



DEVELOPING WASPAS-RTB METHOD FOR RANGE TARGET-BASED CRITERIA: TOWARD SELECTION FOR ROBUST DESIGN

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Abstract. Recently, considerable attention has been devoted to application of multi-attribute decision-making (MADM) method in materials selection. Normalization can be considered as a foundation for rational MADM methods, which should deal with target-based criteria in addition to cost and benefit criteria. Although a good number of applications have been reported for point target criteria in MADM problems, in selection problems related to engineering design, it might be better to let the material and design criteria vary over a range in order to increase flexibility in subsequent design stages. The mentioned point supports a readily adaptable design in changing the customer requirements, which is also significant in offering a robust design. In this research, performance of three promising target-based normalization methods was investigated using simulation experiments to examine the effect of simulation parameters. The effect of parameters and normalization methods was examined using analysis of variance (ANOVA). Moreover, the best structure formula was identified to propose an inclusive range target-based normalization method. The suggested normalization method was used to enhance the capability of Weighted Aggregated Sum Product Assessment (WASPAS) method and applied to a real-word problem dealing with benefit-, cost-, and point target-based criteria as well as the range criterion.

Keywords: target-based criteria in MADM, ANOVA, selection, normalization, robust design, WASPAS-RTB.

JEL Classification: C02, C44, D81.

Introduction

Changing the material set in an already established technology is a rare event and can be considered as a revolution. Traditionally, selection of a new material was usually carried out by resorting to previous experiences or applying “trial-and-error” scheme. Recently, there has been an increasing interest in the subject of multi-attribute decision-making (MADM) methods applied to material selection and design (Alemi-Ardakani *et al.* 2016; Hafezalkotob

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et al. 2016a; Xue *et al.* 2016; Chatterjee *et al.* 2011) to avoid utilization of inappropriate materials and make sure that costs are kept to a minimum. Searching for suitable materials is a key part of engineering design process and is a prerequisite for solving a chain of different engineering selection problems such as process, machine, tool, supplier, and even personnel selections. In most of MADM methods, dimensionless or normalization of decision matrix elements is one of the crucial steps; however, it is found that most of the current normalization methods have shortcomings in tackling all necessary requirements (Jahan, Edwards 2015). While many normalization methods may appear to be minor variants of one another, these nuances can have important consequences for inference and decision-making processes. Furthermore, design decision-making matrix consists of target criteria in addition to cost and benefit criteria. However, normalization methods considering target criteria have received much less attention. Target criteria are applicable in many areas, especially implant material selection in which the material must possess properties identical to those of human tissues (Bahraminasab, Jahan 2011). In another example explained by Stanujkic *et al.* (2013) addressing computer selection, IT specialists can provide some recommendations (preferences/targets) in relation to characteristics of computers. An alternative, i.e. computer, whose performances are equal to desirable performances, compared to all attributes, is potentially the best alternative. Furthermore, target criteria are crucial in patch repair material selection applications ranging from aerospace to rehabilitation of reinforced concrete structures in maintenance of infrastructures, where the repair materials should have similar properties to those of the main material considering a number of criteria such as thermal expansion coefficient. Furthermore, sometimes in some applications for evaluating alternatives in presence of defined criteria/optimal values in standards and/or regulations, target criteria should be met (Zavadskas *et al.* 2016; Adan *et al.* 2007). Difficulties arise when a point target criterion is extended to range. Early in the design timeline, some of the design requirements may be uncertain. Rather than setting point targets, in order to increase flexibility in the following design stages, the material and design criteria can be allowed to vary over a range. There are even less methods introduced for normalization of criteria and ranking of material and design selection problems with range target-based criteria. This study first presents a brief overview of the recent history of MADM addressing material selection, normalization methods, and applications of WASPAS approach, describes the observed gap in previous studies, and finally specifies the objectives of the current study. Section 2 is divided into three subsections. The first subsection describes a preliminary method for addressing the following question “What are the limitations of current point target-based normalization methods and which approach is the best one?” The second subsection proposes a range target-based normalization method, and the last subsection describes how the method can enhance the capability of Weighted Aggregated Sum Product Assessment (WASPAS) method. The first part of section 3 presents the results of simulation analysis described in section 2.1, and then applicability of the suggested tool is exemplified through a material selection case study in section 3.2. In section 4, effectiveness of the new method as well as the role of range target-based criteria in material selection to offer a robust design is further discussed. The final section concludes with inferences provided by the undertaken research.

1. Literature review

The pertinent literature has been reviewed attending to material selection methodologies, normalization methods in MADM, and applications of WASPAS method. The recognized research gap as well as objectives of the current study is presented after thorough review of the literature.

1.1. Brief literature review on application of MADM method in material selection

Seminal works on material selection in the light of multi-criteria decision-making (MCDM) method were undertaken by Ashby research group (Ashby 1989, 2000; Sirisalee *et al.* 2004, 2006). An array of studies conducted by Edwards discussed strategic substitution of new materials for old ones (Edwards 2004), selecting materials for optimum use in engineering components (Edwards 2005), and also supporting design decision-making (Edwards, Deng 2007) in the subject. Farag (2013, 2008) described the quantitative methods employed for material selection and substitution. As Ashby *et al.* (2004) states: "Achieving the match with design requirements involves four basic steps. (1) A method for translating design requirements into a specification for material and process. (2) A procedure for screening out those that cannot meet the specification, leaving a subset of the original menu. (3) A scheme for ranking the surviving materials and process, identifying those that have the greatest potential. (4) A way of searching for supporting information about the top-ranked candidates" (p.1). Surveys such as those conducted by Sapuan *et al.* (2009) and Brifcani *et al.* (2012) have described that a vast array of materials with diverse properties available to the designers make the material selection process a difficult and time-consuming task. Jahan *et al.* (2010) have shown that a growth in studies addressing material evaluation and selection problems using the MCDM approaches has been observed from 2006. Over recent years, there has been an increasing amount of literature both on development of new MADM methods for material selection (Kabir, Lizu 2016; Hafezalkotob *et al.* 2016b; Shan *et al.* 2016; Ardeshirilajimi *et al.* 2015) and real applications (Al-Oqla, Sapuan 2016; Al-Oqla *et al.* 2016; Mastura *et al.* 2016; Hafezalkotob, A., Hafezalkotob, A. 2016; Ishak *et al.* 2016; Alemi-Ardakani *et al.* 2015). However, if decision-making models could be developed based on the nature of engineering design problems, more official applications can be reported.

1.2. Brief literature review on normalization methods of selection criteria

MADM models are defined by a decision matrix which has the following parts: alternatives A_i ($i = 1, \dots, m$) which decision makers have to choose, criteria C_j ($j = 1, \dots, n$), and element r_{ij} which is the rating of alternative i with respect to criterion j as shown in Table 1. Furthermore, r_j^{\max} , r_j^{\min} , σ_j , T_j are the maximum value in alternatives associated with criterion j , minimum value in alternatives associated with criterion j , standard deviation of r_{ij} ($i = 1, \dots, m$), and target value for criterion j , respectively. Performance ratings for different criteria are measured by different units; however, all the elements must be dimensionless in the decision matrix to offer a valid comparison. The mentioned point is very significant in material selection in which the same material properties may be measured in different convertible units.

Table 1. A typical multiple attribute decision-making problem

	C_1	C_2	...	C_n
A_1	r_{11}	r_{12}	...	r_{1n}
A_2	r_{21}	r_{22}	...	r_{2n}
A_3	r_{31}	r_{32}	...	r_{3n}
\vdots	\vdots	\vdots		\vdots
A_m	r_{m1}	r_{m2}	...	r_{mn}

The normalization process must eliminate units of criterion functions without exerting any effects on the final result (Opricovic, Tzeng 2004).

A number of matters including capability of removing the scales, symmetry in normalization for cost and benefit criteria, transforming other types of criteria to the benefit ones, rank reversals, and handling negative values are important aspects worth considering for evaluation of the efficiency of normalization methods (Jahan, Edwards 2015). Figure 1 presents the mentioned important aspects that must be considered in developing a normalization method. Capability of removing the scales is a basic rule, which means that in the case of normalizing identical data with different units or scales, the same results should be obtained. Symmetry of normalized values, when comparing cost and benefit criteria, is another chief aspect in evaluating normalization methods. Some methods just remove the scale of criteria; but they cannot convert cost criteria to benefit criteria. Although such a transformation is not necessary for all MADM methods, it usually reduces the calculations required to be performed in the subsequent stages. Phenomenon of rank reversals is another issue, in which the ranking changes when an alternative is added to or removed from the decision problem. In some cases, this may lead to what is called total rank reversal, where the order of preferences is totally inverted. The reason for rank reversal can be application of an improper normalization technique (Barzilai, Golany 1994). The last expected property for normalization methods is capability of presenting acceptable normalized values when there are negative values in the decision matrix.

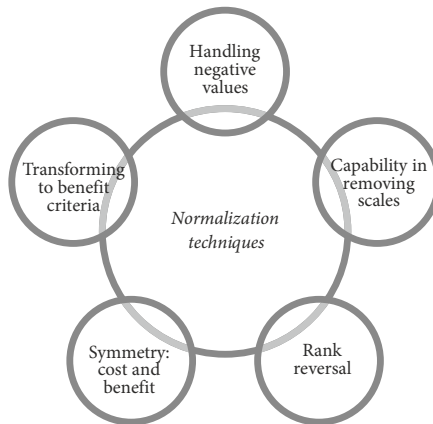


Figure 1. Expected properties for normalization methods

Milani *et al.* (2005) compared the effect of some well-known normalization methods on ranking of alternatives in a material selection case study. Similarly, in a critical review of normalization methods, Peldschus (2008) compared various normalization approaches. In a pioneering research, Zavadskas and Turskis (2008) proposed a new logarithmic dimensionless approach that may be more appropriate for situations in which the values of criteria differ considerably. The proposed method is recently used for multi-criteria analysis of projects' performance in construction (Zavadskas *et al.* 2014a). Celen (2014) used four popular normalization procedures in context of TOPSIS method to evaluate the financial performances of Turkish deposit banks. Nayak *et al.* (2014) analyzed the impact of various normalization methods on four intelligent forecasting models i.e. a simple ANN model trained with gradient descent (ANN-GD), genetic algorithm (ANN-GA), a functional link artificial neural network model trained with GD (FLANN-GD), and genetic algorithm (FLANN-GA). Stanujkic *et al.* (2013) pointed to cases where decision-makers expressed their preferences for each selection criteria. Therefore, they extended the linear scale transformation Max-Min method to include the preferred performance ratings (point target). Stanujkic and Zavadskas (2015) presented a modified simple additive weighting (SAW) method based on decision-makers' preferred levels of performances. Jahan and Edwards (2015) identified, classified, and evaluated thirty-one normalization methods for application in material selection problems. The examined methods also included those normalize target-based criteria in addition to cost and benefit criteria. Vafaei *et al.* (2016) investigated the most appropriate normalization techniques for the Analytical Hierarchy Process (AHP) multi-criteria method by taking into account five normalization methods.

1.3. Literature review on applications of WASPAS method

Weighted Aggregated Sum Product Assessment (WASPAS) is one of the most recently developed MADM methods which was originally proposed by Zavadskas *et al.* (2012). It is the mixture of two well-known MADM approaches, the weighted sum model (WSM) and the weighted product model (WPM). Applications and developments of WASPAS method have been reported in many studies. It was used for assessment and selection of appropriate solutions for occupational safety (Dejus, Antucheviciene 2013). Capability of WASPAS for exact ranking of alternatives was shown by solving eight manufacturing selection problems (Chakraborty, Zavadskas 2014). An extended version of WASPAS method for application in uncertain decision-making environments was proposed by Zavadskas *et al.* (2014b). In the proposed method, decision-maker(s)' uncertainty in stating their judgments and evaluations with respect to criteria importance and/or alternatives performance on criteria was expressed by interval-valued intuitionistic fuzzy numbers (IVIF). Furthermore, WASPAS was utilized to evaluate and rank alternative applications of nanotechnology, as one of the main and strategic industries in Iran, for future planning (Ghorshi Nezhad *et al.* 2015). Moreover, WASPAS with fuzzy values was applied to select the best shopping center construction site in Vilnius (Turskis *et al.* 2015). In another study, WASPAS with Grey Values was implemented for selecting the right contractor in construction industry due to its capabilities in handling imprecise information. To assess existing dwelling houses and refurbish them to satisfy en-

ergy efficient requirements and humans' needs, the MADM-opt method was developed and applied in the WASPAS technique (Zavadskas *et al.* 2016). Together, these studies indicate that WASPAS method enjoys wide acceptance.

1.4. Gap of previous studies and objectives of the current research

Review of the literature indicates that in areas such as material selection, where numerous choices with similar performances exist and a lot of various criteria influence the selection results, a more precise normalization and of course MADM approach would be required. Reviewed studies in section 1.2 have only dealt with normalization of decision matrix with consideration of just cost and benefit criteria; while few of them have included point target-based criteria, which are important in many MADM problems including material selection. No attention has been devoted to the effectiveness of point target-based normalization methods, particularly with application of ANOVA analysis. Early in the design timeline, some of the design requirements may be uncertain. There are even less methods introduced for normalization of material and design selection problems with range target-based criteria. In order to increase flexibility in the later design stages, target value of material and design selection criteria can be allowed to vary over a range to increase flexibility in subsequent design stages. Therefore, this study aims at extending the scope normalization research to range target-based criteria (Perez *et al.* 2016).

The major contributions of this paper are: (1) comparing efficiency of point target-based normalization methods using a systematic approach, (2) developing a new normalization method for addressing range target-based criteria in addition to cost and benefit criteria, (3) addressing the gap in the WASPAS literature for problems involving target criteria, and (4) providing an example on material selection to elucidate details of the proposed method as well as the concepts of point and range target-based criteria.

2. Materials and methods

2.1. Simulation analysis of Point Target-based normalization methods

Computer simulation was used to compare the promising target-based normalization methods listed in Table 2. The reason for using simulation was its flexible and versatile method, which allows generating a range of problems, and replicating them several times. This provides a vast database of results from which we can study the patterns of solutions provided by different factors.

For this research the simulation study is conducted as follows:

Step 1: Creating table of full factorial simulation experiments with respect to the following factors, in which each random number is generated from independent normal distribution (here $\mu = 45$). The range constitutes a vector or a $m \times 1$ matrix.

- Factor A, Location of target value: Lower than all data, Between data, Higher than all data.
- Factor B, Variability or standard deviation of data: Low ($\sigma = 3$), High ($\sigma = 30$).
- Factor C, Number of alternatives: Low ($m = 4$), High ($m = 15$).
- Factor D, Normalization methods: Norm (1), Norm (2), Norm (3).

Table 2. Promising normalization methods for cost, benefit, and target criteria

Number	Normalization method	Formula
Norm (1)	Non-monotonic normalization (Shih <i>et al.</i> 2007) approach	$n_{ij} = e^{-\frac{(r_{ij}-T_j)^2}{2\sigma_j^2}}$
Norm (2)	Comprehensive normalization method (Jahan <i>et al.</i> 2011)	$\frac{ r_{ij}-T_j }{e^{\min\{r_j^{\min}, T_j\} - \max\{r_j^{\max}, T_j\}}}$
Norm (3)	Target-based normalization technique (Jahan <i>et al.</i> 2012)	$1 - \frac{ r_{ij}-T_j }{\text{Max}\{r_j^{\max}, T_j\} - \text{Min}\{r_j^{\min}, T_j\}}$

The range for the factors is typical of those found in many material selection applications. Two levels for variability and three levels for target values were assumed. This is representative of a typical MADM problem. To keep this simulation size manageable, number of replications is 10 for each combination, thus producing (3 target value levels) × (2 variability levels) × (2 Number of alternatives levels) × (3 Normalization methods levels) × (10 replications) = 360 vectors of data.

Step 2: Generates experimental designs table (Using Design Expert software version 7) according to the factors defined in step1. The simulated vector of data is defined as r_{ij} , $i = 1, 2, \dots, m$ for a hypothetical criterion j .

Step 3: Measure angle between vector of original data (generated in step 2) and vector of normalized values. In multi criteria analysis problems, among various ways to represent the conflict between alternatives, Deng (2007) used the concept of alternative gradient to represent the conflict of decision alternatives. Here this idea is applied to measure the degree of conflict between the original data (rate of alternatives for the hypothetical criterion j), and normalized values. However, the differences can be also measured by the correlation coefficient.

Assuming that O and N are the original data and normalized values for a specific criterion, respectively, these two groups of data can be considered as two vectors in the “ m ” dimensional space. The angle between O and N in the “ m ” dimensional space can be a good measure of conflict between original data and normalized values. As shown in Figure 2, O_i and N_j is in no conflict if $\theta_{ij} = 0$, the conflict is possible if $\theta_{ij} \neq 0$ i.e. $\theta_{ij} \in (0, \frac{\pi}{2})$. This occurs

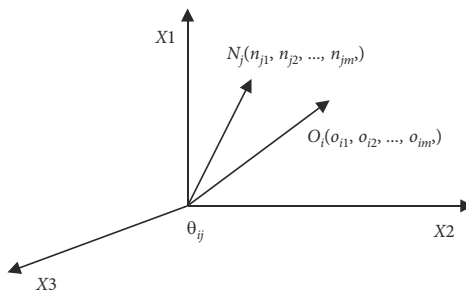


Figure 2. Degree of conflict between original data and normalized one

because when $\theta_{ij} = 0$ the gradients of both the alternatives O_i and N_j are simultaneously in the same increasing direction and there is no conflict between them. The degree of conflict between alternatives O_i and N_j is determined by Eq. (1). $(r_{i1}, r_{i2}, \dots, r_{im})$ and $(n_{j1}, n_{j2}, \dots, n_{jm})$ are the elements of O_i and N_j respectively, where θ_{ij} is the angle between the gradients of the two vectors.

$$\cos\theta_{ij} = \frac{\sum_{k=1}^m n_{ik}r_{jk}}{\left[\left(\sum_{k=1}^m n_{ik}^2 \right) \left(\sum_{k=1}^m r_{jk}^2 \right) \right]^{1/2}} \tag{1}$$

Step 4: Evaluate the effect of each factor and possible interactions using Design Expert software version 7.

2.2. Extension of Point Target-based normalization to range

Target criteria are applicable in many MADM problems, including medical decision making, design selection, and materials selection in particular biomedical material selection where the biomaterial properties should be as close as possible to the replacing tissue. Target criteria, either point or range, can be also used in patch repair material selection for different applications, ranging from aerospace to rehabilitation of reinforced concrete structures in the maintenance of infrastructures. In criteria, such as modulus of elasticity and thermal expansion coefficient, the repair materials must be compatible with the main body material. Furthermore, sometimes in some applications, to evaluate alternatives in the presence of criteria defined in standards and/or regulations, target criteria should be met.

Recently, two methods were suggested for range target-based normalization. Zeng *et al.* (2013) proposed VIKOR method with enhanced accuracy to overcome the shortcoming of traditional VIKOR that works only in handling benefit and cost attributes. Eqs. (2–3) show the proposed normalization formula for handling criteria with range targets as well as cost and benefit criteria, respectively. Zeng *et al.* (2013) ranked iodine deficiency disorder in ten regions using three benefit criteria and two range target-based criteria.

$$n_{ij} = \begin{cases} \frac{r_{ij} - C}{\sum_{i=1}^m (r_{ij} - C)} & \text{if } r_{ij} > C; \\ \frac{B - r_{ij}}{\sum_{i=1}^m (B - r_{ij})} & \text{if } r_{ij} < B; \\ 1 & \text{if } C \leq r_{ij} \leq B. \end{cases} \tag{2}$$

In medical decision-making, most patient data (e.g. a laboratory test report) have normal reference ranges. For an attribute with normal distribution, the normal reference range is usually defined as the set of values that 95% of the normal population falls within. Therefore, in Eq. (2), B can be obtained from $\mu - 1.96 \times \sigma$, and C is $\mu + 1.96 \times \sigma$. If the rate of alterna-

tive “i” for criterion “j” falls inside the historical normally distributed data (B and C), the normalized value will be 1. In addition, Eq. (3) was proposed for cost and benefit criteria.

$$n_{ij} = \begin{cases} \frac{r_j^{\max} - r_{ij}}{\sum_{i=1}^m (r_j^{\max} - r_{ij})} & \text{for benefite criteria;} \\ \frac{r_{ij} - r_j^{\min}}{\sum_{i=1}^m (r_{ij} - r_j^{\min})} & \text{for cost criteria.} \end{cases} \tag{3}$$

As presented in Figure 1, the normalization approach must fulfill several properties. However, the main weakness of this method is the failure to remove the scales precisely. While it is a basic rule that in normalizing identical data with different units or scales, the same results must be obtained. For example, density has units [kg/m³] or [g/cm³]; for temperature, the Fahrenheit (TF) scale is used in the U.S.A., but most of the rest of the world use the Celsius (TC) scale, and in science, it is often more convenient to use the Kelvin (TK) scale ($T_F = \frac{9}{5}T_C + 32$, $T_C = T_K - 273$). These “convertible” units affect material properties such as heat transfer coefficient or thermal conductivity. Normalization methods must be able to eliminate the ‘convertible’ units of criterion functions, ($\phi_{ij} = \alpha * r_{ij} + \beta$), and return the same result for all scales. It was shown in (Jahan, Edwards 2015), the sum-based normalization methods including Eqs. (2 and 3) suffer from this shortcoming.

Perez *et al.* (2016) presented a range target-based normalization method (Eq. (4)) in the context of Reference Ideal Method (RIM). They described the method using an example concerning personal selection (driver). Perez *et al.* (2016), indicated that, in practice, the ideal solution is not necessarily one of the extreme values, but may be, in fact, a value somewhere in between. In the case of driver selection, if the age is one of the criteria, the desired age for candidate person should be between 30 and 35 years old. Assume that the age range of our candidates is between 23 to 60 years old; it is then evident that those methods that cover only cost and benefit criteria or even point target-based criteria do not work in such situations. Figure 3 demonstrates the schematic of the relation between data and normalized values based on Eq. (4).

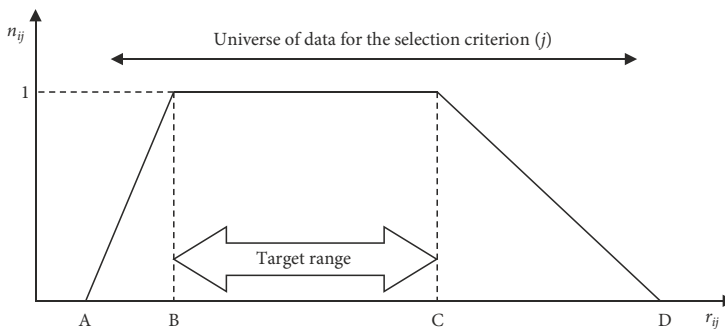


Figure 3. Normalized values and variation of target range in the universe of discourse

According to the location of r_{ij} , three formulas are presented for normalization in Eq. (4). Where the interval $[B, C]$ is the reference ideal and the interval $[A, D]$ is a range that belongs to a universe of discourse ($r_{ij} \in [A, D]$). The more distance of r_{ij} from the reference ideal is, the less the normalized value is.

$$n_{ij} = \begin{cases} 1 - \frac{\min\{|r_{ij} - B|, |r_{ij} - C|\}}{|D - C|} & \text{if } (C < r_{ij} < D) \wedge (C \neq D); \\ 1 - \frac{\min\{|r_{ij} - B|, |r_{ij} - C|\}}{|B - A|} & \text{if } (A < r_{ij} < B) \wedge (A \neq B); \\ 1 & \text{if } C \leq r_{ij} \leq B. \end{cases} \tag{4}$$

Let us consider the age criterion, such that the range is $[A, D] = [23, 60]$, the target range is the $[B, C] = [30, 35]$. Considering the two values of, $x = 25$ and $x = 40$, with the same distance from the targets ($B - 5 = 25$ and $C + 5 = 40$), the normalized values will be obtained, based on Eq. (4), as follows:

$$r_{ij} = 25 \Rightarrow n_{ij} = 1 - \frac{\min\{|r_{ij} - B|, |r_{ij} - C|\}}{|B - A|} = 1 - \frac{\min\{|25 - 30|, |25 - 35|\}}{|30 - 23|} = 0.286;$$

$$r_{ij} = 40 \Rightarrow n_{ij} = 1 - \frac{\min\{|r_{ij} - B|, |r_{ij} - C|\}}{|D - C|} = 1 - \frac{\min\{|40 - 30|, |40 - 35|\}}{|60 - 35|} = 0.8.$$

It is expected to observe the same normalized values, when there is the same distance from the target ranges. Although the presented normalization method (Perez *et al.* 2016) fulfils most of the requirement of an ideal normalization approach, it seems that it had accentuated the problem of asymmetry in the normalized values so that it can influence the result of MADM. In order to preserve the maximum initial information in relation to initial attribute values and values of other criteria, it is necessary to check the symmetry of normalized values in comparing cost, benefit, and target-based criteria.

The evidence presented in this section suggests the need for a more comprehensive normalization method. Eq. (5) describes the proposed formula for range target-based criteria for possible application in MADM techniques.

$$n_{ij} = \begin{cases} 1 - \frac{\min\{|r_{ij} - T_{uj}|, |r_{ij} - T_{lj}|\}}{\max\{|B - T_{uj}|, |A - T_{lj}|\}} & (A < r_{ij} < T_{lj}) \text{ or } (T_{uj} < r_{ij} < B); \\ 1 & T_{lj} \leq r_{ij} \leq T_{uj}. \end{cases} \tag{5}$$

Figure 8 shows schematic of data and normalized values (n_{ij}) for a criterion with range target. The target range will be somewhere in the universe of data between “A” and “B”. It means the target range may vary among the extreme values of the range (See Figures 4, 5 and 6). The target can be even a point between the minimum and the maximum values, instead of range.

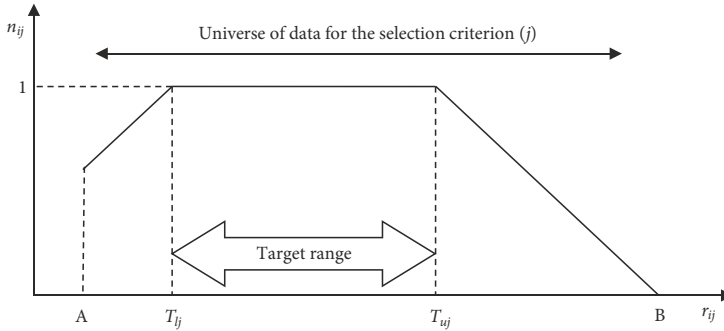


Figure 4. Schematic of normalized values in the proposed method with range target in the middle of data

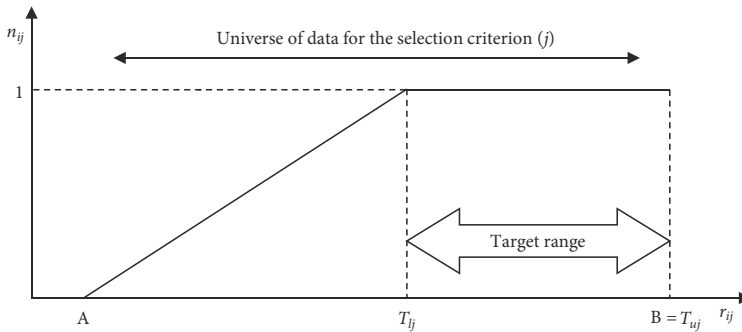


Figure 5. Schematic of normalized values in the proposed method with range target in the upper bound of data

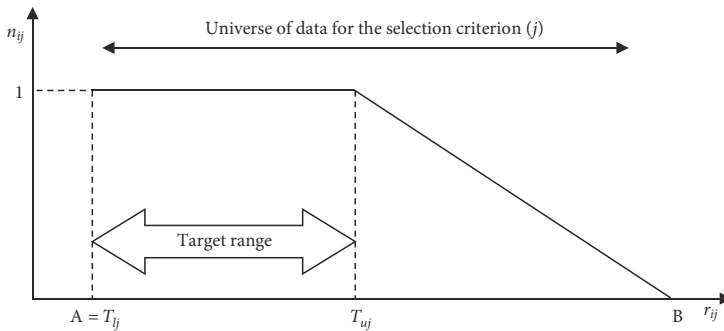


Figure 6. Schematic of normalized values in the proposed method with range target in the lower bound of data

It seems that the proposed method can fulfil all properties described in Figure 1 while overcoming the shortcomings of the available approaches (Perez *et al.* 2016; Zeng *et al.* 2013). When a range target criterion changes to a point target criterion, T_{lj} and T_{uj} close together in which $T_{lj} = T_{uj} = T_j$. In this case, we obtain Eq. (6) for normalization, thus it is possible to

affirm this approach, which is extremely similar to Norm (3) in Table 3, which has the most promising structure (see the results described in Section 3.1).

$$n_{ij} = 1 - \frac{|r_{ij} - T_j|}{\max\{|B - T_j|, |A - T_j|\}} \tag{6}$$

An efficient approach was presented for the normalization of cost, benefit, and target-based criteria from point to range. This can be used to increase the quality of design decision-making techniques through improving the current widely accepted MADM techniques including COPRAS (Liou *et al.* 2016), ELECTRE (Figueira *et al.* 2016), MOORA, EVAMIX, TOPSIS, VIKOR (Mardani *et al.* 2016), and WASPAS.

2.3. Extension of WASPAS method with Range Target-Based (WASPAS-RTB) normalization approach

By considering the matrix presented in Table 1, the following steps are suggested for WASPAS method with range target-based normalization approach (WASPAS-RTB).

Step 1) The decision matrix is normalized using Eq. (7), where the normalized generic element of the decision matrix is denoted by n_{ij} . The target range $[T_{lj}, T_{uj}]$ will be somewhere in the universe of data $[A, B]$.

$$n_{ij} = \begin{cases} 1 - \frac{\min\{|r_{ij} - T_{uj}|, |r_{ij} - T_{lj}|\}}{\max\{|B - T_{uj}|, |A - T_{lj}|\}} & (A < r_{ij} < T_{lj}) \text{ or } (T_{uj} < r_{ij} < B); \\ 1 & T_{lj} \leq r_{ij} \leq T_{uj}. \end{cases} \tag{7}$$

When a range target-based criterion changes to a point target-based criterion, T_{lj} and T_{uj} close together in which $T_{lj} = T_{uj} = T_j$. The above formula can be also used for cost and benefit criteria. For benefit criteria, target is the maximum value in the universe of data ($T_j = B$), and for cost criteria target, it is the minimum value in the universe of data ($T_j = A$). It should be noted that in the WASPAS-RTB method, Eq. (7) is applied instead of Eqs. (8 and 9) that were used in the original version of WASPAS method.

For benefit attributes:

$$n_{ij} = \frac{r_{ij}}{\max_i r_{ij}}, j = 1, \dots, n; i = 1, \dots, m. \tag{8}$$

For non-benefit attributes:

$$n_{ij} = \frac{\min_i r_{ij}}{r_{ij}}, j = 1, \dots, n; i = 1, \dots, m. \tag{9}$$

Step 2) To compute WASPAS-RTB weighted normalized decision matrix, these two actions must be performed. The first one is assigned to the summarization process of WASPAS:

$$\tilde{x}_{ij,sum} = (n_{ij} * 100) * w_j, j = 1, \dots, n; i = 1, \dots, m \tag{10}$$

and for multiplication part;

$$\tilde{x}_{ij,mult} = \begin{cases} (n_{ij} * 100)^{w_j} & n_{ij} \neq 0 \\ 1 & n_{ij} = 0 \end{cases}, j = 1, \dots, n; i = 1, \dots, m. \tag{11}$$

Given that the normalized values (n_{ij}) are between zero and one [0, 1], multiplication to 100 (Eq. (11)) helps to avoid obtaining less amount for the weighted normalized values ($\tilde{x}_{ij,mult}$). Furthermore, $\tilde{x}_{ij,mult}$ would be 1 (neutral) when n_{ij} is 0. Multiplication to 100 is also added to Eq. (10) to provide a final result between 0 and 100 in step 3.

Step 3) A joint equation of the weighted aggregation of additive and multiplicative methods to determine the total relative importance of the alternatives was defined as follows:

$$Q_i^\lambda = \lambda \sum_{j=1}^n \tilde{x}_{ij,sum} + (1-\lambda) \prod_{j=1}^n \tilde{x}_{ij,mult}, \quad j = 1, \dots, n; \quad i = 1, \dots, m. \tag{12}$$

Finally, the candidate alternatives can be ranked based on the Q-values, i.e. the best alternative would be the one having the highest Q-value. When the value of λ is 0, the WASPAS method coincides with WPM, while for $\lambda = 1$, WASPAS corresponds to WSM.

3. Results

3.1. Analysis of simulation experimental results for the promising Point Target-Based criteria

Measure of performance, the angle between original data and the normalized one were analyzed using Design Expert software version 7. Table 3 shows the result of analysis of variance (ANOVA), so that the Model F-value of 67.97 implies that the model is significant. There is only a 0.01% chance that a “Model F-Value” this large could occur due to other reasons.

Table 3. ANOVA results for angle between original data and the normalized values

Source	Sum of Squares	Df	Mean Square	F Value	p-value (Prob > F)
Model	131198.6	25	5247.946	67.96762	<0.0001
A-Location of target value	39608.64	2	19804.32	256.4913	<0.0001
B-Variability	744.7832	1	744.7832	9.645896	0.0021
C-Number of alternatives	1318.269	1	1318.269	17.07327	<0.0001
D-Normalization method	44383.59	2	22191.8	287.4122	<0.0001
AB	16351.76	2	8175.881	105.8881	<0.0001
AC	127.0686	2	63.53428	0.82285	0.4401
AD	5713.156	4	1428.289	18.49817	<0.0001
BC	6.708377	1	6.708377	0.086882	0.7684
BD	19760.99	2	9880.494	127.9651	<0.0001
CD	850.8209	2	425.4104	5.50961	0.0044
ABC	512.8463	2	256.4231	3.321008	0.0373
ABD	1820.012	4	455.0029	5.89287	0.0001
Residual	25788.96	334	77.21244		
Lack of Fit	1212.984	10	121.2984	1.59915	0.1055
Pure Error	24575.97	324	75.85176		

Values of “Prob > F” less than 0.05 indicates that the model terms are significant. Therefore, this table is quite revealing in several ways. In this case, A, B, C, D, AB, AD, BD, CD, ABC, ABD are significant model terms.

Values greater than 0.1 indicate that the model terms are not significant. Therefore, ACD, BCD, and ABCD were removed. BC was kept to support hierarchy (ABC).

The “Lack of Fit F-value” of 1.60 implies that the Lack of Fit is not significant relative to the pure error. There is a 10.55% chance that a “Lack of Fit F-value” this large could occur due to noise. Non-significant lack of fit is good; since we want the model to fit. As shown in Figure 7, when the target value is in the middle of data, the methods present more reasonable outputs (the less is the angle, the better is). However, when there is high variability in the data, the quality of normalization methods is the same for target values between and bigger than data.

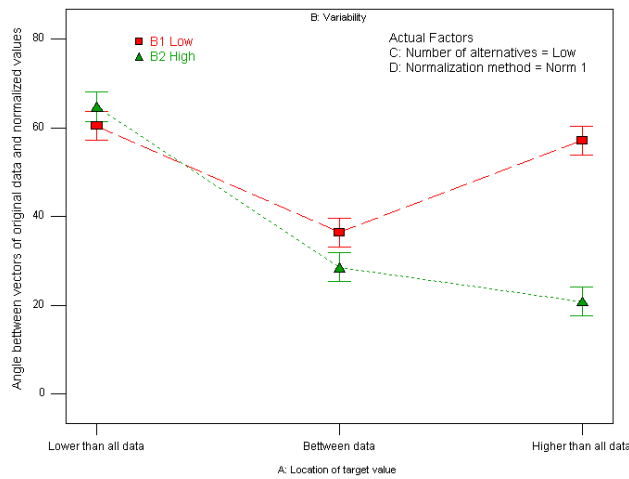


Figure 7. Interaction effects of variability and location of target values on angle between vectors

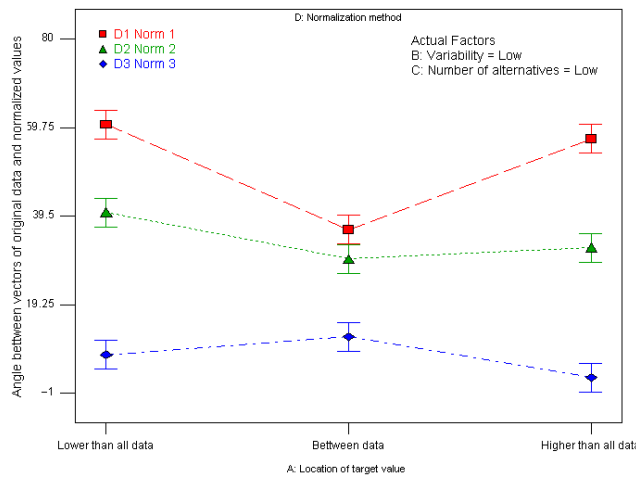


Figure 8. Interaction effects of normalization methods and location of target values on angle between vectors

Figure 8 shows that Norm 1 is more sensitive to location of target value comparing to the other normalization techniques.

Figure 9 shows that although in Norm 3 the angle between original data and normalized values is less than other methods, the error increases by increasing the variability of data.

Figure 10 reveals, that Norm 3 is not too much sensitive to the number of criteria comparing to other normalization methods.

It seems that normalized values by Norm 3 have less sensitivity to the location of target value, variability of data, and number of alternatives. It can be concluded that Norm 3 has the best structure followed by Norm 2 and Norm1 due to less sensitivity to the simulation parameters (source of noise variations).

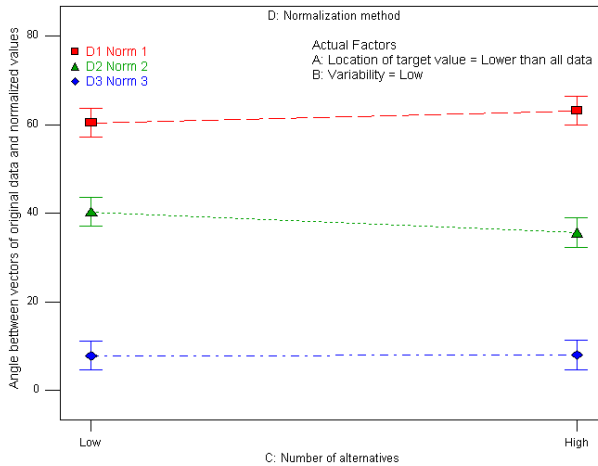


Figure 9. Interaction effects of variability and normalization methods on angle between vectors

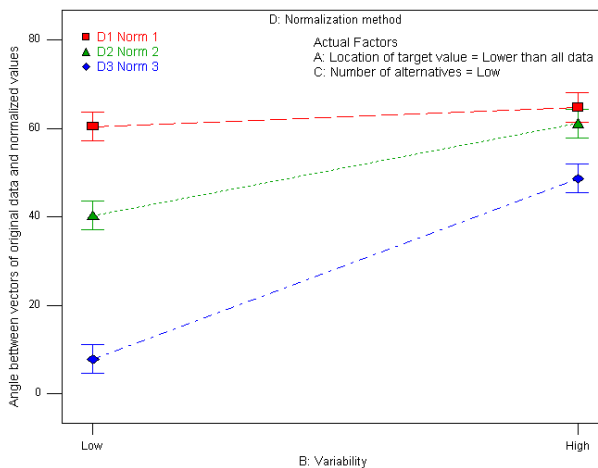


Figure 10. Interaction effects of normalization methods and number of alternatives on angle between vectors

3.2. Application of WASPAS-RTB method for protective coating material selection

This case study deals with the selection of coating material on a substrate made of aluminium alloy (Al-7075, 175 HV), in order to protect the substrate from the abrasive wear occurred during the sliding movement against a high-strength cast iron (290 HV) counterpart. Figure 11 shows the components schematically in which the aluminium component with its coating moves while the cast iron is stationary. A critical issue is the surface integrity of aluminium substrate with the coating material, while the mating part (i.e. cast iron) undergoes a limited wear. Furthermore, the strength of Al-7075 matrix is an important mechanical characteristic to be preserved and strengthened. Thus, in this application, the choice of material requires constraining by compatibility with other materials. The ceramic particles were used to reinforce the Al-7075 matrix using Cold Spray process (Cavallini *et al.* 2013).

Appropriate filler hardness can improve the Al-7075 substrate resistance to abrasive wear and reduce damaging actions to the integrity of the counterpart made of cast iron. Young’s modulus of the filler is influential in load distribution between the components and it should be ascertained that the contribution of filler in the Young’s modulus of the cermet (E_{CM}) is such that the E_{CM} is close to that of substrate (ES). The Young’s modulus of cermet can be gained by the Eq. (13).

$$E_{CM} \propto E_m v_m + E_f v_f \tag{13}$$

Where E_m signifies the Young’s modulus of the Al-7075 matrix, which in this case study is the same as the substrate, E_s , and E_f is the Young’s modulus of the filler. The v_m and v_f stand for the volume fraction of the matrix and the volume fraction of filler, respectively. Another important criterion is the coefficient of thermal expansion (CTE) of filler, which should not cause differential thermal expansion between matrix and reinforcement, and between the cermet and substrate. Thermal conductivity is also considered to protect the Al-7075 substrate from heat. Moreover, the filler should have adequate wettability by the Al-7075 matrix to provide cohesive links with the matrix. In addition to these cases, density, workability and cost are also considered to select the best material. By applying this case study, the capability of WASPAS-RTB approach to explicitly address the target criteria is demonstrated. Here, approximately 40% of the attributes are point and range target-based, and the rest are cost and benefit criteria. This implies the importance of this class of criteria in the MADM algorithm.

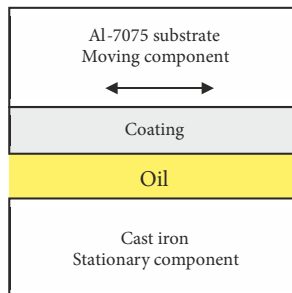


Figure 11. Schematic of the wear couple: protective coating material selection

A set of candidate materials that can be used to make filler to reinforce the Al-7075 matrix is listed in Table 4, which include Al₂O₃ (94% purity), TiN (99% purity), TiC (99% purity), TiO₂ (99% purity), SiC (99% purity), SiN (99% purity), WC (99% purity), CrN (99% purity), AlN (99% purity). In addition to the list of the materials, Table 4 shows the importance of selection criteria (weights) and the technical data regarding the candidate materials for the required criteria.

Table 5 shows the normalized decision-making matrix. The normalized values were obtained from Eq. (7). Tables 6 and 7 present the weighted normalized decision matrix that was respectively calculated according to Eqs (10 and 11). Table 8 presents three criteria of optimality, which are calculated according to Eq. (12), where $\lambda = 0.5$. There is a good agreement between $Q_i^{(1)}$ and $Q_i^{(2)}$, and this can contribute to verifying the extended WASPAS-RTB method.

As shown in Table 8, TiO₂ is the best option based on WASPAS-RTB method. There are considerable similarities between the obtained results and the ranking is calculated according to C-VIKOR method (Cavallini *et al.* 2013). However, the first choice in these two methods is different. In addition to the dissimilarity of the used algorithms, there is a slight change in the input data. In this study, criterion of filler Young's modulus, extended from point target to range target to is used to demonstrate the capabilities of the proposed method. C-VIKOR recommended materials to designers as Al₂O₃> TiO₂> SiC > SiN > CrN> WC > TiN> TiC > AlN. Target value for the criterion of filler Young's modulus was 300 GPa, while range target value was considered from 200 to 300 GPa.

Table 4. Material selection for protective coating on an aluminium alloy substrate

	Filler hardness (HV)	Filler Young's Modulus (GPa)	Filler CTE (10 ⁻⁶ /°C)	Filler density (gr/cc)	Filler thermal conductivity (W/m K)	Wettability (null)	Workability [null]	Cost (€/kg)
Objective type	Point target	Range target	Point target	Min	Max	Max	Max	Min
Universe of data [A, B]	[1100, 2900]	[300, 720]	[2.3, 23]	[3.1, 15.72]	[11.7, 160]	[2, 5]	[1, 3]	[8.5, 100]
Target [T _{lj} , T _{uj}]	[1100, 1100]	[200, 300]	[23, 23]	[3.1, 3.1]	[160, 160]	[5, 5]	[3, 3]	[8.5, 8.5]
Al ₂ O ₃	1175	300	8.1	3.69	18	5	3	8.5
TiN	2500	600	9.4	5.22	19.25	4	1	38
TiC	2900	439	8.3	4.94	20	2	1	40
TiO ₂	1100	230	9	4.25	11.7	4	3	22
SiC	2800	410	4	3.1	120	2	1	13
SiN	1580	310	3.3	3.3	30	4	2	33
WC	2300	720	3.8	15.72	84.82	2	1	17
CrN	1100	400	2.3	6	19.2	4	3	100
AlN	1100	330	4.5	3.26	160	4	3	100
Weight	0.184	0.172	0.172	0.043	0.086	0.064	0.086	0.193

Table 5. Normalized decision-making matrix

	Filler hardness (HV)	Filler Young's Modulus (GPa)	Filler CTE ($10^{-6}/^{\circ}\text{C}$)	Filler density (gr/cc)	Filler thermal conductivity (W/m K)	Wettability (null)	Workability [null]	Cost (€/kg)
Objective type	Point target	Range target	Point target	Min	Max	Max	Max	Min
Al ₂ O ₃	9.583	100.000	28.019	95.325	4.248	100.000	100.000	100.000
TiN	2.222	28.571	34.300	83.201	5.091	66.667	0.000	67.760
TiC	0.000	66.905	28.986	85.420	5.597	0.000	0.000	65.574
TiO ₂	100.000	100.000	32.367	90.887	0.000	66.667	100.000	85.246
SiC	0.556	73.810	8.213	100.000	73.028	0.000	0.000	95.082
SiN	7.333	97.619	4.831	98.415	12.340	66.667	50.000	73.224
WC	3.333	0.000	7.246	0.000	49.305	0.000	0.000	90.710
CrN	100.000	76.190	0.000	77.021	5.057	66.667	100.000	0.000
AlN	100.000	92.857	10.628	98.732	100.000	66.667	100.000	0.000

Table 6. Weighted normalized decision matrix: Summation ($\tilde{x}_{ij, sum}$)

	Filler hardness (HV)	Filler Young's Modulus (GPa)	Filler CTE ($10^{-6}/^{\circ}\text{C}$)	Filler density (gr/cc)	Filler thermal conductivity (W/m K)	Wettability (null)	Workability [null]	Cost (€/kg)
Al ₂ O ₃	1.763	17.200	4.819	4.099	0.365	6.400	8.600	19.300
TiN	0.409	4.914	5.900	3.578	0.438	4.267	0.000	13.078
TiC	0.000	11.508	4.986	3.673	0.481	0.000	0.000	12.656
TiO ₂	18.400	17.200	5.567	3.908	0.000	4.267	8.600	16.452
SiC	0.102	12.695	1.413	4.300	6.280	0.000	0.000	18.351
SiN	1.349	16.790	0.831	4.232	1.061	4.267	4.300	14.132
WC	0.613	0.000	1.246	0.000	4.240	0.000	0.000	17.507
CrN	18.400	13.105	0.000	3.312	0.435	4.267	8.600	0.000
AlN	18.400	15.971	1.828	4.245	8.600	4.267	8.600	0.000

As indicated by the ranking order, TiO₂ and Al₂O₃ are the first and second ranked materials. This can be mainly due to their hardness, Young's modulus, coefficient of thermal expansion, and wettability as well as workability. The hardness values of these materials are much lower than WC, SiC, TiC and TiN. However, high hardness is preferable to avoid wear, so that materials with extremely high hardness suffer from brittleness. In addition, their wettability is also better than carbide ceramics, which contributes to the articulation and reduction of wear. The moduli of these materials are closer to those of substrate rather than the other alternatives. This contributes to more uniform stress distribution and load transfer

Table 7. Weighted normalized decision matrix: Multiplication ($\tilde{x}_{ij,mult}$)

	Filler hardness (HV)	Filler Young's Modulus (GPa)	Filler CTE ($10^{-6}/^{\circ}\text{C}$)	Filler density (gr/cc)	Filler thermal conductivity (W/m K)	Wettability (null)	Workability [null]	Cost (€/kg)
Al ₂ O ₃	1.516	2.208	1.774	1.216	1.132	1.343	1.486	2.432
TiN	1.158	1.780	1.837	1.209	1.150	1.308	1.000	2.256
TiC	1.000	2.061	1.784	1.211	1.160	1.000	1.000	2.242
TiO ₂	2.333	2.208	1.819	1.214	1.000	1.308	1.486	2.358
SiC	0.897	2.096	1.436	1.219	1.446	1.000	1.000	2.409
SiN	1.443	2.199	1.311	1.218	1.241	1.308	1.400	2.290
WC	1.248	1.000	1.406	1.000	1.398	1.000	1.000	2.387
CrN	2.333	2.107	1.000	1.205	1.150	1.308	1.486	1.000
AlN	2.333	2.180	1.502	1.218	1.486	1.308	1.486	1.000

between the components. Meanwhile, the CTEs of both TiO₂ and Al₂O₃ are higher than the other materials except for TiN, so that provide smaller difference in thermal expansion and reduce the risk of thermal cracks. These properties make them suitable for using as filler materials in this application. On the other hand, tungsten carbide as the last ranked material is extremely hard and stiff (hardness of 2300 HV and modulus of 720 GPa) with limited workability and machinability. Meanwhile, WC has high density and extremely low CTE.

Table 8. Three criteria of optimality

	$Q_i^{(1)}$	$Q_i^{(2)}$	Q_i	Raking
Al ₂ O ₃	62.547	39.691	51.119	2
TiN	32.582	15.551	24.067	7
TiC	33.303	11.574	22.439	8
TiO ₂	74.394	52.156	63.275	1
SiC	43.141	11.473	27.307	6
SiN	46.963	26.384	36.673	4
WC	23.607	5.856	14.731	9
CrN	48.118	13.246	30.682	5
AlN	61.912	26.885	44.398	3

4. Discussion

There is a need to study the strengths and weaknesses of different decision-making methods (Zavadskas *et al.* 2014c). Many decision methods developed for engineering design have neglected a number of specific elements that should be taken into account for materials and design selection problems.

4.1. Discussion of effectiveness of the new method

To make dimensionless methods applied and accepted more widely in design decision-making problems, from materials to civil engineering, as well as other applications of MADM such as medical decision-making problems, extensions to model architectures for problem settings are needed. Despite all progress made in the development of different target-based dimensionless methods, there is no definite answer to question: which technique is the most appropriate one? The sensitivity analysis of promising target-based normalization methods was conducted in the presence of finite changes in one or more of the decision matrix parameters. Although, it is hardly possible to evaluate the effect of various methods of normalization of a decision-making matrix on the obtained numerical results. This research attempted to compare the effectiveness of three promising techniques. Monte Carlo simulation method was applied for the generation of the attribute values. Simulation parameters were the number of alternatives, distribution of data, and locations of target criteria. It was shown that the dimensionless method with Linear-max-min structure (Norm (3)) is more appropriate than “Non-monotonic normalization” and “Comprehensive normalization method” (Norms (1), and (2)) due to less sensitivity to the source of noise variations/simulation parameters. Although, it has been attempted to generate realistic data, for simulation, based on material selection environment, the results on the comparison of target-based normalization methods might not be extendable to all data ranges of different problems.

It was revealed that, for the range target-based criteria, the suggested method can overcome the shortcomings of available techniques. The proposed normalization approach that applied for WASPAS method, can provide acceptable results from the view point of symmetry in the normalized values for the same data, when criteria type is either “cost”, or “benefit”. For example, in the criterion of thermal conductivity, and based on the data presented in Table 4, Figure 12 demonstrates the symmetry of normalized values using the proposed normalization method. It is worth noting that most of dimensionless methods suffer from asymmetry issue (Jahan, Edwards 2015).

The ranking orders of alternatives in the proposed WASPAS-RTB method will not be affected by adding or removing options, while this issue (Rank Reversal) weakens most of MADM methods. Negative values are also converted to positive values using the new

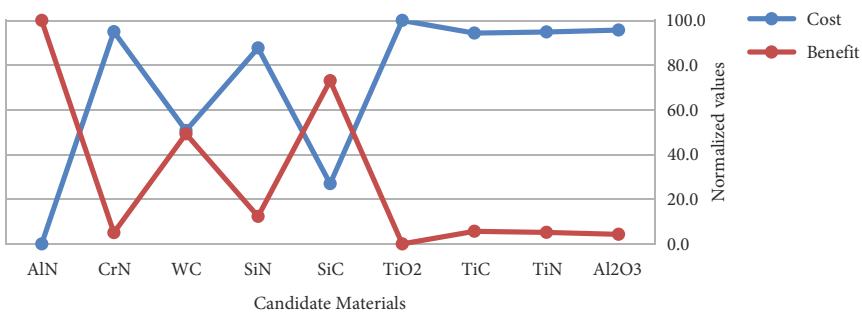


Figure 12. Symmetry of normalized values by the proposed normalization method: Criterion of thermal conductivity considered one time as “cost” type and then as “benefit”

approach. Totally, all expected properties from the viewpoint of normalizing process were covered. The generalizability of these results, however, may be subject to some limitations. For instance, it might not be possible to apply the proposed normalization method to all MADM problems and also use the extended approach (WASPAS-RTB) to all decision-making problems.

4.2. Discussion on material selection for robust design

During the past decades, there was a great focus on product improvement through manufacturing methods, while the emphasis of recent efforts has now moved upstream, such as refining the materials and design. The importance of Quality Function Deployment (QFD) in design process has been emphasized in the literature (Liu 2011), since it can facilitate the identification of preliminary target values in both material and design by taking the customer's voice into account. On the other hand, meeting continuous growing of customer expectations needs innovative designs at lower prices, and faster response times. Designers must be able to either anticipate changes in customer requirements that may occur during the product development process or provide additional design flexibility. It seems that the latter is more practical. Although, recently, the role of QFD in material selection was described (Jahan *et al.* 2016; Prasad, Chakraborty 2013), it has not been well tied with practical material selection in this regard.

Material selection is usually conducted in the early stages of design. Decisions made during this phase are often difficult due to the uncertainty caused by the lack of objective data. However, material selection criteria should be as specific as the design definition will allow. Early in design, the criteria might be "must be transparent", "should be easily manufactured", "must be tough," or "must have low specific modulus". During configuration design, the criteria might be "toughness exceeding 60 MPa", "electrical conductivity between 0.1 and 0.4 $\mu\Omega$ ". Designers, may have some knowledge of the range of these design requirements, but may not be clear as to the exact targets that should be met. Range target helps to readily adaptable, and changing customer requirements, which are also particularly important for robust design. According to (Arvidsson, Gremyr 2008), robust design methodology means "systematic efforts to achieve insensitivity to noise factors [so that] these efforts are based on an awareness of variation and are applicable in all stages of product design". Although many useful statistical tools available for creating robust designs, there is limited attention and even no official introduced technique to consider the concepts of robust design in materials selection stage. The literature emphasizing the more mathematical modelling and predictive aspects of subject, while the author emphasizes how the application of extended decision-making tool provides an opportunity to have flexible design. The connection of material selection with the quality engineering concepts, robust design in particular, on the head of MCDM has not well discovered yet, and more work remains to make an integrated fully robust design methodology.

Conclusions

Different MADM approaches are the results of diverse aggregation, weighing and normalization methods. Normalization is a foundation of a rational decision in engineering design problems, and it must cover target-based criteria from point to range, in addition to cost and benefit criteria that are used in other selection problems. During the early stages of product design, from conceptual design selection to choice of materials, when little is known concerning the design requirements, it is desirable to allow the target design parameters/material properties vary within a certain range rather than setting point targets. In this manner, designs are more flexible in the later stages and can be readily adapted to changing design requirements allowing companies to respond more quickly and at lower costs than their competitors. This verifies the need to update well-accepted MADM methods in this regard. In this paper, at the first stage, the best formula structure of normalization for target-based criteria was selected from promising methods through numerical simulation. Then, the selected one was extended to overcome the shortcomings of available methods. The developed range target-based normalization method was applied in WASPAS technique, and the method was adjusted accordingly. The capability of WASPAS-RTB method in dealing with all types of criteria was demonstrated using a material selection case study. However, the promises of the proposed normalization methods as well as the developed WASPAS technique will be fulfilled only when practical research progress is achieved by implementing the best decisions. Further studies regarding the role of promising normalization methods on increasing quality of MADM methods would be interesting.

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