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TOPSIS-RTCID for range target-based criteria and interval data

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Abstract: The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is receiving considerable attention as an essential decision analysis technique and becoming a leading method. This paper describes a new version of TOPSIS with interval data and capability to deal with all types of criteria. An improved structure of the TOPSIS is presented to deal with high uncertainty in engineering and engineering decision-making. The proposed Range Target-based Criteria and Interval Data model of TOPSIS (TOPSIS-RTCID) achieves the core contribution in decision making theories through a distinct normalization formula for cost and benefits criteria in scale of point and range target-based values. It is important to notice a very interesting property of the proposed normalization formula being opposite to the usual one. This property can explain why the rank reversal problem is limited. The applicability of the proposed TOPSIS-RTCID method is examined with several empirical litreture's examples with comparisons, sensitivity analysis, and simulation. The authors have developed a new tool with more efficient, reliable and robust outcomes compared to that from other available tools. The complexity of an engineering design decision problem can be resolved through the development of a well-structured decision making method with multiple attributes. Various decision approches developed for engineering design have neglected elements that should have been taken into account. Through this study, engineering design problems can be resolved with greater reliability and confidence.

Key words: interval data, uncertainty in data, range target-based criteria, multi-attribute decision making.

1. Introduction

In comparison to normal (everyday) decision making, the process of materials selection (Jahan et al., 2016), process selection, machine selection, and product design is much more difficult due to the large number of varying criteria. The role of multi-attribute decision making (MADM) is to design and develop tools to help evaluate alternatives. In a decision making environment, there are frequently situations where the final solution should be simultaneously analyzed based on "nadir" and best optimal solutions. The technique for order preference by similarity to ideal solution (TOPSIS) is a user-friendly decision making method with this advantage. TOPSIS has actually received a sufficient level of consideration from research and industrial communities, that global interest to work on TOPSIS has dramatically increased (Behzadian et al., 2012).

When doubt exists in the forecast of outcomes, all decisions there after have uncertainty and no one can ever predict the future with absolute certainty. Typically, there are two kinds of uncertainty with engineering design problems; uncertainty in loading and service conditions, and uncertainty of data in the design decision- matrix. It is possible to partially deal with the first type of uncertainty by providing design

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flexibility in products using range target criteria. Product design flexibility is the capability of a product to be redesigned rapidly and cost-effectively (Tilstra et al., 2015). Uncertainty of data in the design decision matrix includes materials and design performance indices. Alternatively, the uncertainties related to material properties are because of variations in aspects such as structure and processing, and environment such as temperature and humidity. Also, variations in surface roughness, sharp edges, residual stress and identification marks are caused by manufacturing processes. This uncertainty comes to the decision context as a spreadsheet of interval, grey, fuzzy, and linguistic numbers, and stochastic or probabilistic values. There are approaches available to solve decision making problems comprising grey numbers or interval values. In this research TOPSIS is restructured to include interval values. The reformed version articulates TOPSIS improvement from two perspectives: (1) defining a new normalization formula that better suits TOPSIS for including target values, and (2) to conFigure a weighed ranking index. It is also important to notice a very interesting property of the proposed normalization formula as being opposite to the usual one. It does not introduce any additional dependence between the elements of a given column in the normalized decision matrix. This property can explain why the rank reversal problem is limited. The proposed Range Target-based Criteria and Interval Data Model of TOPSIS (TOPSIS-RTCID) identifies the negative ideal solution (NIS) and positive ideal solution (PIS) from normalized criteria interval values. Therefore, the PIS and NIS are not related to a single alternative but to all of them.

This paper describes the development of TOPSIS-RTCID. The next section is separated into three subsections and reviews pertinent current knowledge on multi-criteria decision analysis tools that directly relate to MADM and TOPSIS. The first subsection appraises recent progress in MADM methods using target-based criteria and interval data. The second subsection evaluates new developments in TOPSIS. The last subsection identifies the objectives of the current research work as well as the gap in previous studies. Section 3 explains the materials and tools required to structure the proposed TOPSIS-RTCID. Section 4 presents several examples from the litriture to test the effect and performance of the proposed TOPSIS-RTCID. Section 5 discusses the application and analysis of the proposed TOPSIS-RTCID and is separated into two subsections: the use of the method in engineering design, and a critical analysis of it. Lastly, the Conclusions section summarizes the key outcomes of the research and suggests areas for further development.

2. Summary of recent knowledge on multi-criteria decision analysis tools

2.1. Review of target-based criteria and interval data in MADM

Several MADM methods have been extended to include grey numbers or interval data. Jahanshahloo et al. (2006) have developed standard TOPSIS for decision making to include interval data. Amiri et al. (2008) have offered a novel Elimination and Choice Expressing Reality (ELECTRE) technique with interval data. A new Multicriteria Optimization and Compromise Solution (VIKOR) method with interval data has been presented by Sayadi et al. (2009) and it was revealed that VIKOR with interval data was better than TOPSIS with interval data. Jahanshahloo et al. (2009) have argued another TOPSIS with interval data that can arrange alternatives by interval efficiency. Tsaur (2011) has proposed linear normalization to consider attitude towards risk when analyzing TOPSIS with interval data (Jahanshahloo et al., 2009) instead of vector normalization. Turskis & Zavadskas (2010) have proposed a new Additive Ratio Assessment (ARAS) using Grey criteria scores (ARAS-G). Hajiagha et al. (2012) have suggested linear programming for multi-dimensional analysis of preference method (LINMAP) for grey numbers. Stanujkic et al. (2012) have combined the concept of interval grey numbers with the Multi-objective Optimization on the Basis of Ratio Analysis (MOORA) method. Dymova et al. (2013) have claimed a direct interval extension for TOPSIS utilising the distance between midpoints of intervals. Baradaran & Azarnia (2013) have developed a method to test the consistency and generate weightings from grey pairwise matrices in a grey analytical hierarchy process (AHP). Yue (2013) has proposed an interval TOPSIS for group decision making. The MULTIMOORA method was developed by Hafezalkotob et al. (2016) with interval data using interval arithmetic and a preference matrix. Ahn (2017) has also worked on grey AHP and developed a simple method for detecting the extreme points in a range of interval ratios, and for creating the dominance relations between alternatives by means of identifying extreme points. For machine selection, Hafezalkotob and Hafezalkotob (2017) have claimed an interval target-based VIKOR with interval data.

Furthermore, Jahan et al. (2011) have developed VIKOR for target-based attributes, taking target values into consideration. The proposed comprehensive VIKOR applied for selecting the materials of a total knee replacement (Bahraminasab and Jahan, 2011). TOPSIS have extended by Jahan et al. (2012) with a more precise normalization technique for using in selection problems concerning point target-based criteria. Meanwhile the VIKOR technique for interval data and target-based criteria have discussed by Jahan and Edwards (2013). A novel mix MADM approch for material selection possessing point target-based and interdependent criteria have suggested by Liu et al. (2014). The MULTIMOORA method with point target-based criteria was extended by Hafezalkotob and Hafezalkotob (2015) for materials selection. Jahan (2018) has developed the Weighted Aggregated Sum Product ASsessment (WASPAS) method for range target-based criteria and applied the proposed technique in a material selection study. Peldschus (2018) has investigated the impact of convex, linear, and concave function profiles for normalization and examined ten different formulae. Jahan & Zavadskas (2018) have extended the ELECTRE method for engineering decision-making cases by target-based criteria and interval data. Perez et al. (2016) have proposed the reference ideal method (RIM) for an “ideal solution” occurring between the maximum and minimum values. However, RIM does not have any provision for interval data in the decision matrix. The RIM have extended recently for a fuzzy multi-criteria decision making environment by Cables et al. (2018). Maghsoodi et al. (2019) have studied a material selection problem by applying a mixed decision-making approach supported by COmbinative Distance-based ASsessment (CODAS) technique containing target-based attributes and Step-Wise Weight Assessment Ratio Analysis (SWARA) method. Liao and Wu (2019) have studied on target-based linear and vector normalization technique in multi-expert multi-criteria decision making.

2.2. Brief review of recent developments in TOPSIS

The TOPSIS method has been improved by modifying its classical model or by incorporating extensions. The extensions can be integrated with the fuzzy approach or other concepts. TOPSIS has also been developed with specific extensions. A modified version of TOPSIS has been coupled to a pre-emptive goal programming model with a comparison to an AHP to illustrate the effect of considering interdependencies in the process of selecting suppliers (Kasirian and Yusuff, 2013). Ye (2015) has extended the fuzzy TOPSIS method with interval neutrosophic uncertain linguistic information. A new version of fuzzy TOPSIS and Grey Relational Analysis (GRA) with various separation measures has been used for selecting “green” logistics service providers (Celik et al., 2016). Hu et al. (2016) have developed a weighted TOPSIS arguing that each criterion has an equally important part in the technique. The weighted TOPSIS is designed to rank the dispersion ability of a node by taking into account different centrality measures as the multi-attribute to the network and suggest a novel algorithm to calculate the weighting of each criterion. Kuo (2017) referred to a TOPSIS using a different ranking index, mentioning that when the number of options exceeds two, the innovative index is an efficient option. In the decision making process, Pythagorean fuzzy sets (PFSs) can deal with uncertain information more flexibly. Liang and Xu (2017) have proposed a hesitant Pythagorean fuzzy TOPSIS with an application of energy project selection. However, Huang and Jiang (2018) claim there is a major restriction in using TOPSIS for more practical problems. As a result, they have developed an optimism coefficient to expand the physical meaning of standard TOPSIS. In this way, decision making can take into account different attitudes toward risk and reward by altering an optimism coefficient. The usability of TOPSIS continues to motivate researchers of information and decision making sciences to further develop the method by novel approaches (Shen et al., 2018). It has been demonstrated that improved and extended versions of TOPSIS can tackle more complex problems than can conventional TOPSIS (Shouzhen and Yao, 2018, Suder and Kahraman, 2018).

2.3. Research gaps and objectives

The use of target criteria, either point or range, are appropriate for many MADM problems, including simultaneous materials and design selection such as selecting materials for biomedical implants where the properties of the material should be matched as closely as possible to the properties of human tissue (i.e. mechanical and physical properties). It has also been used in selecting materials for “patch repair” in different applications, ranging from fixing damage to metal or composite material aircraft structures (e.g. fuselage, wings, etc) while in-service to avoid the need for expensive and time consuming rebuilds by the original equipment manufacturer, to the preservation of reinforced concrete structures (e.g. bridges, buildings, etc) and in the upkeep of key infrastructure (i.e. road and rail networks). As an example, for criteria such as the elasticity modulus and coefficient of thermal expansion, the patch material chosen should be closely compatible with the substrate material, or premature failure can occur. Although, it seems there is a slight growth in the number of MADM methods for addressing target-based criteria and its applications, there is a shortage of TOPSIS methods based on interval values and range target-based criteria, particularly for the avoidance of rank reversal, which seems to be mandatory practice for a more productive decision support system.

The main objectives of this study are to: (1) produce a comprehensive normalization formula for benefit and cost criteria, and point and range target-based criteria (RTC), (2) improve the TOPSIS method based on a proposed normalization approach to avoid rank reversal, and (3) provide a precise model for alternative ranking based on extending the idea of an alternatives' distance to the PIS and NIS, and a new tool for the sensitivity analysis of ranking orders.

3. Materials and methods

In order to find the optimal solution six steps are suggested as follows: composing a decision matrix and normalizying data, weighting process, identifying the PIS and NIS, Measuring the distance of each alternative from ideal and nadir, and finally getting a solution through ranking index. Proposing a new normalization approach and novel ranking index are the key provisions of this paper. Table 1 demonstrates the decision matrix by interval data ($[x_{ij}^L, x_{ij}^U]$), which belongs to a universe of discourse ($A_i \in [A,B]$). Based on the matrix shown in Table 1 and Figure 1, the following stages are proposed for TOPSIS-RTCID.

Table 1. MADM problem by interval data.

Weighting	w_1	w_2	…	w_n
Criterion	Cr_1	Cr_2	…	Cr_n
A_1	$[x_{11}^L, x_{11}^U]$	$[x_{12}^L, x_{12}^U]$	…	$[x_{1n}^L, x_{1n}^U]$
A_2	$[x_{21}^L, x_{21}^U]$	$[x_{22}^L, x_{22}^U]$	…	$[x_{2n}^L, x_{2n}^U]$
A_3	$[x_{31}^L, x_{31}^U]$	$[x_{32}^L, x_{32}^U]$	…	$[x_{3n}^L, x_{3n}^U]$
⋮ A_m	⋮ $[x_{m1}^L, x_{m1}^U]$	⋮ $[x_{m1}^L, x_{m1}^U]$	…	⋮ $[x_{mn}^L, x_{mn}^U]$

Stage 1: Convert the decision-making matrix to normalized values with Equations 1 and 2 where E_{ij} and F_{ij} are shown in Equations 3 and 4.

$$n_{ij}^L = Min\left[1 - \frac{E_{ij}}{\max\{|B - T_j^U|, |A - T_j^L|\}}, 1 - \frac{F_{ij}}{\max\{|B - T_j^U|, |A - T_j^L|\}}\right] \quad (1)$$

$$n_{ij}^L = Min\left[1 - \frac{E_{ij}}{\max\{|B - T_j^U|, |A - T_j^L|\}}, 1 - \frac{F_{ij}}{\max\{|B - T_j^U|, |A - T_j^L|\}}\right] \quad (2)$$

$j=1,2,\ldots,n$ & $i=1,2,\ldots,m$

Where the normalized generic element of the decision matrix is denoted by $[n_{ij}^L, n_{ij}^U]$. The target range $[T_j^L, T_j^U]$ will be located in the universe of data [A, B] (Figure 1).

$$E_{ij} = \begin{cases} \min\{|x_{ij}^L - T_j^L|, |x_{ij}^L - T_j^U|\} & (A < x_{ij}^L < T_j^L) \quad or \quad (T_j^U < x_{ij}^L < B) \\ 0 & T_j^L \le x_{ij}^L \le T_j^U \end{cases} \quad (3)$$

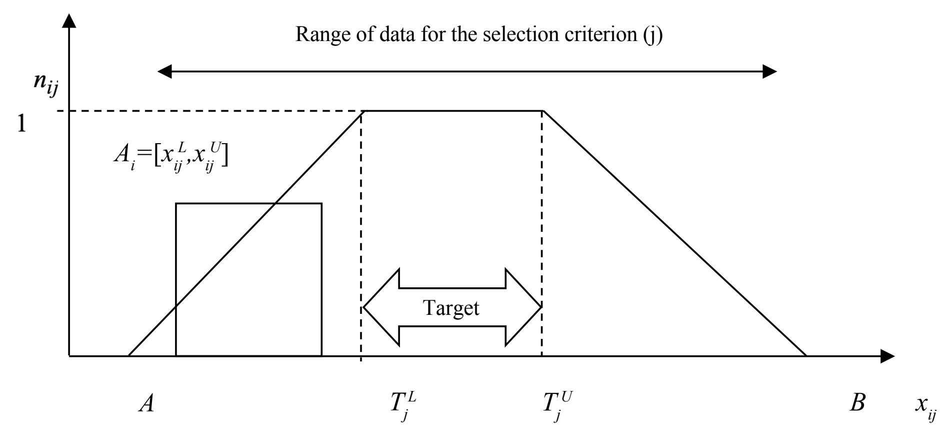

Figure 1. Alternatives, variation of target range and normalized values.

$$F_{ij} = \begin{cases} \min\left\{\left|x_{ij}^U - T_j^L\right|, \left|x_{ij}^U - T_j^U\right|\right\} & (\mathrm{A} < x_{ij}^U < T_j^L) \quad or \quad (T_j^U < x_{ij}^U < B) \\ 0 & T_j^L \le x_{ij}^U \le T_j^U \end{cases} \tag{4}$$

Once a range target-based criterion transforms to a point target-based criterion, T_j^L and T_j^U get nearer together and $T_j^L = T_j^U = T_j$. The formulae can also be used for cost and benefit attributes. In the case of benefit attributes, the maximum value in the universe of data ($T_j = B$) is the target and in the case of cost attributes, the minimum value in the universe of data ($T_j = A$) is the target.

Stage 2: Calculate the weighted normalized decision matrix.

Create the weighted normalized interval decision matrix with Equations 5 and 6 where w_j shows the significance of criteria j ($W = w_1, w_2, \ldots, w_n$).

$$V_{ij}^L = w_j n_{ij}^L \tag{5}$$

$$V_{ij}^U = w_j n_{ij}^U \tag{6}$$

Then, $\overline{V}_{ij} = [V_{ij}^L, V_{ij}^U]$ is the weighted normalized interval decision matrix. The interval $[V_{ij}^L, V_{ij}^U]$ always has positive value by means of the new proposed normalization method.

$$\overline{V} = \begin{vmatrix} [V_{11}^L, V_{11}^U] & \ldots & [V_{1j}^L, V_{1j}^U] & \ldots & [V_{1n}^L, V_{1n}^U] \\ . & \ldots & . & \ldots & . \\ . & \ldots & . & \ldots & . \\ . & \ldots & [V_{ij}^L, V_{ij}^U] & \ldots & . \\ . & \ldots & . & \ldots & . \\ . & \ldots & . & \ldots & . \\ [V_{m1}^L, V_{m1}^U] & \ldots & [V_{mj}^L, V_{mj}^U] & \ldots & [V_{mn}^L, V_{mn}^U] \end{vmatrix}$$

Stage 3: Identify the PIS.

$$\left\{\overline{V}_1^+, \overline{V}_2^+, \overline{V}_3^+, \ldots, \overline{V}_n^+\right\} = \{(\underset{i}{Max}\, \overline{V}_{ij} | i = 1, \ldots, m\ \} \tag{7}$$

Although the possibility method (Sevastianov, 2007) could be applied for the comparison of interval numbers, a comparison based on midpoints of interval numbers is very effective and accepTable (Dymova et al., 2013). Therefore, Δ_{A-B} was used in this research to obtain the PIS and NIS according to Equation 8. Table 2 shows how Equation 8 and aggregate preference (AP) can be used to find the PIS, where $\overline{V}_j^+ = \{(\underset{i}{Max}\, AP_{ij} | i = 1, \ldots, m\ \}$.

$$(\Delta_{A-B}) = \frac{1}{2}((a^L - b^U) + (a^U - b^L)) = \frac{1}{2}(a^L + a^U) - \frac{1}{2}(b^L + b^U) \tag{8}$$

Table 2. Comparison matrix for finding $\overline{V}_j^+$.

	$\overline{V}_{1j} = [V_{1j}^L, V_{1j}^U]$		$\overline{V}_{ij} = [V_{ij}^L, V_{ij}^U]$		$\overline{V}_{ij} = [V_{ij}^L, V_{ij}^U]$
$\overline{V}_{1j} = [V_{1j}^L, V_{1j}^U]$	0	…	$\Delta_{\overline{V}_{ij} - \overline{V}_{1j}}$	…	$\Delta_{\overline{V}_{mj} - \overline{V}_{1j}}$
	.	…	.	…	.
$\overline{V}_{ij} = [V_{ij}^L, V_{ij}^U]$	$\Delta_{\overline{V}_{1j} - \overline{V}_{ij}}$	…	0	…	$\Delta_{\overline{V}_{mj} - \overline{V}_{ij}}$
	.	…	.	…	.
	.	…	.	…	.
$\overline{V}_{mj} = [V_{mj}^L, V_{mj}^U]$	$\Delta_{\overline{V}_{1j} - \overline{V}_{mj}}$	…	$\Delta_{\overline{V}_{ij} - \overline{V}_{mj}}$	…	0
Aggregate preference	$AP_{1j} = \sum_{i=1}^m (\Delta_{\overline{V_{ij}} - \overline{V_{1j}}})$	…	AP_{ij}	…	$AP_{mj} = \sum_{i=1}^m (\Delta_{\overline{V_{ij}} - \overline{V_{mj}}})$
Extremum			*		

Stage 4: Identify the NIS.

$$\left\{\overline{V}_1^-, \overline{V}_2^-, \overline{V}_3^-, \ldots, \overline{V}_n^-\right\} = \{(\underset{i}{Min}\, \overline{V}_{ij} | i = 1, \ldots, m\ \} \tag{9}$$

where $\overline{V}_j^- = \{(\underset{i}{Min}\, AP_{ij} | i = 1, \ldots, m\ \}$

Stage 5: Measure the distance of each alternative from ideal (I^+) and nadir (I^-) by means of Equations 10 and 11.

$$I_i^+ = \sum_{j=1}^n \left(\overline{V}_j^+ - \overline{V}_{ij}\right) = \frac{1}{2}\sum_{j=1}^n ((V_j^{+L} + V_j^{+U}) - (V_{ij}^L + V_{ij}^U)) \tag{10}$$
$$i = 1,2,3,\ldots m$$

$$I_i^- = \sum_{j=1}^n (\overline{V}_{ij} - \overline{V}_j^-) = \frac{1}{2}\sum_{j=1}^n ((V_{ij}^L + V_{ij}^U) - (V_j^{-L} + V_j^{-U})) \tag{11}$$
$$i = 1,2,3,\ldots m$$

Stage 6: Calculate the ranking index.

By taking I^+ as a "cost" criterion (lower the better) and I^- as a "benefit" criterion (higher the better), the problem of ranking can be transformed into an MADM problem with these two criteria. The importance of these criteria in calculating the ranking index must be taken into account (Kuo, 2017). Therefore, if W^- and W^+ are the weightings of the "benefit" and "cost" criteria to represent the comparative importance of the two distance measures, correspondingly (see Equation 12).

$W^{-} + W^{+}=1$

$0< W^{-}<1$ & $0< W^{+}<1$ (12)

Given that both benefit and cost criteria are jointly required, large differences in deformation during the normalization process is not acceptable (Celen, 2014, Peldschus, 2009). Therefore, a pair of well accepted formulae (Jahan and Edwards, 2015) was adopted to normalize the performance measure of all the alternatives with respect to the "benefit" and "cost" criteria. The ranking index can then be calculated according to Equation 13.

$$RI_i = W^{-}\left(\frac{I_i^{-}}{I_{i:Max}^{-}}\right) + W^{+}\left(1 - \frac{I_i^{+} - I_{i:Min}^{+}}{I_{i:Max}^{+}}\right);$$
$$i = 1,2,3,\ldots m; \; -1 < RI_i < 1 \qquad (13)$$

Where $I^{-}_{i:Max}$, $I^{+}_{i:Min}$, and $I^{+}_{i:Max}$ are the maximum values of distance measure to nadir, minimum and maximum value of distance measure to ideal, respectively.

Stage 7: Rank options through the ratio in Stage 6.

The greater the index rate (RI_i), the better will be the performance of any alternative. Also, a sensitivity analysis on different weightings (W^{-} and W^{+}) can be helpful in reaching a better choice.

4. Validating the suggested method

The advantages of the proposed TOPSIS-RTCID is demonstrated using three practical examples from the literature. The first two examples investigate the problem of machine selection with interval data and RTC. The last example shows how the method proposed can improve available TOPSIS for interval data.

4.1. Punching machine selection

This example highlights the information that is relevant in the selection of a punching machine for producing electronic components (Hafezalkotob and Hafezalkotob, 2017). Recent advances in the technology demonstrates the importance of selecting an appropriate punching machine. The interval data and target values for each criterion are shown in Table 3(a). The first step was to obtain the normalized matrix using Equations 1 to 4. In this way, after obtaining E_{ij} and F_{ij} (Table 3(b)), the normalized matrix was produced (Table 3(c)).

The next step involved calculating the values for the weighted normalized matrix. The weightings for each criterion was found in Table 3(d). The weighted normalized matrix, using Equations 5 and 6, was presented in Table 3(e). In this step, the PIS and NIS were generated using the guideline in Table 2. Table 3(f) shows the details of AP calculation for C1. The identified the PIS and NIS are shown in Table 3(g). To obtain the distance measure of each alternative from ideal (I^{+}) and nadir (I^{-}), Equations 10 and 11 were used, respectively. The values were measured and illustrated in Table 3(h).

To find the overall priority of the alternatives, equal weightings were assigned to propose a new formula in the decision-making matrix with two column vectors as (I^{+}) and (I^{-}) possessing assigned weightings. For this purpose, Equation 13 was used and the ranking index of alternatives was obtained. The priority of the alternatives is listed in Table 3(i). M2 was chosen as the top alternative and M4 was ranked as the bottom alternative. Comparing the results obtained with IT-VIKOR (Hafezalkotob and Hafezalkotob, 2017), the consistency of the results was revealed. Also, the ranking orders were similar to those of IT-MULTIMOORA (Hafezalkotob and Hafezalkotob, 2016).

Table 3(a). Interval values for punching machine selection (Example 1).

List of Machines	Interval target values																	
	(10,14)		(2,4)		(2,4)		(1200,2540)		(3,8)		(190,445)		(70,110)		(50,180)		(16,20)	
	Cr_1		Cr_2		Cr_3		Cr_4		Cr_5		Cr_6		Cr_7		Cr_8		Cr_9	
	$[x_{ij}^L, x_{ij}^U]$																	
M_1	8	12	2	3	2	4	0	1270	0	6.4	0	420	0	108	0	180	16	20
M_2	10	14	3	5	2	4	0	2070	0	6.4	0	220	0	97	0	60	16	20
M_3	12	16	3	5	2	4	0	2540	0	6.4	0	445	0	108	0	80	16	20
M_4	14	16	4	6	2	4	0	2535	0	8.0	0	445	0	108	0	60	16	20
M_5	10	14	3	5	4	6	0	2500	0	6.4	0	400	0	110	0	60	12	18
M_6	8	12	2	4	3	5	0	1270	0	6.4	0	200	0	82	0	60	12	18

Table 3(b). The values for E_{ij} and F_{ij} (Example 1).

Machine	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8	Cr_9
	E_{ij}								
M_1	2	0	0	1200	3	190	70	50	0
M_2	0	0	0	1200	3	190	70	50	0
M_3	0	0	0	1200	3	190	70	50	0
M_4	0	0	0	1200	3	190	70	50	0
M_5	0	0	0	1200	3	190	70	50	4
M_6	2	0	0	1200	3	190	70	50	4
	F_{ij}								
M_1	0	0	0	0	0	0	0	0	0
M_2	0	1	0	0	0	0	0	0	0
M_3	2	1	0	0	0	0	0	0	0
M_4	2	2	0	0	0	0	0	0	0
M_5	0	1	2	0	0	0	0	0	0
M_6	0	0	1	0	0	0	0	0	0

Table 3(c). The normalized decision matrix (Example 1).

	Cr_1		Cr_2		Cr_3		Cr_4		Cr_5		Cr_6		Cr_7		Cr_8		Cr_9	
	$[n_{ij}^L, n_{ij}^U]$																	
M_1	0	1	1	1	1	1	0	1	0	1	0	1	0	1	0	1	1	1
M_2	1	1	0.5	1	1	1	0	1	0	1	0	1	0	1	0	1	1	1
M_3	0	1	0.5	1	1	1	0	1	0	1	0	1	0	1	0	1	1	1
M_4	0	1	0	1	1	1	0	1	0	1	0	1	0	1	0	1	1	1
M_5	1	1	0.5	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
M_6	0	1	1	1	0.5	1	0	1	0	1	0	1	0	1	0	1	0	1

Table 3(d). Weightings of criteria (Example 1).

Criterion	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8	Cr_9
Weighting	0.222	0.222	0.222	0.056	0.056	0.056	0.056	0.056	0.056

Table 3(e). Interval and weighted normalized decision matrix (Example 1).

	Cr_1		Cr_2		Cr_3		Cr_4		Cr_5		Cr_6		Cr_7		Cr_8		Cr_9	
	$[V_{ij}^L, V_{ij}^U]$																	
M_1	0	0.222	0.222	0.222	0.222	0.222	0	0.056	0	0.056	0	0.056	0	0.056	0	0.056	0.056	0.056
M_2	0.222	0.222	0.111	0.222	0.222	0.222	0	0.056	0	0.056	0	0.056	0	0.056	0	0.056	0.056	0.056
M_3	0	0.222	0.111	0.222	0.222	0.222	0	0.056	0	0.056	0	0.056	0	0.056	0	0.056	0.056	0.056
M_4	0	0.222	0	0.222	0.222	0.222	0	0.056	0	0.056	0	0.056	0	0.056	0	0.056	0.056	0.056
M_5	0.222	0.222	0.111	0.222	0	0.222	0	0.056	0	0.056	0	0.056	0	0.056	0	0.056	0.000	0.056
M_6	0	0.222	0.222	0.222	0.111	0.222	0	0.056	0	0.056	0	0.056	0	0.056	0	0.056	0.000	0.056

Table 3(f). Calculation of PIS and NIS for C1 (Example 1).

Cr_1			M_1	M_2	M_3	M_4	M_5	M_6
			0 0.222	0.222 0.222	0 0.222	0 0.222	0.222 0.222	0 0.222
M_1	0	0.222	0	0.111	0	0	0.111	0
M_2	0.222	0.222	-0.111	0	-0.111	-0.111	0	-0.111
M_3	0	0.222	0	0.111	0	0	0.111	0
M_4	0	0.222	0	0.111	0	0	0.111	0
M_5	0.222	0.222	-0.111	0	-0.111	-0.111	0	-0.111
M_6	0	0.222	0	0.111	0	0	0.111	0
Aggregate preference (AP)			-0.222	0.444	-0.222	-0.222	0.444	-0.222
$\bar{V}_1^+$				*			*	
$\bar{V}_1^-$			*		*	*		*

Table 3(g). PIS and NIS (Example 1).

	C_1		C_2		C_3		C_4		C_5		C_6		C_7		C_8		C_9	
V+	0.222	0.222	0.222	0.222	0.222	0.222	0	0.056	0	0.056	0	0.056	0	0.056	0	0.056	0.056	0.056
V-	0	0.222	0	0.222	0	0.222	0	0.056	0	0.056	0	0.056	0	0.056	0	0.056	0	0.056

Table 3(h). Distances from PIS and NIS (Example 1).

	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8	Cr_9	I^+
M_1	0.11111	0	0	0	0	0	0	0	0	0.111
M_2	0	0.05556	0	0	0	0	0	0	0	0.056
M_3	0.11111	0.05556	0	0	0	0	0	0	0	0.167
M_4	0.11111	0.11111	0	0	0	0	0	0	0	0.222
M_5	0	0.05556	0.11111	0	0	0	0	0	0.02778	0.194
M_6	0.11111	0	0.05556	0	0	0	0	0	0.02778	0.194
										I^-
M_1	0	0.11111	0.11111	0	0	0	0	0	0.02778	0.25
M_2	0.11111	0.05556	0.11111	0	0	0	0	0	0.02778	0.306
M_3	0	0.05556	0.11111	0	0	0	0	0	0.02778	0.194
M_4	0	0	0.11111	0	0	0	0	0	0.02778	0.139
M_5	0.11111	0.05556	0	0	0	0	0	0	0	0.167
M_6	0	0.11111	0.05556	0	0	0	0	0	0	0.167

Table 3(i). Ranking index of materials and priority (Example 1).

$I^-_{i:Max} = 0.306$		$I^+_{i:Max} = 0.222$		$I^+_{i:Min} = 0.056$		
$W^- = 0.5$				$W^+ = 0.5$		
Machine	M_1	M_2	M_3	M_4	M_5	M_6
Ranking index	0.784	1	0.568	0.352	0.46	0.46
Ranking score	2	1	3	6	4≅5	4≅5
Priority	$M_2 > M_1 > M_3 > M_5 = M_6 > M_4$					
IT-VIKOR (2017)	2	1	3	6	5	4

4.2. Tea dryer machine selection

In this practical example (Hafezalkotob et al., 2016), the problem of selecting a continuous fluid bed tea dryer is evaluated. The selection of the most suiTable technical options available from a set of different machines will lead to the highest quality product (Çakır, 2016). In this example, five candidate tea dryers and nine attributes were included. The range of target values for each criterion can be found in Table 4(a). The weightings of the criteria are: 0.162, 0.152, 0.15, 0.114, 0.055, 0.109, 0.074, 0.153, and 0.032.

The normalized and the weighted interval matrix are shown in Table 4(b) and 4(c), respectively.

Table 4(a). Interval decision matrix for tea dryer selection (Example 2).

Machines list	Interval target values for criteria																	
	0.86	1	0.8	1	0.8	1	0.82	1	0.59	1	0.64	1	0.64	1	0	0.21	0	0.23
	Cr_1		Cr_2		Cr_3		Cr_4		Cr_5		Cr_6		Cr_7		Cr_8		Cr_9	
	$[x^L_{ij}, x^U_{ij}]$																	
M_1	0.79	0.92	0.72	0.86	0.66	0.8	0.42	0.57	0.06	0.21	0.20	0.35	0.38	0.53	0.4	0.6	0.57	0.81
M_2	0.84	0.96	0.34	0.49	0.72	0.86	0.38	0.53	0.06	0.21	0.38	0.53	0.34	0.48	0.57	0.81	0.61	0.83
M_3	0.79	0.92	0.58	0.73	0.66	0.8	0.58	0.73	0.12	0.27	0.19	0.34	0.19	0.34	0.36	0.57	0.35	0.56
M_4	0.75	0.89	0.62	0.77	0.72	0.86	0.42	0.57	0.21	0.36	0.36	0.51	0.34	0.48	0	0.19	0.03	0.21
M_5	0.44	0.59	0.72	0.86	0.28	0.43	0.54	0.69	0.21	0.36	0.20	0.35	0.36	0.51	0.4	0.6	0.61	0.83

Table 4(b). The normalized matrix (Example 2).

	Cr_1		Cr_2		Cr_3		Cr_4		Cr_5		Cr_6		Cr_7		Cr_8		Cr_9	
M_1	0.83	1	0.83	1	0.73	1	0.09	0.43	0.17	0.41	0.06	0.38	0.45	0.77	0.35	0.68	0.03	0.43
M_2	0.95	1	0	0.33	0.85	1	0	0.34	0.17	0.41	0.45	0.77	0.36	0.66	0	0.4	0	0.37
M_3	0.83	1	0.52	0.85	0.73	1	0.45	0.8	0.27	0.5	0.04	0.36	0.04	0.36	0.4	0.75	0.45	0.8
M_4	0.74	1	0.61	0.93	0.85	1	0.09	0.43	0.41	0.64	0.4	0.72	0.36	0.66	1	1	1	1
M_5	0	0.36	0.83	1	0	0.29	0.36	0.7	0.41	0.64	0.06	0.38	0.4	0.72	0.35	0.68	0	0.37

Table 4(c). The weighted interval matrix (Example 2).

	Cr_1		Cr_2		Cr_3		Cr_4		Cr_5		Cr_6		Cr_7		Cr_8		Cr_9	
M_1	0.135	0.162	0.126	0.152	0.11	0.15	0.01	0.049	0.009	0.022	0.007	0.042	0.033	0.057	0.054	0.105	0.001	0.014
M_2	0.154	0.162	0	0.05	0.127	0.15	0	0.039	0.009	0.022	0.049	0.083	0.027	0.049	0	0.061	0	0.012
M_3	0.135	0.162	0.079	0.129	0.11	0.15	0.052	0.091	0.015	0.028	0.005	0.039	0.003	0.027	0.061	0.115	0.014	0.026
M_4	0.12	0.162	0.093	0.142	0.127	0.15	0.01	0.049	0.022	0.035	0.044	0.079	0.027	0.049	0.153	0.153	0.032	0.032
M_5	0	0.058	0.126	0.152	0	0.043	0.041	0.08	0.022	0.035	0.007	0.042	0.03	0.054	0.054	0.105	0	0.012

By pursuing Stages 3 and 4, it is possible to distinguish the positive and negative preferred solutions from the weighted normalized matrix. In the next step, the distances from the PIS and NIS were produced as indicated in Table 4(d). I^+ and I^- values were measured using Equations 8 and 9. The values in Table 4(d) enable us to obtain the ranking index.

In the last step of the proposed TOPSIS-RTCID, the ranking of each candidate was generated and compared with previous works provided in Table 4(e). The proposed TOPSIS-RTCID indicates that M4 is the most favorite candidate for that engineering purpose. This conclusion was also confirmed by the study of Hafezalkotob & Hafezalkotob (2017), who obtained identical results. The stability of the proposed TOPSIS-RTCID was analyzed utilising different values of W in Equation 10 and again, it was revealed that the result was comprehensively sTable (Table 4(f)).

Also, sixteen sensitivity analysis tests were performed as an alternative method for checking the stability of the proposed ranking method. Among these sixteen tests, ten of them resulted in the same ranking as the original ranking produced (highlighted in bold in Table 4(g)). The rest of the sensitivity tests yield a very close similarity between them and the main ranking result.

Table 4(d). Distances from PIS and NIS (Example 2).

	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8	Cr_9	I^+
M_1	0.01	0	0.009	0.041	0.013	0.042	0	0.074	0.025	0.213
M_2	0	0.114	0	0.052	0.013	0	0.007	0.122	0.026	0.334
M_3	0.01	0.035	0.009	0	0.008	0.044	0.03	0.065	0.012	0.212
M_4	0.017	0.021	0	0.041	0	0.005	0.007	0	0	0.092
M_6	0.129	0	0.117	0.01	0	0.042	0.003	0.074	0.026	0.401
										I^-
M_1	0.12	0.114	0.108	0.01	0	0.002	0.03	0.048	0.002	0.434
M_2	0.129	0	0.117	0	0	0.044	0.023	0	0	0.313
M_3	0.12	0.079	0.108	0.052	0.005	0	0	0.057	0.014	0.436
M_4	0.112	0.093	0.117	0.01	0.013	0.039	0.023	0.122	0.026	0.555
M_6	0	0.114	0	0.041	0.013	0.002	0.027	0.048	0	0.246

Table 4(e). Rankings of proposed TOPSIS-RTCID (Example 2).

$I^-_{i:Max}=0.555$			$I^+_{i:Max}=0.401$	$I^+_{i:Min}=0.092$
W^-=0.5			W^+=0.5	
	RI	Ranking	Hafezalkotob & Hafezalkotob (2017) (not weighted)	Hafezalkotob & Hafezalkotob (2017) (weighted)
M_1	0.723931	3	3	3
M_2	0.446489	4	4	4
M_3	0.726533	2	2	2
M_4	1	1	1	1
M_6	0.293318	5	5	5

Table 4(f). Stability of ranking orders based on different preference on importance of distance from ideal and nadir solution.

W^+	W^-	Ranking
0.1	0.9	$M_4>M_3>M_1>M_2>M_5$
0.2	0.8	$M_4>M_3>M_1>M_2>M_5$
0.3	0.7	$M_4>M_3>M_1>M_2>M_5$
0.4	0.6	$M_4>M_3>M_1>M_2>M_5$
0.5	0.5	$M_4>M_3>M_1>M_2>M_5$
0.6	0.4	$M_4>M_3>M_1>M_2>M_5$
0.7	0.3	$M_4>M_3>M_1>M_2>M_5$
0.8	0.2	$M_4>M_3>M_1>M_2>M_5$
0.9	0.1	$M_4>M_3>M_1>M_2>M_5$

Table 4(g). Sensitivity analysis tests by weighting order modification (Example 2).

	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8	Cr_9	Ranking order of the alt.
TOPSIS-RTCID	0.162	0.152	0.15	0.114	0.055	0.109	0.074	0.153	0.032	**M4>M3>M1>M2>M5**
Test 1	0.152	0.162	0.15	0.114	0.055	0.109	0.074	0.153	0.032	M4>M1>M3>M2>M5
Test 2	0.15	0.152	0.162	0.114	0.055	0.109	0.074	0.153	0.032	**M4>M3>M1>M2>M5**
Test 3	0.114	0.152	0.15	0.162	0.055	0.109	0.074	0.153	0.032	**M4>M3>M1>M2>M5**
Test 4	0.055	0.152	0.15	0.114	0.162	0.109	0.074	0.153	0.032	M4>M3>M1>M5>M2
Test 5	0.109	0.152	0.15	0.114	0.055	0.162	0.074	0.153	0.032	**M4>M3>M1>M2>M5**
Test 6	0.074	0.152	0.15	0.114	0.055	0.109	0.162	0.153	0.032	M4>M1>M3>M5>M2
Test 7	0.153	0.152	0.15	0.114	0.055	0.109	0.074	0.162	0.032	**M4>M3>M1>M2>M5**
Test 8	0.032	0.152	0.15	0.114	0.055	0.109	0.074	0.153	0.162	M4>M3>M1>M5>M2
Test 9	0.162	0.15	0.152	0.114	0.074	0.109	0.055	0.153	0.032	**M4>M3>M1>M2>M5**
Test 10	0.162	0.152	0.15	0.114	0.032	0.109	0.074	0.153	0.055	**M4>M3>M1>M2>M5**
Test 11	0.162	0.032	0.055	0.114	0.074	0.109	0.152	0.153	0.15	**M4>M3>M1>M2>M5**
Test 12	0.162	0.032	0.15	0.114	0.152	0.109	0.074	0.153	0.055	**M4>M3>M1>M2>M5**
Test 13	0.162	0.032	0.074	0.114	0.15	0.109	0.152	0.153	0.055	**M4>M3>M1>M2>M5**
Test 14	0.162	0.15	0.074	0.114	0.032	0.109	0.152	0.153	0.055	M4>M1>M3>M2>M5
Test 15	0.162	0.15	0.032	0.114	0.074	0.109	0.152	0.153	0.055	M4>M1>M3>M5>M2
Test 16	0.162	0.055	0.152	0.114	0.15	0.109	0.032	0.153	0.074	**M4>M3>M1>M2>M5**

Figure 2 shows a schematic view of comparing the sensitivity analysis results, where M4 was validated as the best alternative.

5. Rank reversal consideration

The decision matrix for this example is presented in Table 5, which contains three alternatives and four criteria. Cr_1 and Cr_2 are the benefit attribute, and Cr_3 and Cr_4 are the cost attribute. By selecting equal weightings for each criterion, i.e. 0.25, the ranking index is obtained for three alternatives RI_1=0.76, RI_2=1, and RI_3=0.8. Therefore, the ranking of alternatives would be $A_2>A_3>A_1$. Using the method proposed by Dymova et al. (2013), RI_1=0.47, RI_2=0.52, RI_3=0.56, and therefore $A_3>A_2>A_1$.

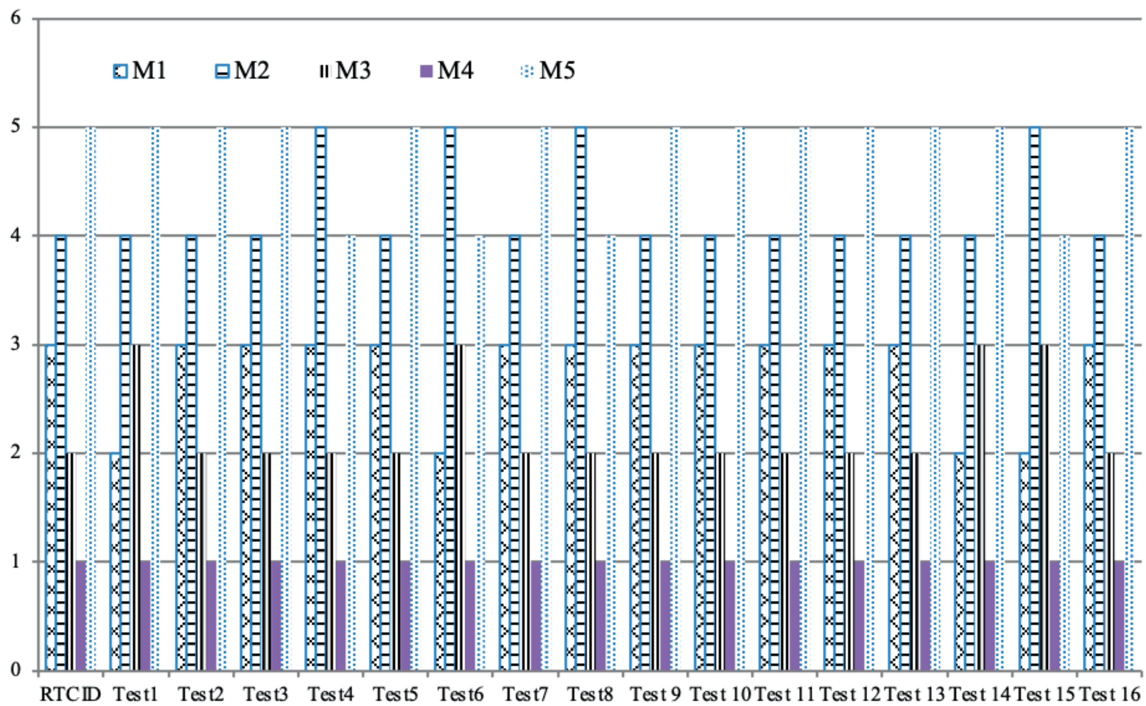

Figure 2. Generated ranking orders from sensitivity analysis tests (Example 2).

Table 5. Decision matrix (Example 3) (Dymova et al., 2013).

	Point target values							
Target	28	28	21	21	13	13	18	18
	$[x_{ij}^L, x_{ij}^U]$							
	Cr_1		Cr_2		Cr_3		Cr_4	
A_1	6	22	10	15	13	19	40	48
A_2	3	4	17	21	20	30	22	28
A_3	25	28	8	10	42	48	18	20

Hence, it can be interpreted that the proposed TOPSIS-RTCID might produce different rankings of options. If a new alternative is added (A_{new}=[26,32], [19,20], [20,28], [16,17]), the priority of the alternatives will be $A_{new}>A_2>A_3>A_1$ using both Dymova et al. (2013) and the suggested approach. This shows that adding an alternative changes the ranking orders for A_3 and A_2 in the method of Dymova et al. (2013), while alternatives maintain their ranking through the proposed method. Therefore, the proposed TOPSIS-RTCID does not create rank reversal because it benefits from a novel normalization formula and a means of calculating the ranking index (Stage 6).

6. Discussion on application and analysis

6.1. Application of proposed method in engineering design

Engineering design decision making often comprises of assessing numerous inconsistent requirements. Classical optimization deals with such problems by considering the most significant requirement as the objective function and assuming the rest of the requirements are constraints (Sen and Yang, 1998, Shishank and Dekkers, 2013). The complexities of engineering design problems usually hide weak points in the selection method used and can be resolved with the aid of MADM. The scope of MADM methods has been explained by a variety of research based on various design applications and case studies (Jahan et al., 2016). Some researchers suggest combining different MADM methods for making precise decisions when there are only minor differences between alternative solutions (Shanian and Savadogo, 2009, Milani et al., 2005). Uncertain decision systems originate from incomplete and unclear rules and regulations or inaccurate information during the decision-making procedure. As mentioned above, former studies of integrated MADM approches with interval data and target-based criteria, have not deeply analyzed range target-based criteria. Also, an inability to link with computer databases, in the case of a lot alternatives and criteria, is another drawback of the available approaches. Normally, towards the end of the design process, a short-list of candidates will have been generated to meet the minimum design requirements. To find the candidate that can maximize the overall performance under "all" the given criteria, it is possible to apply compensatory types of MADM (Alemi-Ardakani et al., 2016). Typically, in engineering design selection problems, the good performance of a candidate for a design criterion can compensate for the poor performance of an alternative candidate. This characteristic and the capability to deal with a database is available in the proposed method. Hazelrigg (2003) proposed ten properties for the validation of a design option selection method. For example, the method must allow the comparison of different design alternatives when conditions are unpredictable and as a consequence outcomes are ambiguous. Hazelrigg (2003) also explained that design selection methods should be used in such a way that adding a new design option does not make current alternatives less beneficial. The wrong choice of candidate material and/or equipment will cause extra cost and further errors in the system, therefore the new MADM tool assures design confidence and offers a more convenient to use solution.

6.2. Critical analysis of proposed method

Decision makers have been convinced that TOPSIS can be utilized within complex models and therefore enhance the precision and reliability of results. It is due to its unique structure and simple solution procedure. Although the conventional form of TOPSIS is still preferred to other methods and its efficiency is approved by a high percentage of decision science experts, the classic model of TOPSIS does not satisfy uncertain conditions and vague data. One of the problems of MADM methods is problem of rank reversal. The order of preference of alternatives changes while an alternative is included or excluded from the decision problem if rank reversal occurs (Garca-Cascales and Lamata, 2012). Some methods show the rank reversal problem. AHP and TOPSIS have been blamed for possible rank reversal caused by adding or deleting an alternative (Wang and Luo, 2009, Perez et al., 2016). A couple of tests were therefore designed to illustrate if rank reversal occurs or not in the proposed method. Again, the authors used the decision matrix from Example 2 (M_4>M_3>M_1>M_2>M_5). Firstly, one alternative (M2) was deleted. Then, it was seen that the ranking index (RI) for other alternatives was produced as RI_4=1, RI_3=0.71, RI_1=0.699, and RI_5=0.23. Therefore, the order of ranking would be: M_4>M_3>M_1>M_5. It is evident that the elimination of M_2 did not affect the original rankings of the alternatives and therefore the proposed method does not suffer from rank reversal. Secondly, a new alternative was added, i.e. M_{new}. The priority of the alternatives after application of the proposed method was then: M_4>M_3>M_1>M_{new}>M_2>M_5, which declares adding an alternative does not show any rank reversal at all. The authors repeated generating random values for M_{new} for a hundred times. Overall, it was confirmed that the proposed TOPSIS-RTCID method is highly reliable and robust towards eliminating or incrementing a decision alternative. It was shown that the problem of rank reversal has two causes (Garca-Cascales and Lamata, 2012): (1) the normalization method used and (2) the choice of positive and negative ideal solutions. Therefore, to solve rank reversal, it is necessary to concentrate on the causes of the problem. The proposed TOPSIS-RTCID method achieves the core contribution in decision making theories through a distinct normalization formula for cost and benefits criteria in scale of point and range target-based values. It should be mentioned that one of the interesting properties of the proposed normalization formula in comparison with the usual one is that it does not introduce any additional dependence between the elements of a given column in the normalized decision matrix. This property can explain why the rank reversal problem is limited. However, it is possible to create quite simple methods but the requirement of providing reliable results often places limitations on their application.

7. Conclusions

The results of this current research work will contribute to helping solve practical engineering design decision making problems which have uncertain environments in terms of data and objectives, as well as provide invaluable new insight into MADM methods. This paper described a new contribution in the field of multi-criteria analysis tools for reliable selection in uncertain decision-making environments, especially in engineering design problems. An improved model of TOPSIS was created with the aid of interval data and the aggregation of target values for decision criteria. The validity of a MADM method could be undermined by rank reversal issues. However, when compared to the original TOPSIS or VIKOR methods, the proposed TOPSIS-RTCID method provides a consistent basis for decision makers and addresses the issue of instability in ranking orders as a consequence of adding or subtracting alternatives. It was demonstrated that the result of ranking using the proposed TOPSIS-RTCID method is in agreement with recent methods developed, but provides an easier method of calculation. The authors believe that the proposed TOPSIS-RTCID method is acceptable and has sufficient robustness to deal with real engineering design problems. Further research could usefully explore how the proposed TOPSIS-RTCID method can be applied in group or team based decision-making problems. Also, continued effort is needed to extend range target-based criteria and interval data to other MADM methods.

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