correlation between attributes (dependency of attributes).

Also, in the implementing the steps given in Section 2.1, the dependencies issues in the illustrated example above can be solved using the different normalization methods. The result of the proposed IF-TOPSIS$_{EF}$ model using different normalization methods is showed in Table 4. In comparing the three normalization methods for the TOPSIS methodology, it is not hard to see that the ranking results are same for all three normalization methods. This clearly shows that the proposed IF-TOPSIS$_{EF}$ model are able to accurately address, capture and resolve the effect of correlation between attributes (dependency of attributes).

**Example 2:** Let us consider another practical MADM problem originally reported by Li (2005), to demonstrate the effect of dependent attributes on the final ranking result. Careful observation of the decision matrix as given in Table 5 shows some few dependencies of the criteria on each other (i.e. data having the same fuzzy values). In this case, we determine the best alternative with respect to the criteria

**Table 3. Traditional TOPSIS model with various normalization modes**

| | ID Method | Ranking | DN Method | Ranking | LMM | Ranking |
|---|---|---|---|---|---|---|
| $A_1$ | 0.594 | 2 | 0.488 | 4 | 0.761 | 4 |
| $A_2$ | 0.524 | 4 | 0.551 | 2 | 0.779 | 2 |
| $A_3$ | 0.543 | 3 | 0.500 | 3 | 0.772 | 3 |
| $A_4$ | 0.460 | 5 | 0.482 | 5 | 0.724 | 5 |
| $A_5$ | 0.651 | 1 | 0.568 | 1 | 0.872 | 1 |

**Table 4. The proposed model with various normalization modes**

| | ID Method | Ranking | DN Method | Ranking | LMM | Ranking |
|---|---|---|---|---|---|---|
| $A_1$ | 0.858 | 3 | 0.799 | 3 | 0.858 | 3 |
| $A_2$ | 0.873 | 2 | 0.803 | 2 | 0.872 | 2 |
| $A_3$ | 0.853 | 4 | 0.798 | 4 | 0.848 | 4 |
| $A_4$ | 0.820 | 5 | 0.791 | 5 | 0.813 | 5 |
| $A_5$ | 0.902 | 1 | 0.806 | 1 | 0.904 | 1 |

**Table 5. Decision matrix**

| | $C_1$ | $C_2$ | $C_3$ |
|---|---|---|---|
| $A_1$ | (0.75, 0.1) | (0.6, 0.3) | (0.8, 0.2) |
| $A_2$ | (0.8, 0.15) | (0.68, 0.2) | (0.45, 0.5) |
| $A_3$ | (0.4, 0.45) | (0.75, 0.05) | (0.6, 0.3) |

using the traditional TOPSIS method and then the IF-TOPSIS$_{EF}$ model with the following normalization modes; Ideal normalization (IN) method, Distributive normalization (DN) method and Linear Max-Min normalization (LMM) method. The criteria weight vector is given as $w = \left(0.25, 0.4, 0.35\right)^T$ , respectively.

Just like example 1 above, in using the implementation steps given in Table 1 and in Section 2.1 for the TOPSIS methodology and that of the IF-TOPSIS$_{EF}$ model respectively, the dependencies issues in the illustrated example 2, above can be solved using the different normalization methods. The result of the traditional TOPSIS methodology using different normalization methods is showed in Table 6. In comparing the three normalization methods for the TOPSIS methodology, it is not hard to see that there is a clear difference in the ranking results, which proves that the traditional TOPSIS methodology is unable to accurately address, capture and resolve the effect of correlation between attributes (dependency of attributes).

Also, in the implementing the steps given in Section 2.1, the dependencies issues in the illustrated example above can be solved using the different normalization methods. The result of the proposed IF-TOPSIS$_{EF}$ model using different normalization methods is showed in Table 7. In comparing the three normalization methods for the TOPSIS methodology, it is not hard to see that the ranking results are same for all three normalization methods. This clearly shows that the proposed IF-TOPSIS$_{EF}$ model

**Table 6. Traditional TOPSIS model with various normalization modes**

| | ID Method | Ranking | DN Method | Ranking | LMM | Ranking |
|---|---|---|---|---|---|---|
| $A_1$ | 0.547 | 1 | 0.563 | 3 | 0.544 | 1 |
| $A_2$ | 0.523 | 2 | 0.588 | 2 | 0.510 | 2 |
| $A_3$ | 0.433 | 3 | 0.589 | 1 | 0.438 | 3 |

**Table 7. The proposed model with various normalization modes**

| | ID Method | Ranking | DN Method | Ranking | LMM | Ranking |
|---|---|---|---|---|---|---|
| $A_1$ | 0.770 | 1 | 0.903 | 1 | 0.904 | 1 |
| $A_2$ | 0.751 | 3 | 0.821 | 3 | 0.821 | 3 |
| $A_3$ | 0.764 | 2 | 0.840 | 2 | 0.840 | 2 |

are able to accurately address, capture and resolve the effect of correlation between attributes (dependency of attributes).

Furthermore, in Table 8, the main differences between the IF-TOPSIS$_{EF}$ model and the traditional fuzzy TOPSIS method have been presented. From the computational steps of the IF-TOPSIS$_{EF}$ model, the differences noted in the table, represent some of the key improvements that have made over the traditional fuzzy TOPSIS method.

## 4. CONCLUSION

In this paper, some examples have been presented to show the effectiveness of the Intuitionistic fuzzy TOPSIS model which is based on exponential-related function (IF-TOPSIS$_{EF}$) originally proposed in (Aikhuele & Turan, 2016; Aikhuele & Turan, 2016) for dealing with attributes dependency issues. This was achieved by implementing the traditional TOPSIS model originally proposed by Hwang & Yoon (2000) using several normalization methods and then compared the results with the ones from the proposed IF-TOPSIS$_{EF}$ under the same condition. The study contributes, and have extended the state of the art in the study of TOPSIS methodology by addressing, capturing and resolving the effect of correlation between attributes otherwise called dependency of attributes.

The computational results from the two (2) examples, shows that the traditional TOPSIS model are not consistent and are unable to effectively address and handle attribute dependencies issues. However, for the proposed IF-TOPSIS$_{EF}$ model, the

**Table 8. Theoretical comparison of the methods**

| Difference | IF-TOPSIS$_{EF}$ Model | Fuzzy TOPSIS Method |
|---|---|---|
| Scale | Intuitionistic fuzzy numbers | Fuzzy triangle numbers |
| Normalization | Without prior normalization when no clear dependents of data, otherwise it is normalized | Normalization |
| Separation distance measure | Exponential related function | Euclidean distance |
| Dependent and independent attributes | Assume all contemplated attributes are dependent | Assume all contemplated attributes are independent |
| Attribute weights | Subjective and objective approach | Subjective approach |
| Uncertainty | More flexible, practical and capable in handling uncertainty in practice. | Handle uncertainty in practice. |
| Membership function | The model represents membership function in three grades that is the membership degree $\mu$, non-membership degree $v$, and hesitancy degree $\pi$. | It represents just one grade of membership function that is the membership degree $\mu$. |
| DMs risk attitude | Accounts for DMs risk attitude | Not considered |
| Bias condition and Assessment | Capture both the positivity bias and negativity bias with the used of the Exponential related function. | Not considered |

ranking results for the three normalization modes shows that the model is capable of addressing, capturing and resolving the effect of correlation between attributes otherwise called dependency of attributes. Finally, with the results from the case examples presented, the study can conclude therefore that, the IF-TOPSIS$_{EF}$ provides a better alternative method over the traditional TOPSIS method in solving MCDM problems. In the further, the model will be use to solve key multi-attribute decision-making problems.

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