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A Linear Trade-off Group TOPSIS method with application for Internet of Things devices ranking

Constanta Zoie Radulescu^a*, Marius Radulescu^b, Radu Boncea^a

^aNational Institute for Research and Development in Informatics, 8-10, Mareşal Averescu, Bucharest, 011455, Romania ^b"Gheorghe Mihoc-Caius Iacob" Institute of Mathematical Statistics and Applied Mathematics of the Romanian Academy, Calea 13 Septembrie, No.13, Bucharest, 050711, Romania

Abstract

Multi-criteria methods are decision-making methods used when considering multiple criteria simultaneously in decision-making processes. Among the multi-criteria methods, a widely used method that has proven its effectiveness in many applications is the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS). In this paper we propose a modification of the TOPSIS method by using another way of calculating the relative closeness coefficient (RCC) and taking into account a group of decision makers. The modified version of the TOPSIS method, which we shall call the Linear Trade-off Group TOPSIS method (LTG-TOPSIS), replaces the RCC from the classical TOPSIS method with one that depends on a parameter that takes values in the unit interval. By using the parameter, the RCC is calculated as a linear combination between distances of an alternative to the ideal and anti-ideal solutions. This approach facilitates a management of the compromise between the two distances. An implementation of the LTG-TOPSIS method is analysed for a IoT devices ranking. By varying the parameter of the proposed method, a set of IoT devices rankings is obtained and the change in the ranking is studied. A comparison of the rankings obtained with LTG-TOPSIS and with the classical TOPSIS method is performed.

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Keywords: TOPSIS method; Group Best Worst Method; Linear Trade-off method; Relative closeness coefficient, IoT devices ranking

* Corresponding author. Tel.: +4-075-585-7943. *E-mail address:* zoie.radulescu@ici.ro.

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1. Introduction

Multi-criteria methods, also known as multi-criteria decision-making (MCDM) methods or multiple criteria decision analysis (MCDA) methods, are decision-making methods used when considering multiple criteria simultaneously in decision-making processes. These methods are particularly useful when decision makers (DMs) need to evaluate and compare alternatives across multiple criteria, each with its own importance or weight [1], [2]. These methods provide a structured framework for decision-making and have applications in various fields such as construction, project management, safety and risk management, manufacturing, technology, information management, strategic management, information and communication technology, business intelligence, remote sensing, software evaluation, education and social policy, Internet of Things (IoT) [3-5].

Although there are many multi-criteria methods available, no method is ideal and can be considered universal acceptable for use in all decision-making contexts. The selection of a relevant multi-criteria method for a given problem is essential in obtaining an adequate solution.

Among the multi-criteria methods, a widely used method that has proven its effectiveness in many applications is the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [6], [7]. TOPSIS has been extensively used for solving multicriteria decision making problems. It has over 18 000 citations [8] and is considered as one of the fundamental MADM methods. TOPSIS is a popular multi-criteria method known for its simplicity, sound mathematical foundation, ease to apply in multi-criteria problems [9]. It uses both quantitative and qualitative data but is sensitive to variations in criteria weights and normalization methods. TOPSIS assumes that the criteria are independent and, in some cases, it can cause the inversion of the rank. TOPSIS aims to identify the alternative that is closest to the ideal solution and farthest from the anti-ideal solution. Various modifications and extensions of the TOPSIS method have been studied and comparative analyses were realized. A recent detailed literature review for different versions of the TOPSIS method is provided in [10].

The TOPSIS method contains a series of steps of the decision-making process, including: weighting the criteria, defining, normalizing and weighting the decision matrix, determining the ideal and anti-ideal solutions, calculating the Euclidean distances of the ideal and anti-ideal solutions, calculating the RCCs and the ranking of alternatives. The weighting of criteria can reflect the individual preferences of a Decision Maker (DM).

In this paper we propose a modification of the TOPSIS method by using another way of calculating the RCC and taking into account a group of DMs. The modified version of the TOPSIS method, which we shall call the Linear Trade-off Group TOPSIS method (LTG-TOPSIS), replaces the RCC from the classical TOPSIS method with a coefficient that depends on a parameter that takes values in the unit interval. More precisely by using the parameter, we will calculate the RCC as a linear combination between distances of an alternative to the ideal and anti-ideal solutions. In this way, a compromise will be made between the two distances.

The TOPSIS method requires discrete criteria weights calculated before the calculations are done. In this paper, the weights of the criteria for each DM are calculated with the Group Best Worst Method (GBWM) method. The BWM method [11] is a relatively new and popular method for obtaining criteria weights in multi-criteria decision-making problems.

In the last years the number of interconnected devices in Internet of Things (IoT) worldwide is forecast to almost double from 15.1 billion in 2020 to more than 29 billion IoT devices in 2030. In 2030, the highest number of IoT devices will be found in China. It is forecasted around 8 billion consumer devices [12]. Research related to selection in IoT has developed a lot in recent years. Multi-criteria methods can help address IoT selection problems by providing a structured approach to evaluating and comparing different alternatives based on multiple criteria [13].

An implementation of the LTG-TOPSIS method is analysed for a IoT devices ranking. By varying the parameter of the proposed method, a set of solutions are obtained and the change in the ranking of the IoT devices is studied. A comparison of the rankings obtained for various values of the parameter with the ranking obtained with the classical TOPSIS method is performed.

The remainder of the paper is structured as follows. Section 2 contains the LTG-TOPSIS method described in steps. In section 3 is presented an application of the proposed method for IoT devices ranking. Conclusions are given in Section 4.

2. The linear Trade-off Group TOPSIS method

The LTG-TOPSIS method is presented in the following. Input data

- A set $D = \{D_1, D_2, \dots, D_p\}$ of p decision makers (DMs).
- A set of *n* criteria $C = \{C_1, C_2, ..., C_n\}$. A criterion C_j can be a maximum (benefit) or minimum (cost) criterion. A weight is associated with each criterion in set *C*. The vector of criteria weights is denoted by $\mathbf{w}=(w_j), j=1, 2, ..., n$. The weight w_j shows the importance of the criterion C_j . The weights usually have numerical values in the range (0,1) and the sum of the criteria is equal to 1. The criteria weights are calculated based on the Group BWM method.
- A set of m alternatives $V = \{V_1, V_2, \dots, V_m\}$.
- Trade off parameter λ that varies in the unit interval [0;1].

Group BWM Method

Step 1. For every k=1,2,...,p, the D_k selects the best criterion C_{Bk} and the worst criterion C_{Wk} from the set C. Step 2. The D_k expresses his/her preferences regarding the best criterion C_{Bk} over the other criteria.

Denote by: a_{Bkj} the preference of the D_k for the best criterion C_{Bk} over criterion C_j . a_{Bkj} is an integer number between 1 to 9 from the BWM scale.

Denote by: a_{jWk} the preference of the D_k for the best criterion C_{Wk} over criterion C_j . a_{jWk} is an integer number between 1 to 9 from the BWM scale.

Step 3. The vectors of criteria weights $\mathbf{w}_k = (w_{kj})$; j=1, 2, ..., n; k=1, 2, ..., p for the p DMs are calculated with the help of BWM. In order to obtain the most consistent weights with the pairwise comparisons, the maximum distance between the pairwise comparisons and their corresponding weight ratios should be minimized. As a result, for every k=1, 2, ..., p we obtain a nonlinear optimization problem:

$$\min\left[\max_{1 \le j \le n} \left(\left| w_{Bk} - a_{Bkj} w_{kj} \right|, \left| w_{kj} - a_{jWk} w_{Wk} \right| \right) \right] \\ \sum_{j=1}^{n} w_{kj} = 1 \\ 0 < w_{Wk} \le w_{kj} \le w_{Bk}; \ j = 1, 2, ..., n$$
(1)

The decision variables in the model (1) are $\mathbf{w}_k = (w_{kj})$. The problem (1) can be transformed into an equivalent linear programming problem:

$$\min_{j=1}^{n} [\xi_{k}]$$

$$\sum_{j=1}^{n} w_{kj} = 1$$

$$0 < w_{Wk} \le w_{kj} \le w_{Bk}$$

$$-\xi_{k} \le a_{Bkj} w_{kj} - w_{Bk} \le \xi_{k}$$

$$-\xi_{k} \le a_{jWk} w_{Wk} - w_{kj} \le \xi_{k}; j = 1, 2, ..., n$$

$$(2)$$

In the model (2) the decision variables are $\mathbf{w}_k = (w_{kj})$ and ξ_k ; j=1, 2, ..., n; k=1, 2, ..., p. For every k=1, 2, ..., p the linear programming model (2) is solved. Denote by: $\mathbf{w}_{*k} = (w_{*kj})$ and ξ_{*k} the optimal solutions of model (2). Note that w_{*kj} ; j=1, 2, ..., n are the weights computed from the evaluations of D_k . Step 4. For every D_k the consistency ratio CR_k of the model is calculated using the following formula:

$$CR_k = \xi_{*k} / CI \tag{3}$$

where *CI* is the consistency index (Table 1) and $a_{BWk} = a_{Bkj} \ge a_{jWk}$.

a_{BWk}	1	2	3	4	5	6	7	8	9
CI – consistency index (max ξ_k)	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

If CR_k is in the interval [0;1] then the comparisons made by D_k are consistent. If CR_k is not in the interval [0;1] then the comparisons are inconsistent and the D_k must repeat comparisons in pair (go to step 2).

Step 5. The entries of the final vector of group criteria weights $\mathbf{w} = (w_i), j = 1, 2, ..., n$ is calculated as follows:

$$w_j = \frac{\sum_{k=1}^{p} w_{*kj}}{p} \tag{4}$$

LTG-TOPSIS method

Step 6. The evaluation matrices $\mathbf{E}_k = (e_{ijk})$; i=1, 2, ..., m; j=1, 2, ..., n; k=1, 2, ..., p for the p DMs are built. The value e_{ijk} shows the evaluation made by the D_k of alternative V_i for criterion C_i .

The entries of the total evaluation matrix $\mathbf{E} = (e_{ij})$ are calculated as an average of the p evaluation matrices \mathbf{E}_k :

$$e_{ij} = \frac{\sum_{k=1}^{p} e_{ijk}}{p}$$
(5)

Step 7. The total evaluation matrix is normalized and weighted. The normalization is done to bring the entries of the evaluation matrix **E** into the interval [0;1] and to have compatible units. The normalization method in LTG-TOPSIS method is the "vector normalization". The entries of the normalized matrix $\overline{\mathbf{E}} = (\overline{e_{ij}}), i = 1, 2, ..., m; j = 1, 2, ..., n$ are calculated. To preserve the type of criterion, only the normalization for the maximum criteria is used:

$$\bar{e}_{ij} = \frac{e_{ij}}{\sqrt{\sum_{k=1}^{m} (e_{kj})^2}}$$
(6)

The entries of the weighted normalized matrix $\mathbf{\overline{E}} = \begin{pmatrix} \bar{e}_{ij} \\ e_{ij} \end{pmatrix}$ are calculated as $\vec{e}_{ij} = w_i \times \vec{e}_{ij}$.

Step 8. The positive ideal solution $\mathbf{A}^+ = (a_j^+)$ and negative ideal solution $\mathbf{A}^- = (a_j^-)$ are determined as follows:

$$a_{j}^{+} = \begin{cases} \max_{i}^{e} \text{ if } C_{j} \text{ is a maximum criterion} \\ \min_{i}^{i} e_{ij} \text{ if } C_{j} \text{ is a minimum criterion} \\ \min_{i}^{i} e_{ij} \text{ if } C_{j} \text{ is a minimum criterion} \end{cases} \qquad a_{j}^{-} = \begin{cases} \min_{i}^{e} e_{ij} \text{ if } C_{j} \text{ is a maximum criterion} \\ \max_{i}^{e} e_{ij} \text{ if } C_{j} \text{ is a minimum criterion} \end{cases}$$
(7)

Step 9. The relative Euclidian distances to the ideal solutions are calculated. The vectors $\mathbf{D}^+ = (d_i^+)$ and $\mathbf{D}^- = (d_i^-)$ are calculated with respect to the positive and negative ideal solutions as follows:

$$d_{i}^{+} = \left(\sum_{j=1}^{n} \left| \stackrel{e}{e}_{ij} - a_{j}^{+} \right|^{2} \right)^{1/2}; \qquad d_{i}^{-} = \left(\sum_{j=1}^{n} \left| \stackrel{e}{e}_{ij} - a_{j}^{-} \right|^{2} \right)^{1/2}$$
(8)

In the classical TOPSIS method the RCCs are calculated in the vector $S=(s_i); i=1, 2, ..., m$.

$$s_{i} = \frac{d_{i}^{-}}{d_{i}^{+} + d_{i}^{-}}$$
(9)

The best alternative V_i corresponds to the greatest s_i .

To obtain the ranking of the alternatives, the entries of the vector **S** are ordered in descending order. Let $\mathbf{R}=(r_i)$; i=1, 2, ..., m be the vector whose entries are the ranks of the alternatives. The r_i is the rank of s_i .

If
$$s_i = \max_k (s_k)$$
 then $r_i = 1$. If $s_i = \min_k (s_k)$ then $r_i = m$

In the modified LTG-TOPSIS method the RCCs are calculated in the vector $\mathbf{S}^*(\lambda) = (s_i^*(\lambda)); i = 1, 2, ..., m \text{ and } \lambda \in [0, 1]$. The *i*-th entry of vector $\mathbf{S}^*(\lambda)$ is defined as follows:

$$s_i^*(\lambda) = (1-\lambda) \times d_i^- - \lambda \times d_i^+ \tag{10}$$

The best alternative when λ is fixed is the alternative corresponding to the entry of the vector $S^*(\lambda)$ that has the maximum value.

To obtain the ranking of the alternatives, the entries of the vector $S^*(\lambda)$ are ordered in descending order.

Let $\mathbf{R}^*(\lambda) = (r_i^*(\lambda)); i = 1, 2, ..., m$ and $\lambda \in [0;1]$ be the vector whose entries are the ranks of the alternatives. $r_i^*(\lambda)$ is the rank of $s_i^*(\lambda)$.

If
$$s_i^*(\lambda) = \max_k (s_k^*(\lambda))$$
 then $r_i^*(\lambda) = 1$. If $s_i^*(\lambda) = \min_k (s_k^*(\lambda))$ then $r_i^*(\lambda) = m$.

A variation of λ changes in the order of alternatives. An analysis of these changes is analysed.

3. The LTG-TOPSIS application for IoT devices ranking

In the following we shall apply the above-described LTG-TOPSIS multi-criteria method for ranking a set of IoT devices.

A set of five DMs: $D = \{D_1, D_2, ..., D_5\}$ and a set of eight criteria $C = \{C_1, C_2, ..., C_8\}$ are considered. The criteria are described in Table 2.

Table 2.	The	criteria	used	for	IoT	devices	ranking
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Criteria	Description	Criteria symbol	Criteria Type
Functionality	Selected IoT devices should be able to perform the intended functions required by the use case or application.	C1	Max
Performance	IoT devices should be able to operate accurately and reliably under different conditions. Performance metrics such as response time, accuracy, and precision can be used to evaluate different devices. Performance measures such as processing power, memory, and storage capacity should be considered, especially if the devices are expected to process or store large amounts of data.	C2	Max

Reliability	IoT devices should be reliable and able to operate in a variety of environments and conditions without failure. They should have a low failure rate, and the manufacturer should provide support in the event of a failure.	СЗ	Max
Scalability	IoT devices should be able to handle large volumes of data. It is essential to consider the ease of adding new devices to the system and the ability of the devices to communicate with each other.	<i>C4</i>	Max
Security	IoT devices should have built-in security features such as: encryption, authentication and access control to ensure data privacy and integrity.	C5	Max
Compatibility	IoT devices should be compatible with other system components, such as: sensors, communication protocols and platforms, to ensure a seamless integration that complies with standards and ensures efficient data exchange.	<i>C6</i>	Max
Energy consumption	IoT devices should have low power consumption to extend battery life and reduce the frequency of battery replacement. This is especially important for devices that are located in remote or hard-to-reach locations.	<i>C</i> 7	Min
Cost	IoT devices should be cost-effective, considering both the initial purchase cost and the total lifetime cost of ownership.	<i>C8</i>	Min

The criteria weights are calculated using the DMs evaluations and the Group BWM method. For every k=1, 2, ..., 5 the linear programming model (2) is solved. The group criteria weights are calculated based on equation (4) and are presented in Table 3.

Table 3. The criteria weights

Criteria	C_{I}	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Criteria weights	0.25132	0.16262	0.04646	0.02218	0.10841	0.05421	0.08131	0.27350

A set of ten IoT devices $V = \{V_1, V_2, ..., V_{10}\}$ is selected.

The evaluation matrices \mathbf{E}^k , k=1, 2, ..., 5 for the five DMs are built. The total evaluation matrix \mathbf{E} is calculated based on equation (5). The total evaluation matrix is normalized and weighted (Table 4). The positive ideal solution \mathbf{A}^+ and negative ideal solution \mathbf{A}^- are determined based on equations (7). In the last two rows of Table 4 are displayed vectors \mathbf{A}^+ and \mathbf{A}^-

Table 4. The total normalized and weighted evaluation matrix

IoT devices /	C_I	C_2	C_3	C_4	C_5	C_6	<i>C</i> ₇	C_8
Criteria								
V_{I}	0.064	0.042	0.014	0.008	0.031	0.019	0.027	0.085
V_2	0.064	0.045	0.013	0.005	0.033	0.015	0.027	0.099
V_3	0.085	0.056	0.016	0.007	0.039	0.017	0.031	0.113
V_4	0.074	0.048	0.014	0.006	0.033	0.017	0.031	0.099
V_5	0.085	0.056	0.015	0.008	0.035	0.016	0.022	0.085
V_6	0.089	0.051	0.015	0.007	0.031	0.017	0.022	0.071
V_7	0.080	0.057	0.016	0.006	0.039	0.020	0.018	0.085
V_8	0.076	0.047	0.013	0.007	0.031	0.015	0.027	0.071
V_{9}	0.091	0.057	0.016	0.008	0.035	0.018	0.027	0.085
V_{10}	0.082	0.052	0.013	0.007	0.035	0.016	0.022	0.057
\mathbf{A}^{+}	0.091	0.057	0.016	0.008	0.039	0.020	0.018	0.057
A ⁻	0.064	0.045	0.013	0.005	0.031	0.015	0.031	0.113

The relative Euclidian distances to the ideal solutions are calculated. The vectors \mathbf{D}^+ and \mathbf{D}^- are calculated based on equations (8). The vector **S** is calculated in classical TOPSIS method based on equation (9) (Table 5).

IoT Devices	\mathbf{D}^+	D	Classic, TOPSIS RCC	Classic TOPSIS Ranks
V_{I}	0.044	0.029	0.401	7
V_2	0.053	0.015	0.219	10
V_3	0.059	0.025	0.302	8
V_4	0.049	0.018	0.272	9
V_5	0.030	0.038	0.560	6
V_6	0.018	0.051	0.733	2
V_7	0.030	0.039	0.563	5
V_8	0.026	0.045	0.630	3
V_{9}	0.030	0.042	0.583	4
V_{10}	0.012	0.061	0.831	1

Table 5. The relative distances to the ideal solutions, classical TOPSIS RCCs and IoT devices ranks.

In the modified LTG-TOPSIS method the vectors $\mathbf{S}^*(\lambda)$ are calculated based on equation (10).

By variation of parameter λ from 0 to 1 with step 0.01, a number of 100 vectors $S^*(\lambda)$ are obtained.

The ranks of the IoT devices are entries of the vector $\mathbf{R}^*(\lambda)$. Changes in the IoT devices ranks are analyzed in comparation with the IoT devices ranks computed with the Classical TOPSIS method (Table 6).

Table 6. Changes in the IoT devices ranks by variation of parameter λ

IoT Devices		LTG	Classic			
	λ=0	=0 λ =0.43 λ =0.67 λ =0.		λ=0.76	λ=1	TOPSIS Ranks
V_{I}	7	7	7	7	7	7
V_2	10	10	9	9	9	10
V_3	8	9	10	10	10	8
V_4	9	8	8	8	8	9
V_5	6	6	6	5	5	6
V_6	2	2	2	2	2	2
V_7	5	5	5	6	6	5
V_8	3	3	3	3	3	3
V_{9}	4	4	4	4	4	4
V_{10}	1	1	1	1	1	1

From Table 6 one can note that for variation of the parameter λ from the value $\lambda=0$ to the value $\lambda=0.42$ the ranks obtained with the LTG-TOPSIS method are identical with the ranks obtained with the Classical TOPSIS method.

If the parameter λ varies in the interval [0.43; 0.66] then the ranks of alternatives V_3 and V_4 differ by a position compared to the ranks from the Classical TOPSIS method.

If the parameter λ varies in the interval [0.67; 0.75] then the ranks of alternatives V_2 and V_4 differ by one position and the rank of V_3 differs by two positions compared to the ranks from the Classical TOPSIS method.

If the parameter λ varies in the interval [0.76; 1] then the ranks of alternatives V_2 , V_4 , V_5 and V_7 differ by one position and the rank of V_3 differs by two positions compared to the ranks from the Classical TOPSIS method.

4. Conclusions

The TOPSIS multi-criteria method obtains a ranking of the alternatives by calculating the alternatives RCCs. Its aim is to find alternatives that are as close as possible to the positive ideal solution and as far as possible from the negative ideal solution. The compromise between the two distances is obtained with a fractional RCC. By ordering these coefficients in descending order, a ranking of the considered alternatives is obtained. In this paper, a modified

version of the TOPSIS method is proposed that calculates the RCCs with the help of a parameter λ . This parameter varies in the range [0;1]. For a value close to 1 of the parameter λ , the RCC of the LTG-TOPSIS method is closer to the ideal positive solution, and for a value of the parameter λ close to 0, the RCC of the LTG-TOPSIS method is closer to the ideal negative solution.

The proposed method is applied to ranking of a set of IoT devices in relation to several considered criteria, among which are cost, functionality, performance and security. A comparison between the rankings obtained with the Classical TOPSIS method and the rankings obtained with the help of the proposed method, for different values of λ in the interval [0;1] is carried out. It is found that, for the presented application, the alternatives rankings of the proposed method do not differ significantly from the alternative rankings of the Classical TOPSIS method but the new method offers the advantage of a management of the compromise between the distances from the positive ideal solution and the negative ideal solution. In addition, the LTG-TOPSIS is a simple, powerful and flexible method, to solve decision making ranking problems.

Our modified TOPSIS method can not only be applied to IoT devices ranking but also can be used for solving other decision problems in which several alternatives are considered that are evaluated according to a set of criteria.

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