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ORIGINAL ARTICLE

A framework for weighting of criteria in ranking stage of material selection process

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Abstract Material selection is an onerous process of design activities which needs to be carefully carried out in order to increase the probability of success. A lot of multi-criteria decision-making methods have been proposed in material selection, many of which require quantitative weights for the attributes. Since weights play a very significant role in the ranking results of the materials, this paper presents a framework for determining importance degree of criteria to overcome the shortcomings of this subject in material selection. Furthermore, the suggested framework covers the situation of interdependent relationship between the criteria which has not been surveyed in material selection yet. An example was considered to illustrate how this framework is conducted. On the basis of the numerical results, it can be concluded that the proposed method can soundly deal with the material selection problems.

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Nomenclature

Parameters

A_i	Alternatives or materials (i=1,…,m)
c_j	Criteria or material properties (j=1,…,n)
x_{ij}	Elements of decision matrix
$x_j^{\max}$	Maximum element in criteria j
$x_j^{\min}$	Minimum element in criteria j
w_i	Weight or importance of criteria

Formulas

1–3	Entropy weighting method
4–5	Weighting formula in standard deviation method
6–10	CRITIC weighting method
11–15	PSI weighting method
16–18	Proposed framework

1 Introduction

Selection of the best material among a host of alternatives can greatly impact the eventual success or failure of a product in the market. An improper choice can negatively affect productivity, profitability, and undermine the name of an enterprise because of the growing demands for extended producer responsibility [1]. In engineering design process, approximately, always more than one material is suitable for an application, and the final selection is a compromise that brings some advantages as well as disadvantages [2]. Scholars proposed different steps for material selection [3–5], but it seems that comparing candidate materials, ranking, and choosing the best one are similar stages in material selection process. The large number of current and on growing materials coupled with the complex relationships between the different selection parameters often make the selection of a material for a given component a difficult task [3]. A lot of multi-criteria decision-making methods (MCDM) have been proposed to address this issue [6]. Many of these methods require quantitative weights for the attributes [7–12]. Since weight of attribute plays a very significant role in the ranking results of the alternatives, one crucial problem is to assess the weights or relative importance of material properties [13]. Furthermore, the reasonableness of the weight assignment has an important impact on the reliability and accuracy of the decision results [14].

In all studies on material selection, the criteria are assumed to be independent, while they likely affect each other. Some methods proposed in the past for weighting of criteria in material selection, not only none of these approaches have considered the interdependency of the criteria, but also proposed objective weighting methods in this field suffer from shortcomings. Thus, due to the importance of doing the correct trade-offs among the objectives, efforts need to be extended to consider interdependency among the criteria. Therefore, there is a need for an explicit, systematic, and logical scientific procedure to guide decision makers (DM) or designers to determine the importance degree of criteria. This is considered in this paper using a framework which covers objective, subjective, and dependency weights. It is believed that the proposed framework is able to overcome the shortcomings of the weighting methods in material selection.

The remainder of this paper is organized as follows: Some weighting methods in MCDM are briefly reviewed in the next section, and then in section 3, a framework for weighting of material properties is proposed. In order to illustrate the suggested framework, a case study is presented in section 4. Finally, the paper is closed in section 5 with a conclusion.

2 Weighting methods

Weighting methods, which try to define importance of the criteria, can be categorized into three groups: subjective methods in which the role of assigning the importance to the criteria is put on the shoulders of the DM or designer, objective methods in which DM has no role in determining the importance of the criteria and, the combined weighting scheme of the two previous groups.

2.1 Subjective methods

The subjective methods determine the weight of attributes solely based on preference information of attributes given by expert evaluation, and can be according to the previous experience, particular constraints of design [9], or designer's preferences [15]. These methods can be categorized as follows:

2.1.1 Direct weighting procedure

There are numerous techniques to directly determine the subjective weights. They include SWING [16], TRADE-OFF [17, 18], direct rating [16, 19], point allocation (PA) [20], Delphi method [21], and Simple Multi-attribute Rating Technique (SMART) [22, 23]. In these methods, the decision maker allocates numbers to directly describe the weights of the attributes. For instance in SMART, attributes are first ranked based on importance, and then rated relative to the least important one. Usually, giving rates begins with assigning ten points to the least important attribute. The relative importance of the other attributes is then evaluated by giving them points from ten upwards. The research of Pöyhönen and Hämäläinen [18] showed that in DIRECT, SWING, and TRADE-OFF methods, weights do not differ from each other. Furthermore, the revised Simos' weighting method, which is based on a "card playing" procedure, was used in material selection by Shanian et al. [24]. The method is simple and practical, but it occasionally leads to the same weights in an uncontrolled manner [25].

2.1.2 Pair-wise comparison

In the pair-wise comparison methods, participants are presented a worksheet and are asked to compare the importance of two criteria at a time. Then, the relative importance is scored, and the results are normalized to a total of 1.0. This method is easy to calculate. The results are clear, and especially distinctive for issues about qualitative factors which are used for decision making or evaluation. Pair-wise comparison methods include AHP [8, 26, 27], digital logic approach (DL) [7], modified digital logic approach (MDL) [28], eigenvector [29], and weighted least square method [30]. The last two methods let calculation of attributes' weights while there is inconsistency at DM's idea in pair-wise comparison. Among these methods, DL and MDL enjoy a wide acceptance in material selection. According to Pöyhönen and Hämäläinen [18], the inconsistency in AHP depends on the applied evaluation scale, and it increases either by higher number of attributes or judging the important degree. Furthermore, Shirland et al. [31] used goal programming as a mathematical programming model to determine the weights based on triad comparison of the attributes.

2.2 Objective methods

The objective methods obtain the weights only based on the known data of the problem. Objective weighting methods would be useful when a decision maker is non-existent. Also, the objective weighting is particularly appropriate for situations where reliable subjective weights cannot be obtained [32]. These approaches can be classified as follows:

2.2.1 Mean weight

The mean weight (MW) [32] method determines objective weights by $w_j = \frac{1}{n}$, where n is the number of criteria. This is based on the assumption that all of the attributes are of equal importance. Mean weight (equal importance) should be used either when there is no information from the DM or when there is not enough information to distinguish the relative importance of criteria.

2.2.2 Entropy

According to information theory, entropy is a criterion for the amount of uncertainty represented by a discrete probability distribution, in which there is an agreement that a broad distribution represents more uncertainty than does a sharply packed one [33]. In entropy method [10, 34, 35], the attributes with performance ratings that are very different from each other have higher importance for the problem due to more influence on ranking outcomes [36, 37]. In other words, an attribute has less importance if all candidate materials have similar performance ratings for that attribute. The method determines the weights of the attributes through the Eqs. (1, 2 and 3).

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \qquad i = 1, \ldots, m; j = 1, \ldots, n \tag{1}$$

$$E_j = -\left(\sum_{i=1}^{m} p_{ij} \ln(p_{ij})\right) / \ln(m) \qquad j = 1, \ldots, n \tag{2}$$

$$w_j = \frac{1 - E_j}{\sum_{k=1}^{n} (1 - E_k)} \qquad j = 1, \ldots, n \tag{3}$$

2.2.3 Standard deviation method

Standard deviation method (SD) [13], similar to entropy approach, assigns a small weight to an attribute if it has similar attribute values across alternatives. The SD method determines the weights of the criteria in terms of their SDs through the Eqs. (4 and 5). The application of this method in material selection was recently suggested by Rao and Patel [38].

$$w_j = \sigma_j \Big/ \sum_{j=1}^{n} \sigma_j \qquad j = 1, \ldots, n \tag{4}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} (x_{ij} - \bar{x}_j)^2}{m}} \qquad j = 1, \ldots, n \tag{5}$$

SD technique is not as accurate as entropy approach because its results may be affected by range of different criteria while the normalization process (Eq. (1)) in entropy prevents this misleading.

2.2.4 Criteria importance through inter-criteria correlation

An objective weighting method of criteria importance through inter-criteria correlation (CRITIC) based on the SD approach proposed by Diakoulaki et al. [13]. They first normalized the criteria using Eqs. (6) and (7), then applied Eq. (8) for calculating of correlation. Correlation is commonly used to measure the dependency between two variables. Eqs. (9) and (10) was employed for calculation of weights.

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \qquad i = 1, \ldots, m; \quad j = 1, \ldots, n \quad \text{For benefit criteria} \tag{6}$$

$$r_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \qquad i = 1, \ldots, m; \quad j = 1, \ldots, n \quad \text{For cost criteria} \tag{7}$$

$$\rho_{jk} = \frac{\sum_{i=1}^{m} (r_{ij} - \bar{r}_j)(r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^{m} (r_{ij} - \bar{r}_j)^2 \sum_{i=1}^{m} (r_{ik} - \bar{r}_k)^2}} j, k = 1, \ldots, n \tag{8}$$

$$w_j = c_j \Big/ \sum_{k=1}^{n} c_k \qquad j = 1, \ldots, n \tag{9}$$

$$c_j = \sigma_j \sum_{k=1}^{n} (1 - \rho_{jk}) \qquad j = 1, \ldots, n \tag{10}$$

2.2.5 Preference selection index

Maniya and Bhatt [39] proposed the preference selection index (PSI) method for material selection based on a simple additive weighting method (SAW) or weighted properties method (WPM). Eqs. (11, 12, 13 14 and 15) were suggested by them for weighting of criteria according to preference variation value (PV) in PSI.

$$r_{ij} = \frac{x_{ij}}{x_j^{\max}} \quad i = 1, ..., m; j = 1, ..., n \text{ For benefit criteria} \tag{11}$$

$$r_{ij} = \frac{x_j^{\min}}{x_{ij}} \quad i = 1, ..., m; j = 1, ..., n \text{ For cost criteria.} \tag{12}$$

$$PV_j = \sum_{i=1}^{m} (r_{ij} - \overline{r}_j)^2 \qquad where\ \overline{r}_j = \frac{\sum_{i=1}^{m} r_{ij}}{m} \tag{13}$$

$$\varphi_j = 1 - PV_j \tag{14}$$

$$w_j = \frac{\varphi_j}{\sum_{j=1}^{n} \varphi_j} \tag{15}$$

PSI measures weights according to the degree of convergence in performance rating of each attribute. The motive and rationale of this objective weighting method have not been explained by authors, while Shannon's entropy and SD methods calculate weights according to the degree of divergence in performance rating of each attribute. Therefore, decision makers should be aware of this great contrast when they decided to adopt this approach to obtain the objective weights.

Furthermore in PSI, it is possible for PV to be greater than one and consequently results in negative weights, while negative amount is not acceptable for showing the degree of importance in MCDM.

2.3 Integrated methods

Sometimes, the weights determined by objective methods are inconsistent with the DM's subjective preferences. Contrariwise, the judgments of the decision makers occasionally absolutely depend on their knowledge or experience, and the error in weights to some extent is unavoidable. It can be seen, none of the two approaches are perfect, and the integrated method might be the most appropriate for determining the criteria weights. Currently, a number of combinations [9, 40] or optimal weighting methods have been proposed and developed by scholars. Ma et al. [41] proposed a subjective and objective integrated approach to determine attribute weights using mathematical programming model. Xu [42] showed that the objective weighting method introduced by Ma et al. [41] does not adhere to the rule of entropy method. Furthermore, recently Wang and Luo [43] proposed a method for determining the weights of attributes based on integration of correlation coefficient (CC) and SD such that DM's subjective preferences can be taken into account. But this method needs a lot of computation and does not consider pair-wise comparison of attributes. Also, it was revealed that CCSD weights may sometimes be close to CRITIC weights.

Although there exist a lot of weighting techniques in MCDM, determining the importance of criteria with inter-dependency between criteria has not been considered in material selection yet. Furthermore, some recent proposed objective weighting methods in material selection (SD and PSI) have shortcomings. Thus, in order to address this issue, the next section suggests a framework for weighting of criteria in ranking stage of material selection process.

3 The proposed combinative weighting method

MCDM involves determining the optimal alternative among multiple, conflicting, and interactive criteria [44]. In MCDM, many of criteria are often highly correlated [45, 46], and the incorporation of several interdependent criteria could yield misleading results, while the arbitrary omission of some criteria entails the removal of more or less useful information sources [13]. Furthermore, an attribute cannot often be considered separately because of the complementarities between them. For example, in the case of steel, there is a common relationship between the Brinell hardness number and the ultimate tensile strength (UTS); similar relationships can be shown for brass, aluminum, and cast irons. These kinds of relations have been reported widely in material engineering for different mechanical properties [47, 48]. Moreover, in the conceptual design stage which designers are more interested in sensorial aspects of materials [2, 49], the interdependency would be more significant, because the technical and sensorial properties of materials have to be considered simultaneously and these two have an obvious relationship. For instance, both sensorial criteria of transparency and smoothness are used for conveying the meaning of sexy in a product [49], while there are relations between these two aspects and mechanical properties. One way to address this issue is to obtain the relation among criteria and then to derive the final weights by considering the influences among them.

The existing methods for material selection do not reflect interdependencies among criteria, while considering these interdependencies, may reduce the risk of wrong selection when there are a lot of materials with very similar performances. Although the analytic network process (ANP) can capture this matter, it needs more comparisons than the AHP, and it would be quite demanding. Furthermore, the key for the ANP is to determine the relationship structure among features in advance [50] and to answer the questions precisely, while it is usually hard for DM to give the true relationship structure by considering many criteria (especially in material selection). Moreover, according to Jee and Kang [9], the procedure of material selection should be objective in order to minimize personal bias and time of a new product design. Hence, in this paper, a framework is suggested for weighting with considering interdependency between criteria such that objective weights are prerequisites of subjective weights. Also, the proposed model is able to reduce the number of criteria systematically. Based on the result of the correlation test [51], if it can be concluded that there is a relationship between two criteria, one of them will be adequate and the other one can be eliminated. The idea of correlation's effect on the weight is originally about this issue that when correlation of criteria with other attributes is high, it should have less importance due to the role of other criteria. The suggested framework consists of the following steps:

Step (1): Calculate objective weight using the entropy method for situations in which either all data are quantitative, or the qualitative ones are convertible to the corresponding numbers, otherwise use only subjective weighting (Fig. 1). Entropy method is suggested because it enjoys a strong mathematical structure and does not have the weak points of PSI and SD techniques.

Step (2): Calculate inter-criteria correlation and if the number of criteria is high, decision making to remove unnecessary criteria.

$$R_{jk} = \begin{cases} \dfrac{\sum_{i=1}^{m}(x_{ij}-\bar{x}_j)(x_{ik}-\bar{x}_k)}{\sqrt{\sum_{i=1}^{m}(x_{ij}-\bar{x}_j)^2\sum_{i=1}^{m}(x_{ik}-\bar{x}_k)^2}} & \text{If objectives of criteria } j \text{ and } k \text{ are same} \\ & j \text{ and } k = 1,2,3,\ldots,n \\ -\dfrac{\sum_{i=1}^{n}(x_{ij}-\bar{x}_j)(x_{ik}-\bar{x}_k)}{\sqrt{\sum_{i=1}^{m}(x_{ij}-\bar{x}_j)^2\sum_{i=1}^{m}(x_{ik}-\bar{x}_k)^2}} & \text{If objectives of criteria } j \text{ and } k \text{ are different} \end{cases} \tag{16}$$

In Eq. (16), m is the number of materials, n is the number of criteria, $\bar{x}_j$ and $\bar{x}_k$ are the average values of criteria j and k and R_{jk} is the correlation between criteria j and k. A value of R near 0 indicates little correlation between criteria, while a value near 1 or −1 indicates a high level of correlation. The advantage of suggested formula in Eq. (16) over the existing one in Eq. (8) is that it does not need normalization of criteria (Eqs. (6 and 7)), while the final results are the same.

An excessive set of criteria leads to more analytical effort and can make communication with the results of the analysis more difficult. Yurdakul and Tansel [51] suggested limiting the number of the criteria around seven, because models with lower number of criteria are usually more sensitive to changes in weights of criteria. Decision making to remove a criterion from the decision matrix should be carried out carefully based on the idea of DM. Moreover, according to Fig. 1, high correlation with a criterion or other criteria needs to be considered as well as less objective weights.

Step (3): Calculate weight of correlation's effect according to Eq. (17).

$$w_j^c = \frac{\sum_{k=1}^{n}(1-R_{jk})}{\sum_{j=1}^{n}\left(\sum_{k=1}^{n}(1-R_{jk})\right)} \quad j = 1,2,3,\ldots,n \tag{17}$$

Step (4): According to Fig. 1 in the situation with the low number of criteria, direct weighting techniques are suggested for subjective weighting and, either MDL or AHP is proposed for the high number of criteria. Weighted least-square technique is also suggested when there is inconsistency in DM judgments because it is easier than eigenvector approach [30]. In material selection, scholars always look for logical and simple

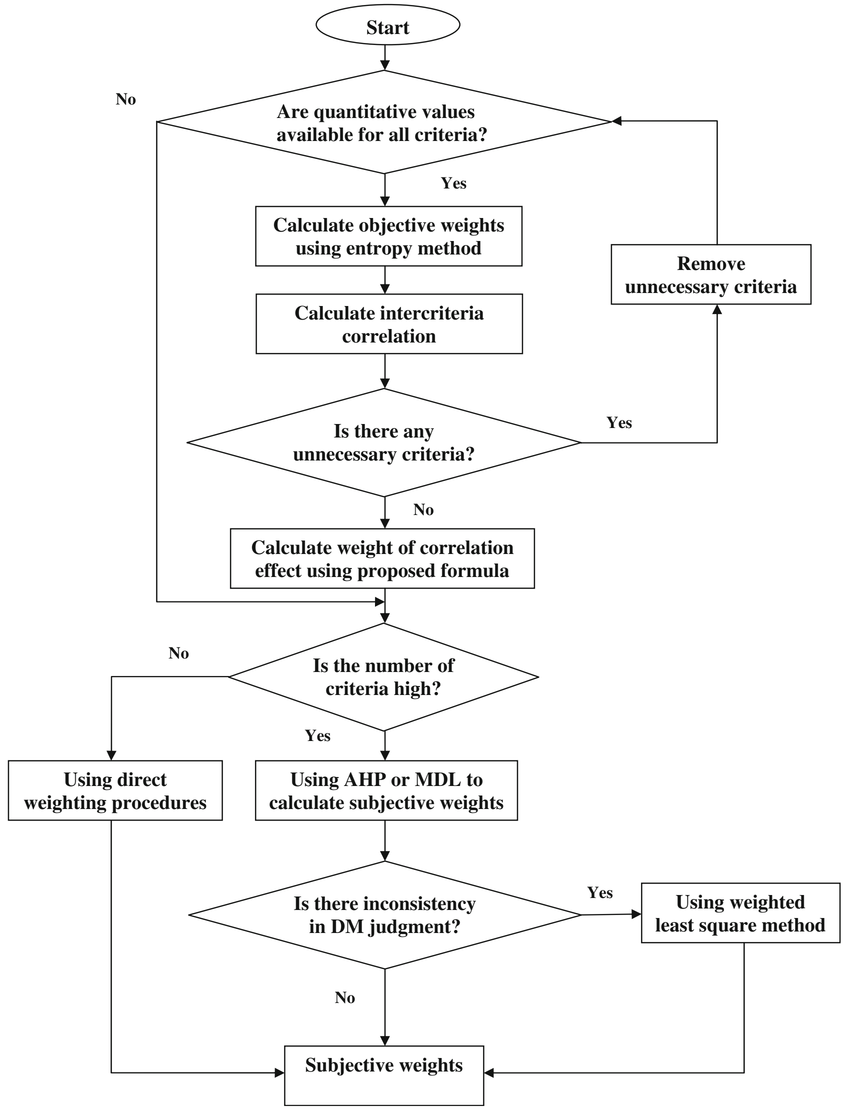

Fig. 1 The suggested flowchart for objective, subjective, and dependency weight in material selection

methods to help designers and decision makers in engineering design applications.

Step (5): Combine the weights according to the suggested formula in Eq. (18), where w_j^o, w_j^s, and w_j^c are the objective, subjective, and correlation effect's weights, respectively.

$$W_j = \frac{\left(w_j^o * w_j^s * w_j^c\right)^{\frac{1}{3}}}{\sum_{j=1}^{n} \left(w_j^o * w_j^s * w_j^c\right)^{\frac{1}{3}}} \quad j = 1, 2, 3, \ldots, n \qquad (18)$$

To sum up, this paper provides a framework for designers in subjective and objective weighting of material selection's criteria, which has slightly improved the weighting procedure of MCDM. This improvement is attributed to a systematic process presented for both objective and subjective approaches, less amount of computation for correlation effect's weight compared to CRITIC technique and a novel formula for combining the three types of weight.

4 Case study

This example is about material selection of mass produced non-heat-treatable cylindrical cover sheet [10, 24, 35] which is in the group of highly sensitive components. In this well-known material selection problem, the sheet should operate

Table 1 Material performance indices/properties

Objective Material's No.	Min D	Max CS	Max UT	Min SB	Min BF	Max SL	Max H	Max YS	Max EM	Max TD	Max TC	Min C
1	8.25	560	940	0.78	15,183	2,916	380	560	138	465	105	18.64
2	8.65	460	600	0.71	12,472	2,395	220	460	125	465	205	13.99
3	8.94	50	210	0.08	1,355	260	45	50	122	460	398	3
4	8.95	340	380	0.48	9,218	1,770	115	340	135	460	390	3.46
5	2.67	190	295	0.25	2,0317	1,966	87	191	73.59	741	152	2.81
6	8.06	690	1030	1.55	5,909	2,174	350	800	190	189	17	5.99
7	8.63	95	270	0.17	2,711	520	63	100	116	174	185	3.32
8	7.08	267	355	0.48	1,957	720	110	265	205	329	50	1.04

D density (milligram per cubic meter), *CS* compressive stress (megapascal), *UT* ultimate tensile stress (megapascal), *SB* spring back index, *BF* bend force index, *SL* static load index, *H* hardness (Vickers), *YS* yield stress (megapascal), *EM* elastic modulus (gigapascals), *TD* thermal diffusivity (square centimeters per hour), *TC* thermal conductivity (Watts per meter Kelvin), *C* cost of base material (Canadian dollars per kilogram), *1* copper-2-beryllium (cast), *2* copper–cobalt–beryllium (cast), *3* electrolytic tough-pitch, h.c. copper, soft (wrought), *4* electrolytic tough-pitch, h.c. copper, hard (wrought), *5* wrought aluminum alloy, *6* wrought austenitic stainless steel, *7* commercial bronze, CuZn10, soft (wrought), *8* carbon steel (annealed)

under static load and carry out heat transfer. The heat conduction through a thermally loaded conductor requires a sheet of metal, which is bent around a heat transfer medium. The sheet thickness depends on the required heat transfer circumstances. This sheet must be able to support an immobile compressive weight and be able to hold against any denting during the hardening process. Material selection criteria, their values, objectives in each criteria, and alternative sheet materials are shown in Table 1.

Based on the proposed flowchart in Fig. 1, since all data in Table 1 are quantitative, entropy technique is used for calculating objective weight. Shanian and Savadogo [35] used entropy earlier, so this result is available. Then, it is tried to demonstrate dependency of the criteria. Table 2 presents the correlation of criteria (R_{jk}). For example, the objectives in two criteria of the ultimate tensile stress (UT) and hardness (H) are the same and according to Eq. (16), the correlation is 0.99.

$$R_{UT,H} = \frac{\sum_{i=1}^{8} (x_{i,UT} - \overline{x}_{UT})(x_{i,H} - \overline{x}_H)}{\sqrt{\sum_{i=1}^{8} (x_{i,UT} - \overline{x}_{UT})^2 \sum_{i=1}^{8} (x_{i,H} - \overline{x}_H)^2}} = 0.99$$

This result is due to the direct relationship between the ultimate tensile stress and the hardness in metals, and it shows that the occurrence of dependencies among criteria is frequent in material selection. Since evaluating the criteria without

Table 2 The calculated correlation coefficient values for criteria pairs (R_{jk})

Objectives Criteria	Min D	Max CS	Max UT	Min SB	Min BF	Max SL	Max H	Max YS	Max EM	Max TD	Max TC	Min C
D	1	0.17	0.2	0.17	−0.61	0.14	−0.19	−0.17	−0.4	0.64	−0.33	0.26
CS	0.17	1	0.96	−0.94	−0.3	0.81	0.94	0.99	0.48	−0.21	−0.54	−0.62
UT	0.2	0.96	1	−0.92	−0.25	0.76	0.99	0.96	0.43	−0.27	−0.58	−0.68
SB	0.17	−0.94	−0.92	1	0.09	−0.62	−0.86	−0.98	−0.59	0.39	0.6	0.39
BF	−0.61	−0.3	−0.25	0.09	1	−0.78	−0.32	−0.24	0.57	−0.75	0.13	0.48
SL	0.14	0.81	0.76	−0.62	−0.78	1	0.81	0.77	−0.06	0.31	−0.34	−0.76
H	−0.19	0.94	0.99	−0.86	−0.32	0.81	1	0.93	0.38	−0.19	−0.56	−0.76
YS	−0.17	0.99	0.96	−0.98	−0.24	0.77	0.93	1	0.5	−0.26	−0.56	−0.55
EM	−0.4	0.48	0.43	−0.59	0.57	−0.06	0.38	0.5	1	−0.65	−0.48	0.06
TD	0.64	−0.21	−0.27	0.39	−0.75	0.31	−0.19	−0.26	−0.65	1	0.3	−0.1
TC	−0.33	−0.54	−0.58	0.6	0.13	−0.34	−0.56	−0.56	−0.48	0.3	1	0.2
C	0.26	−0.62	−0.68	0.39	0.48	−0.76	−0.76	−0.55	0.06	−0.1	0.2	1

Table 3 Calculating the importance degree of criteria by proposed model

	D	CS	UT	SB	BF	SL	H	YS	EM	TD	TC	C
W^o	0.0173	0.0907	0.0645	0.1173	0.1214	0.0784	0.1001	0.0989	0.0166	0.0366	0.1099	0.1482
W^s	0.0163	0.0867	0.0576	0.1137	0.1137	0.0677	0.1046	0.1046	0.0155	0.0344	0.1074	0.1777
W^c	0.0821	0.0684	0.0695	0.1056	0.0960	0.0737	0.0727	0.0710	0.0796	0.0873	0.0973	0.0967
W	0.0295	0.0841	0.0659	0.1160	0.1137	0.0757	0.0945	0.0934	0.0283	0.0495	0.1083	0.1413

taking into account the dependency may become misleading [45], the weights of criteria based on the proposed framework are calculated and shown in Table 3. Although criteria of D, EM and TD have low-objective weight (W^o), Table 2 does not show any high correlation between them and other criteria, so, all criteria are kept for calculation of correlation weight. It can be seen from Table 3 that criteria of CS and UT have fewer correlation weight comparing to other criteria, a part of this result is due to the high correlation between CS, UT, YS, and H in these materials. This result shows that considering the dependency of criteria in determining the importance of criteria changes the final weight and may alter ranking orders of materials.

For subjective weight, due to the large number of criteria, either AHP or MDL can be used (Fig. 1). Since Rao and Davim [27] calculated weights of the same problem using AHP, their results are used here. Final weights are also calculated according to Eq. (18) and demonstrated in Table 3.

Shanian and Savadogo [10, 35] and, Rao and Davim [27] solved the same problem earlier using ordinary TOPSIS, block TOPSIS, VIKOR and ELECTRE. Rao and Davim [27] used AHP for weighting of criteria, while Shanian and Savadogo [35] applied entropy, and both applied TOPSIS for ranking. Here, we only demonstrate proposed framework, so in order to make a comparison, TOPSIS considered for ranking of materials.

From Table 4, it is clear that considering correlation weight beside of objective weight [35] changes ranking orders by 5% (1-Spearman's rank correlation coefficient= 1–0.95=0.05). Also, it is obvious that considering correlation weight besides of subjective weight [27] changes ranking orders by 10%. To avoid disadvantages of using only objective or subjective weighting methods, combination of all weights (proposed framework) is used here.

Shanian and Savadogo [35] suggested applying different MCDM methods together for material selection of such highly sensitive components, but it seems that to obtain precise weight should be considered first to get more reliable results. However, the adoption of a specific weighting approach depends on the DM's preference and the decision environment, due to dreadful consequences of wrong selection, the designers must use the most reliable method in the process of material selection.

5 Conclusion

Through the numerical example, it was shown that the traditional assumption used in MCDM modeling that the

Table 4 Ranking orders of the materials using TOPSIS with different weighting methods

Material's No.	Rank using objective weight[35]	Objective and correlation weight		Rank using subjective weight[27]	Subjective and correlation weight		Proposed framework for weighting	
		Closeness to ideal solution	Rank		Closeness to ideal solution	Rank	Closeness to ideal solution	Rank
1	8	0.3962403	8	8	0.3672454	8	0.4434	8
2	7	0.4520519	7	7	0.4290217	7	0.4674	7
3	2	0.6643113	2	3	0.6735635	2	0.5909	2
4	1	0.6713760	1	1	0.6867243	1	0.6279	1
5	6	0.5459547	5	6	0.5749806	5	0.5148	6
6	5	0.5043888	6	5	0.5246568	6	0.5424	5
7	4	0.6272289	3	4	0.6409196	3	0.5590	4
8	3	0.6188331	4	2	0.6420751	4	0.5749	3

criteria should be independent has not been established in material selection. Thus, in the suggested methodology, a systematic framework for weighting was developed to provide insights for designers and decision makers, and to overcome the shortcomings of the current methods. An advantage of the method over the classical approaches is that not requiring the hypothesis of preferential independence; and it may be considered more comfortable and appropriate in material selection process. From the weighting process of the case study, two main interesting points can be described as follows: First, it can be highlighted that the correlation between criteria is realistic in material selection; thus, ranking of materials without attention to the dependency of material properties causes to doubtable final solution. Because ignoring the dependency of criteria makes the model unrealistic and the decision maker who accepts an optimal solution from the model cannot be sure that he/she has made the correct trade-offs among the objectives. Second, the presented method for incorporating all kinds of weights can help to avoid the subjectivity from the personal bias of designer and confirm the objectivity, so it provides a procedure to acquire more strong decisions. On the basis of the numerical results, it can be concluded that the proposed method can soundly deal with the material selection problems with the dependency on criteria. Moreover, the weighting procedure in MCDM was slightly improved due to a systematic process that was presented for objective, subjective, and correlation weights. So the proposed framework is able to strengthen the existing MCDM material selection procedures especially when there are numerous alternatives with interrelated criteria.

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References

1. Chan JWK, Tong TKL (2007) Multi-criteria material selections and end-of-life product strategy: grey relational analysis approach. Mater Des 28:1539–1546
2. Karana E, Hekkert P, Kandachar P (2008) Material considerations in product design: a survey on crucial material aspects used by product designers. Mater Des 29:1081–1089
3. Farag MM (2002) Quantitative methods of materials selection. In: Kutz M. (ed) Handbook of materials selection. Wiley, 1–24
4. Chiner M (1988) Planning of expert systems for materials selection. Mater Des 9:195–203
5. Ashby MF, Brechet YJM, Cebon D, Salvo L (2004) Selection strategies for materials and processes. Mater Des 25:51–67
6. Jahan A, Ismail MY, Sapuan SM, Mustapha F (2010) Material screening and choosing methods—a review. Mater Des 31:696–705
7. Farag M (1997) Materials selection for engineering design. Prentice-Hall, New York
8. Rao RV (2008) A decision making methodology for material selection using an improved compromise ranking method. Mater Des 29:1949–1954
9. Jee DH, Kang KJ (2000) A method for optimal material selection aided with decision making theory. Mater Des 21:199–206
10. Shanian A, Savadogo O (2006) A material selection model based on the concept of multiple attribute decision making. Mater Des 27:329–337
11. Jahan A, Ismail MY, Mustapha F, Sapuan SM (2010) Material selection based on ordinal data. Mater Des 31:3180–3187
12. Zhou CC, Yin GF, Hu XB (2009) Multi-objective optimization of material selection for sustainable products: artificial neural networks and genetic algorithm approach. Mater Des 30:1209–1215
13. Diakoulaki D, Mavrotas G, Papayannakis L (1995) Determining objective weights in multiple criteria problems: the critic method. Comput Oper Res 22:763–770
14. Rongxi Z, Jianrong X, Dayi H (2009) Approach of determining interval entropy weight based on the subjective preference of decision-maker and its application in Control and Decision Conference, Guilin
15. Shanian A, Savadogo O (2006) TOPSIS multiple-criteria decision support analysis for material selection of metallic bipolar plates for polymer electrolyte fuel cell. J Power Sourc 159:1095–1104
16. Von Winterfeldt D, Edwards W (1986) Decision analysis and behavioral research. Cambridge University Press, Cambridge
17. Keeney RL, Raiffa H (1993) Decisions with multiple objectives: preferences and value tradeoffs. Cambridge University Press
18. Pöyhönen M, Hämäläinen RP (2001) On the convergence of multiattribute weighting methods. Eur J Oper Res 129:569–585
19. Bottomley PA, Doyle JR (2001) A comparison of three weight elicitation methods: good, better, and best. Omega 29:553–560
20. Doyle JR, Green RH, Bottomley PA (1997) Judging relative importance: direct rating and point allocation are not equivalent. Organ Behav Hum Decis Process 70:65–72
21. Hwang CL, Lin MJ (1987) Group decision making under multiple criteria: methods and applications. Springer
22. Edwards W (1977) How to use multiattribute utility measurement for social decision making. IEEE Trans Syst Man Cybern 7:326–340
23. Ward E, Hutton BF (1994) SMARTS and SMARTER: improved simple methods for multiattribute utility measurement. Organ Behav Hum Decis Process 60:306–325
24. Shanian A, Milani AS, Carson C, Abeyaratne RC (2008) A new application of ELECTRE III and revised Simos' procedure for group material selection under weighting uncertainty. Knowl Base Syst 21:709–720
25. Figueira J, Roy B (2002) Determining the weights of criteria in the ELECTRE type methods with a revised Simos' procedure. Eur J Oper Res 139:317–326
26. Saaty TL (1990) How to make a decision: the analytic hierarchy process. Eur J Oper Res 48:9–26
27. Rao RV, Davim JP (2008) A decision-making framework model for material selection using a combined multiple attribute decision-making method. Int J Adv Manuf Technol 35:751–760
28. Dehghan-Manshadi B, Mahmudi H, Abedian A, Mahmudi R (2007) A novel method for materials selection in mechanical design: combination of non-linear normalization and a modified digital logic method. Mater Des 28:8–15
29. Saaty TL (1977) A scaling method for priorities in hierarchical structures. J Math Psychol 15:234–281
30. Chu ATW, Kalaba RE, Spingarn K (1979) A comparison of two methods for determining the weights of belonging to fuzzy sets. J Optim Theory Appl 27:531–538

31. Shirland LE, Jesse RR, Thompson RL, Iacovou CL (2003) Determining attribute weights using mathematical programming. Omega 31:423–437
32. Deng H, Yeh CH, Willis RJ (2000) Inter-company comparison using modified TOPSIS with objective weights. Comput Oper Res 27:963–973
33. Pratyyush S, Jian-Bo Y (1998) Multiple criteria decision support in engineering design. Springer, Berlin
34. Hwang CL, Yoon K (1981) Multiple attribute decision making—methods and applications. Springer, Berlin
35. Shanian A, Savadogo O (2009) A methodological concept for material selection of highly sensitive components based on multiple criteria decision analysis. Expert Syst Appl 36:1362–1370
36. Zeleny M (1982) Multiple criteria decision making. McGraw-Hill, New York
37. Asgharpour MJ (1999) Multiple criteria decision making. Tehran University Publications, Tehran
38. Rao RV, Patel BK (2010) A subjective and objective integrated multiple attribute decision making method for material selection. Mater Des 31:4738–4747
39. Maniya K, Bhatt MG (2010) A selection of material using a novel type decision-making method: preference selection index method. Mater Des 31:1785–1789
40. Wang YM, Parkan C (2006) A general multiple attribute decision-making approach for integrating subjective preferences and objective information. Fuzzy Set Syst 157:1333–1345
41. Ma J, Fan ZP, Huang LH (1999) A subjective and objective integrated approach to determine attribute weights. Eur J Oper Res 112:397–404
42. Xu X (2004) A note on the subjective and objective integrated approach to determine attribute weights. Eur J Oper Res 156:530–532
43. Wang Y-M, Luo Y (2010) Integration of correlations with standard deviations for determining attribute weights in multiple attribute decision making. Math Comput Model 51:1–12
44. Chen SJJ, Hwang CL, Beckmann MJ, Krelle W (1992) Fuzzy multiple attribute decision making: methods and applications. Springer-Verlag New York, Inc, Secaucus
45. Ramík J, Perzina R (2010) A method for solving fuzzy multi-criteria decision problems with dependent criteria. Fuzzy Optim Decis Making 9:123–141
46. Angilella S, Greco S, Lamantia F, Matarazzo B (2004) Assessing non-additive utility for multicriteria decision aid. Eur J Oper Res 158:734–744
47. Durst O, Ellermeier J, Berger C (2008) Influence of plasma-nitriding and surface roughness on the wear and corrosion resistance of thin films (PVD/PECVD). Surf Coating Tech 203:848–854
48. Jiang Y, Li B, Tanabashi Y (2006) Estimating the relation between surface roughness and mechanical properties of rock joints. Int J Rock Mech Min Sci 43:837–846
49. Karana E, Hekkert P, Kandachar P (2009) Meanings of materials through sensorial properties and manufacturing processes. Mater Des 30:2778–2784
50. Lee JW, Kim SH (2000) Using analytic network process and goal programming for interdependent information system project selection. Comput Oper Res 27:367–382
51. Yurdakul M, Tansel ÇY (2009) Application of correlation test to criteria selection for multi criteria decision making (MCDM) models. Int J Adv Manuf Technol 40:403–412