Materials and Design 65 (2015) 335–342

Contents lists available at ScienceDirect

Materials and Design

journal homepage: www.elsevier.com/locate/matdes

Review

A state-of-the-art survey on the influence of normalization techniques in ranking: Improving the materials selection process in engineering design

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ARTICLE INFO

Article history:
Received 8 July 2014
Accepted 9 September 2014
Available online 17 September 2014

Keywords:
Normalization
Target-based criteria
Materials selection
Multi-attributes decision-making
Ranking
Design performance indices

ABSTRACT

Considerable effort has been spent on the development of normalization models in multi-attribute decision-making (MADM) but despite all of these there is no definitive answer to question: which technique is the most appropriate? Therefore, after a thorough review of the literature, thirty-one methods were identified, classified and evaluated for use in materials selection problems. The objective of this paper is to examine the shortcomings of normalization methods and suggest ways of improving their use in the engineering design decision-making process. The emphasis is placed on materials selection, for problems that include target criteria, as well as cost and benefit considerations, typically seen in more challenging applications such as aerospace and biomedical engineering. It is shown that although many normalization methods may appear to be minor variants of each other, these nuances can have important consequences in engineering design decision-making. To conclude, some dimensionless methods are roposed. The result of this research investigation will help ensure engineering decision makers in general improve their current use of MADM methods but in particular aid designers in developing suitable design performance indices for materials selection.

1. Introduction

The need for a diversity of decision-making methods for tackling different design problems has encouraged researchers to develop new techniques. The utilization of multi-criteria decision-making (MCDM) methods as part of the engineering design process can provide an opportunity for producing better products. Searching for suitable materials is a key part of the engineering design process, and is a multi-dimensional problem where many 'boxes should be ticked' at the same time [1]. The use and development of materials in engineering design has had four stages of progression [2], including 'using materials available on site', 'optimization of specific classes of materials', 'selected materials' and finally 'tailored materials' or 'materials by design strategies'. Although nowadays there is a tendency towards the development of multi-functional materials using multi-objective design strategies [3,4], there is still a lot of fundamental materials research being conducted without careful consideration being given to its practical application [5]. This justifies the need for the greater strategic use and development of materials selection tools as an integral part of the product design process. As a result, multi-attribute decision-making (MADM) methods, which are one of the main subgroups of MCDM methods, are being developed for 'data-mining' in order to reduce the incidence of costly mistakes [6,7]. MADM methods differ in criteria weightings determination, normalization and aggregation; as a result the final selection and ranking might be changed for a specific problem. The normalization of decision matrix elements, that convert all the criteria values into non-dimensional form, is a crucial step in most MADM techniques. A lot of normalization methods have been developed, and the review of the literature indicates that most of them only focused on benefit and cost criteria, and target-criteria that are important in design [8,9], and medical decision-making applications [10] received much less attention. For design application, the often large quantity and conflicting nature of the criteria involved make it difficult to correctly choose and use the most appropriate method(s), and hence adversely affect the quality of design decision-making. Reich [11] is probably the best known critic of decision-making methods in engineering design. He argues that there is a need for (1) demonstrating limitations of methods in real practice and for (2) addressing new issues/criteria when dealing with selection methods in standard problems.

What is known about the efficiency of normalization methods is largely based upon empirical studies that compare a limited number of methods [12–14]. In view of the large number of

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http://dx.doi.org/10.1016/j.matdes.2014.09.022
0261-3069/

normalization techniques currently available, a comparative study would help reveal all of the pros and cons of each technique, and provide important insight for engineering design decision-makers.

2. MCDM for supporting materials selection and engineering design

It is recognized that people are consuming materials more rapidly than ever but they are also using an increasing diversity of materials [15], and this is one of the hallmarks of modern industrialized society. Consequently, engineers and designers are always on the lookout for new materials and improved processes to manufacture better products more efficiently and thus maintain competitive advantage and increase profit margins [16,17]. The selection of the most appropriate materials not only affects the capability of manufacturing systems and satisfaction of customers but also impacts environmental issues. Therefore, the effectiveness of materials selection can be much more than other selection problems such as software selection [18], project selection [19], and system selection [20]. Changing the materials set in an established technology is a rare event and can be considered as a revolution [1]. Furthermore, materials selection is the prerequisite for a chain of different engineering selection problems, for instance: process selection, machine selection [21], tools selection [22], material handling equipment selection [23], supplier selection [24], and personnel selection [25].

In order to maximize locating the most appropriate material, it is desirable to use a database of material properties that not only contains the properties of currently available materials but also includes the properties of newly developed (not proven) materials as well as the calculated properties of potential (hypothetical) materials (e.g. derived from computational materials design). Then, intelligently interrogate the complete database of current, new and potential materials to search for a material with the desired properties or characteristics [1]. Also, knowing the basis of the materials enables an appropriate risk assessment to be made if a choice needs to be made between materials that are well established or novel. Clearly, MCDM can increase the detection power of all suitable materials for longer lasting success of a technological sector (Fig. 1). However, the conflicting requirements of multiple design attributes make selecting materials to meet all the desired requirements difficult, with some material properties being above and other material properties being below the requirements. Whilst not meeting design requirements is undesirable, exceeding design requirements leads to inefficiencies. Also, the need to consider a large number of possible materials adds to the difficulties in making a selection. In practice, this often leads to compromise in terms of the number of materials considered (limited to a number of familiar materials only) and allowing some of the design requirements to not be entirely satisfied (partially met only). MCDM allows many materials and design attributes to be considered simultaneously, leading to more successful identification of suitable materials that meet the desired design requirements.

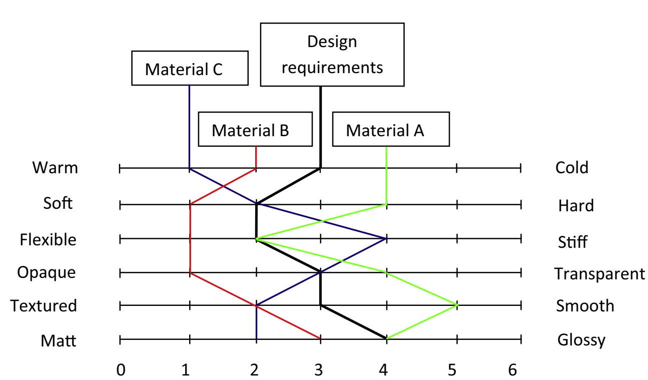

Fig. 1. Matching material characteristics against target design requirements: the need for MCDM approach [26].

3. Materials and methods

Most MADM models require a normalization stage, which is defined by a decision matrix that has the following parts: alternatives $A_i (i = 1, \ldots, m)$, which decision makers have to choose, criteria $C_j (j = 1, \ldots, n)$, relative importance of criteria (or weightings) w_j, and a decision matrix with r_{ij} elements, which is the rating of alternative i with respect to criterion j as shown in Table 1. Performance ratings for different criteria measure by different units but in the decision matrix, in order to have a valid comparison, all the elements must be dimensionless. Although it is hardly possible to evaluate the effect of various methods of normalization of a decision-making matrix on the numerical results, this paper attempts to compare the effectiveness of current normalization techniques.

This section describes the aspects considered important for evaluation/developing a normalization method (Fig. 2).

3.1. Capability in removing scales

It is a basic rule that when normalizing identical data with different units or scales, the same results are obtained. The same criterion function can be demonstrated using different 'convertible' units, for example, density can have units [kg/m^3] or [g/cm^3]. For temperature, the Fahrenheit (T_F) scale is used in the USA but most of the rest of the world uses the Celsius (T_C) scale, and in science it is often more convenient to use the Kelvin (T_K) scale. These 'convertible' units affect material properties such as heat transfer coefficient or thermal conductivity, with temperature being related as follows: $T_F = 9/5T_C + 32$ $T_C = T_K - 273$.

Table 1
A typical multiple attribute decision-making problem.

	w_1 C_1	w_2 C_2	… …	w_n 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}
⋮	⋮	⋮		⋮
A_m	r_{m1}	r_{m2}	…	r_{mn}

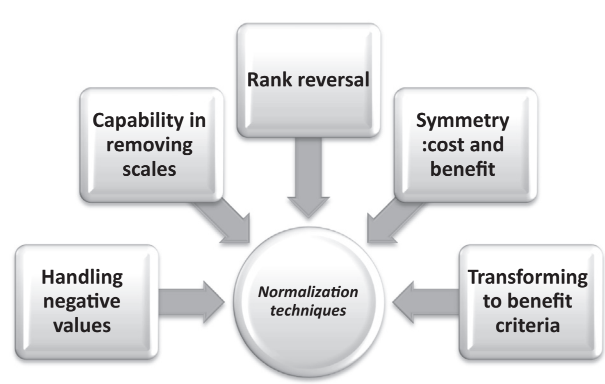

Fig. 2. Expected properties for normalization methods.