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RESEARCH ARTICLE

CODAS, TOPSIS, and AHP Methods Application for Machine Selection

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Abstract: Currently, companies have the need to make a robust analysis about the performance of their processes. In this regard, this article proposes the use of tools focused on the selection of machines, methods such as Combinative Distance-Based Assessment (CODAS), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Analytic Hierarchy Process (AHP). In this study, it is sought to optimize the decision for equipment selection through multicriteria decision-making methods, maximizing the process reliability, since it is something that is demanded by the market, thus improving the quality of the finished product offered by companies. Thereby, this work addresses the comparison of these methods using real data from a case of study involving a machine selection for a pastry company, specifically it is looking for a certain kind of mixer machine that will help to improve the times of process and the quality of the final product. It shows how easy and relevant these methods are for small businesses and huge companies to motivate them to improve their selection processes explaining each method and then the application for each one comparing the results and finally doing a projection for this company's best choice.

Keywords: multicriteria decision-making, equipment selection, multicriteria decision-making (MCDM), CODAS, TOPSIS, AHP

1. Introduction

The multicriteria decision-making (MCDM) methods are mathematical systems that refer to making decisions in the presence of multiple, usually conflicting, criteria. It can be in different contexts like personal, business, government, and a lot of application areas (Hwang et al., 1981). Multicriteria methodology is important in any type of industry that wants to improve processes as a decision-making derivation, without losing quality, reliability, and obtaining the best results. Likewise, one of its main characteristics is the way in which the methodology combines the different factors found in the evaluation that will be carried out. In addition, a range of tools is available for conducting multicriteria evaluations that help decision-making in any type of industry that is desired to focus on, it can be private or public, on the side of marketing, processes, to increase sales, etc. They are also known as analytical techniques, which are often more complex than strategic and economic techniques since they integrate both types of criteria: quantitative or qualitative; they analyze the information as consequences and uncertainties. Also, they are usually more realistic in terms of numbers and thus obtain more accurate results in evaluations (Villanueva Ponce & García Alcaraz, 2013). Suppose that following an FMEA (Failure Mode and Effects Analysis) analysis, there arises a requirement to choose the better way to get away the failure mode and attack the root cause, but you have many complex and full of criteria solving options, that is where a method like this could solve the decision (INFRASPEAK, 2015; Robles, 2017). To effectively obtain the best results, it should be considered what type of tools to use, the best way to get more focused results is using more than just two methods, we consider three at least to start normalizing and comparing rankings, two methods may show different rankings but a third one could probably give to the applicant a different view for how the criterion weights were disenrolling during each method calculation. The three methods used for this application are CODAS, TOPSIS, and AHP; first, one the CODAS ("Combinative Distance-Based Assessment") method is used in different disciplinary fields for decision-making where there is a lot of information and data to be evaluated. Likewise, this method utilizes the Euclidean distance (E_i) as the primary distance and the Taxi distance (T_i) as the secondary measure, and they are calculated according to the negative ideal point (Sansabas-Villalpando et al., 2019). On the other hand, the TOPSIS ("Technique for Order of Preference by Similarity to Ideal Solution'') method is a MCDM tool, which is used to select the best alternative of the proposals in the field in which it is happening or want to work in (Aguarón-Joven et al., 2015). The AHP ("Analytic Hierarchy Process'') is a tool frequently used in quality management, for the choice of suppliers, selection of personnel, selection of purchases, selection of forms, etc. AHP is an evaluation-based method. AHP is a method based on evaluation, which through different standards allow the prioritization of processes, whose final objectives include optimizing management decisions. Such methods

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are widely used under the situations that needs to prioritize different issues. The AHP technology helps the analyst to organize key aspects of the problem into a hierarchical structure like a family tree, reducing decision-making (Osorio & Orejuel, 2008).

In this case, the application scope is a disadvantage; it appears that all the criteria data are resulting just in numerical tables and other companies probably do not want to put hands on the involving methods or any MCDM technique due to this. We are applying this just for a company, and not for many criteria but that is the being for the motivation, take advantage of the actual company problem and use it like an example of how these methods work, showing the structure and algorithms to build the matrixes to next apply them showing how to take the decision and best choice. The reader should take this as an invitation to know more about the MCDM and if it is possible apply this kind of methodology in your industry or business. As a result of the long-term impact on the process, there is a great deal of responsibility and difficulty involved with selecting the appropriate machine (Štirbanović et al., 2019).

2. Problem Statement

MCDM is a problem that is always seen in real life, even in the most "insignificant" aspect of daily life. All the activities carried out require in one way or another to evaluate aspects, alternatives, or options that are frequently in conflict with each other to take a decision, thus expecting that the decision made is the best option to get the best result or the expected outcome for a situation being faced at that moment, whether in the long or short term.

The following tools will be applied in a pastry company, having to choose which is the best machinery for a certain type of process carried out in the business. This company must choose which from the five options of machinery is the best choice and to it, we asked for the most important characteristics (criteria) the employer is looking for to improve production. The data collected are shown in Table 1 containing the criteria like the price in Mexican peso (MXN), the capacity of the mixer (liters), the warranty, the product weight (kilos), and the speed levels. These are shown through the columns; the different product brands are collected in the left rows and the criteria weights are the importance for the company to each criterion expressed in percent.

The criteria weights are chosen by the company in question, as you can see, the weights are dispersed as parts of one hundred percent, each part represents the priority for the machine characteristics. In this case, the price is the first criterion that the company puts an eye on (40%), later the liter capacity (30%), next the warranty (20%), and the product weight and speed level have the same weight (5%)

3. Analytic Hierarchy Process

The evaluation of a set of alternatives in terms of a set of decision criteria is a part of every activity, and these criteria frequently conflict with one another (Aziz et al., 2016); the AHP is a method used to evaluate different options considering all the criteria related to them, it is mainly based on the experience and the data used in the process. Likewise, the AHP is systematic tool, and it does not solve specific problems, but rather it solves subproblems of a general problem of a complete system (Saaty, 2008). This method divides the problem or choices into a hierarchy of problems which are considered in comparisons and these are made using an absolute scale that judges and represents a unit of weight within the matrix; this denomination of judgment will be that of one element over another (criterion over criterion considering the weight) (Dožića & Kalić, 2015). As a result, the development of a hierarchy of attributes with at least three levels has made it possible to visually structure a multicriteria problem during the decision-making process, objective of the problem, the alternatives in the environment, and alternatives that concur in the lower part (Berumen & Llamazares, 2007). The data are evaluated by means of a prioritization principle shown in Table 2 comparing each criterion with the others (Saaty, 2012). AHP measures the consistency (C) of judgments through consistency ratio (PC), in this case the last one equals < 10%, in a comparison matrix we can show the consistency index (CI) by calculating it (1) or using a preset for a random matrix (Ceballos et al., 2013) (Table 3).

$$C = \frac{\lambda\ Max - n}{n - 1} \tag{1}$$

3.1. AHP application

The machinery data will be added into an AHP template previously made in Excel, shown in Table 4; after that, the next tables were generated by following the mixer comparisons with each criterion (Tables 5, 6, 7, 8, and 9) and next to it every table goes with the normalized version of the comparisons (Tables 10, 11, 12, 13, 14, 15). To obtain the outcome in this situation, Table 16 shows how the final weights for criteria are distributed and with it, the final ranking for do a selection.

The resulting ranking is numerically weighted, being the best choice the minimum (number 1) and the worst or the nonideal option the maximum number (number 5).

Based on the information in Table 2, we assign each criterion located in the rows an importance value over the values located in the columns, for example, for the price compared to itself will be 1 (equal importance), otherwise, in price versus capacity changes giving us a 3 (moderate importance of price over capacity) and so with the following shifted to the right. In the comparison of capacity versus price, specifically in the second row is placed the inverse to that we had already placed in the previous comparison (price-capacity) and along the row are placed the other valuations referring to the scale of pairwise. The integers are the valuations

Table 1
Initial data of machinery criteria

Criteria	Price	Capacity	Warranty	Product weight	Speed
Weights	40%	30%	20%	5%	5%
Mixer A GUMAJE	18,600 MXN	30 liters	0.58	150 kilos	3
Mixer B Gutstark Home	15,798 MXN	30 liters	0.25	85 kilos	1
Mixer C Rbanda	14.999 MXN	10 liters	1	48 kilos	3
Mixer D Migsa	17,121.6 MXN	20 liters	1	77 kilos	1
Mixer E Migsa	25,599 MXN	40 liters	1	97 kilos	1

Table 2
Scale for pairwise comparisons

Intensity	Meaning	Rationale
1	"Equal Importance"	"Two activities contribute equally to the objective achievement"
3	"Moderate importance of one factor over another"	"Experience and judgment slightly favor one activity over another"
5	"Strong or essential importance"	"Experience and judgement strongly favor one activity over another"
7	"Very strong or demonstrated importance"	"An activity is favored very strongly over another; its dominance demonstrated in practice"
9	"Extreme importance"	"The evidence favoring one activity over another is of the highest possible order of affirmation"
2,4,6,8	"Intermediate or compromise values"	"When compromise is needed between the adjacent judgments"
Reciprocals	"For inverse comparison"	

Table 3
Consistency index of a random matrix

Matrix size	2	3	4	5	6	7	8	9	10
IA	0	0.580	0.90	1.120	1.240	1.320	1.410	1.450	1.490

Table 4
AHP criteria comparison matrix

Criteria comparison matrix					
Criteria	Price	Capacity	Warranty	Product Weight	Speed
Price	1	3	5	7	7
Capacity	1/3	1	3	5	5
Warranty	1/5	1/3	1	3	3
Product Weight	1/7	1/5	1/3	1	1
Speed	1/7	1/5	1/3	1	1
Total	1.81	4.73	9.66	17	17

Table 5
Mixer comparison matrix with respect to price

Mixer				
A	B	C	D	E
1	1/5	1/7	1/5	3
5	1	1/3	3	7
7	3	1	5	9
5	1/3	1/5	1	7
1/3	1/7	1/9	1/7	1
18.33	4.67	1.78	9.34	27

Table 6
Comparison matrix with respect to capacity

Mixer				
A	B	C	D	E
1	1	5	3	1/7
1	1	5	3	1/7
1/5	1/5	1	1/3	1/3
1/3	1/3	3	1	1/5
7	7	3	5	1
9.53	9.53	17	12.33	1.81

Table 7
Comparison matrix with respect to warranty

Mixer				
A	B	C	D	E
1	1/3	1/5	1/5	1/5
3	1	1/7	1/7	1/7
5	7	1	1	1
5	7	1	1	1
5	7	1	1	1
19	22.33	3.34	3.34	3.34

Table 8
Comparison matrix with respect to product weight

Mixer				
A	B	C	D	E
1	5	9	7	3
1/5	1	5	3	1/3
1/9	1/5	1	1/3	1/7
1/7	1/3	3	1	1/5
1/3	3	7	5	1
1.78	9.53	25	16.33	4.67

Table 9
Comparison matrix with respect to product weight

Mixer				
A	B	C	D	E
1	7	1	7	7
1/7	1	1/7	1	1
1	7	1	7	7
1/7	1	1/7	1	1
1/7	1	1/7	1	1
2.42	17	2.42	17	17

Table 10
Normalized criteria comparison matrix

Normalized matrix					Weighting
0.55	0.63	0.52	0.41	0.41	0.50
0.18	0.21	0.31	0.29	0.29	0.26
0.11	0.07	0.10	0.18	0.18	0.13
0.08	0.04	0.03	0.06	0.06	0.05
0.08	0.04	0.03	0.06	0.06	0.05

Table 11
Normalized matrix with respect to price

Normalized matrix					Average vector
0.05	0.04	0.08	0.02	0.11	0.06
0.27	0.21	0.19	0.32	0.26	0.25
0.38	0.64	0.56	0.54	0.33	0.49
0.27	0.07	0.11	0.11	0.26	0.16
0.02	0.03	0.06	0.02	0.04	0.03

Table 12
Normalized matrix of capacity

Normalized matrix					Average vector
0.10	0.10	0.29	0.24	0.08	0.17
0.10	0.10	0.29	0.24	0.08	0.17
0.02	0.02	0.06	0.03	0.18	0.06
0.03	0.03	0.18	0.08	0.11	0.09
0.73	0.73	0.18	0.41	0.55	0.52

Table 13
Normalized matrix of warranty

Normalized matrix					Average vector
0.05	0.01	0.06	0.06	0.06	0.05
0.16	0.04	0.04	0.04	0.04	0.07
0.26	0.31	0.30	0.30	0.30	0.29
0.26	0.31	0.30	0.30	0.30	0.29
0.26	0.31	0.30	0.30	0.30	0.29

Table 14
Normalized matrix of product weight

Normalized matrix					Average vector
0.56	0.52	0.36	0.43	0.64	0.50
0.11	0.10	0.20	0.18	0.07	0.13
0.06	0.02	0.04	0.02	0.03	0.03
0.08	0.03	0.12	0.06	0.04	0.07
0.19	0.31	0.28	0.31	0.21	0.26

of importance given and those that seem to be fractions are the inverse to cases already appeared, for example, if we had already compared price over capacity (3) in capacity against price will be the inverse (1/3) or if in price against guarantee we gave a value (5) in guarantee against price is the inverse (1/5).

To do the normalized matrix, we take every number from Table 4 and it is divided by the respective column total, for example the first one, price over price is showing 1, that 1 is divided by 1.81 giving 0.55 and the next one, price over capacity is showing 3, that 3 is divided by 4.73.

Table 15
Normalized matrix of product weight

Normalized matrix					Average vector
0.41	0.41	0.41	0.41	0.41	0.41
0.06	0.06	0.06	0.06	0.06	0.06
0.41	0.41	0.41	0.41	0.41	0.41
0.06	0.06	0.06	0.06	0.06	0.06
0.06	0.06	0.06	0.06	0.06	0.06

Table 16
Final weights showing the AHP ranking

Price	Capacity	Warranty	Product Weight	Speed	Weighting	Ranking
0.06	0.17	0.05	0.5	0.41	0.24	2
0.25	0.17	0.07	0.13	0.06	0.14	4
0.49	0.06	0.29	0.03	0.41	0.25	1
0.16	0.09	0.29	0.07	0.06	0.13	5
0.03	0.52	0.29	0.26	0.06	0.23	3
0.19	0.20	0.19	0.19	0.2		

The weighting column on the right is very easy to get; we just calculated the average from every row.

Now the comparisons for each machine over the rest will begin, based on each of the criteria using the same scale of pairwise, we give an important value in which machine is more important or weighs more for the criterion in question compared to the others. After completing each matrix used for comparison are the normalized ones and the averages are obtained.

At the end, we grouped the last average weighting from Tables 11, 12, 13, 14, and 15 and we did another average weighting for the new matrix, then the ranking was chosen by giving numbers from the 1 to 5 for the values in descending order.

4. Combinative Distance-Based Assessment

This method is another reliable way to solve problems with distinct criteria and different situations. Developed by Keshavarz Ghorabaee, this method was made to solve complex decision problems; according to the negative ideal solution (the opposite best criteria in each criterion category) it calculates the Euclidean distance and the Taxicab as measures to give the relative assessment (Bolturk, 2018).

The steps of the CODAS method are as follows:

Step 1: Build the decision matrix.

$$L_1 = [L_{ij}]_{nxm} = \begin{bmatrix} L_{11}\, L_{12} & \cdots & L_{1m} \\ L_{21}\, L_{22} & \cdots & L_{2m} \\ \vdots \quad \vdots & \ddots & \vdots \\ L_{n1}\, L_{n2} & \cdots & L_{nm} \end{bmatrix} \tag{2}$$

Step 2: Compute the normalized decision matrix.

$$n_{ij} = \begin{cases} \dfrac{L_{ij}}{\max\limits_{i} L_{ij}} & if\ j \epsilon N_b \\ \dfrac{\min\limits_{i} L_{ij}}{L_{ij}} & if\ j \epsilon N_c \end{cases} \tag{3}$$

Step 3: Calculate the normalized weight of the matrix.

$$r_{ij} = \omega_j n_{ij} \tag{4}$$

Step 4: Determine the negative ideal solution.

$$ns = [ns_j]_{1xm} \tag{5}$$

where $ns_j = \min_i r_{ij}$

Step 5: Calculate the Euclidean (E_i) and Taxi (T_i) distances of alternatives from the negative ideal solution.

$$E_i = \sqrt{\sum_{j=1}^{m} (n_{ij} - ns_j)^2} \tag{6}$$

$$T_i = \sum_{j=1}^{m} |n_{ij} - ns_j|$$

Step 6: Develop the relative assessment matrix.

$$R_a = [h_{ik}]_{nxn} \tag{7}$$

where $h_i k = (E_i - E_k) + (\varphi(E_i - E_k) \times (T_i - T_k))$

Step 7: Determine the assessment score of each alternative.

$$L_i = \sum_{k=1}^{n} l_{ik} \tag{8}$$

Step 8: Sort the alternatives by decreasing assessment scores (L_i) and hence select the best choice among the alternatives.

4.1. CODAS application

The data of the machinery are filled into the method that was previously made in Excel, shown in Table 17 (step 1) after that, the next tables were generated by following the steps in the original method (steps 2–6) (Tables 18, 19, 20, 21, and 22). For the result in this case, Table 23 shows how the final weights for criteria are distributed and with it, the final ranking for do a selection.

The resulting ranking is numerically weighted, being the best choice the minimum (number 1) and the worst or the nonideal option the maximum number (number 5)

For the first step, we organize the original values on the matrix and for each column (criterion) we get the average as the average price or average warranty.

Table 17
Step 1: CODAS decision matrix

Mixers	Price C1	Capacity C2	Warranty C3	Product Weight C4	Speed C5
A	18,600	30	0.58	150	3
B	15,798	30	0.25	85	1
C	14,999	10	1	48	3
D	17,121.60	20	1	77	1
E	25,599	40	1	97	1
Average data values	**14,999**	**40**	**1**	**150**	**3**

Next, the normalization of the data is given by dividing each original data from Table 17 by the total from the column in question, for example dividing the price from the mixer A by the average price gives 1.24 (the first data from the normalized matrix).

Here, we multiply the original criteria weights with the average normalization criteria values, for example, the first average normalized value is for the price (1.23) we multiply that with the original price weight (40% or in this case 0.40) and for each average value we multiply the rest until we get the normalized weights.

Table 18
Step 2: Normalized decision matrix

	Normalization				
A	1.24	0.75	0.58	1.00	1.00
B	1.05	0.75	0.25	0.56	0.33
C	1.00	0.25	1.00	0.32	1.00
D	1.14	0.50	1.00	0.51	0.33
E	1.70	1.00	1.00	0.64	0.33
Average	1.23	0.65	0.77	0.61	0.60

Table 19
Step 3: Normalized weight of the matrix

Determining weights				
0.49	0.19	0.15	0.03	0.03

Table 20
Step 4: Negative ideal solution: Weighted matrix

Weighted matrix				
0.608	0.142	0.889	0.030	0.029
0.514	0.142	0.038	0.017	0.009
0.490	0.047	0.153	0.009	0.029
0.559	0.095	0.153	0.015	0.009
0.833	0.190	0.153	0.019	0.009

Table 21
Step 5: Negative ideal solution

Negative solution				
0.5	0.07	0.03	0.02	0.02

Table 22
Step 6: Euclidean and Taxi distances of alternatives

$\mathbf{E_i}$	0.18
	0.13
	0.10
	0.13
	0.41
$\mathbf{T_i}$	0.36
	0.16
	0.13
	0.24
	0.66

Table 23
Steps 7–8: Assessment score of each alternative and classified alternative

	Relative assessment matrix							
	E$_i$	0.18	0.13	0.1	0.13	0.41	Hi	Ranking
E$_i$	**T$_i$**	0.36	0.16	0.13	0.24	0.66		
0.18	**0.36**	0	-0.17	0.19	0.36	0	0.37	4
0.13	**0.16**	0.05	0.01	0.13	0.17	0.05	0.43	2
0.1	**0.13**	0.08	0.05	0.1	0.13	0.08	0.46	1
0.13	**0.13**	0.05	0.05	0.13	0.13	0.05	0.42	3
0.41	**0.41**	-0.22	-0.23	0.42	0.41	-0.23	0.14	5

For this matrix, we multiplied the original normalized matrix values with the new normalized weights, for example, the first normalized value (Machine A, normalized price equals 1.24) and all the values from that column (price) are multiplied with the first normalized weight (in this case 0.49).

To get the negative ideal solution, we select from every column the minimum value, this is the most opposite value for the one that we are looking for in every criterion.

The Euclidean distance is given by extracting the square root for the sum of the data from each machine (row) of the weighted matrix minus the data from the negative solution squared. For the Taxi, we perform another operation that is to obtain the sum of the absolutory values for every value of the weighted matrix minus the data of their respective negative solution.

The relative assessment matrix is given by using the Euclidean distance and Taxi as the step six formula (7); we take all these values and organize them vertically and horizontally. Every matrix space will be filled with the sum of the difference between the horizontal distance value (E$_i$) and the vertical Taxi value (T$_i$) plus the same operation φ times and this plus the difference between the horizontal distance value (T$_i$) and the vertical Taxi value (E$_i$). Finally, on the right, we summarize every row value to get the H$_i$ value that we use to order the ranking numbers by giving numbers from the 1 to 5 for the values in descending order.

5. TOPSIS Method

It is a method used in different areas, where a problem has arisen to select an alternative; it has been used in transportation systems, designs, processes, human resources, etc. Thus, in the industry it is used for the selection of machinery, materials, among others (Villanueva Ponce & García Alcaraz, 2013). It was proposed by Hwang et al., (1981) and faced the problem of setting orders in the model. It uses alternatives to ideal alternatives and anti-ideal alternatives (Behzadian, 2012). This method is the second most common of the MCDM approaches, and it identifies weights for each criterion and shows the geometric distance between all the alternatives, the best choice will be the best solution to these distances (Amudha et al., 2021). Since many of the attributes used in evaluation may be expressed in different units or scales, the method makes possible to combine multiple heterogeneous attributes into a single dimension (Arturo Real y Vásquez, 2011).

The following steps of the TOPSIS method proposed in 1981 are presented here (Hwang et al., 1981)

Step 1: Evaluate each alternative $A_i,\ i = 1, 2, \ldots, m$ under each criterion $C_j,\ j = 1, 2, \ldots, n$ and formulate the ratings X_{ij} in a decision matrix as given in Table 24.

Table 24
Decision matrix

	C_1	C_2	...	C_n
A_1	X_{11}	X_{12}	...	X_{1n}
A_2	X_{21}	X_{22}	...	X_{2n}
...	...	...	...	...
A_m	X_{m1}	X_{m2}	...	X_{mn}

Step 2: Normalized the ratings, if there are two kinds of criteria, by using Equation (9) and hence formulate a normalized decision matrix $N = [n_{ij}]$ where

$$n_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^{n} (X_{ij})^2}}, \qquad j = 1, 2, \ldots n \tag{9}$$

Step 3: Let $w_j \geq 0,\ \sum w_j = 1$ be the weight vector of the criteria. Then construct the weighted normalized decision matrix $V = [v_{ij}]$ where

$$v_{ij} = w_j \cdot n_{ij} \tag{10}$$

Step 4: Construct the PIS ("positive ideal solution") and NIS ("negative ideal solution"), denoted by A^+ and A^- as

$$A^+ = \{v_1^+,\ v_2^+, \ldots, v_n^+\} = \left\{\left(\max_i v_{ij} \mid j \in j\right), \left(\min_i v_{ij} \mid j \in j'\right)\right\} \tag{11}$$

$$A^- = \{v_1^-,\ v_2^-, \ldots, v_n^-\} = \left\{\left(\min_i v_{ij} \mid j \in j\right), \left(\max_i v_{ij} \mid j \in j'\right)\right\}$$

where j and j' are the indices that represent "desirable" and "undesirable" criteria.

The ideal solution is where all the attributes are the alternatives optimal values. Therefore, the anti-ideal solution is where the attributes are the values that are not desired at all or are the least favorable within the alternatives (Anaokar et al., 2018).

Step 5: Compute the distance measure from PIS and NIS as

$$d_i^+ = \sqrt{\Sigma_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2}, \qquad i = 1, 2, \ldots, m \tag{12}$$

$$d_i^- = \sqrt{\Sigma_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}, \quad i = 1, 2, \ldots, m$$

Step 6: Compute the relative closeness R_i degree to the PIS as.

$$R_i = \frac{d_i^-}{(d_i^+ + d_i^-)}, \qquad i = 1, \ldots, m \tag{13}$$

If $R_i = 1$, A_i then equal to A^+ (Ideal solution). If $R_i = 0$, A_i then equal to A^- (anti-ideal solution). That is, the closer the ratio is to 1, the higher the priority of the i^{th} alternative.

Step 7: Sort the values in descending order and select the best one.

5.1. TOPSIS application

We consider the same example as described above to illustrate the applicability of the TOPSIS method. The data of the machinery are filled into the study as same as described in Table 1. The steps of the methods are implemented as below.

Step 1: The rating of each alternative is given in Table 25.

Step 2: Since each criterion is of different capacity, so by Equation (9), we obtain the normalized matrix as given in Table 26. For instance, the number 0.44 is obtained by dividing the price value 18,600 to its column sum square root (i.e., 42,059.06).

Step 3: Take the weight vector of each criterion as 0.4, 0.3, 0.2, 0.05, 0.05 and hence by using Equation (10), we get weighted normalized matrix V as

$$V = \begin{pmatrix} 0.1769 & 0.1441 & 0.0629 & 0.0345 & 0.0327 \\ 0.1502 & 0.1441 & 0.0271 & 0.0195 & 0.0109 \\ 0.1426 & 0.0480 & 0.1085 & 0.0110 & 0.0327 \\ 0.1628 & 0.0961 & 0.1085 & 0.0177 & 0.0109 \\ 0.2435 & 0.1922 & 0.1085 & 0.0223 & 0.0109 \end{pmatrix}$$

Step 4: By Equation (11), we have

$$V^{+} = \left\{ \begin{array}{c} (C_1, 0.1426), \ (C_2, 0.1922), \ (C_3, 0.1085), \\ (C_4, 0.0345), \ (C_5, 0.0327) \end{array} \right\}$$

$$V^{-} = \left\{ \begin{array}{c} (C_1, 0.2435), \ (C_2, 0.0480), \ (C_3, 0.0271), \\ (C_4, 0.0110), \ (C_5, 0.0109) \end{array} \right\}$$

To obtain both the positive and negative ideal solutions, we select from every column value the "best choice" like a minimum or maximum value, for example, in the positive ideal solution we select the best value depending on the criteria, on the price values we want the cheapest value so we select the minimum value in that column, otherwise for capacity we want the maximum space for the machine so we select the maximum value the same for warranty (we want more warranty time), the product weight talks about the materials quality and resistance so we want the most heavy machine and finally the speed levels, we want the maximum. For the negative ideal solution, we just select the opposite of those selected in the positive ideal solution (if in the positive we selected the maximum of any value, here we select the minimum).

Step 5: Utilizing the Euclidean distances (12), we get

$$d_1^{+} = 0.0746 \ ; \ d_2^{+} = 0.0984 \ ; d_3^{+} = 0.1461 \ ; \ d_4^{+} = 0.1020 \ ; \ d_5^{+} = 0.1039$$

$$d_1^{-} = 0.1264 \ ; \ d_2^{-} = 0.1342 \ ; \ d_3^{-} = 0.1314 \ ; \ d_4^{-} = 0.1244 \ ; \ d_5^{-} = 0.1659$$

Step 6: By Equation (13), we get

$$R_1 = 0.6289 \ ; \ R_2 = 0.5768 \ ; \ R_3 = 0.4736 \ ; \ R_4 = 0.5495 \ ; \ R_5 = 0.6149$$

Step 7: Since $R_1 > R_5 > R_2 > R_4 > R_3$ and hence mixer A is the best alternative.

5.2. Results

Observe that in the final stages of each method application are tables with "the final rankings" those are the results, the purpose of all the mathematical applications for the criteria. These results can differ through different methods, not only in the selected three but also in many others, to have a better view to compare the rankings; Table 27 references the methods and machines (to remember the best choice).

How to evaluate the rank on a set of method alternatives based on a variety of criteria is a crucial aspect of MCDM analysis, but thanks to the ranking comparison, now we are close to know the best choice; Figure 1 shows that there is a coincidence between two methods, AHP and CODAS (Garcia-Bernabeu et al., 2015). These two methods share the number one choice concentrated in the machine letter C, according to these two the ***Rbanda Mixer*** is the better choice to buy new equipment, based on the criteria.

Table 25
Input decision matrix

Criteria	Price	Capacity	Warranty	Product Weight	Speed
Mixer A GUMAJE	18,600	30	0.58	150	3
Mixer B Gutstark Home	15,798	30	0.25	85	1
Mixer C Rbanda	14,999	10	1	48	3
Mixer D Migsa	17,121.60	20	1	77	1
Mixer E Migsa	25,599	40	1	97	1

Table 26
Normalized decision matrix

	Criteria				
	Price	Capacity	Warranty	Product Weight	Speed
Mixer A GUMAJE	0.4422	0.4802	0.3146	0.6892	0.6547
Mixer B Gutstark Home	0.3756	0.4804	0.1356	0.3906	0.2182
Mixer C Rbanda	0.3566	0.1601	0.5424	0.2205	0.6547
Mixer D Migsa	0.4071	0.3203	0.5424	0.3538	0.2182
Mixer E Migsa	0.6086	0.6405	0.5424	0.4457	0.2182

Table 27
Ranking comparison

Machine	Ranking AHP	CODAS	TOPSIS
Mixer A GUMAJE	2	4	1
Mixer B Gutstark Home	4	2	3
Mixer C Rbanda	1	1	5
Mixer D Migsa	5	3	4
Mixer E Migsa	3	5	2

Figure 1
Ranking comparison

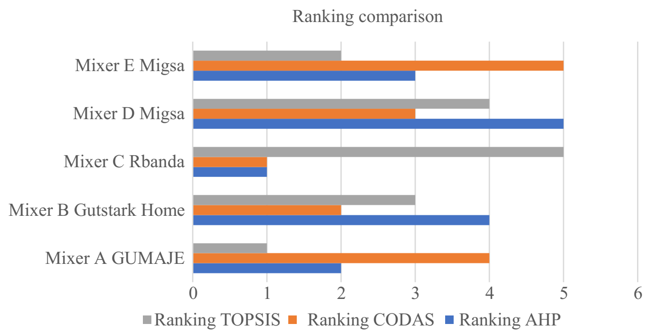

Table 28
Ranking comparison ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Rows	6	4	1.5	0.5	0.73728	3.837853355
Columns	0	2	0	0	1	4.458970108
Error	24	8	3			
Total	30	14				

CODAS and AHP share two instances with the ranking number one for this machine, but for TOPSIS this is the last option, if we do an average ranking, we get a 2.33 ranking and the Machine A (GUMAJE) shows the same average ranking, maybe we can consider both as final options but if we want to make sure this decision an ANOVA may solve this showing if the hypothesis of the equal averages is true. Table 28 shows the *F value* and the *F crit*; therefore, we can accept that there is a good probability that the averages are equal, in this case Machines A and C. If you are straight with the final rankings, you may consider the Machine A as a second-best choice.

Furthermore, disparities exist between these two approaches, after the number one ranking, the rest of the ranking values are dispersed and varied, if we mention the TOPSIS method, we will talk about a big difference between the rest, there is no coincidence between ranking, the only exception is the one in the ***Rbanda Mixer***.

6. Conclusions

The application area sure is amazing, if you look for research articles with the application of MCDM methods you will see this kind of calculations in various fields of science and technology as computer science, artificial intelligence, and sustainable engineering (Stojcic et al., 2019). However, this was a simple three method view in an equipment selection, if the interest persists, we can explode more areas, criteria, and methods that can help a user or a business to take a decision, simple or deep, including invests or catalogs for the different choices in our life. The point of view through these methods gives to the applier a new way to select and judge the different choices for a specific subject. We may apply this to select new supplier or project criteria for optimizing the OEE in your company, your business, or your own productivity (Ibermatica, 2020).

We must add that these methods are extremely useful when it comes to exercising a judgment on the acquisition of a good, not only at the company level but also included in the personal environment, because it is somewhat conflictive to decide on so many criteria of interest, precisely all these criteria are the factors that make harder to think which the best choice is. With the comparison of different kinds of elements that do not share a numerical similitude the decision is harder, just imagine yourself trying to invest in different kind of business, or buying a new computer, we all want the best business or computer in the market. Maybe you are thinking that making a decision is not so complex, you have done it all your life but the truth is that it is the opposite, it is considered a system where criteria are involved as information, the same for the individual and the context of the problem, all this is so deep and must be present peacefully in this system (CruzI & Molina, 2010) that is why viewing ourselves immerse in all that numbers and different kind of values to "judge" with these methods is more accurate as far as dealing with different values is treated because every method offers a normalization for the data to work effectively with the weights for each criterion. In the future, we will extend the application of CODAS and other methods to some other extensions of the fuzzy sets such as q-rung orthopair and others (Farid & Riaz, 2021, Farid & Riaz, 2022; Wang & Wang, 2022).

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

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