

A Mathematical Approach To Select Best Person For A Job

Pawan Agrawal
Department of Mathematics
Govt. Raj Rishi College, Alwar, Rajasthan, India

Abstract

One of the fuzzy multi-criteria decision making techniques used in this research is the TOPSIS approach, which is commonly used as a selection tool. The many advantages of this strategy led to its selection for this investigation. With only five alternatives, ten people were qualified for an interview. The fuzzy TOPSIS algorithm is used to rank ten candidates and hire the most qualified candidate.

Keywords: Topsis, Decision making, Fuzzy

Introduction

Based on the theory behind the original TOPSIS, Ren et al. (2007) developed a novel modified synthetic assessment approach called M-TOPSIS. They used it to determine the distance between several options and an ideal reference point that had been improved. Zavadskas et al. (2016) created TOPSIS as a tool that can assist with the resolution of issues pertaining to decision making in the real world. As a result, this study demonstrates the most recent developments of the TOPSIS technique, which were initially given by earlier researchers. The fuzzy TOPSIS method was developed for the purpose of robot selection by Chu and Lin (2003). According to this methodology, the ratings of different alternatives in comparison to different subjective criteria and the weights of all criteria are evaluated in linguistic terms represented by fuzzy numbers. It was necessary to convert the weighted values of the objective criteria into dimensionless indices so that the weighted values of the objective criteria and the language evaluations of the subjective criteria would be compatible with one another. The interval arithmetic of fuzzy numbers was used in order to build the membership function that is a part of each weighted rating. When the entropy method (EM) and the technique for order preference by similarity to ideal solution (TOPSIS) were employed together, the most popular normalising procedures for the EM are summarised in the work that was produced by Chen. This work was cited in the previous sentence (2019). Within the scope of this investigation, the effects of normalisation on the entropy-based TOPSIS methodology are investigated. As a result of the utilisation of information entropy (IE) as an indicator for the purpose of evaluating the diversity of attribute data (DAD), the DAD was the primary focus of this study.

The Steps of the Fuzzy TOPSIS Method:

Step 1: Create a decision matrix

In this study there are 5 criteria and 10 alternatives that are ranked based on FUZZY TOPSIS method. The table below shows the type of criterion and weight assigned to each criterion.

Characteristics of Criteria

	name	type	weight
1	B1	+	(2.000,4.000,6.000)
2	B2	+	(3.000,6.000,7.000)
3	B3	+	(7.000,11.000,19.000)
4	B4	+	(2.000,9.000,13.000)
5	B5	+	(1.000,6.000,9.000)

The following table shows the fuzzy scale used in the model.

Fuzzy Scale

Code	Linguistic terms	L	M	U
1	Very low	1	1	3
2	Low	1	3	5
3	Medium	3	5	7
4	High	5	7	9
5	Very high	7	9	9

The alternatives in terms of various criteria are reevaluated and the results of the decision matrix are shown as follows. Note that if multiple experts participate in the evaluation, then the matrix below represents the arithmetic mean of all experts.

Decision Matrix

	B1	B2	B3	B4	B5
A1	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)
A2	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)
A3	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)
A4	(7.000,9.000,9.000)	(5.000,7.000,9.000)	(3.000,5.000,7.000)	(1.000,3.000,5.000)	(3.000,5.000,7.000)
A5	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)
A6	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,1.000,3.000)	(1.000,3.000,5.000)
A7	(1.000,1.000,3.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)
A8	(1.000,1.000,3.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)
A9	(1.000,1.000,3.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)
A10	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,3.000,5.000)	(1.000,1.000,3.000)	(1.000,1.000,3.000)

Step 2: Create the normalized decision matrix

Based on the positive and negative ideal solutions, a normalized decision matrix can be calculated by the following relation:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right); c_j^* = \max_i c_{ij} \quad ; \quad \text{Positive ideal solution}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right); a_j^- = \min_i a_{ij} \quad ; \quad \text{Negative ideal solution}$$

The normalized decision matrix is shown in the table below.

A normalized decision matrix

	B1	B2	B3	B4	B5
A1	(0.111,0.333,0.556)	(0.111,0.333,0.556)	(0.143,0.429,0.714)	(0.200,0.200,0.600)	(0.143,0.143,0.429)
A2	(0.111,0.333,0.556)	(0.111,0.333,0.556)	(0.143,0.429,0.714)	(0.200,0.200,0.600)	(0.143,0.143,0.429)
A3	(0.111,0.333,0.556)	(0.111,0.333,0.556)	(0.143,0.429,0.714)	(0.200,0.200,0.600)	(0.143,0.143,0.429)
A4	(0.778,1.000,1.000)	(0.556,0.778,1.000)	(0.429,0.714,1.000)	(0.200,0.600,1.000)	(0.429,0.714,1.000)
A5	(0.111,0.333,0.556)	(0.111,0.333,0.556)	(0.143,0.429,0.714)	(0.200,0.200,0.600)	(0.143,0.143,0.429)
A6	(0.111,0.333,0.556)	(0.111,0.333,0.556)	(0.143,0.429,0.714)	(0.200,0.200,0.600)	(0.143,0.429,0.714)
A7	(0.111,0.111,0.333)	(0.111,0.111,0.333)	(0.143,0.143,0.429)	(0.200,0.200,0.600)	(0.143,0.143,0.429)
A8	(0.111,0.111,0.333)	(0.111,0.111,0.333)	(0.143,0.143,0.429)	(0.200,0.200,0.600)	(0.143,0.143,0.429)
A9	(0.111,0.111,0.333)	(0.111,0.111,0.333)	(0.143,0.143,0.429)	(0.200,0.200,0.600)	(0.143,0.143,0.429)
A10	(0.111,0.333,0.556)	(0.111,0.333,0.556)	(0.143,0.429,0.714)	(0.200,0.200,0.600)	(0.143,0.143,0.429)

Step 3: Create the weighted normalized decision matrix

Considering the different weights of each criterion, the weighted normalized decision matrix can be calculated by multiplying the weight of each criterion in the normalized fuzzy decision matrix, according to the following formula.

$$\tilde{v}_{ij} = \tilde{r}_{ij} \cdot \tilde{w}_{ij}$$

Where \tilde{w}_{ij} represents weight of criterion c_j

The following table shows the weighted normalized decision matrix

The weighted normalized decision matrix

	B1	B2	B3	B4	B5
A1	0.222,1.333,3.3) (33	0.333,2.000,3.889) (1.000,4.714,13.571) ((0.400,1.800,7.800)	0.143,0.857,3.857) (
A2	0.222,1.333,3.3) (33	0.333,2.000,3.889) (1.000,4.714,13.571) ((0.400,1.800,7.800)	0.143,0.857,3.857) (
A3	0.222,1.333,3.3) (33	0.333,2.000,3.889) (1.000,4.714,13.571) ((0.400,1.800,7.800)	0.143,0.857,3.857) (
A4	1.556,4.000,6.0) (00	1.667,4.667,7.000) (3.000,7.857,19.000) (0.400,5.400,13.000) (0.429,4.286,9.000) (
A5	0.222,1.333,3.3) (33	0.333,2.000,3.889) (1.000,4.714,13.571) ((0.400,1.800,7.800)	0.143,0.857,3.857) (
A6	0.222,1.333,3.3) (33	0.333,2.000,3.889) (1.000,4.714,13.571) ((0.400,1.800,7.800)	0.143,2.571,6.429) (
A7	0.222,0.444,2.0) (00	0.333,0.667,2.333) ((1.000,1.571,8.143)	(0.400,1.800,7.800)	0.143,0.857,3.857) (
A8	0.222,0.444,2.0) (00	0.333,0.667,2.333) ((1.000,1.571,8.143)	(0.400,1.800,7.800)	0.143,0.857,3.857) (
A9	0.222,0.444,2.0) (00	0.333,0.667,2.333) ((1.000,1.571,8.143)	(0.400,1.800,7.800)	0.143,0.857,3.857) (
A10	0.222,1.333,3.3) (33	0.333,2.000,3.889) (1.000,4.714,13.571) ((0.400,1.800,7.800)	0.143,0.857,3.857) (

Step 4: Determine the fuzzy positive ideal solution (FPIS, A^*) and the fuzzy negative ideal solution (FNIS, A^-)

The FPIS and FNIS of the alternatives can be defined as follows:

$$A^* = \{\tilde{v}_1^*, \tilde{v}_2^*, \dots, \tilde{v}_n^*\} = \left\{ \left(\max_j v_{ij} \mid i \in B \right), \left(\min_j v_{ij} \mid i \in C \right) \right\}$$

$$A^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-\} = \left\{ \left(\min_j v_{ij} \mid i \in B \right), \left(\max_j v_{ij} \mid i \in C \right) \right\}$$

Where \tilde{v}_i^* is the max value of i for all the alternatives and \tilde{v}_i^- is the min value of i for all the alternatives. B and C represent the positive and negative ideal solutions, respectively.

The positive and negative ideal solutions are shown in the table below.

The positive and negative ideal solutions

	Positive ideal	Negative ideal
B1	(1.556,4.000,6.000)	(0.222,0.444,2.000)
B2	(1.667,4.667,7.000)	(0.333,0.667,2.333)
B3	(3.000,7.857,19.000)	(1.000,1.571,8.143)
B4	(0.400,5.400,13.000)	(0.400,1.800,7.800)
B5	(0.429,4.286,9.000)	(0.143,0.857,3.857)

Step 5: Calculate the distance between each alternative and the fuzzy positive ideal solution A^* and the distance between each alternative and the fuzzy negative ideal solution A^-

The distance between each alternative and FPIS and the distance between each alternative and FNIS are respectively calculated as follows:

$$S_i^* = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^*) \quad i=1,2,\dots,m$$

$$S_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-) \quad i=1,2,\dots,m$$

d is the distance between two fuzzy numbers, when given two triangular fuzzy numbers (a_1, b_1, c_1) and (a_2, b_2, c_2) , the distance between the two can be calculated as follows:

$$d_v(\tilde{M}_1, \tilde{M}_2) = \sqrt{\frac{1}{3} [(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]}$$

Note that $d(\tilde{v}_{ij}, \tilde{v}_j^*)$ and $d(\tilde{v}_{ij}, \tilde{v}_j^-)$ are crisp numbers.

The table below shows distance from positive and negative ideal solutions

Distance from positive and negative ideal solutions

	Distance from positive ideal	Distance from negative ideal
A1	15.822	5.73
A2	15.822	5.73
A3	15.822	5.73
A4	0	21.374
A5	15.822	5.73
A6	14.042	7.514
A7	21.374	0
A8	21.374	0
A9	21.374	0
A10	15.822	5.73

Step 6: Calculate the closeness coefficient and rank the alternatives

The closeness coefficient of each alternative can be calculated as follows:

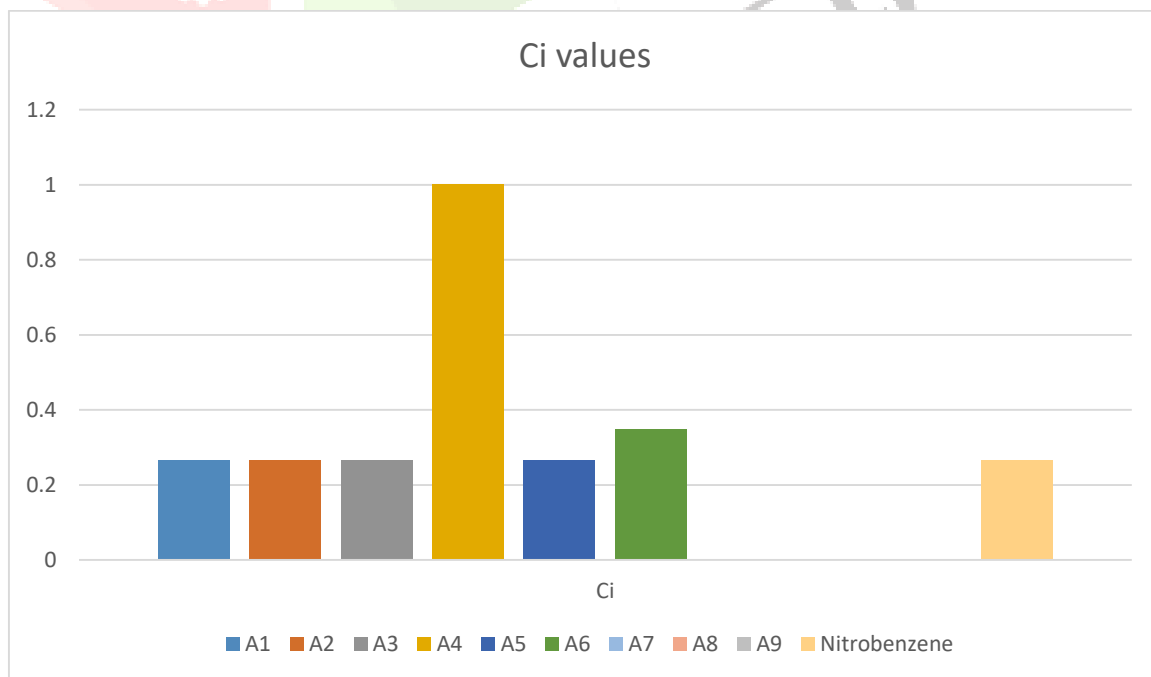
$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

The best alternative is closest to the FPIS and farthest to the FNIS. The closeness coefficient of each alternative and the ranking order of it are shown in the table below.

Closeness coefficient

	Ci	rank
A1	0.266	3
A2	0.266	3
A3	0.266	3
A4	1	1
A5	0.266	3
A6	0.349	2
A7	0	4
A8	0	4
A9	0	4
A10	0.266	3

The following graph shows the closeness coefficient of each alternative.



Closeness coefficient graph

Conclusion:

The TOPSIS method, which is more frequently utilised as a selection instrument, is one of the fuzzy multi-criteria decision making strategies that were utilised in the course of this investigation. This approach was chosen for this inquiry because to its selection. Even though there were only five options, ten individuals met the requirements to be considered for an interview. The fuzzy TOPSIS algorithm is utilised in order to rank ten candidates and hire the individual who possesses greatest qualifications ultimately

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