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Decision Support System for technology selection based on multi-criteria ranking: Application to NZEB refurbishment

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ABSTRACT

Refurbishing existing building into Near Zero Energy Building (NZEB) is a key objective for the European Union. In order to achieve high rate of conversion, new refurbishment process must allow Decision Makers (DMs) (architects or designers) to sort through an ever increasing list of new technologies while taking into account uncertain preferences from multiple stakeholders.

A Decision Support System (DSS) based on Multi-Criteria Decision-Making (MCDM) approaches is proposed. The DSS enables the DMs to browse the solutions space by selecting the relevant criteria, order them by preferences and specify the granularity in the assessment of the technologies regarding each criteria.

This DSS is based on a ranking algorithm that operates on multiple types of quantitative (continuous, discrete, or binary) and qualitative (nominative or ordinal) variables from technological and human sources. An online user interface allows the real-time exploration of the solution space. A sensitivity analysis of the algorithm is conducted to expose the influence of the ranking algorithm parameters and to demonstrate the robustness of this algorithm. The proposed DSS is eventually implemented and validated through a use case concerning the choice of insulating materials considering heterogeneous criteria that model sustainable constraints.

1. Introduction

In a global approach to consider environmental and social issues, The European Union (EU) has decided to define the refurbishment of the existing building stock as a major priority of its economic development. The building sector is a major energy consumer and greenhouse gas producer [1,2] and current studies show that about half of the European building stock in use in 2012 will still be in use in 2050 [3]. That is why the EU aims to encourage initiatives to develop Near Zero Energy Buildings (NZEBs) by renovating existing buildings. According to the European Parliament [3], a NZEB is presented as “a building with very high energy performance where the nearly zero or very low amount of energy required should be extensively covered by renewable sources produced on-site or nearby”. However, the current refurbishment ratio (around 1 % of the building stock per year) is insufficient to enable the EU to meet its commitments, it aims to increase this ratio by up to 2.5 % of the building stock per year.

To enable this acceleration, there is a need to develop new collaborative refurbishment methodologies to reduce time and costs. These new methodologies involve mastering the refurbishment process, its decision-making milestones, and sustainable principles. Indeed, the refurbishment of a building toward NZEB is mainly associated with the concept of Triple Bottom Line (TBL) [4]. In the literature, the authors generally consider economic, environmental and societal decision-making criteria to evaluate the performance of NZEB refurbishment projects [5–9]. These problems are in the core of H2020 REZBUILD project, which has funded this research work. The project aims at providing new refurbishment technologies (such as 3D wall printing) but also a collaborative ecosystem to improve the NZEB refurbishment process performances.

In this article, we focus on the refurbishment process decision milestone that concern the selection of refurbishment technologies and we propose a Decision Support System (DSS). This decisive stage has the particularity of being carried out by a single Decision Maker (DM) (designer/architect), but uses uncertain information derived from the expectations of the end-user and information from a large and increasing amount of technological solutions (i.e. alternatives). Indeed, considering uncertainty during the decision process is a key point as stated in [1,10] (Section 3.1). Moreover, the decision process requires a dynamic interaction between the DM and the DSS to choose the appropriate technologies considering multiple and conflicting criteria.

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Acronyms

DM	Decision Maker.
DSS	Decision Support System.
MCDM	Multi-Criteria Decision-Making.
NZEB	Near Zero Energy Building.
TBL	Triple Bottom Line.
UI	User Interface.

Indeed, in the very detailed literature review proposed in [10], the authors highlight, in addition to the need to consider uncertainty in decision making, the lack of sufficiently fast and effective tools to allow real-time interaction between the DM and the manipulated data.

Thus, the research proposal and decision support tool presented in this paper aim at answering the question "how to help a decision maker to choose a technological solution among a plethora of alternatives considering several conflicting and uncertain decision criteria?" The approach applied in this article to answer this question uses a review of the scientific literature to highlight the shortcomings and limitations of pre-existing tools. These findings allow the identification of the necessary requirements for the design of an innovative DSS that responds, in an original way, to the scientific and operational issues identified in the literature. This work provides an extensive version of [11] addressing the main shortcomings that have been identified in this previous proposition (more details about these changes are available in Section 4).

The next section (Section 2) introduces the decision making process in the sustainable refurbishment activity to highlight its characteristics, to show its complexity, and to demonstrate the need for tools to assist it. Then a study of related work in the literature is conducted (Section 3) in the field of multi-criteria decision making in sustainable refurbishment context (Section 3.1) to extract requirements for the ranking algorithm (Section 3.2) and the user interface (Section 3.3). Based on these requirements, a proposal for a decision support system is made in Section 4 to answer the research question. A sensitivity analysis (Section 5) characterizes the robustness of the proposed solution and an implementation on a realistic refurbishment use case from the literature (Section 6) validates its relevance and efficiency. Finally, Section 7 concludes this article and proposes some perspectives to this research work.

2. Decision making in sustainable refurbishment process

NZEB refurbishment, like any refurbishment project, follows typically a three stages process (Fig. 1) detailed by Nielsen et al. [12]:

- the pre-design phase allows to collect and translate user needs into weighted criteria based on their preferences. A diagnosis of the existing building is also conducted to know the current state of the building to be renovated,
- the design phase allows to propose refurbishment alternatives whose performances (in terms of energy, heat or comfort) are estimated to evaluate alternatives and choose the final design,
- the construction phase allows the implementation of the chosen design.

In our work, after interviews with refurbishment professionals (architects, refurbishment managers and financial, thermal and energy experts), the choice has been made to detail the pre-design and design phases from the process proposed in [12]. We highlight the decision-making milestones and the actors involved in these critical moments of the process. These milestones are the key decisions that need to be made (collectively or not) to move forward in the design process. This process (Fig. 2), organized in five steps, has been analyzed to identify the main milestones in which DSS can help stakeholders:

- Preliminary assessment: the needs and preferences of end-users (customer/owner) are collected. The diagnosis of the building to be renovated is done by the refurbishment manager. The first refurbishment choices are made from the information collected to define priorities. This assessment (milestone 1) can be assist by a DSS because it aims to define the scope of the refurbishment work by setting the overall project objectives (e.g., 15 % energy savings) and setting priorities for the technological solutions to be implemented (for example, changing windows).
- AS-IS modeling and simulations: to confirm the priorities defined in the previous step and to have a basis for comparison for future improvements, the building to be renovated is modeled and simulated to evaluate the AS-IS decision criteria (cost, energy/thermal efficiency, comfort…). The refurbishment manager, the architect and the simulation experts are involved at this stage.
- Refurbishment scenario modeling: architects propose several refurbishment scenarios and model them. They choose, at this stage, among the technological alternatives that will be implemented in each part of the building (windows, insulation, heating system…) and their organization to renovate the building according to the needs and preferences of end-users and to the sustainability objectives. There is a plethora of alternatives for each family of retrofit technologies. This selection phase (milestone 2) could be assisted by multi-criteria DSS to meet the needs of the end-user, the preferences of the designers and the technical constraints.
- Refurbishment scenario simulations: the simulation experts rely on the models previously created to evaluate the different decision criteria for each proposed scenario.
- Refurbishment project decision-making: the "best" scenario, i.e. the one that represents the best compromise between all the decision criteria, is evaluated by architects and/or designers. The selected design is then submitted (depending on the simulation results) by the architects to the customer who has to validate it. The choice of the "best" scenario can also be assisted by a DSS (milestone 3). In the event of non-submission or rejection by the client, the process starts again at the stage of modeling refurbishment scenarios to generate new proposals. If clients accept the proposal made to them, the process of carrying out the refurbishment is started.

The construction sector is increasingly confronted with the need to capitalize and exploit the knowledge generated throughout the value chain and DMs lack perspectives and skills (in data analytic) to create, analyze and use available data [13]. In our case, the three decision-making milestones of the design process, presented above, involve a large amount of very diverse data that must be collected from multiple stakeholders in different domains and from multiple and heterogeneous information systems. Therefore, the use of this data without support tools in the decision process is complex and difficult to achieve and relies solely on experience or expertise.

To improve NZEB construction performance and to align with EU time and cost reduction targets, the focus is made on milestone 2 "selection of refurbishment technologies", where designers (or architects) are the DMs. The decision(s) has to be made among a set of alternative technologies for a specific function (e.g. the choice of an insulation material), regarding several criteria (price, environmental impact, aesthetic properties etc.). The DM follows typically an exploratory decision process with huge uncertainty about the epistemic choice at the beginning of the process, due to its lake of expertise/problem knowledge regarding the different criteria to be considered.

3. Related work

As previously mentioned, the problem encountered by architects or designers in milestone 2 of the refurbishment process consists in comparing numerous technological solutions allowing to fulfill the

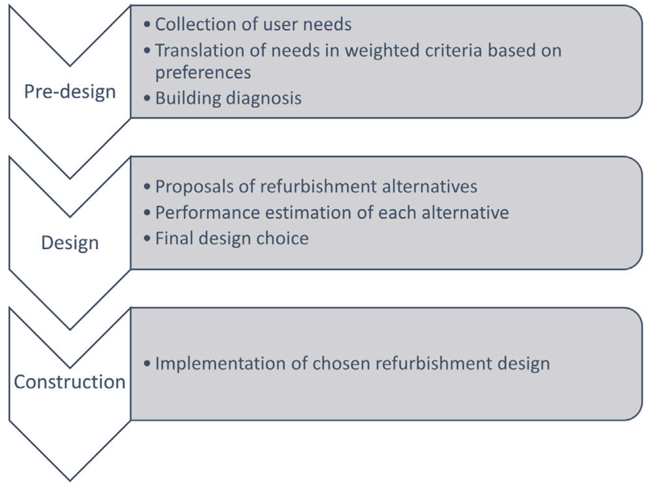

Fig. 1. Refurbishment process based on [12].

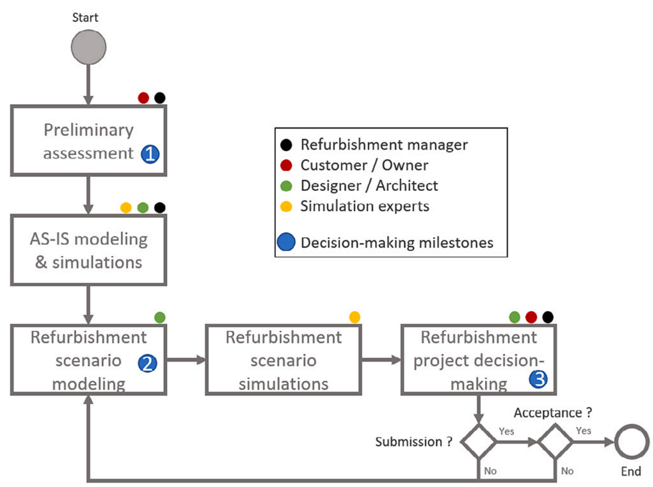

Fig. 2. Refurbishment design process.

same need according to several often conflicting criteria. For example, the building insulation can be realized by different insulating materials having various characteristics which meet more or less the expectations of the designer. This type of decision making is called "Multi-Criteria Decision-Making (MCDM)". The remainder of this section is dedicated to a literature review of MCDM tools used in the context of sustainable refurbishment (Section 3.1) and a focus on ranking algorithms (Section 3.2) and user interfaces (Section 3.3) allowing to implement this type of tools.

3.1. MCDM In refurbishment sector

According to Tan et al. [14], MCDM "compares and ranks decision-making schemes by integrating component – and often conflicting – indicators from all information sources into a single overall indicator". This definition fits well with decision-making in the context of sustainable refurbishment. Indeed, these problems are characterized [1,10,14–16] by:

- conflicting objectives such as improving energy efficiency by minimizing refurbishment costs,
- many constraints and limitations on the structure of the building to be renovated, its environment or legislation,
- the need to synthesize a complex decision problem (i.e. with multiple objectives and constraints) in a simple and understandable way for non-expert decision makers (e.g. a ranking of alternatives to identify the "best" possible solution).

In the decision-making framework of the building refurbishment process, much remains to be done to achieve sustainable refurbishment as the authors of [1] have stated in their literature review. The main cause of decision complexity in this context is, in our view, the combination of a variety of performance objectives. As stated in [17], most of existing studies about sustainable refurbishment focus on energy consumption and CO2 emission as main decision criteria [7,9,18]. However, authors of [17] argued there is a need to consider more complex context by expanding decision criteria to other sustainable issues (including social or economic aspects more extensively). This complexity is also reinforced by the difficulty in gathering the information needed to evaluate the criteria for making decisions [15]. This difficulty is, in part, due to the diversity of information sources and, therefore, the heterogeneity of the data collected. Indeed, as stated in [19], the hybridization of technological data and human knowledge is one of the challenges that must be considered in the design of a DSS.

These observations are reflected in MCDM tools by numerous assumptions or simplifications but also by time-consuming algorithms such as the group decision framework incorporating outranking preference model and characteristic class proposed by Kadziński et al. [20] or decision support based on neural networks proposed by Zavadskas et al. [21].

Therefore, in [10], the authors identify two main research challenges for decision making in refurbishment: the development of fast and efficient methods based on existing algorithms and considering uncertainty to avoid overly simplistic decisions. This point of view is also reinforced in [1] where the authors identify the integration of uncertainties (related to climate change, servicization, political and human changes…) as essential to define the best refurbishment alternative, for the entire building life cycle, in terms of energy efficiency but also costs and other societal or environmental indicators.

From the discussion above based on literature review and on the shortcomings and limitations identified in previous studies, we highlight that a DSS for the sustainable refurbishment process must consider:

- the heterogeneity of the objectives, i.e. the need to compromise between the decision time and the complexity (and thus the accuracy) of algorithms in terms of number of criteria and completeness. We define as a priority the simplification of tools and algorithms so that they are sufficiently flexible and adaptable to the changes inherent to the sustainable refurbishment industry;
- the heterogeneity of data sources, i.e the need to integrate and hybridize technological data and human knowledge to assess decision criteria knowing that combining technological and human knowledge can improve the decision process [22]. This need is reflected in the DSS capability to use both quantitative and qualitative criteria to support decision-making.

Another important consideration on MCDM methods is its capability to manage uncertainty:

- uncertainty due to data imperfection [23]. Data, even if complete (which is not always the case in real applications), can be uncertain or inexact;
- uncertainty due to problem knowledge. DMs may have doubts about their preferences or about the importance to the final decision of a difference between two alternatives under a given criterion.

Thus DMs should be able to adjust their preferences by adding uncertainty to the values of the concerned criteria. This uncertainty allows to adjust the granularity of the studied data observation, in the sense of [23], so that the rankings of two technologies that are similar, but not identical, are not too different.

Therefore, next subsections aim to highlight the tool requirements, in terms of decision-support algorithms (Section 3.2) and user interface (Section 3.3), which are derived from these findings.

3.2. Ranking algorithms for MCDM

The decision problem addressed in this paper is a MCDM ranking problem, i.e. the classification of a discrete number of alternatives considering a set of evaluated criteria (qualitative and/or quantitative) [24]. This decision problems have been widely addressed in the literature, and many methods (and variants) have been proposed to aggregate the criteria such as utility function mechanisms, pair wise comparison or lexicographic approaches.

In the utility and value functions family, the Weighted Sum Model (WSM) is the most known [25]. It has the advantage of being simple and easy to deal with MCDM problems [24]. Moreover, for combinatorial problems, it does not increase the complexity. The limits have also been widely discussed [26], such as the difficulty to model the trade-off weights (or the importance within criteria) [27] and the need to normalize criteria [24]. Several improvements have been proposed to the WSM, like WPM (Weight Product Model) [28] or COPRAS (COmplex PRoportional ASsessment) [29]. All this methods can be considered “a priori” methods (DM expresses priority’s before computing). The aggregation logic is compensatory, this implies that a poor performance on one criterion (e.g. carbon footprint) can be compensated by a better performance on another (e.g. financial cost) [30].

Another family of methods regroups the pair-wise comparison approaches:

- MACBETH (Measuring Attractiveness by a Categorical Based Evaluation TecHnique which is specific for qualitative criteria) [31] and AHP (Analytic Hierarchy Process) [32] are popular non-compensatory methods. They define a utility function while comparing pairwise all the criteria/alternatives.
- Outranking methods such as ELECTRE [33] or PROMETHEE+ GAIA (Preference Ranking Organization METHod for Enrichment Evaluations with Geometrical Analysis for Interactive Aid) [34,35] use pairwise comparison but are partially or non-compensatory and are based on the principle that one alternative may have a degree of dominance over another [36]. They are mainly designed to solve complex decision problems including groups of people and involving a lot of human perceptions and judgments [37].

By construction, all pair-wise comparison approaches are time-consuming and difficult to implement with numerous criteria [38]. Non-compensatory ranking methods can also be lexicographic approaches which are only applicable if the DM can provide a “lexicographic” list of criteria prioritization [39,40]. Moreover, discriminate alternatives based on close scores could not be adequate [41].

Thus, to sum up considering these findings, we argue that an “adaptable” (or flexible) DSS based on MCDM methods must allow DM to interact with data in order to:

1. define the decision matrix, i.e. select the criteria to be considered within the alternative’s database;
2. give relative weight to the considered criteria based on DM’s perception of priorities and integrate these preferences in an aggregation mechanism. There are many methods that could be implemented to model and aggregate DM priorities, but most of them are complex and time consuming with numerous data. Weighted sum mechanisms are interesting approaches given its simplicity;
3. consider the uncertainty and inaccuracy of the DM’s preferences. Thus, the ranking algorithm must avoid discriminating while comparing alternatives with close scores (near equivalent) on a given criteria.

It should also be noted that the digital interface that allows DMs to interact with the ranking algorithm has an important impact in decision support. This importance of the digital interface becomes critical when the DMs are not experts in data visualization, as in our case where architects are experts in building refurbishment and not in data science. Thus the following subsection focuses on the interaction between users and DSS.

3.3. Interactions between users and DSS

In order to effectively assist users in their choices, it is necessary to understand the human decision-making process. According to Mintzberg et al. [42], the decision-making process is defined as a “set of actions and dynamic factors that begins with the identification of a stimulus for action and ends with the specific commitment to action”. The passage from the detection of the stimulus to the choice of an action requires that DMs acquire situational awareness [43], i.e. that they are able to perceive the elements describing the studied situation, to understand this situation and to project the possible futures that may result from this current state.

This process of acquiring situational awareness requires that users are able to interact with the data via the tool’s parameters in order to understand the impact of these parameters on the final result. Thus, they can project the possible consequences of their settings in order to make a so-called “informed” decision [44].

Thus, the proposed user interface aims to improve users' situational awareness by allowing them to interact in real time and dynamically with the ranking algorithm. The idea is that they can build the cognitive link between the studied situation and the projected situation necessary to make an informed decision with confidence. To achieve this objective, three requirements for the User Interface (UI) have been identified:

- the tool must allow a dynamic interaction and has to react by updating the alternatives ranking in real time according to the evolution of the parameters handled by the user. Thus, the closer the feedback given by the system is to criteria setting the more the cognitive link will be able to establish itself easily;
- as the criteria have relative importance, their manipulation should therefore be done in the same workspace to facilitate their comparison;
- the expression of the users' preferences for the ranking of alternatives must consider two dimensions allowing to characterize the importance of the criteria in relation to each other and the uncertainty of the decision-maker about the importance of certain criteria (as stated at the end of Section 3.2). These two tasks in the interface must be interleaved to allow the user to switch from one to the other seamlessly. The proposed interaction should therefore be done by interaction elements (e.g. sliders) capable of being manipulated in two dimensions to allow this interlacing.

The proposal of a DSS meeting the requirements defined in these last two Sections 3.2 and 3.3 is detailed in the following section.

4. Proposal of a refurbishment technologies ranking DSS

The objective of the DSS, proposed in this article, is to dynamically combine user-defined preferences and chosen criteria to provide a ranking of decision-making alternatives for the "selection of refurbishment technologies" milestone of the refurbishment design process (Fig. 2)

In alignment with the requirements announced in Section 3, the DSS allows the DMs to:

- define the criteria they wish to consider in their decision,
- define the importance, or the relative weight of the different chosen criteria in the final ranking,
- define a granularity for each criterion, in order to avoid discriminating too radically between technologies with similar evaluations according to a given criterion.

In order to show how the DSS works, to highlight the interactions between the DM and the system, and to demonstrate the iterative process, the illustration in Fig. 3 inspired by service experience blueprinting [45] is proposed.

In this context, a first version of a tool combining a dynamic UI and a ranking algorithm has been proposed in [11]. Additional work carried out on this first version (i.e. user tests for the UI and a sensitivity analysis for the algorithm) revealed some shortcomings:

- for the UI, the problems identified were mainly related to the readability of values of importance and granularity parameters, to the understanding of parameter ranges and some graphic and/or functioning malfunctions,
- for the ranking algorithm, the identified problems were related to the management of binary variables and nominal qualitative variables, the management of the criteria ranking rules (i.e. "the higher the better" or "the lower the better") and the existence of a bias in the final ranking when the value of the granularity parameter was different between the criteria.

This section therefore presents an improved version of the DSS described in [11] to address the problems identified above. Section 4.1, 4.2 and 4.3 describe respectively how data is provided for a particular decision type, how users interacts with the DSS, and the way the algorithm works to rank the alternatives.

4.1. Data provision

This phase allows to prepare the data in order to feed the ranking algorithm for a specific problem. This phase is mainly realized by experts of the studied problem, e.g. specialist of insulation materials. Ultimately, with a view to the industrial implementation of the proposed DSS, the idea is that the experts evaluating the alternatives according to the various decision-making criteria should be the technology providers. Indeed, in order to be included in the "portfolio" of solutions available to the designer/architect, the technology providers will also have to provide formalized data about their products according to predefined decision criteria. The mechanism being considered here works in the same way as for vendors who want their products to appear on the marketplace of a large online retailer and who must provide a technical description of these products according to a predefined template. This phase is divided in four steps (A1 to A4 in Fig. 3):

A1. Identify decision alternatives: experts define the different decision-making alternatives, e.g. the different possible technologies for renovating a house. The set of alternatives is denoted $A = \{a_1, a_2, \dots, a_n\}$. Thus, there are n alternatives: $n = \mathrm{Card}(A)$. In the following, index i refers to alternative $a_i \in A$.

A2. Identify decision criteria: experts define the different criteria that will allow to compare the different alternatives. For each criterion, the expert must also define whether the highest or the lowest value is the best and, if necessary, the unit in which the criterion is expressed (Table 1). The set of criteria is denoted $C = \{c_1, c_2, \dots, c_m\}$. Thus, there are m criteria: $m = \mathrm{Card}(C)$. In the following, index j refers to criterion $c_j \in C$. Several types of criteria are possible:

- continuous quantitative criteria, e.g. CO_2 avoidance expressed in kg of CO_2 per year and the highest value is the better,
- discrete quantitative criteria, e.g. insulating panel thickness expressed in millimeters ($PanelThickness \in \{5, 10, 20, 30, 50\}$) and the highest value is the better,
- binary criteria, e.g. translucency of the insulation material expressed without unit on a binary scale with 1 (material is translucent) and 0 (material is not translucent) and the highest value is the better. However, if both cases can be a good solution according to the situation (some applications will need translucent materials and others will need opaque materials), it is necessary to use two criteria: $Transluency \in \{0, 1\}$ and $Opacity \in \{0, 1\}$,
- ordinal qualitative criteria, e.g. energy class expressed without unit on a scale from A^{+++} to G, which can be transformed in a discrete quantitative criterion from 1 (A^{+++}) to 10 (G) with the lower value as the best,
- nominal qualitative criteria which can take x values, e.g. the material shape, expressed without unit with several possibilities that cannot be ordered (e.g. $MaterialShape \in \{panel, coating, foam, shavings\}$). In this case, each nominative qualitative criterion must be transformed in x binary criteria (as many binary criteria as there are possible values for the nominative criterion). For example, the criterion $MaterialShape$ has to be transformed in four binary criterion such as $MaterialShapePanel \in \{0, 1\}$ or $MaterialShapeFoam \in \{0, 1\}$, and so on. There is one and only one binary criterion that takes the value 1 among all the binary criteria generated from the same nominal qualitative criterion for a given alternative.

A3. Evaluate criteria for each alternative: a value, denoted V_{ij}, is assigned to each criterion c_j for each alternative a_i by experts (Table 1). The evaluation differs according to the type of criterion:

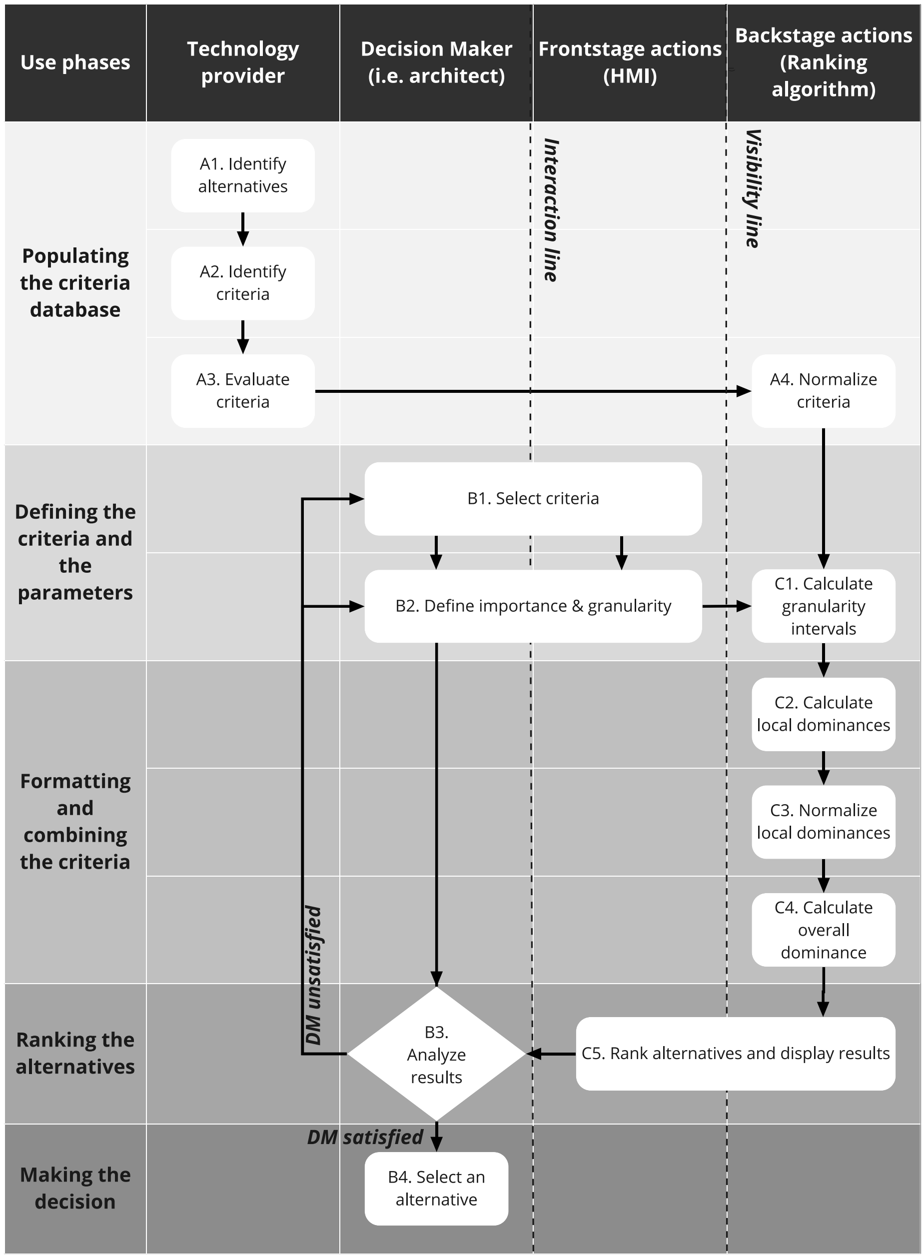

Fig. 3. Representation of the proposed DSS inspired by service experience blueprinting [45].

Table 1
Values of each alternative for all the possible criteria with their units and ranking rules (H = "the higher the better" and L = "the lower the better").

	Criterion c_1	Criterion c_2	⋯	Criterion c_m
Unit	*Unit of* c_1	*Unit of* c_2	⋯	*Unit of* c_m
Ranking rule	*H or L*	*H or L*	⋯	*H or L*
Alternative a_1	V_{11}	V_{12}	⋯	V_{1m}
Alternative a_2	V_{21}	V_{22}	⋯	V_{2m}
⋮	⋮	⋮	⋱	⋮
Alternative a_n	V_{n1}	V_{n2}	⋯	V_{nm}

- for quantitative criterion, a numerical value is assigned to each alternative in accordance with the criterion unit defined previously,
- for binary criterion, a 1 is assigned to each alternative exhibiting the characteristic represented by the criterion and a 0 otherwise,
- for ordinal value, experts assign a score to each alternative within the limits set by the criterion scale. Several elicitation methods can be used to define the score of each alternative in comparison with other alternatives [32] or independently of other alternatives [46],
- at this point, there should be no more nominal qualitative variables.

A4. Normalize criteria: in order to better understand and compare intervals of granularity between criteria in the decision phase (see step B3) and so that the largest value always represents the best alternative regardless of the criterion, it is necessary to normalize the different criteria within the same range. For readability reasons for the human user, the choice has been made to define the normalization range between 0 and 5, but the decision-support algorithm, presented here, can work well with another normalization range. To normalize on the interval $[0, \mathcal{E}]$

Table 2
Normalized values of each alternative and importance and granularity parameters for each chosen criterion.

	Criterion g_1	Criterion g_2	⋯	Criterion g_y
Importance	φ_1	φ_2	⋯	φ_y
Granularity	μ_1	μ_2	⋯	μ_y
Alternative a_1	NV_{11}	NV_{12}	⋯	NV_{1y}
Alternative a_2	NV_{21}	NV_{22}	⋯	NV_{2y}
⋮	⋮	⋮	⋱	⋮
Alternative a_n	NV_{n1}	NV_{n2}	⋯	NV_{ny}

and determine the normalized value of alternative a_i according to criterion c_j, denoted NV_{ij}, the following formulas is used:

- for the criteria defined according to the "the higher the better" rule:

$$NV_{ij} = \mathcal{E} \times \left(\frac{V_{ij} - \min_{1\le k\le n}\left(V_{kj}\right)}{\max_{1\le k\le n}\left(V_{kj}\right) - \min_{1\le k\le n}\left(V_{kj}\right)} \right) \tag{1}$$

- for the criteria defined according to the "the lower the better" rule:

$$NV_{ij} = \mathcal{E} \times \left(1 - \frac{V_{ij} - \min_{1\le k\le n}\left(V_{kj}\right)}{\max_{1\le k\le n}\left(V_{kj}\right) - \min_{1\le k\le n}\left(V_{kj}\right)} \right) \tag{2}$$

- the vector containing all the evaluations of the n different alternatives according to criterion c_j is denoted $NV_j = \left\{NV_{1j}, NV_{2j}, \dots, NV_{nj}\right\}$.

The objective of this phase is therefore to formalize the data that will enable the ranking of the alternatives presented in the following sections. This "setup phase" allows to obtain a list of criteria that can be used to help DMs as well as a list of alternatives, evaluated for each criterion and formalized over the same interval $[0, 5]$ using the rule "the higher the better".

4.2. User interaction

This phase allows to assist DMs by ranking alternatives according to their preferences. These preferences are expressed in 3 different ways:

- by selecting, among the available criteria, those that the DM deems most relevant;
- by defining the importance of each of the chosen criteria on the final ranking;
- by defining the granularity of each of the chosen criteria. Granularity characterizes the level of uncertainty defined by the DM so that rankings of two similar, but not identical, alternatives are not too different.

The algorithm makes it possible to propose to the user a multi-criteria ranking of alternatives by adding two parameters to characterize the importance (to allow the DM to give more or less weight to a criterion compared to the others) and the granularity (to allow the DM to add a degree of uncertainty regarding this criterion to the ranking between similar alternatives).

The interaction between the DM (i.e. architect), and the DSS consists on 4 main steps (B1 to B4, see Fig. 3):

B1. Select decision criteria: users choose, from the list of available criteria $C = \left\{c_1, c_2, \dots, c_m\right\}$, those they wish to use for their current problem. The chosen criteria are noted $G = \left\{g_1, g_2, \dots, g_y\right\} \subseteq C = \left\{c_1, c_2, \dots, c_m\right\}$ with $y \le m$. Thus, there are y chosen criteria: $y = \mathrm{Card}\,(G)$ (Table 2). In the following, index β refers to selected criterion $g_\beta \in G$.

B2. Define importance and granularity parameters: users define the values of the parameters φ_β and μ_β characterizing respectively importance and granularity for each chosen criterion g_β (Table 2):

- Importance parameter allows DMs to specify their judgment about the weight of a criterion g_β compared to others in the ranking of alternatives and can take any value between 0 and 1: $\varphi_\beta \in [0, 1]$.
- Granularity parameter characterizes the level of uncertainty on a criterion g_β defined by DMs to avoid discriminating too closely near-criteria alternatives. Granularity is limited between 0 and 0.2 of the criterion value range to avoid from becoming the only information and ranking from being irrelevant: $\mu_\beta \in [0, 0.2]$.

B3. Analyze results: As evidence, the DM visualizes the ranked alternatives, with the associated scores. Thus, the DM defines whether the obtained result is satisfactory and acts accordingly by:

- selecting an alternative if the DM is satisfied (step B4),
- adding a new criterion to the decision problem if the DM deems it necessary (return to step B1),
- adjusting the importance and granularity parameters of one of the criteria of the decision problem if the DM deems it necessary (return to step B2).

B4. Make a decision: The DM makes a choice.

The use of the DSS allows users to see how the ranking evolves as they add criteria to the ranking zone and/or changes the importance and granularity parameters of the chosen criteria. In this way, DMs can perceive the impact of their choices on the ranking, acquire a better situational awareness [43] and perform an informed decision [44]. Therefore, steps C1 to C5 of the ranking phase, described on the following section, are performed automatically each time there is a change in the list of chosen criteria G or in the parameters φ and μ.

4.3. Ranking phase

Once the user has selected more than one criteria, with the corresponding parameters φ and μ, the algorithm automatically generates the ranked list. This computation consists on five steps described here:

C1. Calculate granularity intervals: an interval $\left[NV_{i\beta}^{Inf}, NV_{i\beta}^{Sup}\right]$ is calculated for each alternative-criterion couple $\left\{a_i, g_\beta\right\}$, centered on the value $NV_{i\beta}$ and proportional to the granularity parameter μ_β by using the following formulas:

$$NV_{i\beta}^{Inf} = NV_{i\beta} \times (1 - \mu_\beta) \tag{3}$$

$$NV_{i\beta}^{Sup} = NV_{i\beta} \times (1 + \mu_\beta) \tag{4}$$

C2. Calculate local dominances: for each criterion g_β, each alternative a_i is compared to the others alternatives to calculate $D_{i\beta}$, the number of alternatives it dominates. Alternative a_i dominates alternative a_k when the value of the inferior interval of a_i ($NV_{i\beta}^{Inf}$) is greater than the value of the superior interval of a_k ($NV_{k\beta}^{Sup}$):

$$D_{i\beta} = \mathrm{Card}\left(\left\{NV_{k\beta}^{Sup},\ NV_{k\beta}^{Sup} < NV_{i\beta}^{Inf}, \forall k \in [\![1;n]\!]\right\}\right) \tag{5}$$

We call a class, a subset of alternatives that have the same number of dominances.

C3. Normalize local dominances: the application of a different granularity parameter to each criterion g_β results in an evolution in the number of dominances. Indeed, the higher the granularity parameter is, the fewer dominated alternatives there are and vice versa. In order to be able to compare the criteria with each other and so that their weights in the final result are not dependent on granularity, a normalization, denoted $ND_{i\beta}$, of local dominances of a criterion $D_{i\beta}$, on the interval $[0,1]$ is performed using the formula below:

$$ND_{i\beta} = \frac{D_{i\beta} - \min_{1\le k\le n}\left(D_{k\beta}\right)}{\max_{1\le k\le n}\left(D_{k\beta}\right) - \min_{1\le k\le n}\left(D_{k\beta}\right)} \tag{6}$$

C4. Calculate overall dominance: to calculate the overall dominance of an alternative a_i, a mean of the normalized dominances $\{ND_{i1}, ND_{i2}, \dots, ND_{iy}\}$, weighted by the importance of each criterion $\{\varphi_1, \varphi_2, \dots, \varphi_y\}$, is calculated using the following formula:

$$OD_i = \frac{\sum_{\beta=1}^{y}\left(ND_{i\beta}\times\varphi_\beta\right)}{\sum_{\beta=1}^{y}\left(\varphi_\beta\right)} \tag{7}$$

C5. Rank alternatives: the alternatives are sorted by decreasing overall dominance to be displayed (C5bis) to the user.

As discussed previously, the alternatives ranking will be computed and displayed each time the user makes a modification either by adding or deleting criteria, or modifying the criteria parameters.

5. Sensitivity analysis of the ranking algorithm

A sensitivity analysis [47] is conducted in order to better understand the influence of the importance (φ) and granularity (μ) parameters as well as the impact of the shape of the different vectors NV_j, i.e. the distribution of data in each criterion, on the algorithm response.

There are two broad categories of methods for conducting a sensitivity analysis. Local methods evaluate a model in a deterministic framework as opposed to global methods that evaluate a model in a stochastic framework [47]. Given the nature of the algorithm and the input parameters to be evaluated in our case, the choice is made to use a local method. Among these local methods, the most common are:

- One-At-a-Time (OAT) method which consists in setting all the parameters except one that varies to analyze its impact on the model response [48]. This method is simple to implement but does not allow to perceive the possible interactions between parameters.
- decomposition by scenarios [47] which consists in defining scenarios allowing to set the input parameters in a coherent way with the possible uses of the model in order to draw conclusions. This method is also simple to implement but it is not intended to study the model's behavior in an "exhaustive" way.
- screening methods aim at exploring the space of possible parameters to get an idea of the general behavior of the model [49,50]. These methods are often associated with the use of a Design Of Experiments (DOE) [51] to obtain a structured and coherent exploration methodology.

The objectives of this sensitivity analysis are to verify the robustness of the ranking algorithm by exploring the different shapes of data distributions that could be used to make a choice and the ranges of the importance and granularity parameters. In other words, the goal is to see if the different combinations of parameters do not generate any aberrant variations in the ranking of alternatives provided by the algorithm. In this context, a screening method based on a DOE has been chosen to conduct this sensitivity analysis.

The protocol used for this sensitivity analysis is described in the following sub-section (Section 5.1). The analyses conducted on the influence of distribution shapes (Section 5.2), granularity μ (Section 5.3) and importance φ (Section 5.4) are then presented. Finally, all the results of this sensitivity analysis are discussed in Section 5.5.

Table 3
Data used for the sensitivity analysis.

Alternatives	Criteria					
	g_1				g_2	g_3
	U	N	C	B		
		$\varphi_1 \in \{0.1, 0.5, 1\}$ $\mu_1 \in \{0, 0.1, 0.2\}$			$\varphi_2 = 0.5$ $\mu_2 = 0$	$\varphi_3 = 0.5$ $\mu_3 = 0$
a_1	2.0506	−0.158	−0.896	1	4.256	4.857
a_2	4.9695	−0.316	0.963	0	3.317	4.341
a_3	0.8266	−0.085	0.796	0	0.216	0.000
a_4	0.2295	−1.055	−0.344	0	1.296	1.168
a_5	1.7950	0.692	−0.947	1	2.368	2.803
a_6	2.1986	2.220	−0.634	0	0.878	1.834
a_7	0.0000	0.223	0.695	1	1.240	1.920
a_8	1.6135	1.803	0.993	0	4.328	3.085
a_9	1.7219	0.246	−0.689	0	3.240	3.248
a_{10}	4.2117	−2.338	0.691	0	1.825	2.464
a_{11}	4.7629	0.149	1.000	1	2.976	2.819
a_{12}	3.2205	1.211	−0.876	1	3.474	0.771
a_{13}	2.5446	−0.109	−0.551	1	5.000	5.000
a_{14}	2.6947	−1.072	−0.938	1	2.301	3.058
a_{15}	3.7798	−0.702	0.680	1	1.734	1.954
a_{16}	0.7470	1.816	0.952	0	0.000	0.733
a_{17}	3.5452	0.717	0.081	0	3.504	4.810
a_{18}	5.0000	1.037	−0.857	1	2.710	2.449
a_{19}	1.0258	−0.057	0.186	1	0.365	0.491
a_{20}	3.6747	−0.143	−0.800	0	4.842	3.434

5.1. Protocol description

To control the different parameters of this study, a protocol has been defined with a configuration using three chosen criteria (g_1, g_2 and g_3) and twenty alternatives $A = \{a_1, a_2, \dots, a_{20}\}$. Two of the chosen criteria (g_2 and g_3) remain fixed in all the simulations. Two uniform distributions (V_2 and V_3) have been generated using the random number generator in Microsoft Excel over an interval $[0,5]$ (Figs. 4.e., 4.f. and Table 3) and the parameters of importance and granularity are also defined ($\varphi_2 = \varphi_3 = 0.5$ and $\mu_2 = \mu_3 = 0$). To carry out this sensitivity analysis, the criterion g_1 varies according to three factors:

- Factor 1 (4 levels): $Shape \in \{U, N, C, B\}$. This factor is intended to highlight the effect of the variation in the shape of the g_1 distribution. Four distributions have been generated using the random number generator in Microsoft Excel (Table 3):
  - U: vector uniformly distributed over an interval $[0,5]$ (Fig. 4.a.),
  - N: vector distributed according to the normal law of mean 0 and standard deviation 1 (Fig. 4.b.),
  - C: vector uniformly distributed over an interval $[0,\pi]$ and then the cosine of each value is calculated to obtain a cosine distribution over an interval $[-1,1]$ (Fig. 4.c.),
  - B: vector uniformly distributed over an interval $[0,1]$ and then each value is rounded to the nearest integer to obtain a binary distribution (Fig. 4.d.).
- Factor 2 (3 levels): $\varphi_1 \in \{0.1, 0.5, 1\}$. This factor is intended to highlight the effect of the variation in importance of the criterion g_1 on the final result.
- Factor 3 (3 levels): $\mu_1 \in \{0, 0.1, 0.2\}$. This factor is intended to highlight the effect of the variation in granularity of the criterion g_1 on the final result.

After defining the conditions to be simulated, a DOE was established. A full factorial experiment was chosen to cover all possible combinations of factors. Thus 36 simulations ($\mathrm{Card}\,(Shape)\times\mathrm{Card}\left(\varphi_1\right)\times\mathrm{Card}\left(\mu_1\right) = 36$) were carried out.

For each simulation performed with a different set of factors, five algorithm responses were collected:

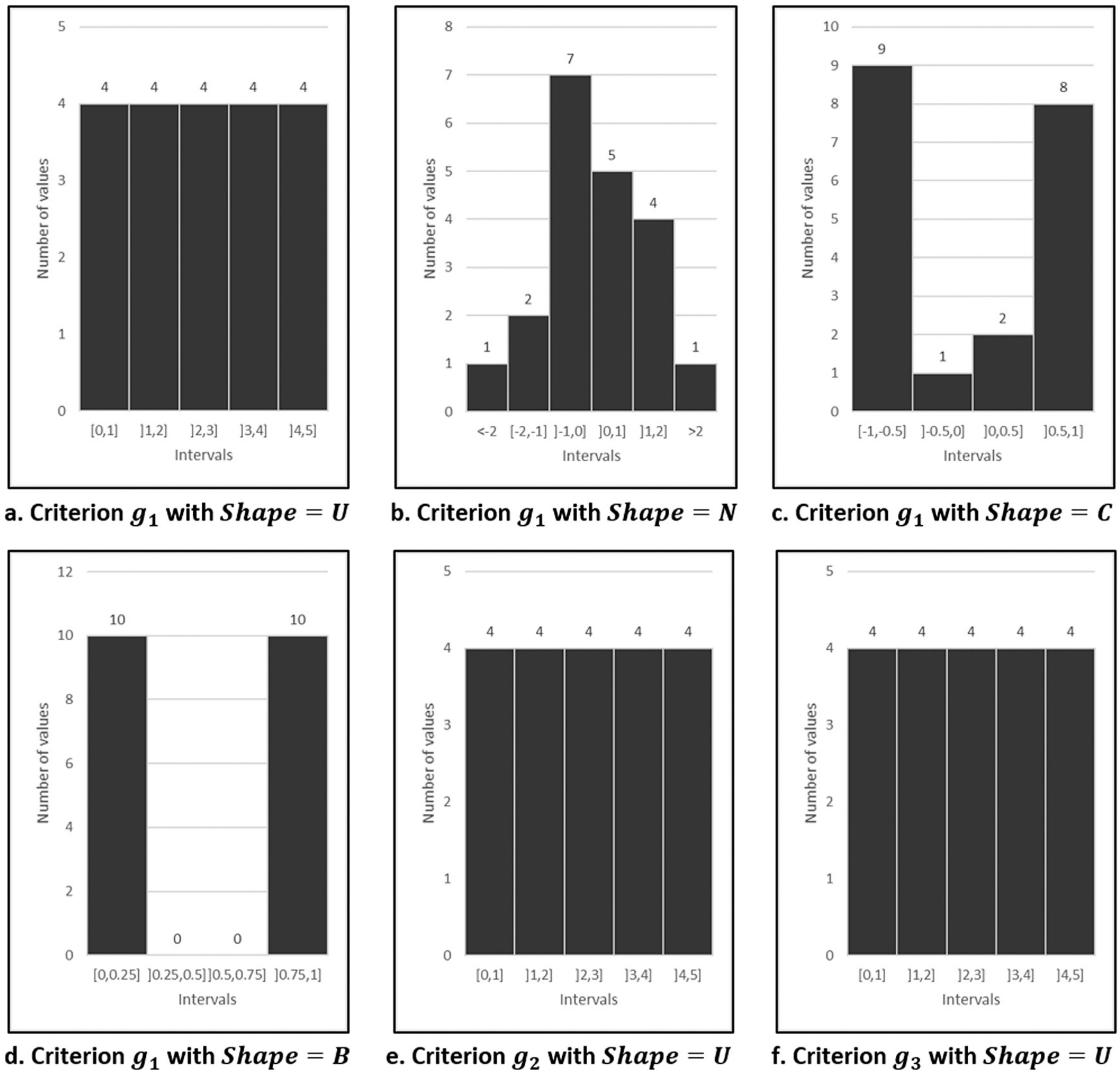

Fig. 4. Shapes of the various distributions.

[A–1] the minimum value of overall dominance ($MIN\_dominance$)
[A–2] the maximum value of overall dominance ($MAX\_dominance$)
[A–3] the difference between the maximum and minimum values of overall dominance ($GAP\_dominance$)
[A–4] the number of different ranks of the final ranking, i.e. the number of clusters of alternatives ($NB\_clusters$)
[A–5] the complete ranking of the alternatives.

5.2. Influence of the distribution shapes on dominance

Before analyzing the importance (φ) and granularity (μ) parameters, it was verified if there were behavior differences between the four distributions defined for the g_1 criterion. To do so, ANOVAs were performed on four measures: $MIN\_dominance$, $MAX\_dominance$, $GAP\_dominance$ and $NB\_clusters$ (i.e. quantitative variables). ANOVAs were conducted according to four statistic groups (i.e. four distribution shapes) and nine units for each of them ($4\times9 = 36$ simulations). Results are given in Table 4.

Statistical analyses confirmed that the distribution shape of criterion g_1 has an impact on the results. In fact, statistical analyses [A–1], [A–2] and [A–3] (above) reveal a significant difference in the dominance of the set of alternatives.

Statistical analysis [A–4] did not show any significant differences between the groups of distributions.

Table 4
ANOVAs results.

Studied response	Measure	$F(3.32)$	p	SS	MSe
[A–1]	$MIN\_dominance$	19.6	< 0.000001	0.12	0.01
[A–2]	$MAX\_dominance$	20.4	< 0.000001	0.12	0.01
[A–3]	$GAP\_dominance$	22.6	< 0.000001	0.36	0.01
[A–4]	$NB\_clusters$	2.00	< 0.134319	14.97	2.50

Due to the differences in results observed according to the distribution shapes, the following analysis (influence of importance and granularity) are carried out on the groups (i.e. behavior of g_1) taken independently.

In order to verify influence of both granularity and importance on the algorithm responses, we have used two types of statistical test: Friedman test to verify difference hypothesis between sorting groups and Krippendorff's Alpha (α_K) to measure "similarity" between sorting groups [52]. It is customary to require $\alpha_K \geq 0.8$ to consider strong reliability [53].

5.3. Influence of the granularity parameter on ranking

To measure the influence of granularity, we have fixed the value of the importance while varying the granularity criterion, and tested the ranking of alternatives (Table 5).

Table 5
Influence of granularity parameter on the ranking: Friedman Test and Krippendorff's Alpha results.

Shape	Test	Importance φ			
		φ_1	0	0.5	1
U	Friedman Test	$Q(2)$	0.08	0.53	0.08
		p-val.	0.961	0.767	0.961
	Krippendorff's Alpha (ordinal)	α_K	0.995	0.977	0.976
N	Friedman Test	$Q(2)$	0.08	0.01	0.08
		p-val.	0.961	0.951	0.961
	Krippendorff's Alpha (ordinal)	α_K	0.999	0.958	0.886
C	Friedman Test	$Q(2)$	0.08	0.48	0.93
		p-val	0.961	0.787	0.628
	Krippendorff's Alpha (ordinal)	α_K	0.988	0.934	0.906
B	Friedman Test	$Q(2)$	0	0	0.08
		p-val.	1	1	0.961
	Krippendorff's Alpha (ordinal)	α_K	1	1	0.93

Table 6
Influence of importance parameter on the ranking: Friedman Test and Krippendorff's Alpha results.

Shape	Test	Granularity μ			
		μ_1	0	0.1	0.2
U	Friedman Test	$Q(2)$	0.98	0.33	0.03
		p-val.	0.613	0.848	0.985
	Krippendorff's Alpha (ordinal)	α_K	0.911	0.911	0.894
N	Friedman Test	$Q(2)$	0.1	2.28	5.7
		p-val.	0.951	0.320	0.058
	Krippendorff's Alpha (ordinal)	α_K	0.824	0.814	0.869
C	Friedman Test	$Q(2)$	0.18	0.03	0.33
		p-val	0.914	0.985	0.848
	Krippendorff's Alpha (ordinal)	α_K	**0.772**	**0.681**	**0.738**
B	Friedman Test	$Q(2)$	0.63	0.63	0
		p-val.	0.730	0.730	1
	Krippendorff's Alpha (ordinal)	α_K	**0.778**	**0.778**	**0.687**

According to the Friedman tests, no significant differences between the rankings for each shape of g_1 ($p - val. \gg 0.05$) are observed. We can therefore infer that the rankings of alternatives generated by the variation in granularity are not significantly different. In other words, the change of "rank" of the alternatives is not sufficiently different from one granularity to another.

Considering Krippendorff's Alpha, we observe strong agreements between the rankings (i.e. $\alpha_K \geq 0.8$). We can infer that there is a "similarity" of alternative rankings. In other words, regardless of the level of granularity chosen, the ranking of alternatives is more or less the same.

5.4. Influence of the importance parameter on ranking

To measure the influence of importance, we have fixed the value of the granularity while varying the importance criterion and tested the ranking of alternatives (Table 6).

According to the Friedman tests, no significant differences between the rankings for each shape of g_1 ($p \geq 0.05$) are observed. It can therefore be inferred that the rankings of alternatives generated by the weight variation of criterion g_1 are not significantly different. In other words, the change of "rank" of the alternatives is not sufficiently different from one importance to another.

Considering Krippendorff's Alpha, for the $Shape = B$ and $Shape = C$, the value of the Alpha coefficient is less than 0.8 (in bold in Table 6). It can be inferred that the rankings generated with the different importance weights are not in "agreement". Overall, it can be said that there is no "similarity" between the rankings of these alternatives. For the $Shape = N$ and $Shape = U$, we observe strong agreements between the classifications ($\alpha_K \geq 0.8$). We can infer that there is a "similarity" of alternative rankings. In other words, no matter how much importance is assigned to criterion g_1, the ranking of alternatives is more or less the same.

5.5. Results synthesis of the sensitivity analysis

We can conclude that granularity parameter is useful for DMs to add their preferences (epistemic uncertainty [23]). The rank of the alternatives is modified but on a non-significant "scale" thus making the algorithm robust in the face of its variations.

Regarding the importance parameter, we can conclude that the algorithm is robust to the variation of the weight of importance when applied to a criterion according to a distribution of Normal or Uniform shapes. However, we can infer that the algorithm is sensitive to the weight of importance when applied to a criterion according to a distribution of Binary or Cosine shapes. In other words, this means that the weight of importance assigned to criterion g_1 has an influence on the ranking of alternatives when this criterion follows a Binary or Cosine shape.

This is a real advantage for the DSS as it allows a filtering effect to be implemented. Indeed, the criteria having a Binary form (and by extension those having a Cosine form) makes it possible to define whether the alternative under consideration has the characteristic represented by the criterion or not. The more the importance applied to this criterion increases, the more the solutions that do not have the characteristic represented by this criterion fall back in the ranking and vice versa. In fact, these solutions are "eliminated" (or filtered) from the top of the ranking.

To sum up, this sensitivity analysis shows that the proposed algorithm is robust and granularity parameter is useful for decision-makers to address epistemic uncertainty.

6. Use case

As mentioned above, the DSS proposal, detailed in this article, is intended to support the milestone "*selection of refurbishment technologies*" (Section 1 and Fig. 2). To illustrate how it works in a practical way,

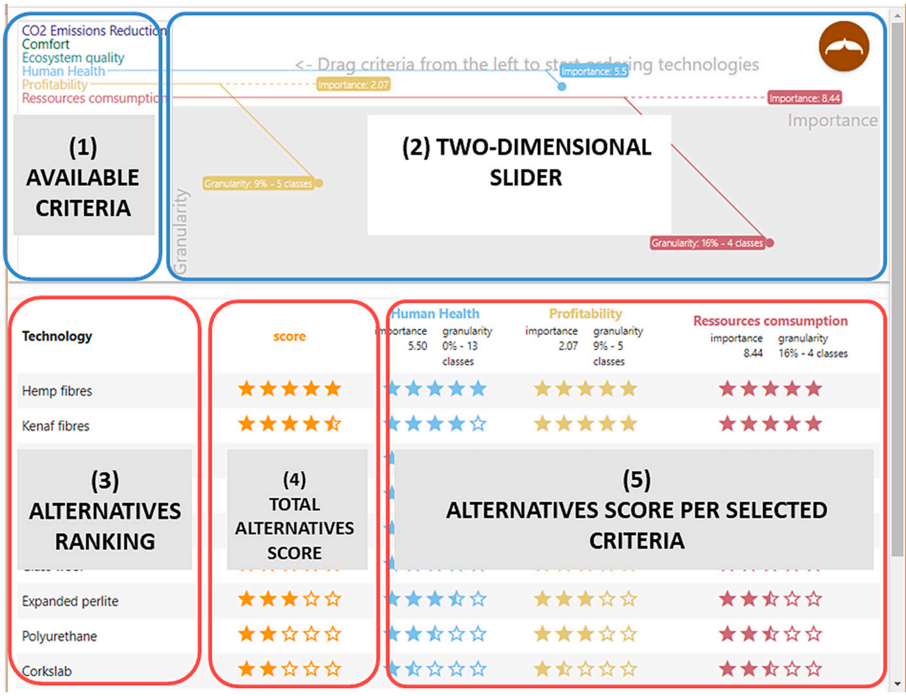

Fig. 5. Proposed UI.

a scenario has been designed based on data from [20]. In addition, an online software demonstrator allowing to test the UI and the DSS with the data set of this use case is available at https://rezbuild-tamarin.herokuapp.com/.

Section 6.1 presents the UI developed to illustrate the use of the DSS, 6.2 describe the scenario, and the performance of this scenario using our DSS is presented in Section 6.3.

6.1. User interface

The proposed UI is divided in two main areas (Fig. 5): inputs and interaction areas (blue boxes) and outputs visualization areas (red boxes).

The inputs and interaction areas allow the user to select the relevant criteria and to introduce the parameters on the chosen criteria that the algorithm uses to rank the alternatives. On the upper left side there is the list of available criteria that can be used (zone 1), and on the top right side there is the two-dimensional sliders (zone 2). There are two main interactions between the user and the DSS (Fig. 6):

- (A): The user can select the criteria to be used on the ranking algorithm using a "drag and drop" interaction. The criteria are thus moved from zone (1) to zone (2), and vice-versa to remove them.
- (B): The user can define the importance and granularity of the selected criteria by sliding the criteria pointer inside zone (2). If the criteria pointer remains in the white area, only importance is considered. If the criterion pointer is introduced in the gray area, then, granularity is also considered. Moving the slider changes the value of importance and granularity at the same time. The label associated to each criterion shows the current values of importance and granularity parameters for this criterion. For the granularity, the number of local dominance class is displayed.

The visualization area allows the user to see the results (output) of the ranking algorithm. On the lower left side (zone 3) there is the list of alternatives that are being evaluated. This list corresponds also to the ranking, and is automatically reordered when there is a modification of the inputs. In the middle of the screen, there is the total score of each alternative (zone 4) and, on the bottom right side, the score for each alternative per criterion (zone 5). The score is presented as a 5-half-star set allowing to distinguish up to 11 classes of alternatives for the criteria. The actual number of classes is displayed along the granularity level.

6.2. Use case scenario

To better understand the functioning of the proposed DSS, this section introduces a scenario that allows the tool to be used in a realistic situation:

Emma, an architect, is engaged on a high standing accommodation refurbishment project. Emma's customer is aware of environmental impact of building life cycle, including material production, building energy consumption during its lifetime as well as the end of life.

One of the technologies that Emma has to select is the roof insulation material. She has access to a catalog of 13 insulation material alternatives which are available on the market (Table 7).

The performance of the materials can be compared from the socio-economic and environmental viewpoints with six quantitative decision criteria.

- *(c1) Comfort: this criterion uses "the lower the better" ranking rule and is expressed in Hours of discomfort, i.e. the annual overall time during which the building temperature is outside the chosen comfort temperature range weighted by how much the limit has been exceeded.*
- *(c2) CO2 emission reduction: this criterion uses "the higher the better" rule and measures the energy savings made by using an insulation technology compared to a case without insulation and is converted into kg of CO2 per year.*
- *(c3) Profitability: this criterion uses "the higher the better" rule and is an outcome of Life Cycle Costing which is a methodology that evaluates the profitability of a technology by considering the costs during the whole life cycle.*
- *(c4) Human health: this criterion uses "the lower the better" ranking rule and is expressed in points. It results from an impact analysis combining several factors affecting the health of users (carcinogens, radiation, ozone layer…).*

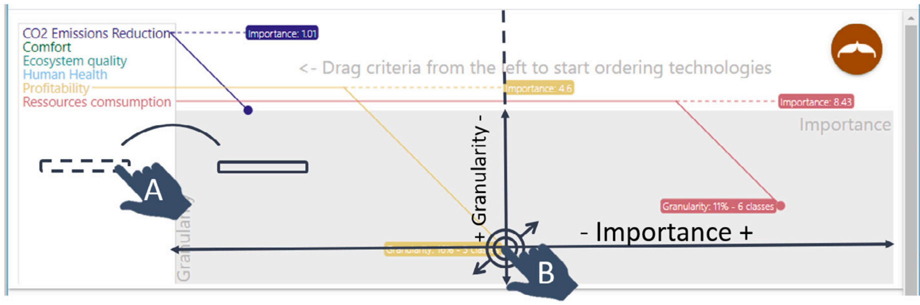

Fig. 6. UI Interaction details.

(c5) Ecosystem quality: this criterion uses "the lower the better" ranking rule and is expressed in points. It results from an impact analysis combining several factors affecting the biodiversity and the environment (ecotoxicity, acidification, land use...).

(c6) Resources consumption: this criterion uses "the lower the better" ranking rule and is expressed in points. It results from an impact analysis combining two factors concerning non-renewable geological resources.

For more detail about the data set or the data gathering process used to obtain these criteria, please refer to [20].

6.3. Use case implementation

Following the user interaction steps, detailed in Fig. 3 (Section 4.2), the decision making process for this scenario is presented here.

B1. DM adds a criterion: Given the context (refurbishment of a high standing accommodation reducing environmental impact), selecting a material that has good comfort performance and which reduces CO2 emissions and resources consumption becomes a priority.
Thus, Emma, the DM, selects three of the criteria to be considered on the insulation materials ranking: (c1) comfort, (c2) CO2 emissions reduction and (c6) resources consumption, which are selected one after the other using the interface (Table 7).

B2. DM defines importance and granularity parameters: To express the customer expectations, Emma gives the same importance to (c2) CO2 emissions reduction and (c6) resources consumption. Both of them are important criteria, so they have a weight of twice the comfort (c1) criteria. This is expressed by Emma on the interface by an importance of 5/10 and an importance of 2,5/10 respectively.
To define the granularity, Emma uses her expertise: she knows that most of the alternatives have a good (c1) comfort performance, with close values, so little granularity is given to avoid discriminating close values (1 %). For (c2) CO2 emissions reduction and (c6) resources consumption, she gives more granularity to clearly discriminate the better ones by: (c2) 5 % and (c6) 9 %). The effect of the granularity on the data is translated to a number of classes: 8 for the (c1) comfort performance and 5 for (c2) CO2 emissions reduction and (c6) resources consumption.
Each time Emma adds (step B1) or adjusts (step B2) the parameters, the DSS computes and displays (updates) the results. This corresponds to steps C1 to C5 as described on Section 4.3. Emma obtains then a ranking of refurbishment insulation materials as shown on Fig. 7, where top 7 alternatives are displayed.

B3. DM analyses results: The 4 first alternatives have almost the same score. Emma should consider her expertise in order to select the alternative to be chosen (i.e. aesthetics).
She can take a decision with the information she has, or consider to add (c3) profitability criteria in order to verify if the economic dimension has a strong impact on the ranking. Fig. 8 shows the ranking after updating the results with (c3) profitability having a strong importance (8/10) comparing with the other criteria, and no granularity.
In this case, the top 7 remains almost the same (only Corkslab is replaced by Expanded perlite). However, Kenaf fibers and rock wool takes the lead with a better score than Polyurethane and Hemp fibers.

B4. DM selects an alternative: Emma can now choose among the top two alternatives based on his expertise, but being sure they are the best ones regarding the criteria she has defined based on the context and her preferences.

Table 7
Use case data set, with normalized data (on [0,5] interval with the rule "the more is the better"), importance (/10) and granularity (%).

	c1	c2	c3	c6
Importance	*2.5/10*	*5/10*	*8/10*	*5/10*
Granularity	1 %	5 %	0 %	9 %
A. A. complete	3.21	3.33	3.86	4.52
Corkslab	4.28	4.26	3.83	3.59
Expanded perlite	4.37	4.29	4.64	3.49
Fiberboard hard	4.65	4.58	3.13	0.00
Glass wool	4.62	4.68	4.47	3.86
Gypsum fiberboard	0.68	0.73	1.18	2.47
Hemp fibers	4.34	4.46	4.78	4.81
Kenaf fibers	4.62	4.65	4.92	5.00
Mineralized wood	3.79	3.75	3.17	2.00
Plywood	0.00	0.00	0.00	0.38
Polystyrene foam	4.54	4.67	4.56	4.50
Polyurethane	5.00	5.00	4.71	3.49
Rock wool	4.65	4.73	5.00	4.75

6.4. Use case results and discussions

As shown through the use case scenario, using the proposed ranking algorithm combined with an appropriate interface can help DM to test preferences and to make an informed choice within a set of alternatives. The resulting ranking can be compared with the one proposed by [20], who implemented a three-stage multi-criteria approach. Instead of ordering insulation material alternatives, they propose to sort them within 3 pre-defined categories. The same data set have been used, and the alternatives assigned using their algorithm to the best class (most sustainable) are the same that we find on our top 6 ranking.

Furthermore, with this upgraded algorithm and UI, three major limits of a previous proposal [11] are addressed (see Section 4):

- UI: The readability of values of importance and granularity parameters is facilitated with the interactive path, coupled to a visualization of the numerical value, and score per criterion. The star system allows lower the cognitive cost of comparing solution. However, the actual value for the alternative regarding each criterion should be presented as an alternate view for the final decision.

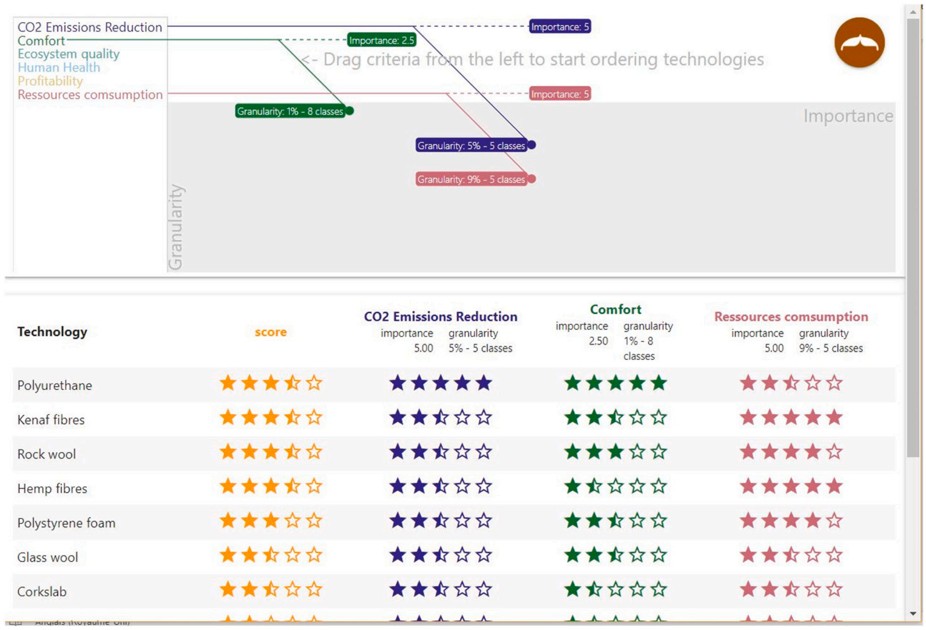

Fig. 7. Use case ranking.

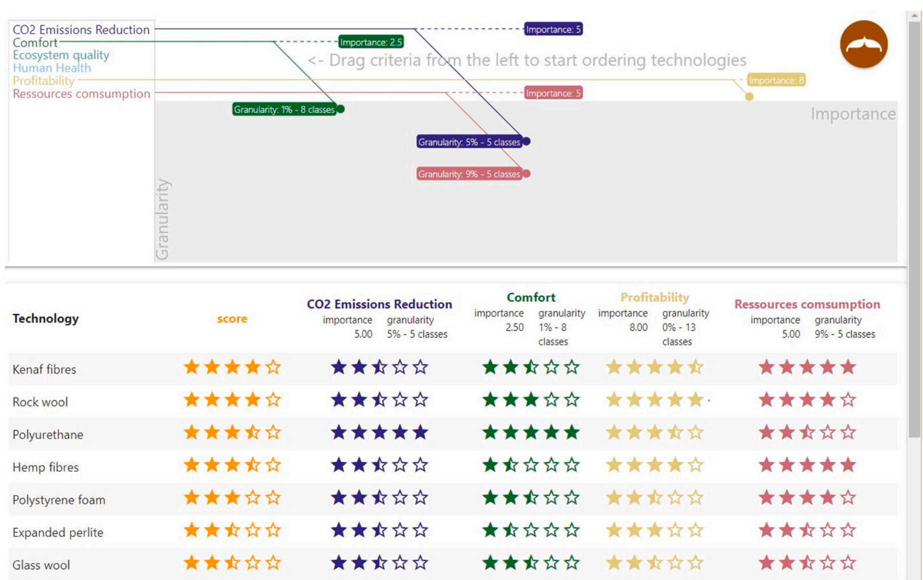

Fig. 8. Use case ranking with profitability criteria.

- Variables: binary and nominal variables can be also included on the ranking exploration, as explained in Section 4. The use case presented on this paper does not consider this kind of variables, but we could have added binary criteria such as "certification" (e.g. is the alternative certified with a "fair trade" label?), or nominal, such as the material color (is the alternative white? is the alternative black? is the alternative red?).
- Bias due to granularity: proceeding with the normalization of the local dominance has allowed to avoid amplification of the granularity through the different stages of the algorithm.

7. Conclusion and perspectives

This paper presents a MCDM ranking solution including an algorithm coupled with an interactive UI, which allows to rank a defined number of alternatives considering a set of criteria. The main objective is to propose a decision-support system for designers who have to choose a solution/technology, while considering conflicting criteria, and uncertainty, within a NZEB refurbishment process. The proposition takes into account the notion of importance between criteria, and granularity to differentiate solutions within a criteria, in order to facilitate an exploration of the solution space and to take an informed decision.

The influence of the importance and granularity parameters have been explored with a sensitivity analysis, as well as the impact of the distribution of input data on the algorithm response. This sensitivity analysis was used to qualify the operation of the proposed DSS. Neither the variations in the values of the importance and granularity parameters used, nor the different shapes of data distribution tested generated any aberrant behavior. This analysis has not yet been conducted on aspect such as the impact of criteria ranking combinations, combinations of variations of importance and granularity parameters according to criteria or combinations of criteria shapes. These tests will be the subject of future works.

The algorithm and UI have also been illustrated and validated through a data set from the literature where insulation materials are evaluated based on six criteria.

As a result, the approach used to achieve the prototype and the tests conducted around its use have made it possible, in addition to showing the usefulness and effectiveness of the proposed tool, to address the main limitations identified in the literature and to propose an original and innovative solution to a real-world problem.

Several perspectives arise from the conducted work. First of all, the proposal has been tested with a given set of data and considering the current decision approach, which is centered on a single decision-maker (a designer who chooses a technology). It could be relevant to test the solution with (i) a larger data set, that includes "all" available market alternatives for a given refurbishment function, and (ii) to consider a collective decision approach, where other stakeholders are involved on this process. Indeed, the involvement of customers or technology providers in the decision-making process using argumentation [54] or group decision [20] mechanisms, could increase the final satisfaction of the customer or add technological expertise to improve the relevance of the chosen solution.

Also, considering the NZEB renovation process, only one of the decision milestones has been addressed (milestone 2). In the context of H2020 REZBUILD project, which aims at providing a Collaborative Refurbishment Platform to achieve a better global performance (i.e. emissions reduction, profitability, refurbishment lead time), the other decision milestones may also benefit from a DSS development.

Finally, the proposal was developed on the context of NZEB refurbishment projects, but the proposed DSS could be used into other application domains. This may allows an extensive validation of algorithm and UI considering decision confidence and the capacity to take "right decisions" through user tests, independently of the context.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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