Systematic combination of insulation biomaterials to enhance energy and environmental efficiency in buildings

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Abstract

Thermal insulation based on biomaterials with low energy embodied is a promising alternative to reduce the energy demand of the actual building stock and help meeting the climatic 2050 EU goals. Despite their appealing properties, these materials are not widely available in the insulation market for a variety of reasons such as a more laborious implementation compared to commercial alternatives. To overcome this limitation and change this trend, this work introduces a systematic method to generate efficient combinations of bio-based materials with reduced cost and environmental impacts that could be manufactured as commercial sandwich or solid panels and fiber mats.

Keywords

Data Envelopment Analysis (DEA); life cycle assessment (LCA); bio-based building materials; thermal insulation; sandwich panels; fiber mats; composites;

Nomenclature

Abbreviations

BCC	Banker, Charnes, Cooper
BSk	Cold semi-arid climate
COP	Coefficient of performance
CTE	Spanish Building Code
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
EU	European Union
EPS	Expanded Polystyrene
GHG	Greenhouse gas
LCA	Life cycle assessment
PCP	Parallel Coordinates Plot
PU	Polyurethane

VRS	Variable returns to scale
XPS	Extruded Polystyrene

Sets

I	Set of inputs i
J	Set of insulation alternatives j
MAT_j	Insulation material *ins* of alternative j
R	Set of outputs r
RS	Reference set of an inefficient DMU

Indexes

cat	Mid-point environmental category in ReCiPe
i	Input
ins	Insulation material
j	Insulation alternative as given by a material and a thickness (DMU)
k	Year in the lifespan of the building
p	Performance indicator (either input i or output o)
r	Output

Parameters and Variables

ALO	Agricultural land occupation (m^2a)
$Cost^{ELE}$	Unitary cost of electricity (in Spain, in this case) (€/kWh)
$Cost_{ins}^{MAT}$	Unitary cost of insulation material *ins* (€/kg)
$Cost_j^{TOT}$	Total cost DMU j (€)
$Elec_j$	Amount of electricity required by insulation alternative j to achieve the thermal comfort of the building (kWh)
FE	Freshwater eutrophication (kg P)
FET	Freshwater ecotoxicity (kg 1,4-DCB)
FD	Fossil depletion (kg oil)
GWP	Climate change (kg CO_2)
HT	Human toxicity (kg 1,4-DCB)
i	Annual increment of the electricity cost
Imp_{cat}^{ELE}	Unitary impact of electricity in Spain for ReCiPe category *cat* (units/kWh)
$Imp_{ins,cat}^{MAT}$	Unitary impact of insulation material *ins* in ReCiPe category *cat* (units/kg)
Imp_{cat}^{TOT}	Total impact of DMU j in ReCiPe category *cat*
$Indicator_{j,p}$	Value of performance indicator p for DMU j
$Indicator_p^{COMP}$	Performance of the composite in indicator p
IR	Ionising radiation (kg U_{235})
m	Number of insulation materials considered
$Mass_{ins,j}$	Amount of insulation material *ins* in insulation alternative j (kg)
ME	Marine eutrophication (kg N)
MET	Marine ecotoxicity (kg 1,4-DCB)
MD	Metal depletion (kg Fe)
n	Number of insulation thicknesses considered
NLT	Natural land transformation (m^2)
OD	Ozone depletion (kg CFC-11)
PMF	Particulate matter formation (kg PM_{10})

POF	Photochemical oxidant formation (kg NMVOC)
s_i^-	Slack of input *i*
s_r^+	Slack of output *r*
$Share_{ins}^{COMP}$	Share of insulation material *ins* in the composite
TAP	Terrestrial acidification (kg SO_2)
TET	Terrestrial ecotoxicity (kg 1,4-DCB)
$Thickness_j$	Thickness of insulation alternative *j*
$Thickness^{COMP}$	Total thickness of the composite
ULO	Urban land occupation (m^2a)
WD	Water depletion (m^3)
ε	Non-Archimedean value to force the positivity of the variables
λ_j	Weight of original DMU *j* in a virtual DMU
θ	Efficiency score
θo	Relative efficiency score of the DMU analysed *o*

1. Introduction

The building sector is responsible for approximately 50% of the total energy consumption and almost 40% of the greenhouse gas (GHG) emissions in Europe [1] [2], being a major contributor to global environmental pollution [3]. This sector has been at the heart of several energy efficiency policies, such as the ambitious 2020 Energy Strategy Plan enacted by the European Union (EU). With this policy, the EU aimed to reduce its greenhouse gas emissions by at least 20% from 1990 levels, increase the share of renewable energy to at least 20% of consumption, achieve energy savings of 20% or more [4] and reduce by 30% the use of primary energy by 2030 [5]. Objectives for 2030 are more strict [6] and they are expected to become even more ambitious by 2050 [7].

Various energy mitigation strategies must be put in place to achieve these targets. In the building sector, a relevant part of the energy is used for heating, cooling and air conditioning [8]. Therefore, insulation represents a promising option to achieve significant environmental and economic savings, with the capacity to decrease the cooling and heating demand of buildings [9]. However, while insulation can reduce the energy requirements of buildings during the use phase, this does not necessarily translate into savings along the whole lifecycle. This is because some insulation materials embody significant amounts of energy in their life cycle as a result of their extraction, manufacturing and deployment phases [10].

According to different researchers [11][12][13], bio-based materials constitute a promising alternative in building insulation due to their low embodied energy. Despite this advantage, their penetration in the market is still rather low [14]. Acknowledging that prefabricated sandwich panels and fiber mats of conventional materials are showing an increasing demand [15], partially due to the ease of their implementation, we argue that the production of composite solutions combining bio-based materials might be a promising strategy to improve their penetration in the market. The combination of different materials into a single panel has some intrinsic advantages such as the capacity to benefit from the properties of several individual materials at the same time (e.g., insulation properties, humidity transfer or water barrier). In this context, the question is how to combine bio-based materials in an optimal manner to obtain a sandwich panel or another composite material with advantageous performance.

To this end, we propose a systematic methodology for the generation of composite insulation materials. Our strategy combines building simulation, Data Envelopment Analysis (DEA) and Life Cycle Assessment (LCA) to automatically select insulation materials and their thickness according to their environmental and economic performance.

The combination of LCA and DEA into a single framework is not new. These two methodologies provide a powerful framework for eco-efficiency assessment (i.e., economic plus environmental performance) that has drawn the attention of researchers in the past due to its synergetic effects. On the one hand, LCA evaluates various aspects associated with the production and development of a product and its potential environmental impact throughout its entire lifecycle (i.e., from the raw material acquisition, processing, manufacturing, use and, finally, its disposal) following defined principles and guidelines [16]. Therefore, it allows quantifying the impact of a product in several environmental categories along its life cycle, preventing burden-shifting effects among the different steps of the supply chain. Then, DEA allows combining this multidimensional (environmental and economic) information into a single efficiency score, without the need to define subjective weights for the different indicators. In particular, DEA evaluates the relative performance of a set of different alternatives (known in DEA as Decision Making Units, DMUs) according to any measurable indicator (inputs and/or outputs). This benchmarking tool assigns an efficiency score to each DMU, thus enabling the identification of the efficient and non-efficient solutions, with the former being assigned an efficiency score of 1 and the latter an efficiency score strictly below 1.

In the last decade, several LCA+DEA approaches have been developed to link the economic and environmental performance of a system or a product and identify efficient alternatives in different contexts [17][18]: vine-growing exploitations [19], technologies for food waste management [20], electricity technologies [21] and solvents [22]. Note that these approaches based on DEA can be indistinctly applied to assess sustainability efficiency [23] (when the three dimensions of sustainability are considered), eco-efficiency [24] (only economic and environmental performance are included) and environmental efficiency (just environmental concerns). The interested reader is referred to recent surveys about DEA applications to environmental studies [25][26].

In the context of buildings, Iribarren et al. [27] used DEA to analyze 175 common external wall configurations belonging to the construction sector of Luxemburg in order to identify those which were environmentally sustainable. Each configuration was obtained by combining three different building blocks as follows: sixteen different bearing structures for external walls, sixteen different materials for insulation (six from renewable resources: cotton, hemp, cork, flax, wood wool panel and wood fiber insulation panel; two from recycling: cellulose fibers and cellulose fiber panel; four from mineral-based materials: mineral wool, glass wool, calcium silicate panel, and foam glass panel; and the remaining four from synthetic materials: EPS 032 and 040, XPS, and polyurethane panel) and, finally, seven complementary materials (such us gypsum or lime-cement plaster, wood fiber or OSB panel, …) for external layers for additional wall configurations. From these 175 configurations, only nine were identified as eco-efficient, and these resorted to hemp, cellulose fiber, cotton and mineral wool, with thicknesses varying from 6 to 25 cm, as insulation materials.

In the pioneering approach by Iribarren et al., DEA was used as a benchmarking tool, providing efficiency scores for different candidate structures. However, here, we propose to use it in a radically different and novel way. Specifically, we exploit the fact that DEA constructs the facets of the so-called efficient frontier by performing linear combinations of efficient DMUs. Provided that such efficient DMUs correspond to different (pure) bio-based materials and that these materials can be physically combined into a sandwich panel [28] or any other commercial standard [13] (e.g., fiber mats), the facets of the efficient frontier can be used to systematically identify composites which are also eco-efficient. With the main purpose of improving the usefulness of the methodology, a filtering step considering manufacturing requirements has also been included to detect composites which are infeasible in practice. The capabilities of the proposed approach are tested by means of a case study where six bio-based materials, with varying thicknesses, are used as the building blocks to generate composite materials.

The remaining of the manuscript is organized as follows. In section 2, we provide a comprehensive description of the proposed methodology, while section 3 presents the case study used to test it. Finally, in section 4, we disclose the results obtained and discuss their practical implications, while drawing the corresponding conclusions in the last section of the manuscript.

2. Methodology

Our systematic approach to generate eco-efficient material combinations merges building simulation, LCA and DEA in a novel unified framework, where DEA lies at its core. In our framework, the starting point is a set of insulation alternatives, each corresponding to a possible combination between n thicknesses and m pure bio-based insulation materials considered (e.g., 20 cm of hemp). Each of these alternatives is modeled as a DMU with associated inputs and outputs that describe the performance of the alternative in different economic and environmental indicators. Note that, here, we do not use DEA in the traditional approach where DMUs are entities consuming inputs (resources) to produce outputs (products or services), but rather as a multicriteria decision-making tool allowing the use of any indicator as input or output [29]. In this context, the conventional choice, also used in this work, is to classify as inputs those indicators that should be minimized, and as outputs those that should be maximized [30].

Bearing this in mind, we proceed to describe briefly our approach, which consists of five different steps (see Figure 1). In this section, we focus on describing an overview of the methodology, while further details on each step are provided in the ensuing subsections.

The first step corresponds to data acquisition (i.e., obtaining the values for inputs and outputs) and is divided in two different sub-steps. In the first one, we simulate a building using the corresponding insulation alternative in order to estimate its energy requirements along the use phase. This step is necessary due to the lack of data about the energy demand of buildings using bio-based materials as thermal insulators. Then, in the second sub-step, we evaluate the total cost and life cycle impact associated with the alternative from a cradle-to-utilization perspective, that is, including extraction, construction and use phases.

Once the values of inputs and outputs have been obtained for each DMU, a dimensionality reduction method is used in the second step of the framework in order to identify potential redundant information between indicators, and ultimately diminish the number of inputs and outputs required to describe each DMU. This is carried out in such a way that redundant categories are eliminated without altering the dominance structure of the solutions. As an example, if the merely removal of a certain indicator would cause any solution to become strictly worse than another, then this indicator will certainly be retained.

In the third step, DEA is performed to systematically identify potential combinations of bio-based materials. To this end, we use a DEA dual model that projects non-efficient solutions onto a given facet of the efficient frontier, thus providing two valuable pieces of information: (i) the materials that could be used to generate an eco-efficient composite (i.e., materials of the alternatives lying at the vertexes of the facet) and (ii) the weights with which they have to be combined to generate the candidate composite.

Some of these candidate composites might be infeasible from a practical point of view, either because they entail too many materials to guarantee proper manufacturing or simply because the selected materials cannot be combined in a single product (e.g., cellulose insulation with fiber materials). Therefore, in step number four, candidate solutions are filtered according to certain rules modelling manufacturing considerations so that only those with practical value are retained for further analyses.

Candidate composites obtained through DEA are deemed eco-efficient assuming linear additive behavior for the performance indicators of the single-materials combined to obtain the composite. The degree of correctness of such hypothesis is validated in the final step of the methodology. To this end, we first proceed analogously as done in step one for original alternatives: composites are simulated in a building model to obtain their associated energy demand and then, this information is used together with lifecycle data to evaluate the cost and the environmental impacts of the alternative from a cradle-to-utilization perspective. With this information at hand, we finally employ DEA again, but this time in its most classical approach, namely, to benchmark the final set of candidate composites against the original eco-efficient single-material options and also against other conventional materials (polyurethane in this case).

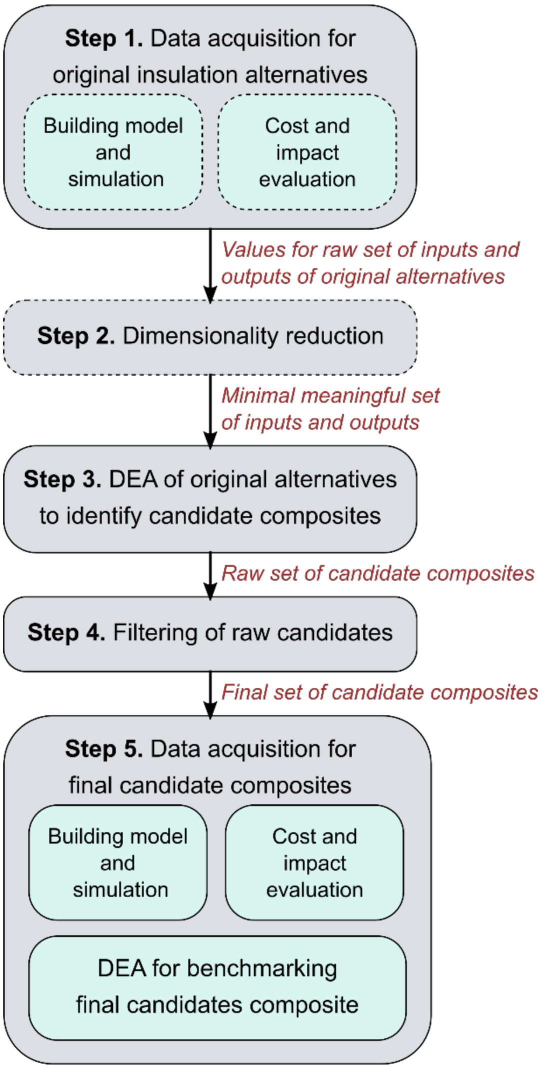

Figure 1: Simplified flow diagram of the proposed model showcasing the key steps (in gray), the sub-steps (in blue) and the optional steps (with dashed line). Products of each step are described in dark red font.

2.1. Model definition, energy simulation and economic and environmental assessment

The initial step in our approach is the acquisition of the data necessary to model each DMU, that is, the value of inputs and outputs of each insulation alternative. In our framework, these correspond to the cost and the environmental impact from cradle-to-utilization, as given by the contribution of two terms: (i) the energy demand of the building during the use phase and (ii) the manufacture of insulation materials.

The former contribution corresponds to the amount of energy required during the whole lifespan of the building to achieve thermal comfort for each alternative, and can be estimated with an energy simulation. This involves the definition of the building structure and bearing materials as well as the operational and climate conditions of the selected siting. In the simulations of the different DMUs, all the parameters remain the same except for the insulation thickness and material, which vary from case to case. With the resulting energy consumption at hand, it is possible to calculate the associated lifecycle cost and environmental impacts assuming local data for energy production. Note that this sub-step could be skipped if these data were readily available in the literature or data repositories.

For the latter contribution, the manufacture of insulation materials, environmental impacts are quantified following LCA with a cradle-to-gate perspective, with the material cost being quantified as an initial investment. The disposal phase is omitted here due to the lack of data.

Note that we only take into account the contribution of the attributes changing from DMU to DMU, while discarding those that are equal for all DMUs (e.g., the materials of the building structure of walls and roof). Further details on the calculations are provided in section 3.4.

2.2. Dimensionality reduction

Ensuring enough discriminatory power in DEA requires following a widely used rule of thumb which relates the number of DMUs assessed with the number of inputs and outputs considered [29]. According to this rule, the number of DMUs should be at least three times larger than the sum of inputs and outputs or than the number of inputs times the number of outputs.

Whilst not mandatory, meeting such criterion may require the implementation of a dimensionality reduction method in order to reduce the number of inputs and outputs, while retaining the essential information unaltered. This analysis can be done in the domain of inputs, outputs or in both, and is particularly useful when dealing with environmental impacts, which many times tend to be correlated [31].

Without loss of generality, we use a dimensionality reduction method based on measuring the delta approximation error [32], that is, the loss of information produced when certain indicators are omitted. This method will result in different indicators retained depending on the error that can be assumed, which gives some room to modelers to shape the methodology at their will. Further information on the specific setup used in this work is given in section 3.5.

It is to be noted that, sometimes, inputs and outputs may differ in orders of magnitude, which can lead to numerical issues when applying dimensionality reduction techniques. In order to avoid these problems, inputs and outputs are normalized between 0 and 1 with the min-max scaling [33] for the dimensionality reduction step. This normalization is only applied in the dimensionality reduction, but not in DEA.

2.3. DEA fundamentals and projections

The proposed framework is underpinned by the DEA methodology, which is used twice along the whole procedure (each time with a different purpose). In step three, DEA is used to systematically obtain promising material combinations (i.e., composites) taking advantage of DEA projections. Later, in step five, DEA is used again, this time to verify the eco-efficiency of the proposed composite alternatives by benchmarking against single-material bio-based alternatives and a conventional insulator.

Conceptually, DEA is a mathematical programming methodology devised to benchmark a set of $|J|$ alternatives (DMUs), each consuming $|I|$ inputs to produce $|R|$ outputs. As previously commented, DEA was designed to assess production units, yet it has been widely implemented in the context of multicriteria decision making [34] to assess the performance of different technologies, systems, products or materials [35][36][37]. DEA assigns an efficiency score (θ) to each benchmarked DMU. Efficient DMUs are those that are not improved by any other DMU in all the inputs and outputs simultaneously. They receive an efficiency score of 1 and are convexly (i.e., linearly) combined to form the so-called efficient frontier. Therefore, in the context of our problem, a DMU (combination of thickness and material) will be deemed inefficient if another one achieves comfort with lower environmental impacts and cost.

On the other hand, inefficient DMUs receive an efficiency score strictly lower than 1, which is inversely proportional to the distance between the DMU and the efficient frontier: the longer the distance between them, the lower the efficiency score. Obtaining these scores requires Indeed, efficiency scores are computed by projecting inefficient units onto the efficient frontier, giving rise to efficient virtual DMUs. These projections are particularly useful since they provide two additional pieces of information. On the one hand, the inputs and outputs of a virtual DMU can be compared to those of the corresponding inefficient DMU to compute improvement targets, i.e., targets that if attained would turn the original DMU into efficient. On the other hand, it also allows to identify the so-called Reference Set (noted here by RS) of the inefficient DMU, which is composed by the efficient DMUs located at the vertexes of the facet of the efficient frontier where the virtual DMU lies. The DMUs at the RS can be used to guide the efforts of the inefficient DMU towards the achievement of its improvement targets.

There are several DEA models available in the literature, differing on the direction used to project DMUs (i.e., the so-called orientation) and the returns to scale considered for building the efficient frontier (i.e., constants *vs* variable), among other features [38]. The selection of the model orientation is particularly key in our approach, since it will drive the projection of inefficient DMUs, and therefore, the materials combinations that we obtain. In this case, we use an input-oriented model, whereby DMUs inputs are proportionally reduced while keeping the outputs constant. Regarding the returns to scale, the model used considers variable returns to scale (VRS). The rationale behind the latter choice is the lack of proportionality between changes in the thickness of the insulation material and the resulting indicators (i.e., impacts and cost). Specifically, we use the radial input-oriented dual model, named BCC model after the original authors (Banker, Charnes and Cooper [38], see Eqs. 1-5). Note, however, that our framework is general enough to accommodate any other DEA formulation.

$$\min \quad \theta_0 - \varepsilon\left(\sum_i s_i^- + \sum_r s_r^+\right) \tag{1}$$

$$\text{s.t.} \quad \sum_j \lambda_j x_{ij} + s_i^- = \theta_0 x_{i0} \qquad \forall i \in I \tag{2}$$

$$\sum_j \lambda_j y_{jr} - s_r^+ = y_{r0} \qquad \forall r \in R \tag{3}$$

$$\sum_j \lambda_j = 1 \tag{4}$$

$$\lambda_j, s_i^-, s_r^+ \geq 0 \qquad \forall i, r, j \tag{5}$$

Here, θ_o is the relative efficiency score of the DMU analyzed, which can vary between 0 and 1, being 1 the maximum possible efficiency (in turn indicating an efficient status) and 0 the minimum one; ε is a non-Archimedean value which forces the strict positivity of the variables; s_i and s_r, correspond to the so-called slacks for inputs and outputs, respectively; and λ_j is the weight assigned to each peer DMU_j in the creation of the virtual DMU.

2.3.1. Composites via DEA projections

In this section we further illustrate the use of DEA in the context of our problem, with particular emphasis on how its projections can be used to derive eco-efficient candidate composites. To this end, we present the following motivating example. Consider six insulation alternatives (DMUs A, B, C, D, E and F), each corresponding to a different combination of thickness (5 or 10 cm) and material (M1, M2 or M3), as given in Table 1. The eco-efficiency of these insulators is to be assessed considering two inputs (i.e., the environmental impact and the cost) and one output (i.e., achieving comfort requirements, modeled as a dummy output of one), whose values are also provided in the table.

Table 1. Data for the motivating example.

			Inputs		Output
DMU	Thickness (cm)	Material	Cost (€)	Impact (points)	Comfort
A	5	M1	1.0	4.0	1.0
B	10	M1	4.0	3.0	1.0
C	5	M2	2.0	4.5	1.0
D	10	M2	2.5	3.0	1.0
E	5	M3	2.0	2.5	1.0
F	10	M3	4.5	2.0	1.0

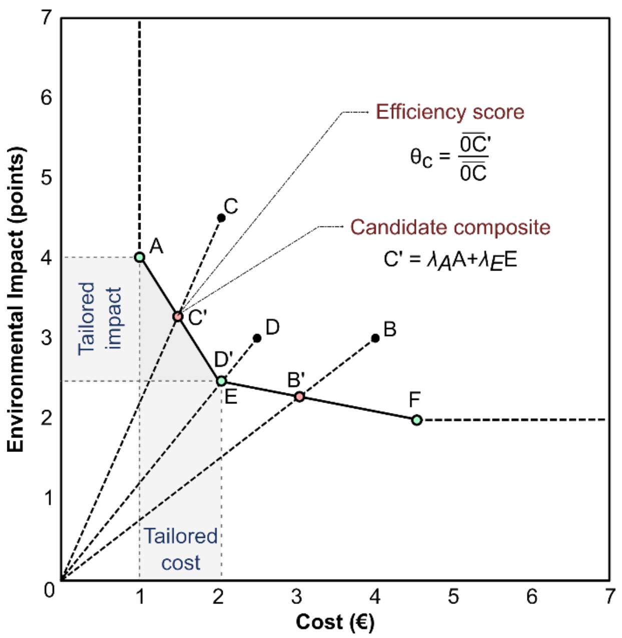

Figure 2: DEA illustrative example for an input-oriented model of two inputs and a dummy output.

In order to address this problem, DEA is applied as shown in Figure 2. Insulation alternatives (i.e., thickness-material combinations) represented by DMUs A, E and F have the lowest input values for the same level of outputs and, for this reason, they are identified as efficient DMUs (identified in the figure with green dots). The line that connects those solutions determines the piecewise linear efficient frontier ($\overline{AEF}$). Contrarily, DMUs B, C and D are inefficient (black dots) because they require higher inputs for the same output, that is, they have to incur a higher cost and/or cause more environmental impact to provide the same comfort level. These second group of DMUs (i.e., the inefficient ones) are projected radially towards the origin (i.e., radial input-oriented projection), as illustrated by the black dashed lines in the figure, giving rise to virtual DMUs B', C' and D' at the intersection with the efficient frontier (see red dots). As illustrated for DMU C in the figure, the efficiency score of inefficient alternatives corresponds to the ratio of the distance from the origin to the virtual DMU (i.e., $\overline{OC'}$) to the distance from the origin to the original inefficient DMU (i.e., $\overline{OC}$).

Additionally, virtual DMUs provide information about the reference set (RS) of each inefficient DMU, that is, which DMUs have to be combined (RS) and in which proportion (λ_j) to form each virtual DMU. In the case of DMU D, the RS is only composed of DMU E, and therefore, this projection does not give any hint on potential composites. The same happens with DMU B, whose RS contains DMUs E and F, both employing insulation material M3. These two examples illustrate why it is necessary to include a filtering step to discard projections that do not lead to a feasible composite. Finally, virtual DMU C' is based on efficient DMUs A and E, which employ insulation materials M1 and M3, respectively. Therefore, virtual DMU C' corresponds indeed to a candidate composite material. From a manufacturing point of view, the amount of materials M1 and M3 that have to be combined to produce C' can be obtained from the corresponding linear coefficients λ_j, which must be applied to the original thicknesses of the alternatives (i.e., λ_j times the original thickness of j). In this particular case, C' will consist of 2.5 cm of M1 (i.e., 0.5 times 5 cm of M1) and 2.5 cm of M3 (i.e., 0.5 times 5 cm of M3). In mathematical terms, the total thickness of the insulation composite ($Thickness^{COMP}$) is given by Eq. (6), while the share of each material *ins* that must be included in the composite ($Share_{ins}^{COMP}$) is computed *via* Eq. (7):

$$Thickness^{COMP} = \sum_j \left(\lambda_j Thickness_j\right) \tag{6}$$

$$Share_{ins}^{COMP} = \frac{\lambda_j Thickness_j}{Thickness^{COMP}} \quad \forall j | \lambda_j > 0, ins \in MAT_j \tag{7}$$

where $Thickness_j$ is the insulation thickness of alternative j and MAT_j is the set providing the insulation material *ins* in DMU j (note that this set contains one element only since DMUs are single material alternatives). Individual material shares from Eq. (7) are obtained on a thickness basis, which is very convenient for the preparation of sandwich panels since manufacturing depends directly on these data. The only exception is the support material of sandwich panels, for which the thickness value obtained from Eq. (7) must be divided by two to obtain ready-to-use information. Then, in the case of fiber mats, weight fractions (rather than thickness fractions) might be required; these are easily computed from thicknesses and the apparent densities of the corresponding individual materials.

Furthermore, there is an additional observation, with practical implications, that can be exploited to generate new materials with tailored performance: any linear combination of the DMUs in a RS necessarily lies on the efficient frontier and is therefore efficient. In essence, this means that it is not strictly necessary to combine alternatives in a RS using the linear weights provided by DEA solution (noted by λ_j*), but rather that these materials can be combined in any proportion to obtain composites with specific values of inputs and outputs within the boundaries defined by the vertexes of the corresponding facet (see gray shadowed regions in Figure 2). Following with the example of C', it is possible to obtain a composite with lower cost but higher environmental impact by increasing the amount of M1 (i.e., larger λ_A), or a composite with lower impact yet higher cost by resorting to more M3 (i.e., larger λ_E). In any case can the cost of the composite be lower than 1 € or the environmental impact lower than 2.5 points, as these limits are dictated by the single-materials are the vertexes of the facet $\overline{AE}$. At the same time, it is not possible to obtain a composite with the lowest cost and impact simultaneously since cost-impact pairs are given by the feasible values of λ_j, which need to add up to 1 (i.e., there is only one degree of freedom in this two-dimensional case). This is illustrated in Eq. (8) for any performance indicator p:

$$Indicator_p^{COMP} = \sum_j \left(\lambda_j Indicator_{j,p}\right) \quad \forall p \tag{8}$$

where $Indicator_{j,p}$ is the value of performance indicator p (input or output) of insulation alternative j and $Indicator_p^{COMP}$ is the resulting performance of the composite in the same indicator. This estimation of expected performance assumes a linear behavior for the combination of materials, which might not hold for some indicators (e.g., thermal resistances are not linearly additive), making it necessary to resort to a validation step later in the overall methodology (see section 2.5).

Finally, it is to be noted that the identification of efficient DMUs is not enough to obtain efficient candidate composites. For instance, DMUs A and F are both efficient and employ different materials (M1 *vs* M3), however, their combination (segment $\overline{AF}$) would be inefficient assuming linear additive performance. In conclusion, DEA projections can be used to systematically obtain combinations of materials which do have the potential to be eco-efficient as well as a range of available combinations for the manufacturer to choose from in order to customize the material performance to within some boundaries.

2.4. Filters

As aforementioned, not all virtual DMUs qualify to be manufactured into real final products, which calls for the use of a filtering step with a set of rules in order to discard solutions with no practical application. Some of these filtering rules might be useful for all cases, yet others might depend on the particular application addressed or simply reflect the manufacturer's preferences. Even in the case of rules with wide applicability, there might be some aspects of the rule that have to be specifically setup for each particular case study. These aspects will be discussed later in the article in the context of the case study (see section 3.6), while in this section only the most general rules will be addressed.

There are mainly two rules with very wide applicability in the generation of composites. The first aims to exclude combinations of alternatives made of the same material, regardless of their potential different thicknesses (recall DMUs B' and D' in Figure 2), while the second involves discarding solutions entailing too many materials since this has the potential to hinder the manufacturing process. The threshold for what can be considered "a reasonable number of different materials" is a modeler's choice and will, again, depend on the particular application and manufacturing process addressed. However, it is important to note that, even when the candidate composite satisfies such threshold regarding the number of materials, it might still be impossible to combine these materials into a single product due to their different nature. As an example, cellulose, which is one of the most common bio-based materials, is usually implemented by blowing it up into the walls or filling air gaps, making it impossible to combine it in an insulating mat or a sandwich panel [39].

2.5. Validation

The final step of the methodology consists of a verification of the performance of the proposed composites. As illustrated through Eq. (8), the inputs and outputs of a virtual DMU are obtained in DEA as a convex combination of the inputs and outputs of the DMUs at the RS, which might give rise to a spurious performance. This is because nonlinear behavior is expected between some properties such as the thickness of the insulation material and the energy requirements, which could in turn affect the cost and impact associated with the use phase of the building.

In order to guarantee that this approximation does not hamper the usefulness of the methodology, we simulate the candidate alternatives obtained using DEA by introducing the corresponding layers of materials (i.e., those obtained with Eqs. (6-7)) in the energy simulation model and obtain the "real" (*in silico*) values for the different inputs and outputs, analogously as done in step one of the methodology for single-material alternatives.

Once the consistency of the solutions in terms of inputs and outputs has been verified, DEA is applied a second time, comparing the real performance of the candidate composites with that of efficient single-material alternatives.

3. Case study

In this contribution, six bio-based building insulation materials (wool, wood, cork, corn, hemp and cotton) are considered as candidates for combination in sandwich panels and insulation mats, with the ultimate aim of facilitating the penetration of these materials in the insulation market. Each of these materials is available in six different thicknesses screening the range between 1 and 26 cm with increments of 5 cm. This generates a total of 36 bio-based insulation alternatives, each modelled as a DMU for the initial DEA.

Additionally, the performance of the bio-based insulators in terms of the total environmental impact and cost will be compared against a conventional insulation material (polyurethane, PU), available also in the same six different thicknesses. This makes a total of 42 DMUs entailing 7 materials and 6 thicknesses for each of them.

Without loss of generality, we assume these alternatives are implemented in a cubicle with the bearing structure described in section 3.2. We use this cubicle because its corresponding thermal simulation has already been validated in a testing site of the University of Lleida with experimental data [40], yet any other building structure could be used in our framework.

3.1. DMU definition

As explained, we model each insulation alternative as a DMU whose eco-efficiency is assessed according to a series of indicators, classified as either inputs or outputs. For the environmental performance, we use as indicators the 18 midpoint categories of the ReCiPe methodology [41]. Among them, some categories (e.g., metal depletion) assess the use of resources (e.g., kg Fe-eq) and, therefore, are modeled as inputs of the DMU. Conversely, other categories such as climate change (GWP) or freshwater eutrophication (FE) quantify the generation of pollutants (i.e., CO_2-eq and kg P-eq), and should, in principle, be considered undesirable outputs in DEA (i.e., they are outputs of the production process but are not desired [30,42]). Despite this, here we follow the approach by Korhonen and Luptacik [43]) according to which undesirable outputs can be modeled as inputs in a benchmarking problem, so that all the 18 midpoints indicators are finally classified as inputs. Meanwhile, the economic performance of the DMU is assessed *via* the total cost, which is also another input of the DMU. This yields a total of 19 inputs: agricultural land occupation, ALO (m^2a); climate change, GWP (CO_2-Eq); fossil depletion, FD (kg oil-eq), freshwater ecotoxicity, FET (kg 1,4-DCB-eq), freshwater eutrophication, FE (kg P-eq), human toxicity HT (kg 1,4-DCB-eq), ionizing radiation, IR (kg U_{235}-eq), marine ecotoxicity, MET (kg 1,4-DCB-eq), marine eutrophication, ME (kg N-eq), metal depletion, MD (kg Fe-eq), natural land transformation, NLT (m^2), ozone depletion, OD (kg CFC-11-eq), particulate matter formation, PMF (kg PM_{10}-eq), photochemical oxidant formation, POF (kg NMVOC), terrestrial acidification, TA (kg SO_2-eq), terrestrial ecotoxicity, TET (kg 1,4-DCB-eq), urban land occupation, ULO (m^2a), water depletion, WD (m^3) , and total cost (€), respectively.

Standard DEA requires DMUs to have both inputs and outputs, yet so far only inputs have been selected for our DMUs. To amend this, we follow a widely extended practice in DEA [27], which consists in including one dummy output in the analysis. This dummy output can be understood as the fulfillment of certain conditions; in our case, the thermal requirements of the building as given by a fixed temperature limit during the year. This comfort requirement is imposed in all the simulations and for this reason, all the modeled DMUs (both original pure materials and candidate composites analyzed later) achieve a value of 1 for the dummy output, resulting in a total of 19 inputs and 1 output per DMU. Note that the framework is general enough to accommodate other indicators, including any (non-dummy) output, if required.

3.2. Building description

The capabilities of our framework are illustrated through a case study considering the insulation of experimental cubicles of the University of Lleida, located in a testing site in Puigverd de Lleida, Spain. The envelope of this cubicle has an external volume of 2.44×2.55×2.44 m, with one 0.2×1.2 m window in the south facade, and a wall/window ratio of 6. The structural materials used have a conventional Mediterranean profile, given by a plaster layer (1 cm), 14 cm thick perforated bricks, an air gap of 5 cm, and a finishing layer of hollow bricks (7 cm) rendered with 1 cm of cement mortar. The roof consists (from inside to outside) of a plaster finishing (1 cm), a concrete beam and pot floor of 5 cm, a lightweight concrete layer in the form of slopes (3%), and a double asphaltic membrane for waterproofing. The foundations consist of a reinforced concrete slab of 3×3 m and 21 cm thickness. Insulation is then placed inside the air chamber as shown in the scheme of the construction in Figure 3.

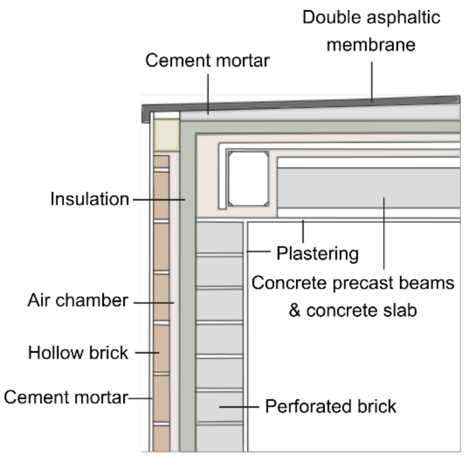

Figure 3: Construction profile of the experimental cubicles of the University of Lleida (adapted from [9]).

3.3. Specifications of the energy model

The development of the energy model of the cubicle requires the combination of three different types of software: (i) a 3D modeling software, (ii) a modeling tool for providing building information and (iii) a thermal simulation engine. The initial step is carried out in SketchUp [44], which is used to provide dimensional information for the building envelope. Within this software environment, the building consists of a set of walls and the roof, which might have windows, but no thickness or structural information.

Then, OpenStudio [45], which is a SketchUp plugin, enables the introduction of additional information into the initial sketch: walls and roof thicknesses, construction materials, internal human occupation, use of appliances and daily schedules for their use and occupation. This model is built to replicate the characteristics (i.e., dimensions and materials) of the experimental cubicle described in the previous section, as well as the climate conditions of BSk – Koppen climate, and has been validated in a previous work for some insulation materials [11]. Note, however, that a different model, based on any other construction profile, could be used without compromising the methodology proposed.

Finally, all this information is sent to EnergyPlus [46], which is used as the engine to run the thermal simulation. EnergyPlus includes the set of equations describing the energy balances of the building, taking into account climate conditions as well as heat and mass transfer balances, and provides the heating and cooling requirements of the building. These requirements are then translated into the corresponding electricity demand assuming a reversible heat pump with a COP of 3. This electricity demand, together with the materials stock used in the building, are used later to evaluate the economic and environmental impact of the different alternatives.

The second and third tasks have to be repeated for all 42 insulation alternatives (and later candidate composites), generating and simulating models which are identical in all aspects except for the insulation material and thickness. This process can be automated *via* a fourth software, jEPlus [47], which is a parametric tool that can read EnergyPlus input files and generate modified replicates (m materials in a range of n thicknesses, including a predefined minimum and maximum thicknesses and steps) to be inputted into the simulation engine. The whole process is illustrated in Figure 4.

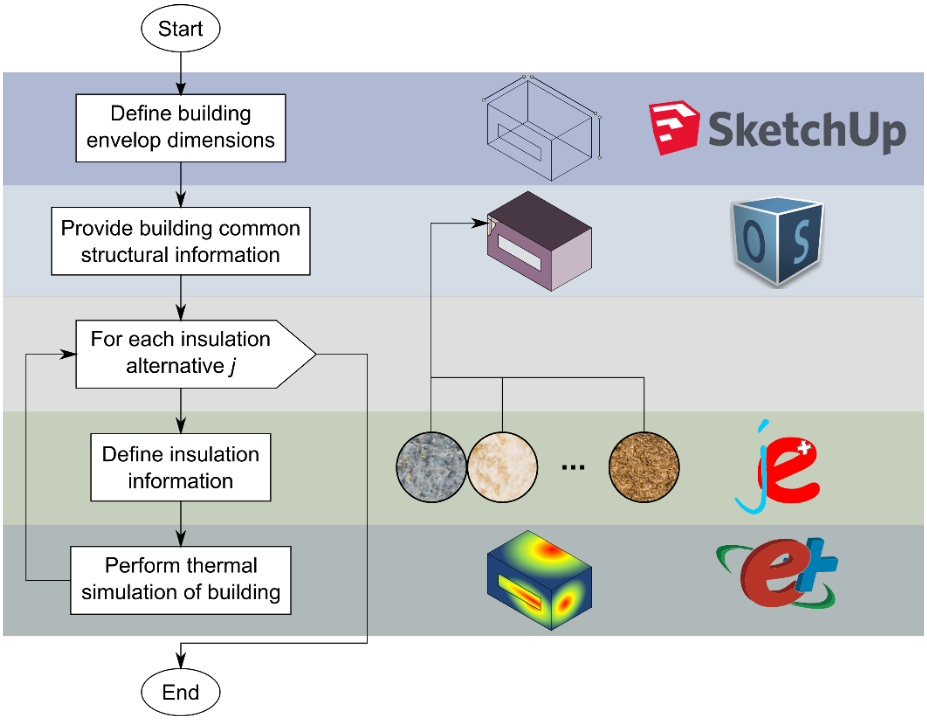

Figure 4: Flow diagram of the proposed methodology and the different software combined to produce de DMU set.

Data for the physical and thermal properties of the construction materials are retrieved from the Spanish Building Code (CTE) [48], ITeC [49], the commercial product suppliers [50–52] or experimental data [53]. These data are presented in Table 2, along with the price used for the cost calculation. Recall that, since structural materials are the same for all the alternatives, their cost and environmental impacts are omitted from the assessment and therefore, from Table 2 as well.

Table 2. Building characteristics of the model and their cost.

	Density (kg/m^3)	Thermal conductivity (W/m·K)	Specific heat (J/kg·K)	Thermal diffusivity (10^{-6} m^2/s)	Market price (€/kg)
CONSTRUCTION					
Plaster	1150	0.570	1000	-	-
Perforated brick	900	0.543	1000	-	-
Hollow brick	930	0.375	1000	-	-
Cement mortar	1350	0.700	1000	-	-
Asphaltic membrane	2100	0.700	1000	-	-
Concrete	2100	0.472	1000	-	-

Steel bars	2100	0.472	1000	-	-
Concrete tiles	1920	0.890	790	-	-
INSULATION					
Cotton	25	0.036	1800	0.80	1.024
Cellulose	45	0.035	1900	0.41	1.071
Cork	110	0.040	1700	0.21	0.909
Corn	50	0.038	1800	0.42	1.100
Hemp	30	0.041	1800	0.76	1.360
Wool	30	0.045	1800	0.83	0.947
Wood	250	0.050	1850	0.11	1.172
Polyurethane	45	0.027	1000	0.60	3.889

3.4. Assessment of inputs and outputs

The 19 inputs (one economic plus 18 environmental) are quantified following a life cycle perspective (from cradle-to-utilization), where only the elements varying from DMU to DMU are considered (i.e., insulation material and energy consumption). Therefore, the cost and impact associated to the rest of the building walls, roof and foundation are omitted; this is a usual procedure in comparative LCA studies [54].

For this research, a dummy output of 1 is used. This output represents the capacity of each alternative to maintain the building with a scheduled set point for winter and summer. The conditions selected corresponds to 20ºC during the heating season and 26ºC during the cooling season, based on the requirements of the ISO 7730 and considering a metabolic activity corresponding to an individual office. This results in a given energy consumption that is used in the calculation of the inputs.

The total cost of each DMU j results from two contributions: the cost of the insulation material (a one-time investment) plus the cost of the electricity consumed during the whole use phase of the building (Eq. (9)). The former is obtained from the amount of insulation material (i.e., kg) and its unitary cost (i.e., €/ kg), and is supposed to be invested during the first year of the building life. Unitary costs for conventional materials have been retrieved from the ITeC database (*i.e.*, polyurethane), whereas those for bio-based materials have been gathered from the corresponding suppliers (see Table 2). On the other hand, the electricity cost is given from the annual electricity demand obtained in the corresponding simulation and the unitary cost of electricity, which assumes a i = 5% increment during lifetime.

$$Cost_j^{TOT} = Mass_{ins,j} Cost_{ins}^{MAT} + \sum_k Elec_j Cost^{ELE} (1+i)^k \qquad \forall j, ins \in MAT_j \qquad (9)$$

Here, $Cost_j^{TOT}$ is the total cost DMU j (€), $Mass_{ins,j}$ is the amount (kg) of insulation material *ins* (e.g., cork) in insulation alternative j (as defined in set MAT_j), $Cost_{ins}^{MAT}$ is the unitary cost of insulation material *ins* (€/kg), k corresponds to each year in the lifespan of the building, $Elec_j$ is the amount of electricity required by insulation alternative j to achieve the thermal comfort of the building (kWh), $Cost^{ELE}$ is the unitary cost of electricity (in Spain, in this case) (€/kWh) and i is the annual increment of the electricity cost.

Similarly, the environmental impact for the 18 different categories of the ReCiPe indicator is quantified for all the insulation alternatives taking into account the contribution of the insulation materials and the electricity from the reversible heat pump (Eq. (10)). Unitary impacts for all materials and electricity have been retrieved from Ecoinvent database version 3.4 (2017), using the entries listed in Table 3 (note that the impact of electricity has been evaluated assuming Spanish mix).

Table 3. Unitary impacts of the insulation materials an electricity.

	ALO (m^2a)	GWP (CO_2-eq)	FD (kg oil-eq)	FET (kg 1,4-DCB-eq)	FE (kg P-eq)	HT (kg 1,4-DCB-eq)	IR (kg U_{235}-eq)	MET (kg 1,4-DCB-eq)	ME (kg N-eq)	MD (kg Fe-eq)	NLT (m^2)	OD (kg CFC-11-eq)	PMF (kg PM_{10}-eq)	POF (kg NMVOC)	TA (kg SO_2-eq)	TET (kg 1,4-DCB-eq)	ULO (m^2a)	WD (m^3)
Market for slab and siding, hardwood, wet, measured as dry mass [GLO] (kg)	0.713	0.02	0.007	$2\cdot10^{-5}$	$6\cdot10^{-7}$	0.003	0.001	$4\cdot10^{-5}$	$5\cdot10^{-6}$	0.001	$9\cdot10^{-6}$	$3\cdot10^{-9}$	$5\cdot10^{-5}$	$2\cdot10^{-4}$	$9\cdot10^{-5}$	$2\cdot10^{-5}$	0.016	$6\cdot10^{-5}$
Market for sheep fleece in the grease [GLO] (kg)	82.25	34.55	1.18	0.567	0.009	0.718	0.164	0.045	0.155	0.467	0.001	$4\cdot10^{-7}$	0.12	0.041	0.791	0.11	0.656	1.263
Market for kenaf fibre [GLO] (kg)	1.725	0.781	0.135	0.026	$3\cdot10^{-4}$	0.032	0.017	0.002	0.003	0.041	$8\cdot10^{-5}$	$4\cdot10^{-8}$	0.002	0.003	0.012	$2\cdot10^{-4}$	0.011	0.505
Market for maize silage, organic [GLO] (kg)	0.225	0.054	0.008	$6\cdot10^{-4}$	$1\cdot10^{-5}$	-0.01	0.002	$9\cdot10^{-5}$	0.001	0.004	$7\cdot10^{-6}$	$3\cdot10^{-9}$	$3\cdot10^{-4}$	$2\cdot10^{-4}$	0.002	$-3\cdot10^{-5}$	0.001	0.009
Market for cork slab [GLO] (kg)	16.81	1.771	0.549	0.002	$1\cdot10^{-4}$	0.221	0.079	0.002	$3\cdot10^{-4}$	0.052	$3\cdot10^{-4}$	$1\cdot10^{-7}$	0.004	0.006	0.009	$2\cdot10^{-4}$	0.02	0.005
Market for cotton fibre [GLO] (kg)	8.509	3.175	0.757	0.037	$6\cdot10^{-4}$	0.463	0.124	0.006	0.014	0.181	$4\cdot10^{-4}$	$3\cdot10^{-7}$	0.01	0.013	0.031	0.197	0.05	1.989
Market for polyurethane, rigid foam [GLO] (kg)	0.21	5.775	2.447	0.027	$5\cdot10^{-4}$	2.032	0.265	0.021	0.006	0.339	$7\cdot10^{-4}$	$1\cdot10^{-6}$	0.012	0.026	0.028	0.002	0.041	0.03

Market for electricity, low voltage [ES] (kWh)	0.026	0.353	0.096	$1\cdot10^{-4}$	$3\cdot10^{-5}$	0.039	0.081	$3\cdot10^{-4}$	$6\cdot10^{-5}$	0.015	$5\cdot10^{-5}$	$5\cdot10^{-8}$	$9\cdot10^{-4}$	0.001	0.003	$2\cdot10^{-5}$	0.003	0.002

$$Imp_{cat,j}^{TOT} = Mass_{ins,j} Imp_{ins,cat}^{MAT} + \sum_k Elec_j Imp_{cat}^{ELE} \qquad \forall cat, j, ins \in MAT_j \qquad (10)$$

Here, Imp_{cat}^{TOT} is the total impact of DMU j in ReCiPe category cat (e.g., impact in agricultural land occupation) (in category-dependent units), $Mass_{ins,j}$ (kg) is the amount of insulation material ins in DMU j as given by set MAT_j, $Imp_{ins,cat}^{MAT}$ represents the unitary impact of insulation material ins in ReCiPe category cat (category-dependent units/kg), k denotes each year in the lifespan of the building, $Elec_j$ is the amount of kWh required to achieve the thermal comfort of the building (kWh) and Imp_{cat}^{ELE} is the unitary impact of electricity in Spain for ReCiPe category cat (category-dependent units/kWh).

3.5. Dimensionality reduction

At this point, the case study consists of a total of 42 DMUs with 19 inputs and one output each. As explained in section 2.2 [38], these figures suggest the necessity to resort to a dimensionality reduction technique in order detect redundant inputs and ensure the discriminatory capabilities of DEA. These methods allow to reduce the number of indicators in multidimensional problems (inputs and outputs in our case) without altering the dominance structure of the alternatives, which is crucial to maintain the dichotomic classification between efficient and inefficient alternatives in DEA (see [55] for the similarities between DEA and Pareto-Koopmans efficiency concepts [56]).

It is advised to carry out this procedure using normalized data in order to avoid numerical issues due to differences in the order of magnitude of input and output values, which ultimately stem from their distinct nature. Without loss of generality, in this contribution, inputs and outputs are normalized using min-max scaling.

Once data is normalized, we apply a dimensionality reduction method based on the calculation of the so-called delta error [32], which has been previously used to identify redundant metrics in sustainability optimization [57], yet the proposed framework is flexible enough to accommodate other dimensionality reduction methods. The method is applied only to inputs, therefore yielding the smallest subset of inputs necessary to keep unaltered the later classification of alternatives between efficient and inefficient. Whilst this step is not mandatory, it simplifies the analysis and increases DEA's discriminatory power.

3.6. Filtration of the systematic combinations

Despite the fact that all the candidate composites suggested in DEA are in principle eco-efficient, there is no guarantee that all of them will be applicable in practice due to technological limitations in combining the corresponding materials. Therefore, filtering rules will depend on the materials assessed and might vary from case to case. In this case study, the following rules are applied:

1. A minimum of 2 different materials needs to be combined.
2. A maximum of 3 different materials can be combined.
3. Composites require layers of a minimum of 1cm of each individual material.
4. A minimum of 5% difference from a reference single-material alternative is necessary.
5. For the manufacture of fiber mats, only long flexible fibers can be combined; in this case these are wool, cotton or hemp.
6. The manufacture of sandwich panels must involve two different kinds of materials: on the one hand, densely packed short fibers or aggregates like corn, wood and cork, and, on the other hand, long fibers like wool, cotton or hemp.
7. For the manufacture of rigid panels, two or three materials like corn, wood and cork must be combined.
8. PU is only used for comparison; composites must be formed by bio-based materials only.

Here, the first rule ensures that a hybrid material is obtained, while the remaining rules aim at ensuring a feasible manufacturing process, firstly by keeping the number of different materials low (second rule), simplifying the manufacturing process by excluding combinations that differ little from a single-layered materials or have thin layers (rules third and fourth) and then by limiting the combinations of materials taking into account the properties of the resulting products (rules fifth to eighth). Note that, while the threshold for the second and fourth rules could be altered at will by the modeler, the remaining rules might have practical implications in the manufacturing process of the composite material. If different materials and/or performance indicators were considered, further filtering rules could be included (i.e., ensuring a flame retardant layer, mechanical resistance, acoustic insulation [58] or a vapor barrier).

The above depicted filtration plays a key role in the methodology, ensuring the practical feasibility of the materials proposed. It helps to discard combinations that would not be feasible in an applied context, as resulting products would not be competitive in the market due to higher manufacturing effort or to the fact that resulting products would not be suitable for the conditions of application. The proposed filters could be completed by a subsequent step evaluating the performance of suggested composites using *in vitro* tests.

4. Results and discussion

In this section, we discuss the results obtained by applying the proposed methodology to the case study described in section 3.

4.1. Inputs and outputs assessment

Results for the 18 life cycle impacts and cost (inputs and outputs) corresponding to each of the 42 insulation alternatives, as well as their energy consumption, are shown in the supplementary material. Additionally, the first two pieces of information are depicted here in a Parallel Coordinates Plot, PCP, (Figure 5), where each input has been normalized across the different DMUs to a range between 0 and 1.

This plot allows to identify the existence of non-conflicting indicators and, therefore, spot opportunities for dimensionality reduction techniques that simplify the subsequent analyses. In a PCP, these conflicts are identified through the intersections of the polylines:

if there are no intersections between a subset of indicators, or if intersections are repetitive, these indicators are said to be non-conflicting or harmonic. This means they provide redundant information and thus, some of them can be excluded from further analyses. As an example, let us turn our attention to the four inputs in the shadowed region of Figure 5 (GWP, climate change; FE, freshwater eutrophication; FET, terrestrial ecotoxicity; and ME, metal depletion). The behavior of all the DMUs is similar across this region, with some of the polylines being parallel and others intersecting with each other, but both trends being maintained along these four inputs. This suggests that it might suffice to retain a subset of these inputs in order to explain existing discrepancies among the four of them. Similar patterns are also observed in other regions of the figure (e.g., between objectives PMF and TA), showing a plethora of opportunities for dimensionality reduction.

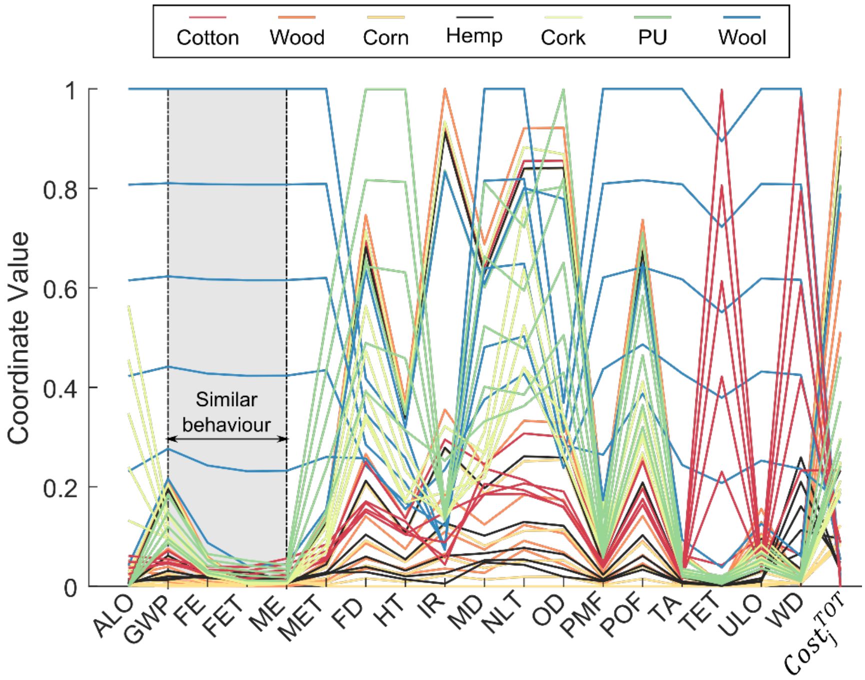

Figure 5: PCP of the normalized inputs for all the DMUs. For each of the seven materials, six different polylines appear, each corresponding to a different thickness (from 1 to 26 cm, with a 5 cm step).

In conclusion, it is expected that a high amount of inputs, such as GWP (climate change), FE (freshwater eutrophication), ME (metal depletion), FD (fossil depletion), NLT (natural land transformation) will be reduced, while others showing more conflicts, as is the case of ALO (agricultural land transformation) or the $Cost_j^{TOT}$, will probably remain after the objective reduction.

4.2. Dimensionality reduction

The dimensionality reduction method described in section 3.5 is applied imposing an accepted delta error of 0%. This means that inputs are only eliminated if this causes no information to be lost. Results reveal that only six inputs are required in order to maintain the dominance structure of the problem, and that these six inputs are unique (i.e., there are no other combinations of six inputs producing the same result). Retained inputs are ALO (agricultural land occupation), FET (fresh water ecotoxicity), IR (ionizing radiation), MD (metal depletion), TET (terrestrial ecotoxicity) and $Cost_j^{TOT}$. Their values for the 42 DMUs are represented in a heatmap in Figure 6. These are the data that will be used in the following steps of the methodology.

	Thickness (cm)	ALO (m^2a)	FET (kg 1,4-DCB-eq)	IR (kg 1,4-DCB-eq)	MD (kg Fe-eq)	TET (kg 1,4-DCB-eq)	$Cost_j^{TOT}$ (€)
Cotton	1	240	1.01	559.7	105.1	1.57	2634
	6	442	1.92	239.0	51.2	8.563	1142
	11	723	3.15	164.2	43.0	15.62	807
	16	1018	4.44	133.3	42.9	22.7	678
	21	1318	5.76	118.2	45.8	29.77	622
	26	1621	7.08	110.5	50.1	36.85	602
Wood	1	243	0.79	598.8	111.3	0.166	2899
	6	394	0.36	269.0	50.3	0.082	1768
	11	622	0.25	181.7	34.4	0.064	1777
	16	866	0.21	143.1	27.5	0.06	2016
	21	1116	0.19	120.6	23.6	0.06	2330
	26	1367	0.17	105.5	21.1	0.063	2679
Corn	1	180	0.74	554.1	103.0	0.152	2620
	6	92.7	0.36	229.2	42.9	0.061	1172
	11	83.9	0.30	151.0	28.6	0.037	883
	16	89.1	0.30	116.8	22.5	0.026	801
	21	99.4	0.32	98.4	19.3	0.019	793
	26	112	0.36	87.2	17.5	0.014	819
Hemp	1	190	0.92	554.2	103.2	0.154	2614
	6	151	1.46	229.8	44.4	0.074	1138
	11	190	2.32	152.1	31.4	0.061	820
	16	244	3.24	118.4	26.5	0.061	710
	21	303	4.18	100.6	24.6	0.065	674
	26	363	5.13	89.9	24.0	0.071	672
Cork	1	713	0.80	565.2	106.2	0.162	2673
	6	3271	0.65	250.6	53.6	0.109	1280
	11	5908	0.82	182.8	47.0	0.124	1046
	16	8560	1.06	160.8	48.8	0.151	1028
	21	11217	1.32	154.7	53.6	0.183	1085
	26	13876	1.58	155.2	59.6	0.217	1172
Wool	1	1111	7.21	513.5	100.4	1.408	2416
	6	5748	39.4	207.4	68.7	7.658	987
	11	10463	72.0	149.4	83.1	13.98	724
	16	15192	104.6	130.3	104.7	20.31	645
	21	19924	137.3	124.6	128.7	26.64	628
	26	24659	169.9	124.9	153.9	32.97	639
PU	1	166	1.02	515.1	99.5	0.17	2456
	6	79.1	2.35	216.9	62.8	0.232	1225
	11	71.1	4.01	166.7	72.3	0.363	1161
	16	75.5	5.71	155.3	89.0	0.504	1278
	21	84.2	7.43	157.0	108.1	0.648	1457
	26	94.7	9.17	164.6	128.3	0.795	1665

Figure 6. Heatmap with retained input values for each DMU. Higher values are represented in red while lower values are depicted in green.

A preliminary analysis of the data shows that wool has the highest environmental impact in ALO (agricultural land transformation) due to the high feed crop area required by sheeps [59], followed by cork owing to the amount of land necessary to grow cork oaks, from which cork can only be extracted every 10 years approximately. On the other hand, hemp, corn and PU have a much lower impact in this category, with the former two being high-yielding, fast-growing crops, and the latter being obtained from fossil fuels. It is noticeable that thinner layers of insulation result in high IR (ionizing radiation). This is because the thinner the insulation material, the more energy is required to maintain the comfort within the dwelling and therefore, the higher the contribution of the electricity mix on the total impact of that alternative. In the case of Spain, where the share of nuclear energy is approximately 20% of the total mix, this results in a noticeable increase in the ionizing radiation [60]. Similarly, cost is also high in all the alternatives involving thin layers of insulation as a result of the electricity cost in the Spanish retail market (0.23€/MWh, 15% higher than the average in the EU in 2016 [61]). In cork and PU, the high cost of the material carries more weight, which explains the increase of cost with thickness.

In brief, hemp and wood have the lowest environmental impacts, while cork and cotton present larger burdens due to their manufacturing processes [62] and the amount of pesticides and water used to farm [63]. The worst environmental impacts in most the categories correspond to wool as a result of livestock farming and wool treatment during manufacturing, causing severe impacts on soil salinity and erosion, as well as a high amount of greenhouse gases [64]. Regardless of the material, all the combinations between 1 and 6 cm thick, show high $Cost_j^{TOT}$ and IR (ionizing radiation) due to the amount of electricity needed for heating and cooling the building.

4.3. Initial DEA results: efficiency assessment

At this point, DEA is applied to the 42 DMUs considering the reduced set of inputs in order to identify efficient alternatives and candidate composites. Efficiency scores are presented in Figure 7, where efficient solutions show a score of 1 and have their thickness is depicted in green. Results reveal that 12 out of 42 insulation alternatives are efficient, with 11 of them involving bio-materials and one PU. This means that some bio-based alternatives show a performance at least as good as that of PU and even better if any non-optimal thickness of insulation of the later is used (i.e., different from 11 cm). This result is in agreement with previous observations by Torres-Rivas et al.[11].

The alternative entailing 11 cm of PU is efficient mainly because it shows the lowest impact in ALO (agricultural land occupation). In the case of bio-based alternatives, optimal thickness range 21 to 26 cm since energy savings surpass impacts and costs incurred during material manufacturing. Exceptions to this rule are corn, which become efficient from 11 cm onwards (due to its low environmental impact and the reuse of a by-product [65]), and wood, which is efficient starting at 16 cm (mainly owing to its low impact in FET (freshwater ecotoxicity)). As expected for the climate chosen for the case study (BSk - Koppen classification, with a temperature range between 1 and 12 ºC on average in the coldest month, and between 19 and 33 ºC in the warmest), insulation layers below 10 cm are never efficient regardless of the insulation material employed, which advocates for using thicker insulation layers in such cold climates.

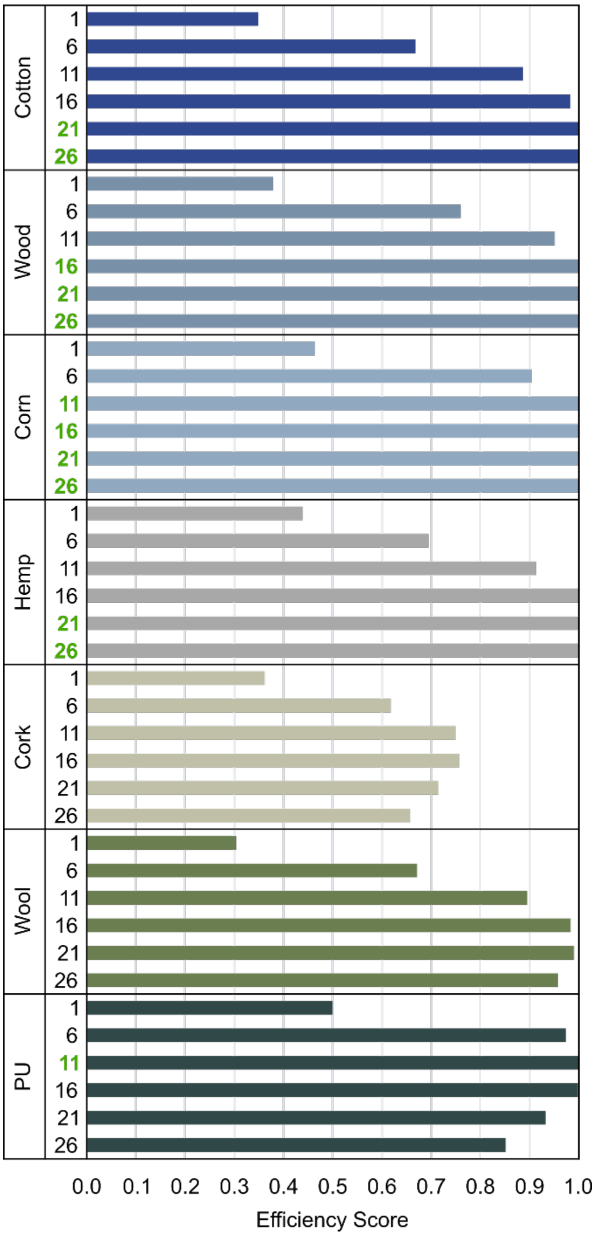

Figure 7: DEA efficiency scores. The numbers beside the materials provide the thicknesses of the insulation layers, with green labels indicating an efficient alternative.

The 30 inefficient alternatives include all the alternatives involving cork and wool. This is because these two materials never achieve the best performance in any input, being always inferior to other alternatives. Despite this, wool is close to achieving an efficient status with layers of 16 and 21 cm, due to their low cost. Conversely, cork is always far from being efficient despite having lower values than wool in most of the inputs. In a traditional DEA, one would now analyze the reason of the inferior performance of inefficient alternatives in an attempt to spot opportunities for improvement. However, in the proposed framework, we use these alternatives as a source for potential candidate composites, as described in the next section.

4.4. Identification of potentially efficient composites

Inefficient DMUs were projected onto the efficient frontier, giving rise to virtual DMUs with the potential to become feasible building products (fiber mats, sandwich panels or rigid panels). Results from these projections are shown in Figure 8, where each row corresponds to an inefficient solution being projected to produce the corresponding virtual DMU and inner cells provide the information about the resulting candidate composite. Specifically, the contribution of each single-material alternative (i.e., material and thickness) being part of the composite is indicated by the columns. As an example, when the first inefficient DMU (1 cm of cotton) was projected onto the efficient frontier, the resulting virtual DMU was obtained by combining 11 cm of corn with 11 cm of PU, with relative weights of 98.7%-1.3%, respectively.

		Composite ingredients													
Inefficient DMUs		Cotton		Wood			Corn				Hemp		PU	Filter	ID#
		21	26	16	21	26	11	16	21	26	21	26	11		
Cotton	1						0.987						0.013	4 8	
	6	0.156							0.816		0.028			3	
	11	0.441							0.540		0.018			3	
	16	0.738							0.253		0.009			3	
Wood	1			0.010			0.990							3 4	
	6			0.275			0.725								A
	11			0.649			0.351								B
Corn	1						0.988						0.012	4 8	
	6						0.994						0.006	4 8	
Hemp	1						0.972						0.028	4 8	
	6								0.974		0.026			3 4	
	11								0.634		0.366				C
	16								0.291		0.709				D
Cork	1			0.137				0.863							E
	6	0.002							0.981		0.018			3 4	
	11	0.002							0.925		0.073			3	
	16	0.003							0.877		0.120			3	
	21	0.004							0.842		0.155			3	
	26	0.004							0.816		0.181			3	
Wool	1	0.013							0.520		0.467			3	
	6		0.138									0.862			F
	11		0.338									0.662			G
	16		0.541									0.459			H
	21		0.715									0.285			I
	26		0.856									0.144			J
PU	1						0.943						0.057	4 8	
	6						0.463						0.537	8	
	16							0.237					0.763	8	
	21							0.409					0.591	8	
	26							0.531					0.469	8	

Figure 8: Heatmap of the candidate composites systematically obtained from DEA projections. Rows correspond to inefficient DMUs and columns to efficient alternatives that can be used as ingredients to obtain candidate composites. Inner cells provide the contribution of each efficient DMU in the composite, with light color (yellow) corresponding to lower contributions and dark color (bright orange) to higher. The second to last column corresponds to the filtering rules excluding a given alternative (if the alternative is discarded, the whole row is shadowed). The last column assigns an identifier to retained candidate composites.

From Figure 8, it can be observed that corn is the main material in most of the candidate alternatives identified with DEA (linear weight larger than 0.500), due to having the lowest impact on most of the environmental categories. A deeper analysis reveals that there are two main types of composites involving corn. Ones are thin rigid panels where corn is combined with wood or PU. These composite alternatives assume a higher energy demand during the use phase, which is compensated with a low embodied impact. The second type of corn-based composites are thicker sandwich panels combining corn with hemp or cotton. Their embodied impact is higher, but they allow to reduce the energy demand during the use phase. Other combinations not including corn were also identified; this was the case of thick fiber mats combining cotton and hemp, also maximizing energy savings during the use phase.

After this, the 30 candidate composites (one per each inefficient DMU) went through the filtration step described previously, where eight filtering rules are applied to discard combinations considered unattractive to the insulation market. The result of this process is also shown in Figure 8, precisely in the second to last column, where the filtering rule(s) violated by each alternative (if any) are depicted using the same numeric code as presented in Section 3.6. Following with the example of the first candidate composite, it violates two of the filters, namely, the difference between the composite and the single-material alternative involving 11 cm of corn lies below 5% (rule number 4), and it also contains PU, which is not a bio-based material (rule number 8). Therefore, it must be discarded, and its row appears shadowed in the figure.

The filtering step resulted in the exclusion of a total of 20 out of 30 efficient combinations: nine including PU (rule number 8), 12 including layers of less than 1 cm (rule number 3) and eight whose composition differed less than 5% from the single-material alternative (rule 4). In this case study, single-material alternatives or combinations with more than three materials did not arise through DEA projections.

The other 10 composites meet all the requirements and therefore, are retained for subsequent analysis. To facilitate referencing, we assign a unique identifier to each of them, as given in the last column in Figure 8. Retained composites include three rigid panels combining corn and wood (A, B and E); two sandwich panels formed by two rigid surface layers (wood or corn) and a soft inner layer (cotton or hemp) (C and D); and five fiber mats combining cotton and hemp (F-J).

To obtain the amount of each material that should be implemented in the final composite, linear weights should be used in combination with the thickness of the material in the efficient alternative associated with that weight. For example, in candidate composite A, the linear weight of the efficient alternative involving 16 cm of wood is 0.275, which would correspond to a layer of wood of 4.4 cm thick. In the case of sandwich panels, this is directly thickness of layer on the final panel (or half the thickness of each external layer in case the material corresponds to the external support), while, for fiber mats, this layer should be understood as the quantity of material to be combined with the other fibers. All these combinations are shown in Figure 9.

Overall, candidate composites show a more balanced performance compared to single-material alternatives, since the weakness of one material in a particular category are compensated by the addition of the second material. For example, if cost is a barrier for the implementation of a given material, a combination with cotton (i.e., the cheapest among the bio-based alternatives) would decrease the cost of the final composite.

Similarly, if a more constraining environmental regulation on FET (fresh water ecotoxicity) appears, composites involving wood would constitute promising alternatives to bring down the impact on this category.

	Thickness (cm)	Cotton (cm)	Wood (cm)	Corn (cm)	Hemp (cm)	ALO (m^2a)	FET (kg 1,4-DCB-eq)	IR (kg 1,4-DCB-eq)	MD (kg Fe-eq)	TET (kg 1,4-DCB-eq)	$Cost_j^{TOT}$ (€)
A	12.38		4.40	7.97		299.2	0.28	148.9	28.30	0.04	1195
B	14.25		10.39	3.86		591.9	0.24	145.9	27.91	0.05	1618
C	21.00			13.31	7.69	173.8	1.74	99.2	21.24	0.04	749.5
D	21.00			6.11	14.89	243.4	3.06	100.0	23.06	0.05	708.9
E	16.00		2.19	13.81		195.5	0.29	120.4	23.17	0.03	967.1
F	26.00	3.58			22.42	536.7	5.39	92.7	27.60	5.14	662.2
G	26.00	8.79			17.21	788.5	5.79	96.8	32.82	12.51	648.2
H	26.00	14.06			11.94	1043	6.18	101.0	38.10	19.97	634.0
I	26.00	18.60			7.40	1263	6.52	104.6	42.64	26.38	621.9
J	26.00	22.26			3.74	1440	6.80	107.5	46.32	31.56	612.0

Figure 9. Composition and performance of the retained composites. The first part of the figure provides the total thickness of the composite together with its composition, with the color indicating the material typology (purple for rigid panels, light blue for sandwich panels and blue for fiber mats). The second part of the figure consists of a heatmap illustrating the performance of the composites in the reduced set of inputs, where higher input values are represented in red and lower in green.

The performance of these composites in terms of inputs, as provided by DEA projections, is also shown in Figure 9. For instance, the comparison of composites C and D reveals that increasing the share of hemp with respect to corn reduces the cost at the expense of incurring higher environmental impacts. Recall that, while only two particular combinations (i.e., specific corn-hemp shares) of these materials were identified through DEA projections, their combination in any proportion would in principle be efficient and lie on the efficient frontier. This property can be exploited, not only to generate new composite materials with tailored performance, but also to adapt the composite composition provided by DEA to the closest commercial standards (i.e., integer value thicknesses), thus simplifying the manufacturing process. For instance, combining insulation alternatives entailing 21 cm of corn and 21 cm of hemp with weights 0.286 and 0.714, respectively, yields a sandwich panel with exactly 6 cm of corn (i.e., two support panels of 3 cm each) and 15 cm of hemp.

Note that, depending on the thicknesses considered for the original insulation alternatives, it could happen that it is not possible to obtain eco-efficient composites employing commercial thicknesses for the individual materials. In such case, which will affect sandwich panels and rigid panels, but not fiber mats since these can be combined in any proportion, it might be worth to explore whether the economic and environmental benefits of targeting unconventional thicknesses surpass the effort of modifying the manufacturing process.

4.5. *Validation of the retained composites*

As aforementioned, input values shown in Figure 8 are those obtained in DEA by linearly combining the performance of the individual materials forming the composite. However, it could be the case that this hypothesis would not hold in practice since impacts or costs might experience a non-linear behavior due to heat transfer laws. Therefore, we next simulate the 10 composite alternatives retained in the same building model as described in section 3.1 in order to reassess their performance in the space of impacts and cost.

In the absence of more detailed information regarding the physical properties of the composites, these are implemented in the simulation by adding a separate layer for each material of the composite, even in the case of fiber mats. The output of the model is the energy demand along the building's lifespan, which is used to calculate the corresponding environmental impact and cost of the composite alternative as described in 3.4.

In Figure 10, results obtained from the simulation are compared with those provided directly by DEA's virtual DMUs. Specifically, there are six pairs of bars for each candidate composite. Each of these pairs provides the normalized value for a given input as obtained from DEA projections (plain bar) or from the simulation (patterned bar) (values to be read in the left-hand side axis). The relative error between the two assessment alternatives (DEA *vs* simulation), obtained prior to normalization, is represented with square markers (to be read in the right-hand side axis). Results evidence that inputs of virtual DMUs and those obtained from the simulation are almost the same, with relative errors lower than 1% in all the cases and with an average error of 0.025%. We can conclude that, at least for the materials involved in this case study, the performance of the composite materials can be accurately predicted from DEA projections, making it possible to avoid modelling and simulation of the composites.

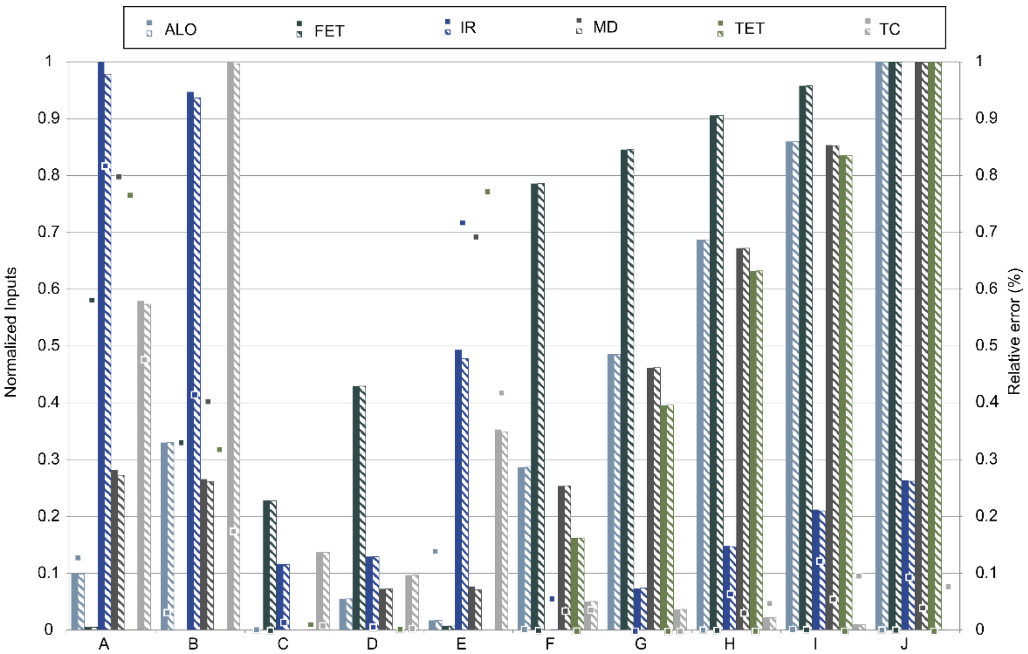

Figure 10: Composites' performance as obtained from DEA predictions (plain bars) and simulation results (patterned bars). Bars correspond to the normalized inputs (as read on the left-hand side axis) while the squares markers represent the relative error (as given by the right-hand side axis).

With impacts and costs from simulation at hand, we finally assess the efficiency of the composite alternatives using DEA in order to verify they are indeed eco-efficient. To this end, composites are benchmarked against the 11 single-material alternatives found efficient in the previous DEA analysis (section 3.4). Results (Figure 11) evidence, that seven out of the ten proposed composites achieve an efficiency score of 1 (identifiers in green), with the remaining ones achieving efficiency scores always above 0.999.

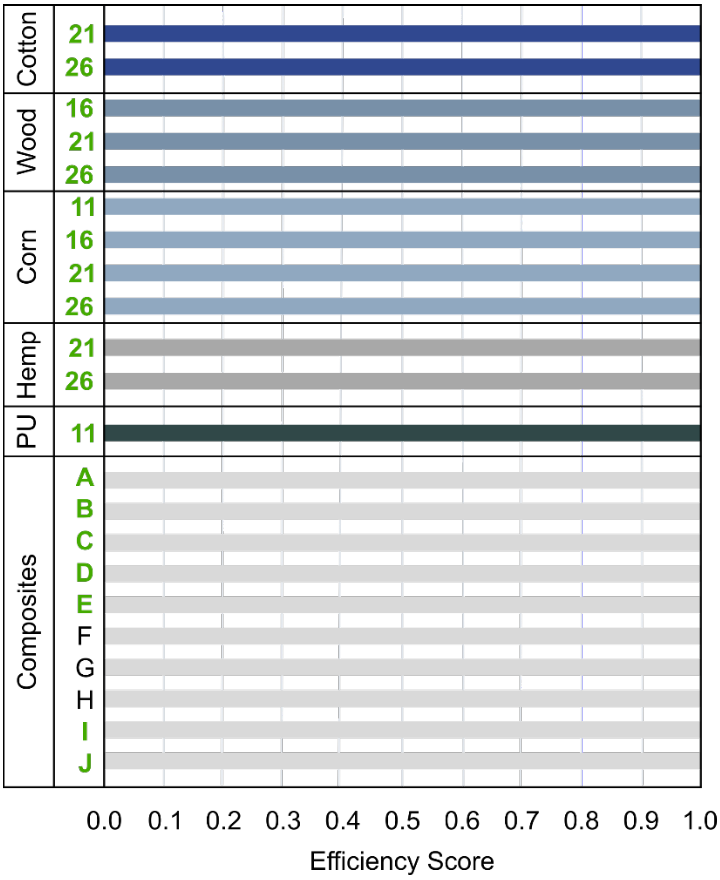

Figure 11: Efficiency scores obtained by benchmarking composite materials against the efficient single-material alternatives.

5. Conclusions

In this contribution, we put forward a systematic methodology to generate eco-efficient composites for thermal insulation. The methodology takes advantage of DEA projections to identify promising combinations of bio-based materials holding the property of being eco-efficient considering their cost and 18 LCA indicators. An additional filtering step is also included to disregard unappealing combinations from a commercial point of view. Once the refined set of candidates has been identified, the methodology allows for fine-tuning the shares of the different materials to be combined so as to obtain composites with tailored performance, or to generate alternatives entailing commercial thicknesses that simplify the whole manufacturing process.

As a testbed, we have illustrated the performance of the methodology considering six bio-based insulation materials and a conventional one (polyurethane) to be implemented in a cubicle-like building. All these materials are available in seven different thicknesses, yielding a total of 42 insulation alternatives that can be used as building blocks for the composites. We found that 12 single-material insulation alternatives were efficient (29% of the total) and, therefore, qualified for becoming part of the final composites. For each of the other 30 (inefficient) alternatives, we generated a particular combination of efficient insulation options using DEA projections. The resulting candidate composites were then filtered, revealing that only 10 were worth retaining: two sandwich panels (21 cm thick each) made of different shares of corn and hemp, three rigid panels combining wood with corn (with total thicknesses of 12.4 cm and 14.2 cm), and five fiber mats entailing cotton and hemp (all with 26 cm). Finally, these composites were benchmarked against efficient single-material options, showing non-inferior performance (efficiency scores between 1 and 0.999).

As a general trend, we found that increasing the amount of cotton in the composites helped to bring the cost down, while adding more hemp and corn lead to reduced impact on agricultural land occupation. Hemp was also identified as the preferred choice to reduce the impact on ionizing radiation, which suggests proficient thermal insulation properties since, in our case, this impact is mainly attributed to the nuclear energy used in the Spanish mix to produce the electricity consumed by the building during the use phase. For the climate studied, thicker insulation layers always yielded lower impacts from energy.

We acknowledge that the promising results from this study were obtained using simulation tools and, therefore, should be complemented with *in vitro* tests in order to obtain accurate estimates of both composite properties as well as manufacturing costs; only then could they be confirmed. Meanwhile, the proposed methodology can help guide the early stages of material design for composites, motivating further interest in the development of commercial products based on bio-materials and, perhaps, incentivize their deployment as insulation solutions for the building sector.

6. Acknowledgment

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