

A comparative analysis of different hybrid MCDM techniques considering a case of selection of 3D printers

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CHRONICLE

ABSTRACT

Article history:

Received January 25, 2015
Received in revised format 28
March 2015
Accepted 3 May 2015
Available online
May 7 2015

Keywords:

3D Printing
ANP
TOPSIS
Similarity Method
PROMETHEE
Hybrid MCDM
Comparative analysis

A multitude of techniques fall under the domain of Multi- Criteria Decision Making (MCDM) which is used to select the best alternative among the available ones. The objective of this paper is to compare some of these techniques with respect to the problem of selection of 3D printers, which is associated with multiple attributes. The weights of the criteria were determined using analytical network process (ANP). Next, the alternatives were ranked using three different MCDM techniques- 1.TOPSIS which ranks alternatives having the shortest distance to the ideal solution as well as the greatest distance from the negative-ideal solution 2. Deng's Similarity based Approach where the most preferred alternative should have the highest degree of similarity to the positive ideal solution and the lowest degree of similarity to the negative-ideal solution and 3.PROMETHEE and GAIA. The solutions for each of these three cases were analyzed thoroughly, and reasons for any deviations were discussed.

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1. Introduction

3D printing is one of different available processes to make a three-dimensional object where additive processes are implemented, in which successive layers of material are laid down under computer control. These objects are in any shape or geometry. Before printing a 3D model from an STL file, it needs to be tested for manifold errors. Especially STL's that have been produced from a model obtained through 3D scanning may contain some manifold errors, which need to be corrected. After that, the STL file requires some process by a software called a slicer, which converts the model into a series of thin layers and generates a G-code file containing instructions tailored to a specific kind of 3D printer. This G-code file can then be printed with 3D printing client software, which loads the G-code, and applies to instruct the 3D printer during the 3D printing process. The 3D printer follows the G-code instructions to lay down successive layers of liquid, powder, paper or sheet material to prepare the model from a series of cross sections. These layers, associated with the virtual cross sections from the CAD model, are joined or automatically fused to build the final shape. The main advantage of this

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technique is the ability to build almost any type of shape or geometric feature. Construction of a model with contemporary techniques can take up to several days, depending on the method applied and the size and complexity of the model. Additive systems can basically reduce this time to a few hours, although it differs widely depending on the kind of machine implemented and the size and number of models being produced, simultaneously.

The three-dimensional (3D) printing is one of the most promising technologies aiming at more flexible inexpensive manufacturing to maintain desired qualities. As stated by Campbell et al. (2011), "3D Printing/Additive Manufacturing (AM) is a revolutionary emerging technology that could up-end the last two centuries of approaches to design and manufacturing with profound geopolitical, economic, social, demographic, environmental, and security implications". The market for 3D printers and services is small but growing rapidly and with the bigger number of alternatives in the market, it is becoming increasingly important to choose the most appropriate one according to reduced cost and the value of customization. This paper deals with the application of three Multi Criteria Decision Making (MCDM) techniques, TOPSIS, Deng's Similarity based method & PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) are used for the selection of the appropriate 3D printer and a comparative analysis of three methods on the basis of the rankings are obtained.

Past works in this field have concentrated on the selection of Rapid Prototyping (RP) machines with the help of other MCDM techniques such as TOPSIS. Bhutia and Phipon (2012) applied TOPSIS to select supplier. Product quality, delivery time, service time and price were chosen as decision criteria. Weights of them were determined by using analytical hierarchy process (AHP). Cheng and Li (2004) used analytical network process (ANP) method for allotting weights to the criteria for selection of contractor, which is a more complicated construction management issue. Deng (2007) used the similarity based approach for purchasing fleet jet fighters and a ranking order quite different from that obtained by using TOPSIS emerged out. This approach was however established as one with strong theoretical background. Amponsah et al. (2012) has applied PROMETHEE method to solve a facility location problem and Gaussian as well as Logistic Preference function was used. They observed that both of these preference function produced same ranking order. Karande and Chakraborty (2012) applied PROMETHEE to select the best NTM process and PROMETHEE –GAIA based graphical approach was used. This reduced mathematical computation to a great extent and made complex decision making problem quite easy. Usual type preference function was used here. Shahroudi and Rouydel (2012) used ANP- TOPSIS multi-criteria decision making approach to evaluate suppliers in Iran's auto industry. Panda et al. (2014) used integrated ANP and Fuzzy TOPSIS technique for selection of Rapid Prototyping Process. Caterino et al. (2009) carried out a detailed comparative analysis of various MCDM methods for seismic Structural Refitting. However no research has yet been performed for selection of 3d printers by utilizing MCDM techniques.

The main objective of this paper is to solve any MCDM problem by using hybrid decision making method where by weights of the criteria obtained by using ANP is utilized for ranking alternatives by TOPSIS, Similarity based approach and PROMETHEE. This paper is aimed at obtaining ranking of alternatives of a 3D printer selection problem by using all these mentioned methods, the purpose being to have a comparative study of all these methods on the basis of different ranking orders obtained.

2. Methods

2.1. ANP

The Analytic Hierarchy Process (AHP) is a theory of relative measurement with absolute scales of both tangible and intangible criteria based on the judgment of knowledgeable and expert people as stated by Saaty (1988). How to measure intangibles is the main concern of the mathematics of the AHP. The Analytic Network Process (ANP) as discussed by Saaty (2001) is a generalization of the Analytic Hierarchy Process (AHP), by considering the dependence between the elements of the hierarchy. Many

decision issues cannot be structured hierarchically because they involve the interaction and dependence of higher-level elements in a hierarchy on lower-level elements. Therefore, ANP is represented by a network, rather than a hierarchy.

2.2. TOPSIS

TOPSIS (Technique of Order Preference by Similarity to Ideal Solution) method was originally introduced by Hwang and Yoon (1981) and received praise from surveyors and operators. TOPSIS is a decision making technique for finding the alternative that is closest to the ideal solution. In this method, options are graded based on ideal solution similarity. If an option is more similar to an ideal solution, it has a higher grade. Ideal solution is a solution that is the best from any aspect that does not exist practically and we try to approximate it. Basically, for measuring similarity of a design (or option) to ideal level and non-ideal, we consider distance of that design from ideal and non-ideal solution.

Step 1: Determine the decision matrix:

$$\begin{bmatrix} X_{11} & X_{12} & \dots & X_{1m} \\ X_{21} & X_{22} & \dots & X_{2m} \\ \dots & \dots & X_{ij} & \dots \\ X_{n1} & X_{n2} & \dots & X_{nm} \end{bmatrix} \quad (1)$$

where x_{ij} is the performance of i^{th} alternative with respect to the j^{th} criteria. Here m is the number of alternatives and n is the number of criteria.

Step 2: Construct normalized decision matrix. This step transforms various attribute dimensions into non-dimensional attributes, which helps comparisons across criteria. Normalize scores or data as follows,

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}^2} \quad (2)$$

Step 3: Construct the weighted normalized decision matrix by multiplying the normalized decision matrix by its associated weights. The weighted normalized value v_{ij} is calculated as:

$v_{ij} = w_j x_{ij}$ for $j=1,2,\dots,n$ where w_j is the weight of the criteria j . This weight or priority is determined by ANP as discussed above.

Step 4: Determine the positive ideal and negative ideal solution.

Positive ideal solution:

$$A^* = \{v_1^*, \dots, v_2^*\} \text{ where, } v_j^* = \max(v_{ij}) \text{ if } j \in J^+ \text{ or, } \min(v_{ij}) \text{ if } j \in J^- \quad (3)$$

Negative ideal solution:

$$A' = \{v_1', \dots, v_2'\} \text{ where } v_j' = \min(v_{ij}) \text{ if } j \in J^+ \text{ or, } \max(v_{ij}) \text{ if } j \in J^- \quad (4)$$

where J^+ is associated with beneficial criteria and J^- is associated with non-beneficial criteria.

Step 5: Calculate the separation measure:

Separation from positive ideal one:

$$S^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^*)^2} \quad (5)$$

Separation from negative ideal solution:

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j')^2}$$

Step 6: Relative closeness to the alternative can be determined as:

$$C_i^* = S_i^- / (S_i^+ + S_i^-) \quad (6)$$

Step 7: Select an alternative with maximum C_i^* or alternative in the descending order based on the value of C_i^* .

2.3. Deng's Similarity Method

This similarity-based method suggested by Deng (2007) effectively makes use of the ideal solution concept in such a way that the most preferred alternative should have the highest degree of similarity to the positive ideal solution and the lowest degree of similarity to the negative-ideal solution. Using this method, a conflict index is calculated between two alternatives to show the degree of conflict between the alternatives. A_i and A_j are the two alternatives concerned in a given multi-criteria analysis problem, these two alternatives can be considered as two vectors in the m -dimensional real space. The angle between A_i and A_j in the m -dimensional real space, shown in Fig. 1 is a good measure of conflict between them.

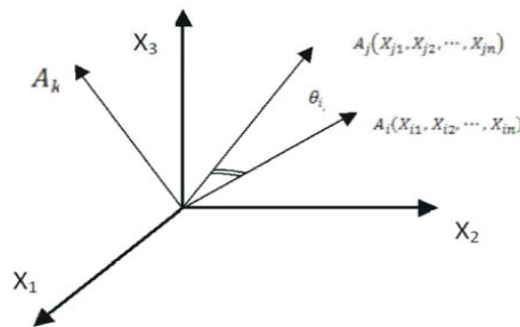


Fig.1. Degree of conflict between alternatives

Step 1: Determine the decision matrix as follows:

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1m} \\ X_{21} & X_{22} & \dots & X_{2m} \\ \dots & \dots & X_{ij} & \dots \\ X_{n1} & X_{n2} & \dots & X_{nm} \end{bmatrix} \quad (7)$$

Step 2: Determine the weighting vector as

$$W = (w_1, w_2, \dots, w_j, \dots, w_m) \quad (8)$$

Step 3: Normalize the decision matrix by the following equation:

$$X_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^n x_{ik}^2}} \quad (9)$$

Normalized decision matrix will be:

$$X' = \begin{bmatrix} x'_{11} & x'_{12} & \dots & x'_{1m} \\ x'_{21} & x'_{22} & \dots & x'_{2m} \\ \dots & \dots & x'_{ij} & \dots \\ x'_{n1} & x'_{n2} & \dots & x'_{nm} \end{bmatrix} \quad (10)$$

Step 4: Calculate the performance matrix as expressed as:

$$Y = \begin{bmatrix} w_1 x'_{11} & w_2 x'_{12} & \dots & w_m x'_{1m} \\ w_1 x'_{21} & w_2 x'_{22} & \dots & w_m x'_{2m} \\ \dots & \dots & w_j x'_{ij} & \dots \\ w_1 x'_{n1} & w_2 x'_{n2} & \dots & w_m x'_{nm} \end{bmatrix} = \begin{bmatrix} y_{11} & y_{12} & \dots & y_{1m} \\ y_{21} & y_{22} & \dots & y_{2m} \\ \dots & \dots & y_{ij} & \dots \\ y_{n1} & y_{n2} & \dots & y_{nm} \end{bmatrix} \quad (11)$$

Step 5: Determine the positive ideal solution and the negative ideal solution by following equations:

Positive ideal solution:

$$A^* = \{y_1^*, \dots, y_n^*\} \text{ where, } y_j^* = \max(y_{ij}) \text{ if } j \in J^+ \text{ or, } \min(y_{ij}) \text{ if } j \in J^- \quad (12)$$

Negative ideal solution:

$$A' = \{y'_1, \dots, y'_n\} \text{ where, } y'_j = \min(y_{ij}) \text{ if } j \in J^+ \text{ or, } \max(y_{ij}) \text{ if } j \in J^-$$

J^+ is associated with beneficial criteria and J^- is associated with non-beneficial criteria.

Step 6: Calculate the degree of conflict between each alternative and positive ideal solution as:

$$\cos \theta_i^+ = \frac{\sum_{j=1}^m y_{ij} * I_j^+}{\sqrt{\sum_{j=1}^m y_{ij}^2 \sum_{j=1}^m (I_j^+)^2}} \quad i=1,2,\dots,n \quad (13)$$

$$\cos \theta_i^- = \frac{\sum_{j=1}^m y_{ij} * I_j^-}{\sqrt{\sum_{j=1}^m y_{ij}^2 \sum_{j=1}^m (I_j^-)^2}} \quad i=1,2,\dots,n \quad (14)$$

Step 7: Calculate the degree of similarity between alternatives and the positive ideal solution and the negative-ideal solution by

$$|C_i| = \frac{\sum_{j=1}^m y_{ij} * I_j^+}{\sqrt{\sum_{j=1}^m y_{ij}^2 \sum_{j=1}^m (I_j^+)^2}} * \sqrt{\sum_{j=1}^m y_{ij}^2}$$

$$S_i^\mp = \frac{|c_i|}{|A_i^\mp|} = \cos\theta_i^\mp * \frac{\sqrt{\sum_{j=1}^m y_{ij}^2}}{\sqrt{\sum_{j=1}^m y_{ij}^{\mp 2}}} \quad i=1,2,\dots,n \quad (14)$$

Step 8: Calculate the overall performance index for each alternative across all criteria by:

$$P_i = S_i^+ / (S_i^+ + S_i^-) \quad (15)$$

Step 9: Rank the alternatives in the descending order of the index value.

2.4 PROMETHEE

Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) is a well established decision support system which deals with the appraisal and selection of a set of options on the basis of several criteria with the objective of obtaining a ranking among them. PROMETHEE can simultaneously deal with qualitative and quantitative criteria. It can deal with uncertain and fuzzy information. It was founded by Brans and Vincke (1985).

Step 1: PROMETHEE method starts with the decision matrix:

$$\begin{bmatrix} f_1(a_1) & f_2(a_1) & \dots & f_n(a_1) \\ f_1(a_2) & f_2(a_2) & \dots & f_n(a_2) \\ \dots & \dots & f_j(a_i) & \dots \\ f_1(a_m) & f_2(a_m) & \dots & f_n(a_m) \end{bmatrix} \quad (16)$$

where $f_j(a_i)$ is the performance of the i^{th} alternative with respect to the j^{th} criteria. Here n is the number of the criteria and m is number of the alternatives. First, a specific preference function needs to be defined ($P_j(a,b)$) that translates the deviation between the evaluations of two alternatives (a and b) on a particular criterion f_j into a preference degree ranging from 0 to 1. This preference index is a non-decreasing function of the observed deviation (d) between the scores of the alternatives on the considered criterion $f_j(a) - f_j(b)$, as shown in Eq. (1). In order to facilitate the selection of a specific preference function, six possible shapes of preference functions are proposed to the decision-maker by Brans (1986). They are usual shape, U-shape function, V-shape function, level function, linear function and Gaussian function.

$$P_j(a,b) = G_j(f_j(a) - f_j(b)) \quad (17)$$

Step 2: In this method the preference is based on the pair-wise comparison of alternatives for each criterion. For this comparison purpose deviation of evaluations of two alternatives are used where higher the deviation higher will be the preference of one alternative to the other, regarding that criteria. This step involves calculation of preference function $P_j(a,b)$. There are mainly six types of generalized preference functions as proposed by Brans and Mareschal (1990). But these preference functions require the definition of some preferential parameters, such as the preference and indifference thresholds criterion and also to determine the parameters involved.

$$P_j(a,b) = \begin{cases} 0 & \text{if } f_j(a) < f_j(b) \\ (f_j(a), f_j(b)) & \text{otherwise} \end{cases}$$

For concrete case we define $p(\cdot)$ function as:

$$p((f_j(a), f_j(b))) = (f_j(a) - f_j(b))$$

In order to indicate clearly the areas of indifference in the neighborhood of $f(b)$:

$$x = f(a) - f(b)$$

Type 1: Usual criteria:

$$P(x) = \begin{cases} 0 & \forall x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$

Type 2: Quasi criteria:

$$P(x) = \begin{cases} 0 & \forall x \leq l \\ 1 & \text{otherwise} \end{cases}$$

Type 3: Criteria with linear preference:

$$P(x) = \begin{cases} x/m & \forall x \leq m \\ 1 & \forall x > l \end{cases}$$

Type 4: Level criteria:

$$P(x) = \begin{cases} 0 & x \leq q \\ 0.5 & q < x \leq q + p \\ 1 & x > q + p \end{cases}$$

Type 5: Criteria with linear preference and indifference area:

$$P(x) = \begin{cases} 0 & x \leq s \\ (x-s)/r & s < x \leq s+r \\ 1 & s+r \leq q+p \end{cases}$$

Type 6: Gaussian Criteria

$$P(x) = \begin{cases} 0 & \forall x \leq 0 \\ 1 - e^{-x^2/2\sigma^2} & \forall x > 0 \end{cases}$$

The value of σ is to be determined the decision maker.

In this paper, only usual criteria and criteria with linear preference have been used.

Step 3: Calculate the overall preference index taking into account weight of the individual criteria. It is calculated as follows:

$$\pi(a, b) = \sum_{j=1}^{j=n} w_j P_j(a, b) \quad (18)$$

Here $\pi(a, b)$ measures the degree with which alternative a is preferred to b' and $\pi(a, b)$ the measure of the degree with which alternative b is preferred to the alternative i .

Step 4: Determine the leaving and entering outflow matrix. Leaving or positive ranking outflow for the i^{th} alternative

$$\varphi^+(i) = \frac{1}{n-1} \sum_b \pi(a, b) \quad (19)$$

Entering or negative ranking outflow for the i^{th} alternative

$$\varphi^-(i) = \frac{1}{n-1} \sum_b \pi(b, a) \quad (20)$$

where m is the number of alternatives.

2.5. The PROMETHEE II complete ranking

Here, each alternative faces $(n - 1)$ number of other alternatives. The leaving flow expresses how much an alternative dominates the other alternatives, while the entering flow denotes how much an alternative is dominated by the other alternatives. Based on these outranking flows, the PROMETHEE I method can provide a partial preorder of the alternatives, whereas, the PROMETHEE II method can give the complete preorder by using a net flow, though it loses much information of preference relations.

Step 5: Determine the net outranking flow for each alternative from the following expression:

$$\varphi(a) = \varphi^+(a) - \varphi^-(a)$$

A higher value of $\varphi(a)$ signifies better alternative. Thus, the best alternative has always the highest $\varphi(a)$ value. From the positive and negative outranking flows, the net outranking flow value can be reformulated, as follows:

$$\varphi(a) = \varphi^+(a) - \varphi^-(a)$$

$$\varphi(a) = \frac{1}{m-1} \sum_{j=1}^n \left(\sum_b [P_j(a,b) - P_j(b,a)] \right)$$

Thus, $\varphi(a) = \sum_{j=1}^n w_j \varphi_j(a)$

where, $\varphi_j(a) = \sum_b [P_j(a,b) - P_j(b,a)]$

where $\varphi_j(a)$ is the single criterion net flow obtained for j^{th} criterion. It is observed that the global net flow of an alternative is the scalar product of vector of the criteria weights and profile vector of that alternative. This property is primarily used for developing the GAIA plane.

	PARAMETERS					
	C1. Print Volume (cu. inch.)	C2. Max. print Speed (mm/sec)	C3. Layer Thickness (μ m)	C4. No. of Extruders	C5. Price per Unit (Rs.)	C6. Manufacturer Filament Price (PLA) (Dollars/Kg)
3D PRINTERS						
A1. MAKERBOT REPLICATOR MINI	3.9×3.9×4.9	80	200	1	146400	48
A2. PRINTRBOT SIMPLE	6×6×6	80	100	1	73100	30
A3. ULTIMAKER 2	9×8.5×8	300	20	1	255500	42
A4. XYZ DA VINCI 1.0	7.8×7.8×7.8	150	100	1	77400	46.65
A5. MAKERBOT REPLICATOR 5.0	9.9×7.8×5.9	100	100	1	289800	48
A6. ALFINIA H	5×5×5	30	150	1	127600	31.99
A7. UP PLUS 2	5.5×5.5×5.3	30	150	1	167100	56.4
A8. DITTO PRO	8.7×6.5×8.7	120	50	1	192800	44.99
A9. AIRWOLF AW3D HD	12×8×12	150	60	1	301600	48
A10. FELIX 3.0	10×8×9	200	50	1	203100	32.6
A11. CUBIFY CUBEPRO	11.2×10.6×9 .06	15	70	1	283500	99
A12. MBOT GRID 2	10×9.0×7.8	120	100	2	146700	29.16

Fig. 2. Different 3D Printer Parameters values

For large number of alternatives it is impossible to determine the relative position of the alternatives with respect to the criteria. In GAIA plane the alternatives are represented by points and the criteria are represented by axes. The net flow is projection of single criteria net flow vector on w . So the relative position of projections of all the alternatives on w determines the complete ranking. On the GAIA plane w is represented as projection of unit vector of weights of all the criteria. This projection is represented as π axis. The π axis directs towards the compromise solution. When more number of criteria are correlated a longer π axis will make the ranking an easy one with greater accuracy. A shorter π axis resulting from more number of conflicting criteria will make the selection of a good compromise solution hard and will yield a solution of lesser accuracy.

3. Results

In the following table (Fig. 2), different types of available 3D printers alongwith their corresponding values of parameters have been shown. The following data have been collected from the manufacturer's website and brochures/ manuals.

3.1 Determination of relative weights of criteria using ANP

The relative weights of criteria, judging the selection of suitable 3D printer for educational institutions, can be determined using an ANP Network of Nodes and Clusters. The clusters include goal, criteria and alternatives. The alternatives' cluster is composed of different 3D printers among which the best one has to be chosen. The priorities list has been laid out in Table 1.

Table 1
ANP priorities list

Criteria	Normalized by cluster	Limiting
C1	0.12627	0.03261
C2	0.12808	0.03308
C3	0.13254	0.03423
C4	0.08029	0.02074
C5	0.32645	0.08432
C6	0.20637	0.05330

3.2 TOPSIS Results

Table 2 shows the decision matrix. Table 3 shows the normalized matrix. Table 4 shows weighted normalized matrix with weights (as determined by using ANP in previous section) of the criteria and Table 5 shows the POSITIVE ideal and negative ideal solution regarding each criteria, and ranks the alternatives. According to TOPSIS, XYZ Da Vinci 1.0 emerges out to be the best solution and Cubify Cubepro emerges out to be the worst solution.

3.3 Deng's Similarity Method Results

Here the Similarity based approach has been used to rank the 3D printers. The Ultimaker 2.0 emerges as the best solution here and the UP Plus 2.0 is the worst solution.

3.4 PROMETHEE Results

A problem of selecting a 3-D printer is solved using Visual PROMETHEE software. Preference parameters have been stated in Table 8. Visual PROMETHEE REPORT is shown in Table 9. Here Mbot Grid emerges out as the best solution, Da Vinci as second choice and Cubify Cubepro is the worst solution as displayed in this Table 9. In the GAIA plane, shown in Fig. 3, a long decision axis indicates a strong decision power which in turns indicates the chosen criteria are not conflicting. Price and filament price and are well correlated but on the other hand, price and speed, speed and volume are not

correlated as these axes are orthogonal. However performance of Airwolf and Replicator 5 are better regarding volume criteria. The performance of Replicator mini and Alfinia H are almost similar. In Fig. 4, a complete ranking of the alternatives as obtained by using PROMETHEE II is shown. In this figure net outranking flow of respective alternatives are also shown.

Table 2

Decision matrix

Alternatives	C1	C2	C3	C4	C5	C6
A1	74.529	80	200	1	146400	48
A2	216	80	100	1	73100	30
A3	637.2	300	20	1	255500	42
A4	474.552	150	100	1	77400	46.65
A5	455.598	100	100	1	289800	48
A6	125	30	150	1	127600	31.99
A7	160.325	30	150	1	167100	56.4
A8	491.985	120	50	1	192800	44.99
A9	1152	150	60	1	301600	48
A10	720	200	50	1	203100	32.6
A11	1075.6	15	70	1	283500	99
A12	702	120	100	2	146700	29.16

Table 3

Normalized decision matrix

Objective	Max C1	Max C2	Min C3	Max C4	Min C5	Min C6
A1	0.0344	0.1673	0.5366	0.2582	0.2075	0.2785
A2	0.0999	0.1673	0.2683	0.2582	0.1036	0.174
A3	0.2948	0.6274	0.5336	0.2582	0.3622	0.2437
A4	0.2196	0.3137	0.2683	0.2582	0.1097	0.2707
A5	0.2108	0.2091	0.2683	0.2582	0.4108	0.2785
A6	0.0578	0.0627	0.4024	0.2582	0.1809	0.1856
A7	0.0741	0.0627	0.4024	0.2582	0.2369	0.3272
A8	0.2276	0.2509	0.1341	0.2582	0.2733	0.2611
A9	0.5331	0.3137	0.1609	0.2582	0.4275	0.2785
A10	0.5331	0.4182	0.1341	0.2582	0.2879	0.1891
A11	0.4977	0.0313	0.1878	0.2582	0.4019	0.5745
A12	0.3248	0.2509	0.2683	0.5165	0.2079	0.1692

Table 4

Weighted normalized decision matrix

Columns	C1(+)	C2(+)	C3(-)	C4(+)	C5(-)	C6(-)
Weights	0.12808	0.12627	0.13254	0.08029	0.32645	0.20637
1	0.00440595	0.021124971	0.071120964	0.020730878	0.067738375	0.057474045
2	0.01279519	0.021124971	0.035560482	0.020730878	0.03382022	0.03590838
3	0.03775798	0.079221798	0.007104144	0.020730878	0.11824019	0.050292369
4	0.02812637	0.039610899	0.035560482	0.020730878	0.035811565	0.055864359
5	0.02699926	0.026403057	0.035560482	0.020730878	0.13410566	0.057474045
6	0.00740302	0.007917129	0.053334096	0.020730878	0.059054805	0.038302272
7	0.00949073	0.007917129	0.053334096	0.020730878	0.077336005	0.067524264
8	0.02915101	0.031681143	0.017773614	0.020730878	0.089218785	0.053883207
9	0.06827945	0.039610899	0.021325686	0.020730878	0.139557375	0.057474045
10	0.04266345	0.052806114	0.017773614	0.020730878	0.093984955	0.039024567
11	0.06374542	0.003952251	0.024891012	0.020730878	0.131200255	0.118559565
12	0.04160038	0.031681143	0.035560482	0.041469785	0.067868955	0.034917804
PIS	0.06827945	0.079221798	0.007104144	0.041469785	0.03382022	0.034917804
NIS	0.00440595	0.003952251	0.071120964	0.020730878	0.139557375	0.118559565

Table 5
Ranking of alternatives using TOPSIS

Alternatives	S_i^+	S_i^-	C_i^+	Ranks
A1	0.116801	0.095835	0.45069979	9
A2	0.087719	0.140148	0.61504299	4
A3	0.093406	0.126455	0.57515885	5
A4	0.069742	0.133389	0.65666491	1
A5	0.12767	0.077719	0.37839904	11
A6	0.109571	0.112165	0.51244571	7
A7	0.118594	0.082668	0.41074818	10
A8	0.088112	0.104614	0.54281208	6
A9	0.117858	0.107528	0.47708376	8
A10	0.074395	0.122878	0.62288301	3
A11	0.151365	0.075685	0.33334067	12
A12	0.070292	0.12642	0.64266542	2

Table 6
Performance matrix for similarity based approach

3D PRINTER	C1	C2	C3	C4	C5	C6	$\cos\theta^+$	$\cos\theta^-$	S_i^+	S_i^-
A1	0.004	0.021	0.071	0.021	0.068	0.057	0.53	0.94	0.51	0.56
A2	0.013	0.021	0.036	0.021	0.034	0.036	0.72	0.89	0.40	0.31
A3	0.038	0.079	0.007	0.021	0.118	0.050	0.81	0.77	1.03	0.61
A4	0.028	0.040	0.036	0.021	0.036	0.056	0.83	0.82	0.62	0.38
A5	0.027	0.026	0.036	0.021	0.134	0.057	0.6	0.93	0.77	0.74
A6	0.007	0.008	0.053	0.021	0.059	0.038	0.51	0.95	0.38	0.44
A7	0.009	0.008	0.053	0.021	0.077	0.068	0.52	0.99	0.50	0.59
A8	0.029	0.032	0.018	0.021	0.089	0.054	0.73	0.91	0.69	0.53
A9	0.068	0.040	0.021	0.021	0.140	0.057	0.73	0.84	1.03	0.73
A10	0.043	0.053	0.018	0.021	0.094	0.039	0.83	0.8	0.84	0.51
A11	0.064	0.004	0.025	0.021	0.131	0.119	0.61	0.93	0.95	0.89
A12	0.042	0.032	0.036	0.041	0.068	0.035	0.83	0.82	0.72	0.44

Table 7
Ranking of 3D printers using similarity based approach

3D PRINTER	Pi	RANKS
A3	0.628	1
A10	0.623	2
A4	0.619	3
A12	0.618	4
A9	0.584	5
A2	0.565	6
A8	0.564	7
A11	0.515	8
A5	0.511	9
A1	0.475	10
A6	0.464	11
A7	0.457	12

Table 8
PROMETHEE preference parameters

ACTIVE	yes	yes	yes	yes	yes	yes
	VOLUME	SPEED	THICKNESS	EXTRUDERS	PRICE	FILAMENT PRICING
MIN/MAX	max	max	min	max	min	min
WEIGHT	12.81	12.63	13.26	8.00	32.65	20.64
PREFERENCE FUNCTION	Liner	Liner	Liner	Usual	Liner	Liner
Thresholds	absolute	absolute	absolute	absolute	absolute	absolute
Q. Indifference	281.498	68.35	42.17	n/a	61372.864	19.06
P. Preference	695.402	159.18	100.81	n/a	156172.864	37.46
S. Gaussian	n/a	n/a	n/a	n/a	n/a	n/a

Table 9
Ranking of 3D printers using PROMETHEE

Actions	Phi	Phi+	Phi-
Mbot Grid 2	0.2192	0.2568	0.0376
Xyz Da Vinci	0.1828	0.2315	0.0487
Printbot simple	0.1417	0.2176	0.0759
Feilix 3	0.1153	0.1790	0.0637
UltirMaker	0.0908	0.2280	0.1371
Ditto Pro	0.0386	0.1144	0.0758
Alfinia H	-0.0202	0.1413	0.1615
Airwolf	-0.0467	0.1680	0.2147
Replicator mini	-0.0915	0.1125	0.2040
UP Plus 2	-0.1125	0.0882	0.2007
Replicator 5	-0.1926	0.0410	0.2335
Cubify Cubepro	-0.3249	0.1103	0.4352

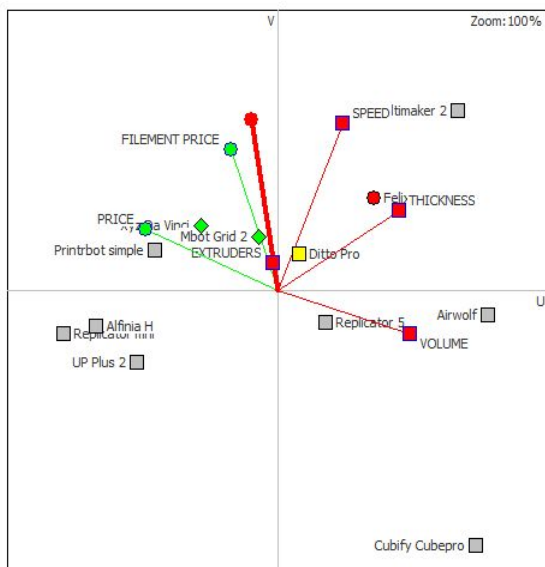


Fig. 3. GAIA Analysis

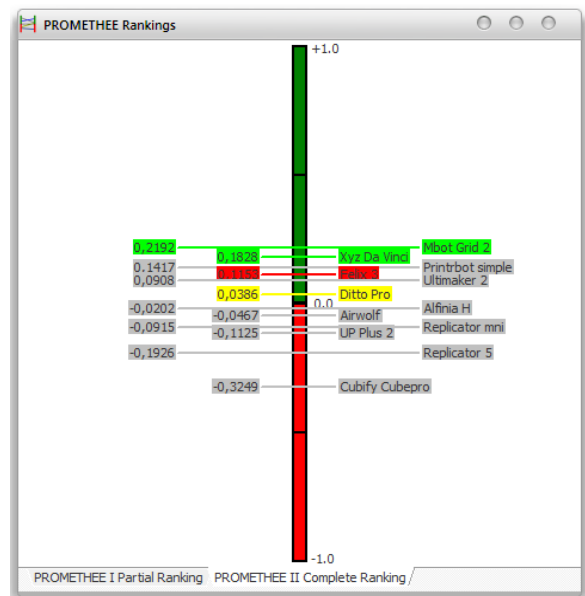


Fig. 4. PROMETHEE II Complete Ranking

Table 10
Comparative analysis of rankings

3D PRINTERS	RANKS BY TOPSIS	RANKS BY SIMILARITY BASED APPROACH	RANKS BY PROMETHEE
A1MAKERBOT REPLICATOR MINI	9	10	9
A2 PRINTRBOT SIMPLE	4	6	3
A3 ULTIMAKER 2	5	1	5
A4 XYZPRINTING DA VINCI 1.0	1	3	2
A5 MAKERBOT REPLICATOR 5.0	11	9	11
A6 ALFINIA H	7	11	7
A7 UP PLUS 2	10	12	10
A8 DITTO PRO	6	7	6
A9AIRWOLF AW3D HD	8	5	8
A10FELIX 3.0	3	2	4
A11CUBIFY CUBEPRO	12	8	12
A12 MBOT GRID	2	4	1

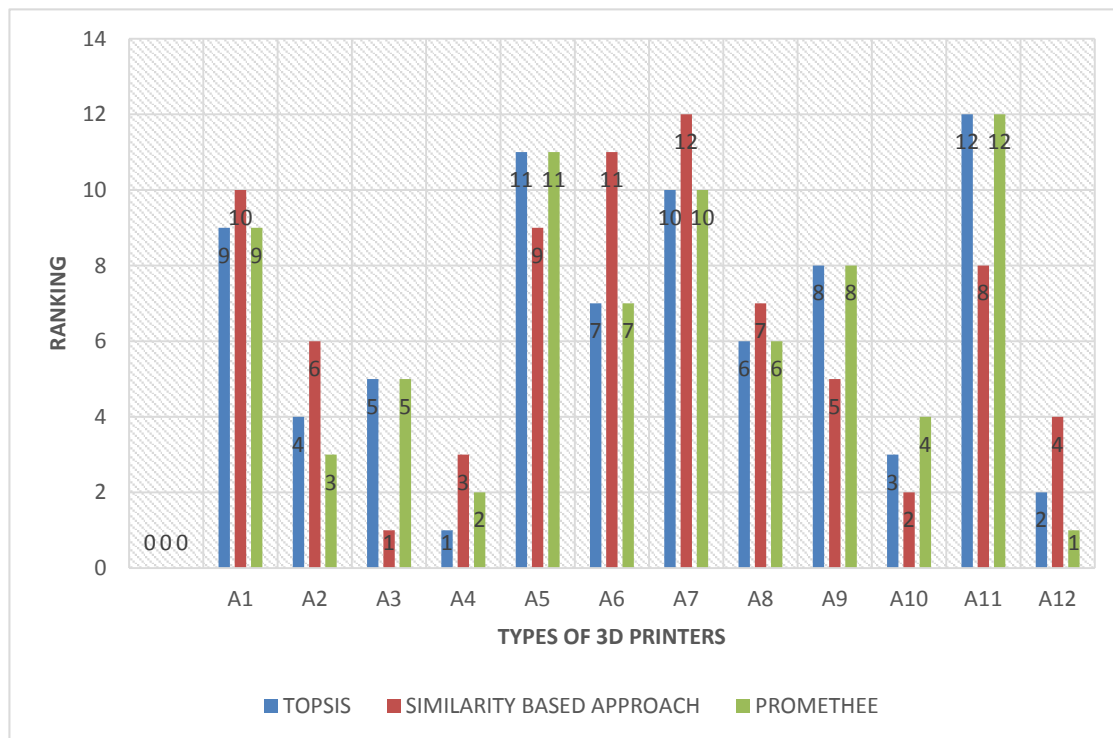


Fig. 5. Graphical analysis of Rankings

4. Conclusion

Three different MCDM techniques, namely TOPSIS, Similarity Approach and PROMETHEE, have been compared with respect to a chosen problem i.e. selection of 3D Printers, the relative weights of the associated criteria having been determined using ANP. Slight deviations are witnessed in the results given by the above three methods namely, TOPSIS, Similarity Based Approach and PROMETHEE. XYZPRINTING DAVINCI 1.0 emerges out to be the best solution as per the TOPSIS method. ULTIMAKER 2 is the best solution as per the Similarity Based Approach. MBOT GRID emerges out to be the best solution as per the PROMETHEE Method. For both TOPSIS and PROMETHEE, the worst solution is the CUBIFY CUBEPRO, but for Similarity Method, the UP PLUS 2.0 is the worst solution. Further investigation, reveals that TOPSIS and PROMETHEE rankings are highly similar to a certain extent as seen in Table 10 and fig. 5, but results of the similarity based approach are markedly different. From the above problem and the varied solutions obtained from using different MCDM

techniques, it can be inferred that under certain circumstances, the use of different MCDM methods sometimes highlight different alternatives as the most appropriate one, and will provide different ranking order of the alternatives. This may be because of the different aggregation and normalization procedures which the methods follow. In conclusion, it can be inferred that the considered MCDM techniques have their own specifics and advantages, which is why the choice of MCDM method becomes a rather complex decision.

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