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Multiple Criteria Assessment of Insulating Materials with a Group Decision Framework Incorporating Outranking Preference Model and Characteristic Class Profiles

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Abstract We present a group decision making framework for evaluating sustainability of the insulating materials. We tested thirteen materials on a model that was applied to retrofit a traditional rural building through roof's insulation. To evaluate the materials from the socio-economic and environmental viewpoints, we combined life cycle costing and assessment with an adaptive comfort evaluation. In this way, the performances of each coating material were measured in terms of an incurred reduction of costs and consumption of resources, maintenance of the cultural and historic significance of buildings, and a guaranteed indoor thermal comfort. The comprehensive assessment of the materials involved their assignment to one of the three preference-ordered sustainability classes. For this purpose, we used a multiple criteria decision analysis approach that accounted for preferences of a few tens of rural buildings' owners. The proposed methodological framework incorporated an outranking-based preference model to compare the insulating materials with the characteristic class profiles while using the weights derived from the revised Simos procedure. The initial sorting recommendation for each material was validated against the outcomes of robustness analysis that combined the preferences of individual stakeholders either at the output or at the input level. The analysis revealed that the most favorable materials in terms of their overall sustainability were glass wool, hemp fibres, kenaf fibres, polystyrene foam, polyurethane, and rock wool.

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1 Introduction

This paper presents a group decision framework for evaluating sustainability of the insulating materials to retrofit traditional rural buildings. The importance of this research derives from the previous studies on both retrofitting solutions tailored to traditional rural buildings as well as judging an overall desirability of coating materials (see, e.g., Krarti 2015; Fabbri et al. 2012; Ma et al. 2012; Yung and Chan 2012; Martínez-Molina et al. 2016). These studies prove that energy efficiency and thermal comfort are crucial for the maintenance of historic buildings.

The context of the study is that of a typical farmhouse in central Italy. The incorporated building model derives from the analysis of over 800 farmhouses surveyed by the census of the scattered rural buildings of the municipality of Perugia (Umbria region). The high landscape values of traditional buildings and the legislation about their preservation prevent external alterations (Mazzarella 2015). Therefore, the most viable solutions are to intervene on the roof of these structures, increasing their thermal inertia with coating materials (Verbeeck and Hens 2005; Kumar and Suman 2013; Taylor et al. 2000).

We comprehensively evaluate the materials for the roof insulation by considering economic, social, and environmental viewpoints. For this purpose, we incorporate a life cycle costing (LCC) approach, a life cycle assessment (LCA), and a dynamic thermal simulation for the evaluation of energy savings and thermal comfort. As such, we aim at identifying the materials that guarantee the indoor thermal comfort, at the same time reducing the consumption of resources in their entire life cycle as well as maintaining cultural and historic significance of the buildings. In this perspective, we differentiate from the vast majority of previous studies concerning coating materials which incorporate a mono-disciplinary approach (Copiello 2017).

To provide an overall sustainability assessment of coating materials, we incorporate Multiple Criteria Decision Analysis (MCDA). MCDA offers a diversity of approaches designed for providing the decision makers (DMs) with a recommendation concerning a set of alternatives evaluated in terms of multiple conflicting points of view. Few applications of MCDA methods for the evaluation of building materials, which are reported in the literature (Ginevicius et al. 2008) deal mainly with the environmental sustainability of materials (Papadopoulos and Giama 2007; Khoshnava et al. 2016). Some combinations of LCA and MCDA were considered by Santos et al. (2017) and Piombo et al. (2016). Applications which included both LCC and LCA for the definition of criteria to be used in MCDA are still rare (Piombo et al. 2016). Decision analysis methods used in the above-mentioned studies involved different variants of AHP (Motuziene et al. 2016; Khoshnava et al. 2016), PROMETHEE II (Kumar et al. 2017), Weighted Sum, TOPSIS (Čuláková et al. 2013), VIKOR, and COPRAS (Ginevicius et al. 2008).

From the viewpoint of MCDA, our study differs from the aforementioned ones in terms of the following major aspects:

- We formulate the considered problem in terms of multiple criteria sorting, thus aiming at assigning the materials to a set of pre-defined and ordered sustainability classes (categories) rather than at ordering them from the best to the worst;
- We assess the insulating materials while taking into account preferences of multiple DMs (owners of rural houses), thus incorporating group decision making tools into the evaluation framework;
- The adopted assignment procedure builds upon outranking-based comparison of the insulating materials with the characteristic profiles composed of the per-class most representative performances on all criteria (Kadziński et al. 2015b);
- The research results are validated against the outcomes of robustness analysis that takes into account all sets of weights compatible with either the ranking of criteria provided by each DM within the revised Simos (SRF) procedure (Figueira and Roy 2002) or a group compromise ranking of criteria that is constructed with an original procedure proposed in this paper.

The remainder of the paper is organized in the following way. In the next section, we review the existing group decision making methods for multiple criteria sorting. Section 3 describes a three-stage decision aiding method that has been used to evaluate the insulating materials while taking into account preferences of a group of stakeholders. Section 4 exhibits comprehensive results of multiple criteria assessment of the insulating materials. The last section concludes.

2 Review of Multiple Criteria Sorting Group Decision Methods

The objective of the case study presented in this paper is to give an easily interpretable comprehensive assessment of the insulating materials' sustainability. This is achieved by assigning them to a set of pre-defined and ordered decision classes based on their performances on multiple criteria (Kadziński et al. 2015b). While computing the sorting recommendation, we account for the preferences of a group of experts and stakeholders. This requires implementation of a group decision making framework.

As real-world situations often involve multiple stakeholders, some methods have been proposed to support groups in making collective sorting decisions (Daher and Almeida 2010). These approaches can be distinguished at different levels. In particular, they differ in terms of a preference model employed to represent preferences of the DMs. Furthermore, an underlying classification rule may involve analysis of a single preference model instance or all sets of parameters compatible with the DMs' preference information. Moreover, sorting methods can be divided with respect to the level on which individual viewpoints are aggregated (Dias and Climaco 2000). Finally, some approaches account for the importance degrees of the involved DMs, while other methods assume that all DMs play the same role in the committee.

Among multiple criteria sorting group decision methods, outranking-based approaches are prevailing. Most decision support systems in this stream incorporate Electre TRI-B (Yu 1992; Roy 1996). For example, Dias and Climaco (2000) proposed an approach that admits each DM to specify imprecise constraints on the parameters of an outranking model, then exploits a set of compatible parameters using robust assignment rule, and finally aggregates individual perspectives in a disjunctive or conjunctive manner (thus, not accounting for the DMs' powers). The former accepts an assignment if it is justified by at least one DM, whereas the latter confirms some classification only if it is consistent with the preferences of all DMs. In this way, a group may agree on some result even if its members do not share the same model parameters. This idea was extended by Damart et al. (2007) to an interactive preference disaggregation approach that accepts assignment examples provided by different DMs. The method incorporates robustness analysis by deriving for each DM the possible class assignments (confirmed by at least one compatible preference model instance) and guides the group on sorting exemplary alternatives by exhibiting the levels of consensus between the DMs. Analogously, Shen et al. (2016) developed an adaptive approach under intuitionistic fuzzy environment that allows to reach a classification with an acceptable individual and group consensus levels. Moreover, de Morais Bezerra et al. (2017) enriched Electre TRI-B with the tools for visualizing the comparison of individual results and procedures for guiding the changes of model parameters for deriving a better consensus.

Furthermore, Jabeur and Martel (2007) proposed a framework, which derives a collective sorting decision at the output level from the individual non-robust classifications by additionally accounting for the relative importance of group members. Then, Morais et al. (2014) used a stochastic variant of Electre TRI-B, called SMAA-TRI, to consider uncertainty in criteria weights and to derive for each DM the shares of the relevant parameter vectors that assign a given alternative to a certain category. An overview of thus obtained individual results leads to a collective recommendation. Conversely, Cailloux et al. (2012) employed assignment examples provided by multiple DMs for reaching an agreement at the input level. In particular, they proposed some linear programming models for deriving a joint set of boundary class profiles and veto thresholds.

As far as outranking-based sorting approaches incorporating a model typical for PROMETHEE are concerned, Nemery (2008) extended the FlowSort method to group decision making. His proposal derives an assignment for each alternative from its relative comparison (strength and weakness) against the boundary or central class profiles specified by each individual DM. A similar idea was implemented by Lolli et al. (2015) in FlowSort-GDSS. The underlying procedure derives class assignments by comparing comprehensive (global) net flows of alternatives and reference profiles. The proposed sorting rules distinguish between scenarios in which analysis of the individual assignments leads to either univocal or non-unanimous recommendation. Although the viewpoints of different DMs are aggregated at the output level, the method defines some consistency conditions on the preference information (in particular, reference profiles) provided by the individual DMs.

The majority of existing value-based approaches derive a sorting recommendation incorporating robustness analysis and not differentiating between the roles played by the DMs. In particular, the UTADIS^{GMS}-GROUP method (Greco et al. 2012) accounts for the assignment examples provided by each DM and derives collective results that concern two levels of certainty. The first level refers to the necessary and possible consequences of individual preference information, which is typical for Robust Ordinal Regression (ROR) (Greco et al. 2010; Kadziński et al. 2015b). The other level is related to the necessity or possibility of a support that a particular assignment is given in the set of DMs. This method was further adapted by Liu et al. (2015) to account for the uncertain evaluations represented with the evidential reasoning approach, to provide some measures on the agreement between the DMs, and to derive a collective univocal assignment.

Conversely, Kadziński et al. (2013) aimed at a joint representation of assignment examples provided by all DMs by a set of additive value functions and investigating the necessary and possible consequences of applying the latter on the set of alternatives. When there is no value function compatible with preferences of all DMs, some linear programming techniques can be used to remove a minimal subset of inconsistent assignment examples. A similar approach was proposed by Cai et al. (2012), though additionally accounting for the DMs' priorities. The latter ones intervene in the selection of a representative value function and in resolving inconsistency in the provided assignment examples. These priorities are updated with the progressive preference elicitation process to reflect the preciseness, quantity and consistency of the example decisions supplied by each DM.

Finally, when it comes to using "if …then …" decision rules for representing preferences of the DMs, one proposed various extensions of the Dominance-based Rough Set Approach (DRSA) (Greco et al. 2001). These accept preference information in form of individual assignment examples. First, Greco et al. (2006) introduced some concepts (e.g., multi-union and mega-union) related to dominance with respect to minimal profiles of evaluations provided by different DMs. Then, Chen et al. (2012) proposed to aggregate the recommendations suggested by individual linguistic decision rules into an overall assignment be means of a Dempster–Shafer Theory. The crucial concepts incorporated in the DRSA sorting method proposed by Sun and Ma (2015) are a dominance relation on the set of multiple sorting decisions (each provided by an individual DM) and a multi-agent conflict analysis framework. Furthermore, Chakhar and Saad (2012) and Chakhar et al. (2016) illustrated how to combine individual approximations of class unions and derive collective decision rules that permit classification of all alternatives in a way consistent with the judgments of all DMs. These approaches measure the contribution of each expert to the collective assignment in terms of the individual quality of classification. Finally, Kadziński et al. (2016) adapted the principle of ROR to a group decision framework with DRSA, thus considering all sets of rules compatible with the individual assignment examples and combining their indications only at the output level.

In this paper, we propose an outranking-based group decision approach that incorporates Electre TRI-rC. Thus, it derives the assignments by comparing alternatives with the characteristic class profiles rather than with the boundary profiles as in Electre TRI-B. The basic procedure we use takes into account a single preference model instance (incorporating criteria weights derived from the SRF procedure) for each DM and aggregates the individual viewpoints at the output level. While still aggregating the preferences at the output level, we extend the basic framework to offer results of robustness analysis with multiple sets of parameters compatible with the DMs' value systems. Additionally, we propose a new algorithm for constructing a group compromise ranking of criteria, hence offering aggregation of the individual viewpoints also at the input level. At all stages, we assume that the involved stakeholders have the same importance degrees. Moreover, instead of providing precise assignments, our framework offers acceptability indices indicating the support that is given to the assignment of each alternative to various classes by different DMs and/or preference model instances compatible with their preferences.

3 Multiple Criteria Decision Analysis Method for the Assessment of Insulating Materials

This section describes a three-stage multiple criteria decision analysis method that has been used to evaluate the insulating materials while taking into account preferences of a group of stakeholders. Firstly, we discuss the Electre TRI-rC method (Kadziński et al. 2015b) that has been employed to assign the materials to a set of pre-defined and ordered classes. It incorporates the SRF procedure to compute the criteria weights (Figueira and Roy 2002). The method has been extended to a group decision setting to derive for each material some group class acceptability indices, which indicate the proportion of stakeholders that accept an assignment of the material to a given class. Secondly, we have adapted Stochastic Multi-criteria Acceptability Analysis (SMAA; Lahdelma and Salminen 2001; Tervonen and Figueira 2008; Tervonen et al. 2007) to the context of Electre TRI-rC and SRF procedure. It has been used to conduct robustness analysis (Roy 2010) for the results obtained in the first part, i.e., to validate their certainty while avoiding the arbitrary choice of criteria weights, which is conducted by the SRF procedure. Thirdly, we have proposed an algorithm for constructing a group compromise ranking of criteria based on the orders provided by the individual DMs. This ranking of criteria has been used as an input for SMAA to offer yet another view on the stability of computed results.

Let us use the following notation (Kadziński et al. 2015a):

- $A = \{a_1, a_2, \ldots, a_n\}$ is a set of alternatives (insulating materials);
- $G = \{g_1, g_2, \ldots, g_m\}$ is a family of evaluation criteria that represent relevant points of view on the quality of assessed alternatives;
- $g_j(a)$ is the performance of alternative a with respect to criterion g_j, $j = 1, \ldots, m$ (when presenting the method, without loss of generality, we assume that all criteria are of gain type, i.e., the greater the performance, the better);
- $C_1, C_2, \ldots, C_p$ are the preference ordered classes to which alternatives should be assigned; we assume that C_h is preferred to C_{h-1} for $h = 2, \ldots, p$.

3.1 Assessment of Insulating Materials Within a Group Decision Framework Incorporating Electre TRI-rC and the SRF Procedure

In this section, we present the Electre TRI-rC method (Kadziński et al. 2015b) that is used to assign the materials to a set of pre-defined and ordered classes. The method derives for each material a possibly imprecise assignment by constructing and exploiting an outranking relation S (Figueira et al. 2013). This relation quantifies an outcome of the comparison between the materials and a set of characteristic class profiles (Rezaei et al. 2017). In what follows, we discuss the main steps of the incorporated approach.

Step 1 For each class C_h, provide the most typical (representative) performances on all criteria g_j, $j = 1, \ldots, m$, thus specifying the characteristic profiles b_h, $h = 1, \ldots, p$ (Almeida Dias et al. 2010). Defining such profiles was found intuitive and manageable by the involved experts, which was the main reason for incorporating Electre TRI-rC in the study. The set of all characteristic profiles is denoted by B.

Steps 2–7 are conducted separately for each Decision Maker ($DM_k, k = 1, \ldots, K$) in $\partial^{\mathrm{K}} = \{DM_1, DM_2, \ldots, DM_K\}$.

Step 2 Determine the weight w_j^k of each criterion g_j, $j = 1, \ldots, m$, using the SRF procedure (Figueira and Roy 2002). This method expects DM_k to:

- Assign some importance rank $l^k(j)$ to each criterion g_j; this is attained by ordering the cards with criteria names from the least to the most important (the greater $l^k(j)$, the greater w_j^k; some criteria can be assigned the same rank, thus being judged indifferent);
- Quantify a difference between importance coefficients of the successive groups of criteria judged as indifferent, L_s^k and L_{s+1}^k, by inserting e_s^k white (empty) cards between them (the greater e_s^k, the greater the difference between the weights assigned to the criteria contained in L_{s+1}^k and L_s^k);
- Specify ratio Z^k between the importances of the most and the least significant criteria denoted by $L_{v(k)}^k$ and L_1^k.

These inputs are used to derive the criteria weights as follows (Figueira and Roy 2002; Corrente et al. 2016):

$$w_j^k = 1 + \frac{\left(Z^k - 1\right)\left[l^k(j) - 1 + \sum_{s=1}^{l(j)-1} e_s^k\right]}{v(k) - 1 + \sum_{s=1}^{v-1} e_s^k}.$$

Steps 3–6 are conducted for each pair consisting of alternative a and profile b_h.

Step 3 For each criterion g_j compute a marginal concordance index $c_j^k(a, b_h)$ defined as follows:

$$c_j^k(a, b_h) = \begin{cases} 1 & \text{if } g_j(a) - g_j(b_h) \geq 0, \\ 0 & \text{if } g_j(a) - g_j(b_h) < 0. \end{cases}$$

The index quantifies a degree to which a is at least as good as b_h on g_j. Let us remark that in our study the experts defined the performances of characteristic profiles on all criteria by selecting them from the performances of the considered materials. This facilitated the preference elicitation process when dealing with a set of criteria with heterogeneous performance scales. In this perspective, when comparing the alternatives with the characteristic class profiles, we decided to exploit only the ordinal character of criteria and not use the discrimination (indifference and preference) thresholds, which can be, in general, employed in Electre. That is, in our application, the outranking of alternative a over profile b_h on g_j means that $g_j(a)$ is at least as good as the most typical (representative) performance for class C_h on g_j of some considered material.

Step 4 Compute a comprehensive concordance index $\sigma^k(a, b_h)$ defined in the following way:

$$\sigma^k(a, b_h) = \frac{\sum_{j=1}^{m} w_j^k c_j^k(a, b_h)}{\sum_{j=1}^{m} w_j^k}.$$

The index quantifies a joint strength of a subset of criteria supporting the hypothesis about a outranking b_h ($aS^k b_h$). Note that in our study, no criterion was judged strong enough to be attributed a power to veto against the outranking relation. Thus, no discordance effect has been considered.

Step 5 Specify the cutting level λ^k (also called majority threshold), and compare $\sigma^k(a, b_h)$ with λ^k to verify the truth of a crisp outranking relation $aS^k b_h$ in the following way:

$$\sigma^k(a, b_h) \geq \lambda^k \Rightarrow aS^k b_h.$$

The truth of relation $b_h S^k a$ can be verified analogously.

Step 6 Use information on the truth or falsity of $aS^k b_h$ and $b_h S^k a$ to check the validity of:

- a being preferred to b_h ($aS^k b_h \wedge not\left(b_h S^k a\right) \Rightarrow a \succ_k b_h$);
- b_h being preferred to a ($b_h S^k a \wedge not\left(aS^k b_h\right) \Rightarrow b_h \succ_k a$);
- a being indifferent with b_h ($aS^k b_h \wedge b_h S^k a \Rightarrow a \sim_k b_h$);
- a being incomparable with b_h ($not\left(aS^k b_h\right) \wedge not\left(b_h S^k a\right) \Rightarrow a ?_k b_h$).

Step 7 For alternative a determine its desired class interval $C^k(a) = \left[C_L^k(a), C_R^k(a)\right]$ by applying the assignment rules of ELECTRE TRI-rC (Kadziński et al. 2015b). To compute the worst class $C_L^k(a)$, compare a successively to b_h, for $h = p-1, \ldots, 1$, seeking the first (i.e., the best) characteristic profile b_h such that:

$$a \succ_k b_h \wedge \sigma^k(a, b_{h+1}) > \sigma^k(b_h, a),$$

and select $C_L^k(a) = C_{h+1}$. When no such a profile is found, $C_L^k(a) = C_1$.

To compute the best class $C_R^k(a)$, compare a successively to b_h, for $h = 2, \ldots, p$, seeking the first (i.e., the worst) characteristic profile b_h such that:

$$b_h \succ_k a \wedge \sigma^k(b_{h-1}, a) > \sigma^k(a, b_h),$$

and select $C_R^k(a) = C_{h-1}$. In case no such a profile is found, $C_R^k(a) = C_p$.

Step 8 Combine the individual class assignments for all DMs into *group class acceptability indices* $E^{\partial}(a, h)$ (Damart et al. 2007; Kadziński et al. 2016). These are defined as the proportion of DMs (stakeholders) that accept an assignment of alternative a to class C_h, i.e.:

$$E^{\partial^{\mathrm{K}}}(a, h) = \frac{\sum_{k=1}^{K} E^k(a, h)}{K},$$

where for $k = 1, \ldots, K$:

$$E^k(a, h) = \begin{cases} 1 & if\ C_h \in C^k(a), \\ 0 & if\ C_h \notin C^k(a). \end{cases}$$

This measure indicates a cumulative support given to the assignment of a to C_h by all group members.

3.2 Stochastic Multi-criteria Acceptability Analysis with Electre TRI-rC

The SRF procedure derives the precise weight values from the ranking of criteria, intensities of preference, and ratio between the most and the least important criteria provided by DM_k applying some arbitrary rule (Figueira and Roy 2002). However, there exist multiple weight vectors compatible with such incomplete preference information. Recently, many researchers have raised the robustness concern in view of the SRF procedure to quantify the impact of uncertainty in the selection of an arbitrary weight vector on the stability of computed recommendation. In particular, Siskos and Tsotsolas (2015) proposed a set of robustness rules for the SRF procedure to obtain tangible and adequately supported results. Then, Govindan et al. (2017) suggested to exploit the whole set of compatible weight vectors to construct the necessary and possible results being confirmed by, respectively, all or at least one compatible vector. Further, Corrente et al. (2017) adapted the stochastic analysis of recommendation with the SRF procedure to the context of Electre III. We follow the latter research direction and integrate Stochastic Multi-criteria Acceptability Analysis (Lahdelma and Salminen 2001; Tervonen et al. 2007) to handle possibly imprecise weight values compatible with the ranking of criteria and to derive robust recommendation with Electre TRI-rC.

SMAA applies the Monte Carlo simulation to provide each DM with the acceptability indices which measure the variety of different preferences (in particular, weight vectors) that confirm the validity of particular elements of the recommendation. In our case, the space $w^k(SRF)$ of weight vectors compatible with preferences of DM_k is defined by the following constraint set $E^k(SRF)$:

$$\left.\begin{array}{c} [O1]\ w_i^k > w_j^k,\ \text{for all } g_i \in L_t^k,\ g_j \in L_s^k \text{ and } t > s, \\ [O2]\ w_i^k = w_j^k,\ \text{for all } g_i,\ g_j \in L_s^k, \\ [O3]\ w_i^k = Z^k w_j^k,\ \text{for all } g_i \in L_{v(k)}^k,\ g_j \in L_1^k\ , \\ [O4]\ w_{j+1}^k - w_j^k > w_{p+1}^k - w_p^k,\ \text{if } e_j^k > e_p^k, \\ [O5]\ \sum_{j=1}^m w_j^k = 1, \end{array}\right\} E^k(SRF)$$

where the interpretation of different constraints is as follows:

- $[O1]$ ensures that criteria ranked better by DM_k will be assigned greater weight;
- $[O2]$ guarantees that criteria deemed indifferent by DM_k will be assigned equal weights;
- $[O3]$ sets the ratio Z between weights of the most and the least significant criteria;

- $[O4]$ respects the intensities of preference for different pairs of criteria that have been quantified with the number of inserted empty cards;
- $[O5]$ normalizes the weights.

These constraints also ensure that all weights are positive. For each DM_k, each weight vector $w \in w^k\,(SRF)$ and each alternative $a \in A$, we compute the resulting class assignment $C_w^k\,(a) = \left[C_{w,L}^k\,(a)\,, C_{w,R}^k\,(a)\right]$ with Electre TRI-rC.

We define the *class range stochastic acceptability index* $CRSAI^k\,(a, [L, R])$ (Kadziński et al. 2013) on a range of classes $\left[C_L^k\,(a)\,, \ldots, C_R^k\,(a)\right]$ with $L \leq R$ as the proportion of compatible weights $w \in w^k\,(SRF)$ that assign alternative a precisely to the range of classes $\left[C_L^k\,(a)\,, \ldots, C_R^k\,(a)\right]$. Formally, the index is computed as follows:

$$CRSAI^k\,(a, [h_L, h_R]) = \int_{w \in w^k(SRF)} m\,(w, a, [h_L, h_R])\,dw,$$

where $m\,(w, a, [h_L, h_R])$ is the class range membership function:

$$m\,(w, a, [h_L, h_R]) = \begin{cases} 1, & if\; C_{w,L}^k\,(a) = C_{h_L} \text{ and } C_{w,R}^k\,(a) = C_{h_R}, \\ 0, & \text{otherwise.} \end{cases}$$

Further, we compute the proportion of $w \in w^k\,(SRF)$ for which C_h is within $\left[C_{w,L}^k\,(a)\,, C_{w,R}^k\,(a)\right]$, i.e., the proportion of weights that either precisely or imprecisely assign a to C_h (Kadziński and Tervonen 2013; Kadziński et al. 2014). Let us define such a *cumulative class stochastic acceptability index* $CuCSAI^k\,(a, h)$ as:

$$CuCSAI^k\,(a, h) = \sum\nolimits_{[h_L, h_R]: h \in [h_L, h_R]} CRSAI^k\,(a, [h_L, h_R])\,.$$

We estimate $CRSAI$s with acceptable error bounds by sampling the space $w^k\,(SRF)$ with the Hit-And-Run (HAR) algorithm (Tervonen et al. 2013). Overall, $CRSAI^k(a,$ $[h_L, h_R])$ and $CuCSAI^k\,(a, h)$ can be interpreted as a support given by DM_k to the assignment of a to, respectively, $\left[C_{h_L}, C_{h_R}\right]$ or C_h.

To measure a cumulative support given to the assignment of a to C_h by all DMs in ∂^{K}, we consider a *cumulative group class stochastic acceptability index* $CuCSAI^{\partial^{\mathrm{K}}}\,(a, h)$, defined as follows (Kadziński et al. 2016, 2018):

$$CuCSAI^{\partial^{\mathrm{K}}}\,(a, h) = \frac{\sum_{k=1}^{K} CuCSAI^k\,(a, h)}{K}.$$

3.3 Selection of a Group Compromise Ranking of Criteria

In this section, we introduce a procedure for deriving a *compromise complete ranking of criteria* based on the rankings provided individually by each DM_k within the SRF procedure. The procedure builds on the algorithm that was introduced by Govindan et al. (2017) for constructing a utilitarian ranking of alternatives. Hence, we adopt an

Table 1 Definition of distances $\delta\left(R_{k'}^{jl}, R_{k''}^{jl}\right)$ between different pairwise relations

$R_{k'}^{jl} \backslash R_{k''}^{jl}$	$g_j \succ_{k''} g_l \left(\succ_{k''}^{jl}\right)$	$g_j \prec_{k''} g_l \left(\prec_{k''}^{jl}\right)$	$g_j \sim_{k''} g_l \left(\sim_{k''}^{jl}\right)$
$g_j \succ_{k'} g_l \left(\succ_{k'}^{jl}\right)$	0	2	1
$g_j \prec_{k'} g_l \left(\prec_{k'}^{jl}\right)$	2	0	1
$g_j \sim_{k''} g_l \left(\sim_{k'}^{jl}\right)$	1	1	0

idea of minimizing a sum of of distances between the compromise ranking and all individual rankings.

When considering a complete ranking of criteria for DM_k, for each pair (g_j, g_l) one of the three relations holds: g_j is preferred to $g_l \quad (g_j \succ_k g_l)$, or g_j is indifferent with $g_l \quad (g_j \sim_k g_l)$, or g_l is preferred to $g_j \quad (g_j \prec_k g_l)$. Let $R_{k'}^{jl}$ and $R_{k''}^{jl}$ denote the relations holding between g_j and g_l in the rankings provided by, respectively, $DM_{k'}$ and $DM_{k''}$ (e.g., $R_{k'}^{jl}$ is $\succ_{k'}^{jl}$ or $\sim_{k'}^{jl}$ or $\prec_{k'}^{jl}$). The distances $\delta(R_{k'}^{jl}, R_{k''}^{jl})$ between $R_{k'}^{jl}$ and $R_{k''}^{jl}$ are provided in Table 1 (for a detailed justification of these values, see Roy and Słowiński 1993). A distance between two rankings of criteria provided by $DM_{k'}$ and $DM_{k''}$ involving all ordered pairs of criteria (g_j, g_l) is defined as follows:

$$\sum_{j,l:j<l} \delta\left(R_{k'}^{jl}, R_{k''}^{jl}\right).$$

In what follows, we present a Binary Linear Program (BLP) for constructing a compromise ranking of criteria for group ∂^{K} involving K DMs. Following Govindan et al. (2017), for each pair of criteria (g_j, g_l), we introduce two binary variables p_{∂}^{jl} and i_{∂}^{jl} (see constraint $[R1]$ in $E^{\partial}\ (SFR)$) with the following interpretation:

- p_{∂}^{jl} represents a weak preference of g_j over g_l in the compromise ranking (i.e., in case $p_{\partial}^{jl} = 1$, then $g_j \succ_{\partial} g_l$ or $g_j \sim_{\partial} g_l$); note that p_{∂}^{jl} and p_{∂}^{lj} can be used to instantiate one of the three relations $\succ_{\partial}^{jl}$, $\sim_{\partial}^{jl}$, or $\prec_{\partial}^{jl}$ for g_j and g_l; that is, if $p_{\partial}^{jl} = 1$ and $p_{\partial}^{lj} = 0$, then $g_j \succ_{\partial} g_l$; if $p_{\partial}^{jl} = 0$ and $p_{\partial}^{lj} = 1$, then $g_j \prec_{\partial} g_l$; if $p_{\partial}^{jl} = 1$ and $p_{\partial}^{lj} = 1$, then $g_j \sim_{\partial} g_l$;
- i_{∂}^{jl} represents an indifference $\sim_{\partial}$ between g_j and g_l (i.e., in case $p_{\partial}^{jl} = 1$ and $p_{\partial}^{lj} = 1$, then $i_{\partial}^{jl} = 1$ and $g_j \sim_{\partial} g_l$; see [R3]).

Since we impose completeness and transitivity on a weak preference relation, we require that $p_{\partial}^{jl} = 1$ or $p_{\partial}^{lj} = 1$ (see $[R2]$) and that $p_{\partial}^{jr} = 1$ and $p_{\partial}^{rl} = 1$ imply $p_{\partial}^{jl} = 1$ (see $[R4]$). When constructing a utilitarian complete ranking of criteria, we aim at minimizing a comprehensive distance between relations ($\succ_{\partial}$, $\prec_{\partial}$, or $\sim_{\partial}$) instantiated for all pairs of criteria in the compromise ranking and relations observed for these pairs in the individual DMs' rankings (for DM_k, the relation between g_j and g_l $(j < l)$ is denoted by R_k^{jl}):

$$\min \sum_{j,l:j<l} \sum_{k=1}^{K} \left[p_{\partial}^{jl} \delta\left(R_k^{jl}, \succ_{\partial}^{jl}\right) + p_{\partial}^{lj} \delta\left(R_k^{jl}, \prec_{\partial}^{jl}\right) + i_{\partial}^{jl}\left[\delta\left(R_k^{jl}, \sim_{\partial}^{jl}\right) - \delta\left(R_k^{jl}, \succ_{\partial}^{jl}\right) - \delta\left(R_k^{jl}, \prec_{\partial}^{jl}\right)\right]\right]$$

$$\left.\begin{array}{l} [RI] \text{ for all } j,l = 1,2,\ldots,m : j \neq l \\ [R1]\, p_{\partial}^{jl}, i_{\partial}^{jl} \in \{0,1\}, \\ [R2]\, p_{\partial}^{jl} + p_{\partial}^{lj} \geq 1, \\ [R3]\, i_{\partial}^{jl} = p_{\partial}^{jl} + p_{\partial}^{lj} - 1, \\ [RII] \text{ for all } j,l,r = 1,2,\ldots,m : j \neq l \neq r \\ [R4]\, p_{\partial}^{jl} \geq p_{\partial}^{jr} + p_{\partial}^{rl} - 1.5. \end{array}\right\} E^{\partial}(SFR)$$

If $g_j \succ_{\partial} g_l$ ($p_{\partial}^{jl} = 1, \quad p_{\partial}^{lj} = 0$, and $i_{\partial}^{jl} = 0$), $g_j \prec_{\partial} g_l$ ($p_{\partial}^{jl} = 0, \quad p_{\partial}^{lj} = 1, i_{\partial}^{jl} = 0$), or $g_j \sim_{\partial} g_l$ ($p_{\partial}^{jl} = 1, \quad p_{\partial}^{lj} = 1, i_{\partial}^{jl} = 1$) has been instantiated in the compromise ranking, it contributes with, respectively, $\sum_{k=1}^{K} \delta\left(R_k^{jl}, \succ_{\partial}^{jl}\right)$, $\sum_{k=1}^{K} \delta\left(R_k^{jl}, \prec_{\partial}^{jl}\right)$ or $\sum_{k=1}^{K} \delta\left(R_k^{jl}, \sim_{\partial}^{jl}\right)$ to a value of the objective function (for a detailed explanation, see Govindan et al. 2017).

Once a group compromise ranking of criteria is constructed, we conduct robustness analysis with SMAA in the same way as described in the previous section for an individual DM. This leads us to deriving *cumulative group compromise class stochastic acceptability indices* $CuCCSAI^{\partial^{K}}(a,h)$.

3.4 Decision Aiding with the Proposed Approach

Multiple criteria sorting decisions can be aided with the proposed group decision making framework through the process illustrated in Fig. 1. It starts with specifying the sets of alternatives, criteria, and ordered classes as well as the alternatives' evaluations (performances) on the criteria.

Then, the preference information is elicited from the involved experts and/or stakeholders. Each stakeholder is required to provide a cutting level as well as a ranking of criteria that incorporates the intensities of preference and the ratio between the importance coefficients of the most and the least significant criteria, as required by the SRF procedure. Moreover, the experts are expected to define a characteristic profile for each class. In our study, the profiles were agreed by multiple experts, but, in general, the methodological framework admits that each stakeholder provides his/her individual set of profiles.

Further, the method derives three types of results. These indicate a support that is given to the assignment of considered alternatives to different classes via the application of Electre TRI-rC for different sets of weights and cutting levels compatible with the preferences of the involved experts. In two cases, the preferences of the individual stakeholders are aggregated only at the output level. Depending on whether these individual preferences are processed using the SRF procedure or the Monte Carlo simulation, the method computes, respectively, group class acceptability indices or

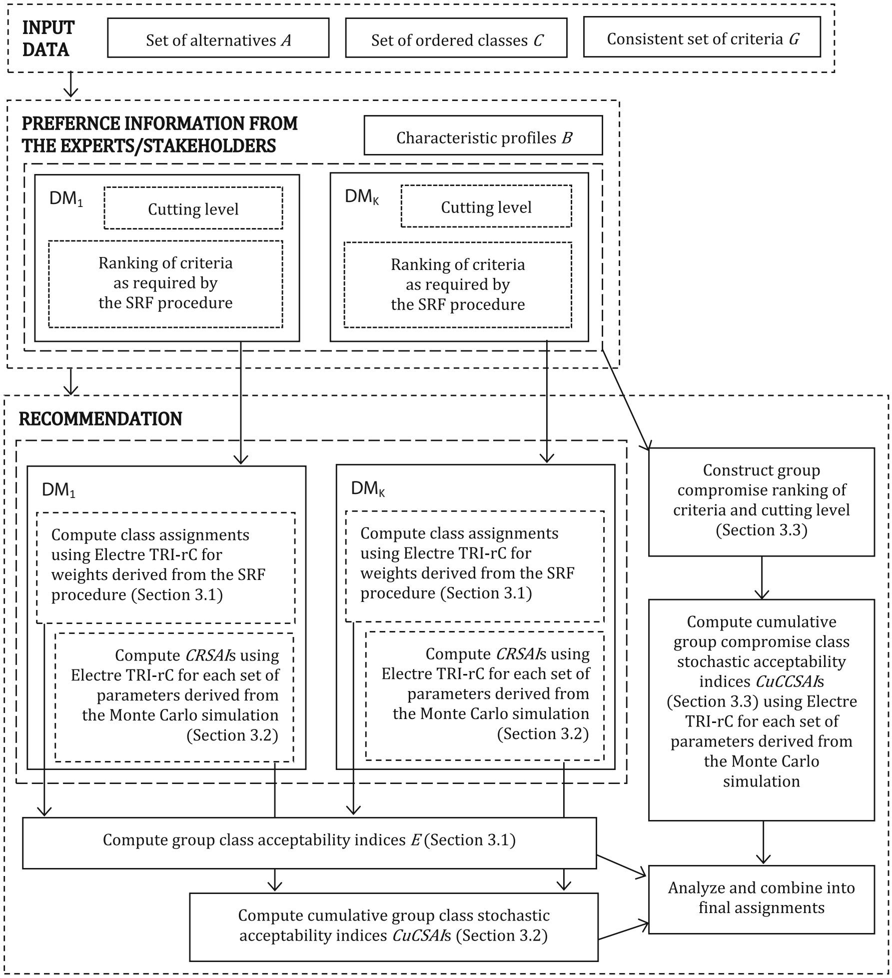

Fig. 1 Decision aiding process with the proposed group decision methodological framework

cumulative group class stochastic acceptability indices. In the third case, the preferences are aggregated at the input level by constructing a group compromise ranking of criteria. Then, the method applies SMAA to derive cumulative group compromise class stochastic acceptability indices.

Finally, these three types of outcomes should be analyzed and combined into the recommended assignments. This is straightforward in case the support given to the assignment of alternatives to decision classes by different results is similar. In case of ambiguous indications by different procedures, the inconsistency needs to be raised by a decision analyst.

Obviously, it is not required to use all three types of procedures and respective results for each study. This may be useful when offering different viewpoints on the robustness of sorting recommendation is desired. Otherwise, one can employ just a single procedure for processing the experts' preferences depending on whether they should be aggregated at the input or output level and whether the robustness analysis should be incorporated into a particular study.

4 Results of Multiple Criteria Assessment of Insulating Materials with the Outranking Preference Model and Characteristic Class Profiles

The study aims at evaluating overall sustainability of coating materials used in buildings retrofitting. We consider 13 materials listed in Table 2 (they are denoted by $A = \{a_1, a_2, \ldots, a_{13}\}$). All materials having a thickness of 15cm were placed internally on the roof of a model building typical for central Italy, and evaluated from the socio-economic and environmental viewpoints. The six relevant criteria which have been used to assess the materials are: *hour of discomfort* (g_1; DH),CO_2 *avoidance* (g_2); *Net Present Value* (g_3; NPV), *human health* (g_4); *ecosystem quality* (g_5), and *consumed resources* (g_6). In what follows, we explain their meaning.

Discomfort degree Hour (g_1; the less, the better) evaluates a thermal performance of a building on an annual basis (CEN 2007) in accordance with the EN 15251 standard. Thus defined, it serves as a measure of comfort. The performance on g_1 is quantified as an overall time during which the temperature falls outside the second comfort category that was considered in the study (Carlucci and Pagliano 2012), and then weighing it by how much the limit has been exceeded. For this purpose, we have used the following equation:

$$g_1(a) = \sum_{i=1}^{8760} \frac{10}{60} |CC_2 - OT_i|$$

where CC_2 is the lower or upper limit of the assumed comfort category, OT_i is the operative temperature at hour $\imath$, and the multiplier $\frac{10}{60}$ refers to an employed time step of 10 minutes.

CO_2 *avoidance* (g_2; the more, the better) measures the energy saved during the building life by using a particular insulating material when compared to the case of no insulation in the following way:

$$g_2(a) = \frac{ES * 277.78 * 406.31}{10^6}$$

where ES is the estimated Energy Saved in GJ at time t with a time horizon of 25 years, 277.78 is a conversion factor to GJ in kWH, while 406.31 is the conversion factor for Italy from kWH to kg of CO_2 per year (EIA, 2015). Therefore, the CO_2 avoided refers only to the use phase, which is not considered in the LCA study.

Net present value (g_3; the more, the better) is the difference between the present values of cash outflows and inflows. On one hand, the outflows involve Primary Energy Input (PEI) cost, installation cost I at time $t=0$, and the dismissing cost EL_T after the lifespan T of the investment (25 years). On the other hand, the inflows refer to the Cost of Energy Saved ES_t in different time periods t. Overall, we have computed

NPV as follows:

$$g_3(a) = -PEI - I + \sum_{t=0}^{T} \frac{ES_t}{(1+i)^t} - \frac{EL_T}{(1+i)^T}$$

where i is the discount rate. For a detailed justification of this measure, see Menconi and Grohmann (2014). Thus defined, NPV can be seen as an outcome of Life Cycle Costing, which is an economic methodology for assessing the profitability of using different alternatives by taking into account the costs they incur at different stages of a life cycle (e.g., construction, operations, and maintenance).

For the assessment of environmental impacts, we have used the Eco-indicator 99 method (Goedkoop and Spriensma 2001) implemented in the *SimaPro* software (Product Ecology Consultants 1990). The method aggregates the results of Life Cycle Assessment into a set of parameters that can be interpreted as damage categories. In general, LCA is useful for identifying the environmental implications of a given alternative through the quantification of consumed resources (e.g., energy, raw materials, water) and related emissions (e.g., emissions into the air, water and soil, waste and co-products) (Paolotti et al. 2017). We used the following three environmental Eco-indicators expressed on a dedicated point scale:

- *Human health* (g_4; the less, the better) which is derived from the analysis of the following normalized impact categories: carcinogens, respiratory organics and inorganics, climate change, radiation, and ozone layer;
- *Ecosystem quality* (g_5; the less, the better) which is made up by the following three normalized impact categories: ecotoxicity, acidification/eutrophication, and land use;
- *Resources* (g_6; the less, the better) which aggregates two normalized impact categories: minerals and fossil fuels.

The LCA focused on the production phase, starting from the production of a raw material to the obtaining of its complete version. We omitted the use and disposal phases, hence implementing an LCA "from cradle to gate" (Paolotti et al. 2016). All the impacts were calculated considering a functional unit of 1 m^3 of insulating material.

The performances of 13 insulating materials with respect to 6 criteria are provided in Table 2. For all materials but hemp fibres, Ecoinvent Database (Ecoinvent 2010) was used as a source of foreground and background data related to both production and assembly processes as well as to the transport, electricity and fuel consumption. Instead, for the hemp processes the underlying data was derived from Zampori et al. (2013).

The objective of the case study is to give an easily interpretable comprehensive assessment of the materials' sustainability. This is achieved by assigning them to a set of three pre-defined and ordered classes: C_1 (low sustainability), C_2 (medium sustainability), and C_3 (high sustainability).

The study involved elicitation of preferences from the two groups of stakeholders. On one hand, a characteristic profile b_h for each class C_h, $h = 1, 2, 3$, has been collectively specified by the experts from the university-based engineering team specialized

Table 2 Performances of 13 insulating materials with respect to 6 criteria

Insulating material	a	g_1	g_2	g_3	g_4	g_5	g_6
Performance unit	–	Hours	kg of CO_2	€	Points	Points	Points
Autoclave aerated complete	a_1	4889.339	158.63	283.41	0.009703	0.000636	0.015876
Corkslab	a_2	3974.451	178.49	282.01	0.022122	0.018376	0.040660
Expanded perlite	a_3	3893.646	179.11	326.26	0.006451	0.000759	0.043280
Fibreboard hard	a_4	3657.799	185.29	243.45	0.039111	0.014516	0.136345
Glass wool	a_5	3681.898	187.35	316.92	0.010608	0.001307	0.033364
Gypsum fibreboard	a_6	7051.231	103.24	135.88	0.047131	0.003916	0.070469
Hemp fibres	a_7	3921.449	182.59	334.10	0.002336	0.003079	0.008207
Kenaf fibres	a_8	3685.510	186.82	341.79	0.004760	0.015137	0.003079
Mineralized wood	a_9	4392.808	167.63	245.45	0.042932	0.004548	0.083149
Plywood	a_{10}	7636.502	87.58	71.26	0.095717	0.201332	0.126167
Polystyrene foam	a_{11}	3750.482	187.13	322.02	0.002801	0.000217	0.016521
Polyurethane	a_{12}	3357.309	194.18	330.35	0.013225	0.000564	0.043280
Rock wool	a_{13}	3659.441	188.45	346.14	0.019183	0.000825	0.009846

Table 3 Performances of the characteristic profiles for three classes

Profile	g_1	g_2	g_3	g_4	g_5	g_6
b_1	7051.231	158.63	135.88	0.042932	0.015137	0.083149
b_2	4392.808	182.59	283.41	0.013225	0.003079	0.043280
b_3	3659.441	187.35	330.35	0.004760	0.000636	0.009846

in the materials and retrofitting of rural buildings. On the other hand, the preferences on the importance of individual criteria have been elicited individually from multiple stakeholders who were owners of rural buildings interested in a renovation of their houses for improving the energetic performance. Thus, they can be perceived as potential consumers of the insulating materials.

When it comes to the characteristic profiles, the experts decided to define them by indicating one of the performances observed in the set of materials. The consensus between the experts on the most typical performance levels for each class has been reached during an interactive focus group. These levels are summarized in Table 3.

4.1 Results of Multiple Criteria Assessment of the Insulating Materials Within a Group Decision Framework Incorporating Electre TRI-rC and the SRF Procedure

The weights representing the importance of individual criteria have been elicited from the rural buildings' owner. In what follows, we call them stakeholders. Overall, we approached 63 owners by explaining them the characteristics of different materials, the interpretation of all criteria and their relation to different phases of the materials' life cycle. Among them, 38 stakeholders (let us denote them by $\partial^{\mathrm{K}} = \{DM_1, DM_2, \ldots, DM_{38}\}$) claimed to understand the meaning and role of different criteria, and expressing their willingness to provide preferences on the criteria importance.

In Table 4, we present the incomplete preference information required by the SRF procedure, which was provided by three selected stakeholders. We also report the computed weights w_j^k and cutting level λ^k. All stakeholders agreed that λ^k should be equal to the sum of weights of the three most important criteria. The complete data for all group members is provided in the supplementary material available as an e-Appendix (the same remark applies to the results discussed in the following sections).

The results of a comprehensive comparison between 13 materials and 3 characteristic profiles are quantified with the comprehensive concordance indices. In Table 5, we present such indices for four exemplary materials for DM_1. Table 5 exhibits also the justification of delivered assignment for the exemplary materials. For instance, a precise assignment of a_6 to C_1 can be explained with b_2 being preferred to a_6 and there existing sufficiently strong support in favor of b_1 outranking a_6 ($\sigma^1 (a_6, b_2) = 0.000 < \sigma^1 (b_1, a_6) = 0.524$).

In Table 6, we report the assignments obtained for all materials for different DMs. In particular, for DM_1 there are 6 materials assigned to the best class ($a_5, a_7, a_8, a_{11}, a_{12}, a_{13}$), 3 materials whose quality is evaluated as medium (a_1, a_2, a_3), and 4 materials judged as bad (a_4, a_6, a_9, a_{10}). The assignments for DM_5 are the same except for a_4 being imprecisely assigned to $[C_1, C_2]$.

The spaces of consensus and disagreement with respect to the assignments obtained for all DMs are quantified with the group class acceptability indices $E^{\partial} (a, h)$ (see Table 7). For example, for a_1 none stakeholder confirmed its assignment to the worst class C_1, 36 out of 38 stakeholders supported its assignment to the medium class C_2, and 3 stakeholders suggested the assignment of a_1 to the best class C_3. These numbers have been translated to the following group acceptability indices: $E^{\partial} (a_1, 1) = \frac{0}{38} = 0$, $E^{\partial} (a_1, 2) = \frac{36}{38} = 0.95$, and $E^{\partial} (a_1, 3) = \frac{3}{38} = 0.08$. On the contrary, for a_2 all stakeholders agreed with respect to its assignment to C_2 ($E^{\partial} (a_2, 2) = \frac{38}{38} = 1.0$), while the results obtained for 6 of them additionally indicated hesitation in terms of its assignment to $C_1 (E^{\partial} (a_2, 1) = \frac{6}{38} = 0.16)$.

The analysis of $E^{\partial} (a, h)$ leads to indicating the assignments which are necessary (in case $E^{\partial} (a, h) = 1$), possible (if $E^{\partial} (a, h) > 0$), and impossible (if $E^{\partial} (a, h) = 0$) in terms of the support they are provided in the group of stakeholders. Additionally, these results clearly indicate the most and the least probable assignments. In particular, for each material we are able to indicate the class with the greatest support among all stakeholders. It is C_1 for a_6, a_9 and a_{10}, C_2 for a_1, a_2, a_3 and a_4, or C_3 for a_5, a_7, a_8, a_{11}, a_{12}, and a_{13}. The support which is given to the assignment of the materials to other classes is significantly smaller. For clarity of presentation, in all tables exhibiting stochastic acceptability indices (Tables 7, 8, 9 and 11), the text in bold indicates the class with the greatest support for a given material.

Table 4 The order of cards with criteria names (ranks $l^k\ (j)$), white cards e_s^k, and ratio Z^k provided by the three selected DMs in the SRF procedure, the weights w_j^k derived from the SRF procedure, and the cutting level λ^k

$DM_1(Z^1 = 10, \lambda^1 = 0.714)$				$DM_2(Z^2 = 5, \lambda^2 = 0.696)$				$\cdots$	$DM_{38}(Z^{38} = 5, \lambda^{38} = 0.682)$			
g_j	$l^1\ (j)$	e_s^1	w_j^1	g_j	$l^2\ (j)$	e_s^2	w_j^2	$\cdots$	g_j	$l^{38}\ (j)$	e_s^{38}	w_j^{38}
g_1	1		0.024	g_3	1		0.049	$\cdots$	$g_1,\ g_3$	1		0.045
		1		g_1	2		0.088				2	
g_3	2		0.085			1		$\cdots$	$g_2,\ g_4,\ g_5,\ g_6$	2		0.227
		2		g_4	3		0.167	$\cdots$				
g_2	3		0.177	g_2	4		0.206	$\cdots$				
		1		$g_5,\ g_6$	5		0.245	$\cdots$				
$g_4,\ g_5,\ g_6$	4		0.238					$\cdots$				

Table 5 Credibility indices and class assignments obtained with ELECTRE TRI-rC for four exemplary materials for DM_1 (cutting level $\lambda^1 = 0.714$)

	b_1	b_2	b_3	$\left[C_L^1(a), C_R^1(a)\right]$		b_1	b_2	b_3	$\left[C_L^1(a), C_R^1(a)\right]$
a_1	$\succ$	$\succ$	$\prec$	$[C_2, C_2]$	a_6	?	$\prec$	$\prec$	$[C_1, C_1]$
$\sigma^1(a_1, b_h)$	1.000	0.799	0.238		$\sigma^1(a_6, b_h)$	0.585	0.000	0.000	
$\sigma^1(b_h, a_1)$	0.177	0.286	1.000		$\sigma^1(b_h, a_6)$	0.524	1.000	1.000	
a_{11}	$\succ$	$\succ$	?	$[C_3, C_3]$	a_{12}	$\succ$	$\succ$	$\prec$	$[C_3, C_3]$
$\sigma^1(a_{11}, b_h)$	1.000	1.000	0.476		$\sigma^1(a_{12}, b_h)$	1.000	1.000	0.524	
$\sigma^1(b_h, a_{11})$	0.000	0.000	0.524		$\sigma^1(b_h, a_{12})$	0.000	0.476	0.738	

Table 6 Class assignments obtained with Electre TRI-rC for all materials and different stakeholders

a	DM_1	DM_2	DM_3	DM_4	DM_5	DM_6	DM_7	DM_8	DM_9	DM_{10}	$\cdots$	DM_{38}
a_1	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$\cdots$	$[C_2,C_2]$
a_2	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$\cdots$	$[C_2,C_2]$
a_3	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$[C_2,C_2]$	$\cdots$	$[C_2,C_2]$
a_4	$[C_1,C_1]$	$[C_2,C_2]$	$[C_1,C_1]$	$[C_2,C_2]$	$[C_1,C_2]$	$[C_1,C_1]$	$[C_2,C_3]$	$[C_2,C_2]$	$[C_2,C_3]$	$[C_2,C_2]$	$\cdots$	$[C_2,C_2]$
a_5	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$\cdots$	$[C_3,C_3]$
a_6	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$\cdots$	$[C_1,C_1]$
a_7	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_2,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_2,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$\cdots$	$[C_3,C_3]$
a_8	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$\cdots$	$[C_3,C_3]$
a_9	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_2,C_2]$	$[C_1,C_1]$	$[C_2,C_2]$	$[C_1,C_1]$	$\cdots$	$[C_1,C_1]$
a_{10}	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$[C_1,C_1]$	$\cdots$	$[C_1,C_1]$
a_{11}	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$\cdots$	$[C_3,C_3]$
a_{12}	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$\cdots$	$[C_3,C_3]$
a_{13}	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_2,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$[C_3,C_3]$	$\cdots$	$[C_3,C_3]$

Table 7 Group class acceptability indices $E^{\partial}(a, h)$

$h \setminus a$	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}
1	0.00	0.16	0.00	0.34	0.00	**1.00**	0.00	0.00	**0.76**	**1.00**	0.00	0.00	0.00
2	**0.95**	**1.00**	**1.00**	**0.76**	0.00	0.00	0.21	0.16	0.24	0.00	0.00	0.00	0.08
3	0.08	0.00	0.00	0.24	**1.00**	0.00	**0.97**	**1.00**	0.00	0.00	**1.00**	**1.00**	**1.00**

4.2 Results of Stochastic Multi-criteria Acceptability Analysis with Electre TRI-rC

To validate the recommendation for insulating materials against the arbitrary choice of weights conducted with the SRF procedure, we applied SMAA. For each stakeholder, we considered a sample of 10000 uniformly distributed weight vectors compatible with the ranking of criteria (s)he provided within the SRF procedure.

Table 8 Class range stochastic acceptability indices $CRSAI^1$ $(a, [L, R])$ and cumulative class stochastic acceptability indices $CuCSAI^1$ (a, h) for all materials for DM_1

	CRSAIs						*CuCSAIs*		
a	$[C_1,C_1]$	$[C_1,C_2]$	$[C_2,C_2]$	$[C_1,C_3]$	$[C_2,C_3]$	$[C_3,C_3]$	C_1	C_2	C_3
a_1	0.000	0.000	0.825	0.000	0.000	0.175	0.000	**0.825**	0.175
a_2	0.000	0.175	0.825	0.000	0.000	0.000	0.175	**1.000**	0.000
a_3	0.000	0.000	1.000	0.000	0.000	0.000	0.000	**1.000**	0.000
a_4	0.717	0.000	0.283	0.000	0.000	0.000	**0.717**	0.283	0.000
a_5	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	**1.000**
a_6	1.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.000	0.000
a_7	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	**1.000**
a_8	0.000	0.000	0.000	0.000	0.175	0.825	0.000	0.175	**1.000**
a_9	1.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.000	0.000
a_{10}	1.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.000	0.000
a_{11}	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	**1.000**
a_{12}	0.000	0.000	0.000	0.000	0.175	0.825	0.000	0.175	**1.000**
a_{13}	0.000	0.000	0.000	0.000	0.175	0.825	0.000	0.175	**1.000**

The analysis of class range stochastic acceptability indices $CRSAI^k$ $(a, [L, R])$ and cumulative class stochastic acceptability indices $CuCSAI^k$ (a, h) indicates the potential variability of the recommendation that can be obtained for each DM for different compatible weight vectors. For illustrative purpose, in Table 8 we provide these indices for DM_1. For some materials, all compatible weight vectors confirm the same assignment. These parts of the recommendation can be deemed as robust (e.g., $CRSAI^1$ $(a_3, [2, 2]) = 1$ or $CRSAI^1$ $(a_9, [1, 1]) = 1$). The same conclusion can be derived from the analysis of the indices which are equal to zero, thus excluding the possibility of the respective assignment. Further, for some other materials the acceptability indices express hesitation with respect to the recommended class though often offering greater support to a particular assignment. For example, although both C_2 and C_3 are possible for a_1, the probability of the previous (C_2) is significantly greater than of the latter (C_3). Finally, the recommendation obtained for various compatible weight vectors can be different, but their intersection can be non-empty. Then, a robust recommendation is confirmed with $CuCSAI^1$ (a, h)=1. It is the case for, e.g., a_{13} which is assigned imprecisely to $[C_2,C_3]$ or precisely to C_3, thus always confirming C_3 as the possible assignment.

When it comes to a group decision perspective, the cumulative group class stochastic acceptability indices $CuCSAI^{\partial^K}$ (a, h) are presented in Table 9. Their values are very similar to the group class acceptability indices E^{∂} (a, h) reported in the previous section. The main differences concern a slightly increased support given to the minority class for some alternatives (see, e.g., a_1 to C_3, or a_2 to C_1, a_8, and a_{12} to C_2).

Overall, the prevailing assignments for all materials are the same as in Sect. 4.1. In this regard, let us emphasize that $CuCSAI^{\partial^K}$ $(a, h) = 1$ (see, e.g., a_{10} to C_1, a_3 to C_2, or a_5 to C_3) confirms an agreement with respect to assignment of a to C_h for all weight

Table 9 Cumulative group class stochastic acceptability indices $CuCSAI^{\partial^K}(a, h)$ for all materials

$h\backslash a$	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}
1	0.018	0.226	0.000	0.338	0.000	**1.000**	0.000	0.000	**0.794**	**1.000**	0.000	0.000	0.000
2	**0.897**	**0.995**	**1.000**	**0.760**	0.000	0.000	0.188	0.222	0.206	0.000	0.000	0.063	0.107
3	0.131	0.000	0.000	0.213	**1.000**	0.000	**0.986**	**0.998**	0.000	0.000	**1.000**	**1.000**	**0.999**

Table 10 The numbers of stakeholders indicating a preference or indifference (in the round brackets) for all pairs of criteria

g_j	g_1	g_2	g_3	g_4	g_5	g_6
g_1	–	14 (2)	22 (8)	15 (2)	11 (2)	10 (2)
g_2	22 (2)	–	25 (2)	17 (9)	4 (16)	3 (16)
g_3	8 (8)	11 (2)	–	12 (1)	9 (2)	9 (1)
g_4	21 (2)	12 (9)	25 (1)	–	6 (10)	7 (10)
g_5	24 (2)	18 (16)	27 (2)	22 (10)	–	1 (31)
g_6	26 (2)	19 (16)	28 (1)	21 (10)	6 (31)	–

vectors compatible with preferences of all stakeholders. Thus, such a recommendation needs to be treated with certainty. Conversely, $CuCSAI^{\partial^K}(a, h) = 0$ (e.g., a_2 to C_3, a_3 to C_1, or a_9 to C_3) indicates the no classification model of any stakeholder confirmed the respective assignment. This makes it excluded from the potential recommendation.

4.3 Results of Stochastic Multi-criteria Acceptability Analysis for a Group Compromise Ranking of Criteria

The results presented in the previous sections were derived by aggregating the outcomes obtained individually for each stakeholder. In this section, we offer another perspective on the stability of results by searching for a compromise between different stakeholders already at the stage of provided preferences. In Table 10, we report the numbers of DMs indicating preference or indifference for all pairs of criteria in the ranking they provided for the purpose of applying the SRF procedure. For example, 14 out of 38 stakeholders preferred g_1 to g_2, 22 stakeholders opted for an inverse preference, and only 2 stakeholders judged this pair indifferent. Conversely, when comparing g_5 to g_6, 31 experts opted for an indifference, and only one claimed that g_5 was more important than g_6.

The information from the DMs' individual rankings has been used as an input for the algorithm constructing a compromise utilitarian ranking of criteria, i.e., the one which is on average the closest to 38 individual rankings. In this way, the following group compromise order of criteria has been constructed:

$$g_5 \sim_{\partial} g_6 \succ_{\partial} g_2 \sim_{\partial} g_4 \succ_{\partial} g_1 \succ_{\partial} g_3.$$

Thus, the greatest importance has been attributed to *ecosystem quality* (g_5) and *resources* (g_6), while the least important criteria are *NPV* (g_3) and *hour of discomfort* (g_1). The relation instantiated for different pairs of criteria is consistent with the opin-

Table 11 Cumulative group compromise class stochastic acceptability indices $CuCCSAI^{\partial K}$ (a, h) for all materials

$h\backslash a$	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}
1	0.000	0.419	0.000	**0.533**	0.000	**1.000**	0.000	0.000	**1.000**	**1.000**	0.000	0.000	0.000
2	**0.581**	**1.000**	**1.000**	**0.467**	0.000	0.000	0.000	0.419	0.000	0.000	0.000	0.000	0.000
3	**0.419**	0.000	0.000	0.000	**1.000**	0.000	**1.000**	**1.000**	0.000	0.000	**1.000**	**1.000**	**1.000**

ion expressed by the significant number of stakeholders. For example, 24 stakeholders ranked g_5 and g_6 as the two most important criteria, while 19 of them ranked this pair tied for the first place. Furthermore, 21 stakeholders judged g_3 as the least important criterion.

Obviously, one needs to bear in mind that the compromise ranking of criteria minimizes the sum of distances between relations observed for all pairs of criteria in all individual rankings. In this perspective, it may not be considered representative by all individuals (see, e.g., DM_7, DM_9, DM_{12}, DM_{17}, DM_{19}, DM_{20}, or DM_{36}) whose preferences are represented in the compromise ranking to a marginal degree (i.e., an overall distance between their ranking and the compromise one is substantial).

Such a compromise ranking of criteria has been used to simulate DMs' joint preferences within SMAA. Consistently with the previous sections, the cutting level λ was assumed to be equal to the sum of weights of the three most significant criteria. The results of robustness analysis are materialized with the cumulative group compromise class stochastic acceptability indices $CuCCSAI^{\partial K}$ (a, h) (see Table 11).

For most materials, the variability of results is lesser than in case of deriving the recommendation by aggregating the individual viewpoints. Indeed, for 11 out of 13 materials there is some class which is recommended with certainty (then, $CuCCSAI^{\partial K}$ $(a, h) = 1$). Also, for all materials but a_4 the class assignments with the greatest support have not changed with respect to those reported in the previous sections. The main differences concern a lesser support for the assignment of a_1, a_4 and a_9 to C_2 in favor of judging the quality of a_1 as high (C_3) and the quality of a_4 or a_9 as low (C_1). Finally, although the assignments of a_2 and a_8 to, respectively, C_2 and C_3 are robust, the acceptability for their assignment to some worse classes (C_1 and C_2, respectively) has increased to 0.419.

4.4 Summary

In view of the results derived from an application of a three-stage multiple criteria decision aiding method to our study (see Tables 7, 9, and 11), we recommended the following assignments for the insulating materials:

- *Low* (C_1): gypsum fibreboard (a_6), mineralized wood (a_9) and plywood (a_{10});
- *Low* (C_1) or medium (C_2): fibreboard hard (a_4);
- *Medium* (C_2): autoclave aerated complete (a_1), corkslab (a_2), and expanded perlite (a_3);

Table 12 Subsets of criteria on which the materials attain at least as good performances as these of the characteristic profiles b_1, b_2, and b_3 of three decision classes

Insulating material	a	b_1	b_2	b_3
Autoclave aerated	a_1	$g_1, g_2, g_3, g_4, g_5, g_6$	g_3, g_4, g_5, g_6	g_5
Corkslab	a_2	g_1, g_2, g_3, g_4, g_6	g_1, g_3, g_6	
Expanded perlite	a_3	$g_1, g_2, g_3, g_4, g_5, g_6$	g_1, g_3, g_4, g_5, g_6	
Fibreboard hard	a_4	g_1, g_2, g_3, g_4, g_5	g_1, g_2, g_3	g_1
Glass wool	a_5	$g_1, g_2, g_3, g_4, g_5, g_6$	$g_1, g_2, g_3, g_4, g_5, g_6$	g_2
Gypsum fibre board	a_6	g_1, g_3, g_6		
Hemp fibres	a_7	$g_1, g_2, g_3, g_4, g_5, g_6$	$g_1, g_2, g_3, g_4, g_5, g_6$	g_3, g_4, g_6
Kenaf fibres	a_8	$g_1, g_2, g_3, g_4, g_5, g_6$	g_3, g_4, g_6	g_3, g_4, g_6
Mineralized wood	a_9	$g_1, g_2, g_3, g_4, g_5, g_6$	g_1, g_3	
Plywood	a_{10}			
Polystyrene foam	a_{11}	$g_1, g_2, g_3, g_4, g_5, g_6$	$g_1, g_2, g_3, g_4, g_5, g_6$	g_4, g_5
Polyurethane	a_{12}	$g_1, g_2, g_3, g_4, g_5, g_6$	$g_1, g_2, g_3, g_4, g_5, g_6$	g_1, g_2, g_3, g_5
Rock wool	a_{13}	$g_1, g_2, g_3, g_4, g_5, g_6$	$g_1, g_2, g_3, g_4, g_5, g_6$	g_1, g_2, g_3, g_6

- *High* (C_3): glass wool (a_5), hemp fibres (a_7), kenaf fibres (a_8), polystyrene foam (a_{11}), polyurethane (a_{12}), and rock wool (a_{13}).

The probability of other assignments was often non-negligible though significantly lower than for the above indicated classes. Nevertheless, the results obtained from the stochastic analysis allowed to nullify the risk of a false declaration that some material was assigned to a class which was not confirmed by any compatible set of weights for any expert.

For each insulating material, the recommended decision can be justified by comparing its performances on different criteria with those of the characteristic class profiles. In Table 12, we indicate the subsets of criteria on which the materials outrank (i.e., are at least as good as) the characteristic profiles. In this regard, let us explicitly explain the most likely assignments suggested for some materials:

- a_{10} is worse than b_1 on all criteria, thus being assigned to the worst class C_1; in the same spirit, a_6 is worse than b_1 on g_2, g_4, and g_5 (thus, on 3 out of 4 considered environmental criteria), and not better than b_2 on any criterion, which makes C_1 its most desired class;
- a_3 is better than b_1 and worse than b_3 on all criteria, which makes its performance vector typical for C_2;
- a_{12} and a_{13} are at least as good as b_2 on all criteria and better than b_3 on four criteria (g_1, g_2, g_3, g_5 or g_1, g_2, g_3, g_6, respectively (note that both scenarios include two accounted socio-economic criteria, g_1 and g_3)), which makes their assignment to C_3 the most justified.

5 Conclusions

We considered a multiple criteria problem of sustainability assessment of insulating materials. We combined Life Cycle Costing, Life Cycle Assessment, and adaptive comfort evaluation to derive performances of these materials on six socio-economic and environmental criteria. The comprehensive assessment of the materials involved their assignment to three preference-ordered sustainability classes. The classification was performed with a group decision counterpart of the Electre TRI-rC method that compares alternatives with the characteristic class profiles defined by the experts.

To derive a recommendation that would reflect viewpoints of a wide spectrum of potential customers, we accounted for the preference information of a few tens of rural buildings' owners being interested in the roof's insulation. The initial recommendation was derived by computing the proportion of stakeholders who accepted an assignment of a particular material to a given class. These results were subsequently validated against the outcomes of a two-fold robustness analysis realized with the Monte Carlo simulation. The latter exploited the space of all criteria weights compatible with either each stakeholder's preference information provided in the SRF procedure or collective ranking of criteria that was derived with an original algorithm proposed in this paper.

The three-stage analysis revealed that the most sustainable materials were glass wool, hemp fibres, kenaf fibres, polystyrene foam, polyurethane, and rock wool. This was mainly due to their favorable performances quantified with the Net Present Value and Eco-indicators. On the contrary, gypsum fibreboard, mineralized wood and plywood were assessed as the least sustainable materials. This can be justified in terms of their poor performances on thermal comfort, human health, and ecosystem quality. Overall, the proposed method provided greater clarity for decision making and guaranteed credibility in the eyes of the traditional rural houses' owners. Moreover, all research results—concerning both materials' performances on the individual criteria and comprehensive sorting recommendation—were well perceived by the experts on insulating materials in Italy.

The proposed framework can be applied to other decision contexts than that of a typical farmhouse in central Italy. This would require, however, accounting for a comfort model as well as warm and cold periods suitable to a particular geographical context, specification of a relevant lifespan for the investment, and adapting life cycle assessment to the reality of a particular study.

From the methodological viewpoint, we envisage the following future developments. Firstly, we plan to extend the SRF procedure to a group decision context so that it tolerates intensities of preference for different pairs of criteria and accepts information on different roles (weights) of the decision makers. Secondly, we aim at extending the proposed group decision framework to methods dealing with choice and ranking problems. This would require elaboration of the algorithms for deriving a compromise recommendation that would appropriately combine results of robustness analysis computed individually for each stakeholder.

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