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ECO-EFFICIENCY IN EARLY DESIGN DECISIONS: A MULTIMETHODOLOGY APPROACH

Abstract

Eco-efficiency is a key concept encompassing economic and environmental aspects to promote a more efficient use of resources and lower emissions. An eco-efficiency perspective in the design of products and services is thus essential in the pursuit of sustainability. This article proposes a novel decision-support methodological approach to assess the environmental impacts and costs in early design stages, aimed at providing informed recommendations to designers, manufacturers and decision-makers. This multimethodology approach integrates a streamlined life-cycle environmental and cost assessment with a data envelopment analysis (DEA) model that derives eco-efficiency ratios and compares alternative designs, without the need to subjectively weigh the different environmental and cost life-cycle metrics. A linear regression model is then used to indicate the most influential decision variables. This approach was applied to a retrofit process of a historic residential building located in Southern Europe. The metrics used to assess the design parameters are: climate change, acidification, eutrophication, non-renewable primary energy, and net present value. A sensitivity analysis on the decarbonization of the electricity mix was also performed. The multimethodology offers valuable guidance to allow decision-makers to progressively specify the decision variables in an iterative way, using robust methods allowing for the statistical validation of results. The case study revealed robust empirical results for building retrofits in Southern European climates, indicating that the variables that most impact eco-efficiency (in both short and long-term) are roof insulation thickness and material followed by exterior wall insulation material. After three variables specification, the average eco-efficiency always increased, with higher gains obtained for the scenarios with the current electricity mix (22-25% increase) and more modest gains obtained for the electricity decarbonization scenarios (8-15% increase).

Keywords: Building retrofits; Data envelopment analysis (DEA); Decision-support tool; Life-cycle assessment (LCA); Net present value; Regression analysis.

List of acronyms[1]

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[1] CCR - Charnes, Cooper and Rhodes; CED - Cumulative energy demand; CO2 - Carbon dioxide; COP - Coefficient of Performance; CSE - Cooling system efficiency; CSPD - Cooling set-point day; CSPN - Cooling set-point night; DM - Decision-makers; DEA - Data envelopment analysis; DMU - Decision making unit; DMUs - Decision making units; EER - Energy Efficiency Ratio; EWIM - Exterior wall insulation material; EWIT - Exterior wall insulation thickness; EWRT - Exterior wall retrofit type; GHG - Greenhouse gas; HSE - Heating system efficiency; HSPD - Heating set-point day HSPN - Heating set-point night; LC - Life cycle; LCA - Life cycle assessment; LCCA - Life-cycle cost assessment; LSF - light steel framing; LWC – lightweight concrete; NPV - Net present value; OLS - Ordinary least square; RF - Roof frame; RIM - Roof insulation material; RIT - Roof insulation thickness; SI - Supplementary Information; VIF - Variance inflation factor; WIND - Window frame + glazing type.

1. INTRODUCTION

Economic growth leads to the increase of production and, consequently, higher environmental impacts (Gómez-Calvet et al., 2016) arising from all life-cycle stages of a product or service. An eco-efficiency perspective is necessary to address environmental challenges (climate change, acidification, eutrophication, etc.), to create more efficient economies and to promote more resilient and sustainable societies. The concept of eco-efficiency was developed in 1992 by the World Business Council for Sustainable Development (WBCSD) and has become widely recognized. It brings together economic and environmental aspects needed to foster economic prosperity with more efficient use of resources and lower emissions (Verfaillie and Bidwell, 2000).

Environmental life-cycle assessment (LCA) and life-cycle cost assessment (LCCA) approaches have been extensively applied to analyze environmental impacts and costs of products, from a systems perspective (Hellweg and Canals, 2014; Rodrigues et al., 2018). The resulting environmental and economic performance indicators can be combined using Eco-efficiency to measure the sustainability performance of different alternatives (Beltrán-Esteve et al., 2017; Torregrossa et al., 2018; Vásquez-Ibarra et al., 2020; Zabalza Bribián et al., 2011).

To develop more efficient products and services, it is important to support decision-making at early design stages, considering energy, environmental and cost aspects. When there are many design variables yielding a large number of possible configurations, decision-makers (DM) need help to reduce the scope of feasible options while keeping their ability to find good outcomes. This is particularly important when it is too costly to assess each configuration using a detailed LCA. Streamlined LCA has been used as a technique to support decisions when little information is available, promoting greater potential in reducing environmental impacts and costs in the early stages of designing products and services. Namely, it is recognized as a key method to evaluate the potential environmental impacts of products and services in the construction sector (Thibodeau et al., 2019).

Streamlined LCA approaches face two challenges addressed in this article. One is the need to compare alternatives evaluated across multiple indicators, which will be addressed using Data Envelopment Analysis (DEA). The second one is the need to narrow down an initially very wide solution space, which will be guided by regression analysis.

DEA (Charnes et al., 1978) is a method based on linear programming to measure the efficiency of a set of Decision-Making Units (DMUs) when the production process involves multiple inputs and multiple outputs. DEA has been applied in several studies for diverse sectors, e.g. hotels (Mariani and Visani, 2019), urban waters (Gidion et al., 2019), bakery products and insulation materials (Galindro et al., 2019), fishing fleets (Laso et al., 2018), wastewater treatment plants (Torregrossa et al., 2018), eco-efficiency of countries (Moutinho et al., 2018), to cite only a few recent examples.

DEA has been used to assess decisions involving multiple evaluation criteria (such as environmental, technical and cost criteria), particularly combined with partial information and multicriteria decision analysis (Gouveia et al., 2015, 2013, 2008; Madlener et al., 2009). Extensive literature review of life-cycle approaches coupled with DEA have been published highlighting the ability of this combination to deal with complex problems (Ewertowska et al., 2017), especially in the field of energy (Martín-Gamboa et al., 2017).

DEA has been combined with conventional LCA to assess the eco-efficiency of several products and systems (Álvarez-Rodríguez et al., 2019; Chiang et al., 2015; Laso et al., 2018; Torregrossa et al., 2018; Vázquez-

Rowe and Iribarren, 2015), including construction materials (Iribarren et al., 2015; Tatari and Kucukvar, 2012). Yet, no specific approach integrates both methods (Laso et al., 2018). As environmental and cost LC assessments are multidimensional and therefore difficult to compare, DEA can be used to summarize the assessments of each alternative into an eco-efficiency ratio, without the need to subjectively weigh the different LC metrics. Additionally, the usefulness of combining DEA models and statistical/econometric methods has been discussed in the literature. For instance, (Poveda, 2011) used a DEA combined with a fixed-effects model. (Kuosmanen, 2006) showed that DEA can be interpreted as a nonparametric least squares regression. (Klimberg et al., 2009) used regression analysis and DEA to forecast bank performance.

DMs lack tools to inform them about the environmental and cost consequences of their decisions, embodying an eco-efficiency perspective. Such tools are particularly needed to support decisions in early design stages when information is limited, but also when the potential of reducing environmental impacts and costs is greater.

The main goal of this article is the development of a novel approach to support early design decisions. This approach is a multimethodology (Mingers and Brocklesby, 1997) as it combines different methods to address the challenges of comparing alternatives and reducing a wide solution space: it combines a Monte-Carlo streamlined LCA-LCCA approach (Rodrigues et al., 2018) with DEA and linear regression. A historical residential building located in Portugal is assessed as a case study, assuming three alternative scenarios concerning the DMs' perspectives: short-term (30 years with 8% discount rate, and three occupants); and two scenarios of long-term - 50 years with 1% discount rate and 3 occupants and 50 years with 1% discount rate and 5 occupants.

The article is organized in five sections. Section 2 describes the methodological approach to develop the decision support tool. In section 3, a case study of a residential building retrofit process is reported. Section 4 presents and discusses the results, offering insights on how this multimethodology can assist DM in diverse settings. Finally, section 5 presents the main conclusions and recommendations of the study.

2. METHODOLOGICAL APPROACH: COMBINING STREAMLINED LCA, DEA AND LINEAR REGRESSION

This section describes a multimethodology approach combining streamlined LCA, DEA and linear regression analysis. The general steps of this approach are depicted in Figure 1. The iterative process begins with the definition of the decision variables to be specified by the DM, the metrics to be assessed and the scenarios (Step 1). This information is introduced in the streamlined LCA-LCCA approach (Rodrigues et al., 2018) to compute the metrics defined (e.g. several impact categories, costs, etc.) (Step 2). The streamlined LCA-LCCA approach simulates a large number of alternative designs resulting from the combination of the design variables and assesses them on multiple indicators. The readers interested in the dynamic energy model used to calculate energy needs and the subsequent computation of environmental and cost impacts are referred to Rodrigues et al., (2018), which presents in detail how these models were built and validated.

DEA is then used to obtain an eco-efficiency score for each one of the numerous alternatives simulated (the DMUs) (Step 3). Through an Ordinary Least Square (OLS) regression (Step 4), it is now possible to identify the design variables with the highest impact on eco-efficiency. At this point, the DM can choose to further specify the decision variables or to complete the analysis with sufficient information to make a decision. For further variable specification, the range for the selected variable is partitioned into specification levels, e.g. low, medium and high level (Step 5) and the level with best eco-efficiency is selected (Step 6), based on the average value or using any other criteria defined by the DM. Finally, the DM can again decide to continue or complete the analysis. To continue the analysis, the decision variables need to be refined according to the previous results. If the same variable is selected, the DM can choose to define either another set of intervals or a single-value. The process can be repeated until a significant number of variables is selected or a high-resolution level (low uncertainty) is achieved.

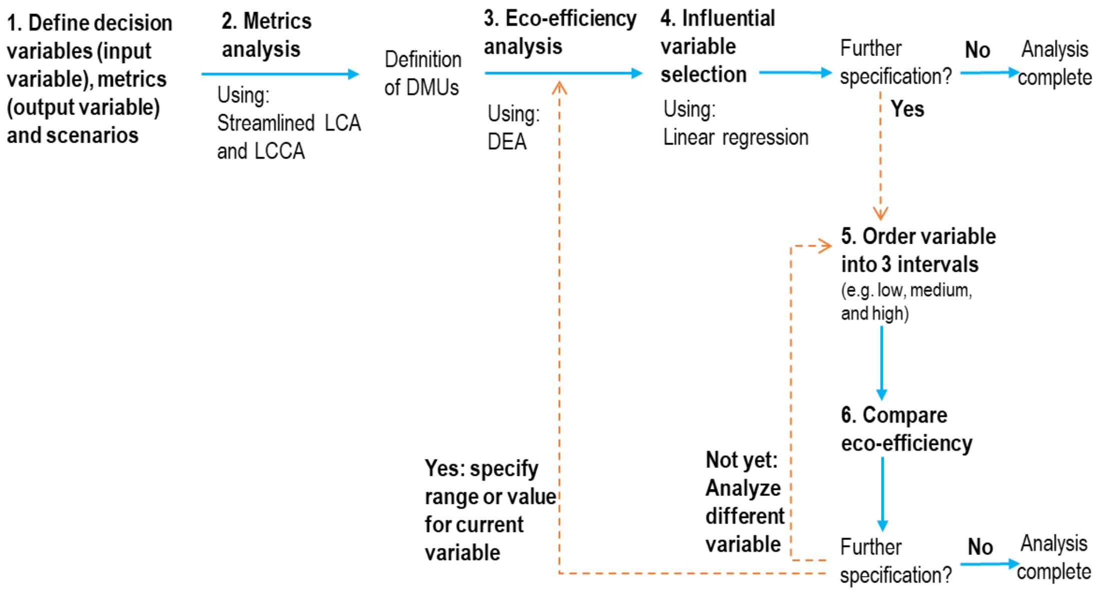


Figure 1. Integrated streamlined LCA-DEA approach analytical process

The streamlined LCA-LCCA results (Step 2) support the decision-making process as they provide more information on the dispersion, the center and the asymmetry of the impacts from the simulated alternatives, allowing to identify and control (if necessary) extreme values (outliers).

To perform the eco-efficiency analysis (Step 3), the DEA Charnes, Cooper and Rhodes (CCR) model (Charnes et al., 1978) was selected, which assumes constant returns to scale. In the formulation of the CCR model, each DMU k *(k* = 1, ..., *n)* is a possible design that uses *r* inputs x_{ik}, (i = 1, …, r) to produce *d* outputs y_{jk} (*j* = 1, …, *d*). The inputs and outputs will depend on the application. A linear programming formulation is presented in model (1) (Charnes et al., 1978):

$$
\begin{gathered}
Max\ Ef_0 = \sum_{j=1}^{d} u_j y_{j0} \\
\text{Subject to,} \\
\sum_{i=1}^{r} v_i x_{i0} = 1 \\
\sum_{j=1}^{d} u_j y_{jk} - \sum_{i=1}^{r} v_i x_{ik} \leq 0,\ k = 1,2,\dots,n \\
v_i, u_j \geq 0\ , \quad i = 1,\dots,r;\ j = 1,\dots,d.
\end{gathered}
\tag{1}
$$

In this formulation, $Ef_0 \in [0,1]$ is the efficiency score for DMU_0 (the DMU under analysis); y_{j0} and x_{i0} are the inputs and outputs of DMU_0; v_i are the weights of the inputs i and u_j are the weights of the outputs j. This formulation, which is referred to as the envelopment model, computes the weights for the inputs and the outputs that maximize the efficiency of DMU_0. Those weights are not subjectively set by a DM but reflect the benevolent perspective of evaluating the DMU under the most favorable weights maximizing its efficiency. If it is possible to choose weights such that Ef_0=1, then DMU_0 is efficient. Otherwise, Ef_0<1 indicates an inefficient DMU (the lower, the worse).

For the eco-efficiency analysis proposed, the inputs correspond to environmental impacts (to minimize), whereas the output is the economic benefit (to maximize). The DEA model is applied to assess the eco-efficiency of every alternative generated by the streamlined LCA-LCCA to summarize the impacts of each alternative into a single eco-efficiency score. The variables with the highest impact on efficiency are determined using OLS regression, considering the statistical significance commonly expressed as a p-value. Model (2) presents the general linear regression model (Asteriou and Hall, 2011):

$$R_t = \alpha + \beta' X_t + e_t \tag{2}$$

R_t is the dependent variable (in this case, the eco-efficiency resulting from the DEA model), α is the regression constant, β is the coefficient vector, X_t is the vector of independent variables (the design variables), and e_t is the error term (residues). Descriptive statistics (min, max, quartiles, median and mean) for the efficiency scores (the output of Step 3) are then presented to the DM together with the indication of which variable is the most influential (the output of Step 4). At this point, the DM can complete the process (if no further specification is necessary) or can specify the variable for further analysis.

To inform the decision of further specifying a variable, Step 5 consists in partitioning the set of DMUs in three subsets corresponding to a low, medium or high level of that variable, presenting descriptive statistics (min, max, quartiles, median and mean) for the efficiency scores separately for each subset. This provides an indication of which levels lead to higher eco-efficiency scores. Comparing these statistics (Step 6), the DM can further specify the variable by choosing an interval (narrowing its range) or even an exact value, and go back to Step 3 for another iteration of the specification cycle. Alternatively, the DM can choose to analyze another variable (repeating steps 5 and 6) or complete the process. The process can be repeated until all the most influential variables are identified and specified as an exact value or a range.

3. APPLICATION OF THE MULTIMETHODOLOGY APPROACH TO RESIDENTIAL BUILDING RETROFIT

This section describes the application of the integrated LCA-DEA approach to the retrofit process of residential buildings in South European climates.

Context and scope definition

Building envelope design, materials and construction have a large influence on heating and cooling loads in buildings, which represented nearly 3.5 $GtCO_2$ of emissions in 2015 (International Energy Agency, 2017). More importantly, early design stage decisions on the building envelope can influence the building's energy demand and emissions over its whole life cycle (LC). Building design and characteristics influence the occupant's sensation of comfort and, therefore, energy demand. Additionally, occupant choices and behavior significantly affects energy use in buildings. Progress has been made towards zero-emission, efficient, and resilient buildings; however, there is still potential to reduce the environmental burden of existing buildings by retrofitting them. In this context, it is important to make adequate choices, particularly in the early design stages of the retrofit process, where decisions have the most (environmental and cost) impact.

Streamlined LCA-LCCA of building retrofitting can provide useful information for the most significant retrofit-related decisions in early design stages. The LC phases, main processes and system boundaries defined for building retrofitting include the demolition (e.g., existing roof, windows), construction retrofit and use phases. As the scope of this streamlined model is to assess retrofit strategies, the initial construction and previous uses of the building are not considered. The end-of-life phase of the building after retrofit is not included because, for residential sector buildings, this phase presents consistently low relative environmental impacts (1-2%) compared to other LC phases (construction and use) (Nemry et al., 2008; Ortiz-Rodríguez et al., 2010; Rodrigues and Freire, 2014). The selected functional unit is the total living area (in m^2) over 30 or 50 years.

Eco-efficiency analysis is able to summarize several LCA-LCCA indicators in a single value, with no need for weighting based on specific preferences of a DM. Within the field of sustainable construction, eco-efficiency analyses can then be used to facilitate communication to the different stakeholders involved in the building sector, helping them to identify environmentally and economically efficient construction systems/materials. Yet, very few studies have addressed eco-efficiency in the building sector and none regarding the whole building. These studies have focused on building materials (Ibáñez-Forés et al., 2013; Zabalza Bribián et al., 2011), as well as on specific building systems, such as partition walls (Ferrández-García et al., 2016).

Decision variables – building design parameters

The main building retrofit decisions in the European context have been focused on improving the thermal performance of the building envelope, namely exterior walls, roofs, and windows. These are the main passive retrofit strategies recommended by the European Union, as they can improve significantly the building thermal energy performance (EPBD (recast), 2010). Thus, the model specifically addresses these retrofit strategies.

Regarding the most important parameters in the building design process, the literature highlights: energy use (Ingrao et al., 2018; Jafari and Valentin, 2018; Kohler and Hassler, 2012; Patiño-Cambeiro et al., 2019), insulation (Assiego De Larriva et al., 2014; Tadeu et al., 2015; Zabalza Bribián et al., 2011), window type (Ariosto et al., 2019), indoor comfort (Assiego de Larriva et al., 2014), roof (Rodrigues and Freire, 2014), and wall systems (Monteiro and Freire, 2012; Zabalza Bribián et al., 2011). The design parameters included in the model were selected to be representative of Southern European building systems and occupancy. They are related to building envelope components to be retrofitted (roof, exterior walls and windows), heating and cooling systems, and occupancy. Other studies have noted the importance of these parameters (Beccali et al., 2013; Lollini et al., 2006; Rodrigues & Freire, 2014, 2017).

The selected main decision variables for building retrofits are presented in Table 1, as well as the metrics selected for the analysis. Four environmental metrics and one energy metric are used to illustrate the performance of this multimethodology using two complementary impact assessment methods: the cumulative energy demand (CED) for non-renewable primary energy, and the ReCiPe mid-point (hierarchist perspective) (Goedkoop et al., 2013) for climate change, terrestrial acidification, marine eutrophication, and freshwater eutrophication. The LC impacts associated with electricity consumption from the Portuguese mix have been included, which are based on (Garcia et al., 2014; Kabayo et al., 2019). A sensitivity analysis was included to illustrate plausible decarbonization pathways of the electricity mix in Portugal for 2050, accounting for the increase of renewable sources share. The short term scenario (30 years of service life of the building and 8% discount rate) was assessed considering three alternative prospective scenarios of greenhouse gas (GHG) emissions reduction (based on the long-term strategy for carbon neutrality of the Portuguese economy by 2050 - https://descarbonizar2050.pt/en/): i) a reduction of 30% (conservative); ii) a reduction of 60% (i.e. the planned reduction according to the Portuguese strategy for carbon neutrality for 2050); and iii) a reduction of 90% (optimistic). For calculation purposes, a linear reduction over the 30 years was considered (as the defined pathway of the Portuguese government has no information about the rate of decline in emissions). These results were compared with the reference scenario with a constant electricity mix over 30 years.

LCCA is performed using net present value (NPV). NPV is commonly used in LCCA studies (Pombo et al., 2016), in particular to assess retrofit and energy efficient strategies for buildings (Gluch and Baumann, 2004; Ibn-Mohammed et al., 2014). Additionally, NPV is also recommended for eco-efficiency analyses (Huppes and Ishikawa, 2007). In this analysis, NPV represents the economic benefit, considering the initial investment, the increase in the property value and the savings in future operation costs (details are presented in Rodrigues et al. 2018). To convert future savings into present value, these are discounted at a given rate per year.

Table 1. Building retrofit process decision variables (design parameters)

Decision variables	Acronyms	Name units [types]	Units
Cooling system efficiency	CSE	Energy Efficiency Ratio (EER)	n/a
Cooling set-point day	CSPD	Temperature in Degrees Celsius	ºC
Cooling set-point night	CSPN	Temperature in Degrees Celsius	ºC
Heating system efficiency	HSE	[Coefficient of Performance] (COP)	n/a
Heating set-point day	HSPD	Temperature in Degrees Celsius	ºC
Heating set-point night	HSPN	Temperature in Degrees Celsius	ºC
Roof frame	RF	Wood, light steel framing (LSF), and lightweight concrete (LWC)	n/a
Roof insulation material	RIM	Thermal conductivity	W/m.K
Roof insulation thickness	RIT	Millimetres	(mm)
Exterior wall insulation material	EWIM	Thermal conductivity	W/m.K
Exterior wall insulation thickness	EWIT	Millimetres	mm
Exterior wall retrofit type	EWRT	No insulation / Interior insulation /Exterior insulation	n/a
Window frame and glazing type	WIND	heat transfer coefficient (U-value)	($W/m^2.K$)
Metrics			
Environmental impact categories			
Climate change	CC		t CO_2 eq
Freshwater eutrophication	FE		t N eq
Marine eutrophication	ME		t P eq
Terrestrial acidification	TE		t SO_2 eq
Energy			
Non-renewable primary energy	NRPE	Megajoule	(MJ)
Cost			
Net Present Value	NPV	Euros	(€)

Notes: Roof frame and Exterior wall retrofit type are dummies variables; n/a denotes not applicable.

Scenarios definition

The scenarios consider one climate zone in Southern Europe, a maritime temperate climate with Mediterranean influence under the Köppen-Geiger classification system (Beck et al., 2018), represented by the city of Coimbra, Portugal. A short-term scenario was defined, assuming a service life of 30 years, an 8% discount rate (used in the NPV calculation) and 3 occupants (a 3-person family is representative of a European household, according to (Eurostat, 2020). By considering a relatively short service life and a relatively large discount rate, savings become less important than the initial investment. This is contrasted with a second scenario, which considers a long-term perspective, with a service life of 50 years and a 1% discount rate, maintaining the same number of occupants. In this scenario, the initial investment is not so relevant because savings will be accounted for during 50 years, with a low discount factor. The selected discount rates represent the current trend in Portugal, which can be considered realistic and sufficiently different based on the evolution of the recent inflation rate (The World Bank, 2019). The third scenario is a variation of the latter, again considering a long-term perspective, but with an occupation of 5 persons representing the typical size of a large family in Europe. In 2019, families with two and three children represented 53% of households with children in Europe, according to Eurostat 2020. The comparison of the second and third scenarios enables the observation of the occupancy influence.

Streamlined LCA-LCCA model

The streamlined LCA-LCCA model used is a statistical-based model that integrates embodied, operational energy and cost assessments to provide environmental and cost estimates for early-stage design decisions of building retrofitting (Rodrigues et al. 2018). It incorporates uncertainty and probabilistic triage to calculate impact predictions and identify influential design parameters (decision variables) for the whole building life-cycle (Hester et al., 2018). The embodied energy (Hester et al., 2017) and cost impacts are calculated in the same parametric model from the same set of inputs, thereby avoiding the difficulties of correcting independent models. The model estimates the distribution of outcomes by using Monte Carlo simulation. Monte Carlo simulation is a technique to quantify uncertainty by defining the probability density for the model inputs, assumed to be independent, which is then propagated to obtain the uncertainty distribution of the output variable. Thus, each uncertain input parameter had to be specified as an uncertainty distribution (Huijbregts et al., 2003), namely a uniform distribution considering an adequate interval (or set of levels) for each parameter. The stochastic streamlined LCA-LCCA results ensuing from the Monte Carlo simulation are then presented in box-plots, which represent the upper and lower values, the 25th percentile, the 50th percentile (median) and the 75th percentile.

DEA model

The *Open Source DEA* software was used to perform the DEA (Step 3). The number of DMUs for the DEA model was set at 3000 (resulting from 3000 iterations of the Monte Carlo simulation). This ensures good coverage of the decision-variable space and the results do not vary significantly from one run to another (experimenting with a higher number of DMUs the conclusions did not change). Table 2 presents the input and output variables (indicators) used to perform the eco-efficiency analysis using the DEA model.

Table 2. DEA specification: inputs and outputs

Inputs	Environmental impact categories (climate change, freshwater eutrophication, marine eutrophication, terrestrial acidification) and non-renewable primary energy
Outputs	NPV
The result is the Eco-efficiency indicator $\boldsymbol{Ef_0}$ for each DMU	

OLS regression

Finally, for the fourth step of the multimethodology, an OLS regression was used to determine which variable has the highest impact on eco-efficiency. At this stage, the Eco-Efficiency Indicator is used as the dependent variable and the independent variables are: CSE, CSPD, CSPN, HSE, HSPD, HSPN, RF, RIM, RIT, EWIM, EWIT, EWRT, and WIND. *Stata* 15 and *EViews* 10^+ software were used to perform the tests and obtain the results presented in the next section.

4. RESULTS

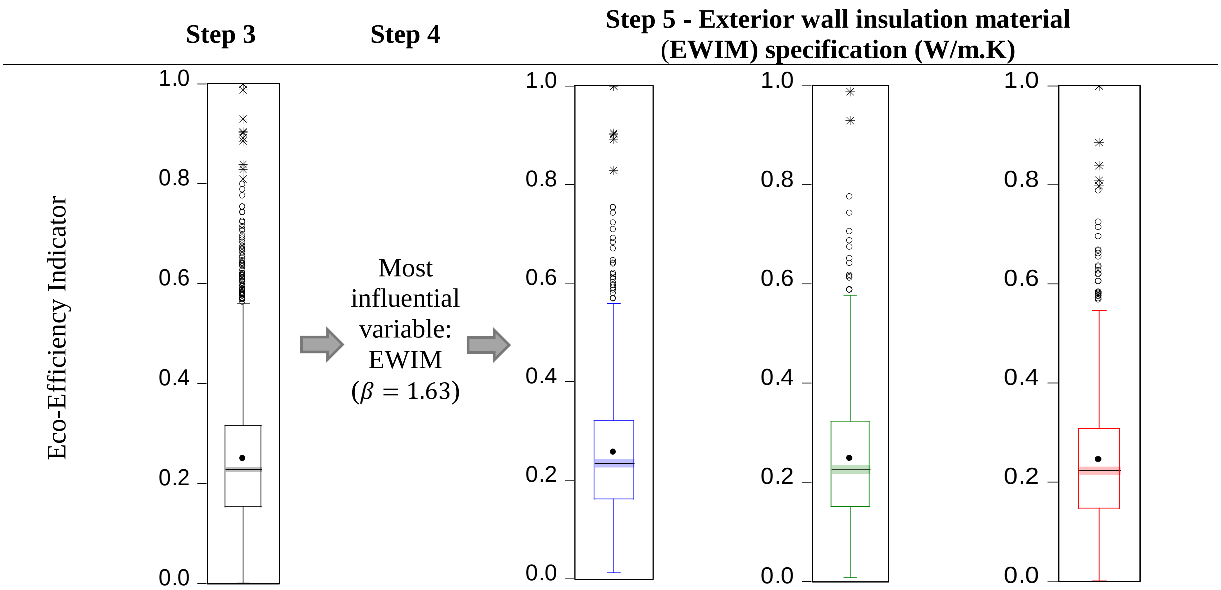
This section presents step-by-step results of the decision process for the three scenarios defined in section 3. The iterative process for each scenario entails defining levels of specification or a single-value for each variable selected at each iteration. For the purpose of the demonstration of the multimethodology, three variables are specified for each scenario.

Short-term scenario (30 years, 8% discount rate and 3 occupants) results

This scenario represents a short-term perspective by considering a relatively short life span of the building and significantly discounting future impacts. The results for the first iteration are summarized in Figure 2. The leftmost box-plot presents the eco-efficiency indicator results from DEA considering all decision variables are still unspecified (Step 3). The regression analysis (Step 4) shows that the EWIM variable presents the greatest influence on the results (a coefficient of 1.63) with a very high statistical significance p-value of 1%. The results of the OLS regression are presented in Supplementary Information (SI) Table S.1, alongside results of tests and diagnostic statistics (Tables S.2, S.3, S.4, S.5 and S.6).

To continue the analysis, the selected variable (EWIM) is then split into three levels of specification (Step 5): low, medium and high thermal conductivity. The 2nd to 4th box-plots depict the distribution of eco-efficiency results for the three levels of specification for this variable, each one corresponding to a group of 1000 DMUs. It is important to note that the efficiency of each DMU in these groups is assessed relatively to the entire set of 3000 DMUs, thus allowing a comparison of the efficiency scores across the three groups. The EWIM low-level presents the best eco-efficiency. This level represents the "no insulation" option, meaning that we should exclude in the next iteration all variables related to the exterior wall insulation (EWIM, EWIT and EWRT). Thus, the first iteration ends with these three variables specified.

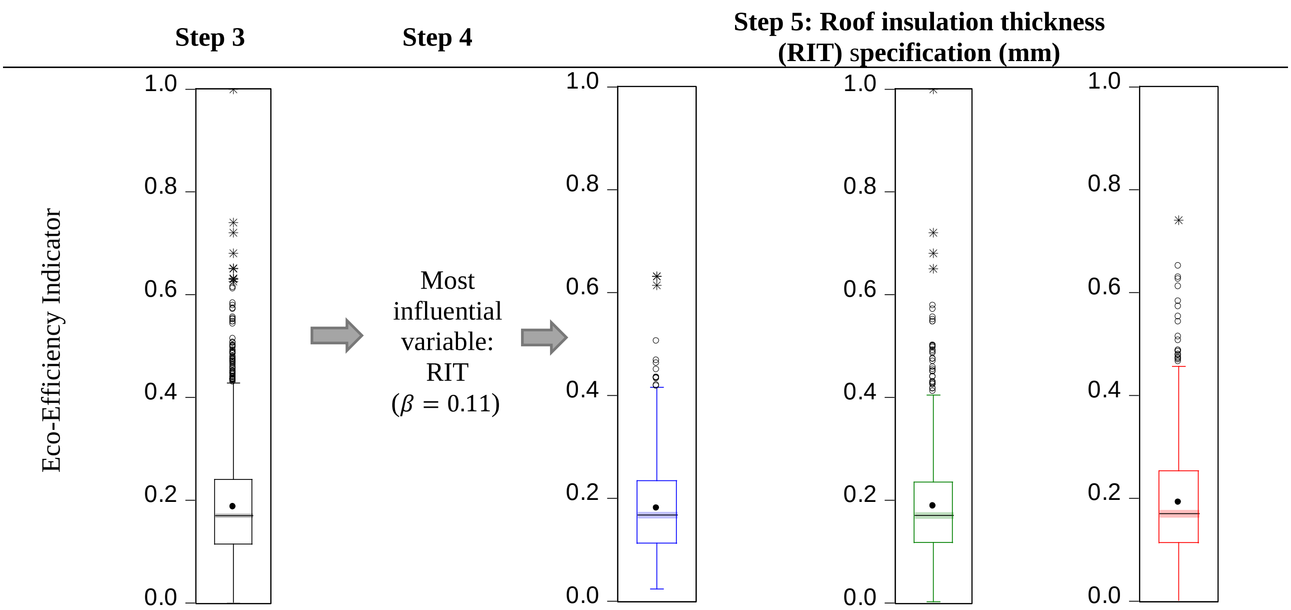
In the second iteration, Step 2 and 3 are repeated, leading to the efficiency scores depicted in the leftmost box-plot in Figure 3. In step 4, a regression analysis was performed on this set indicating that RIT is the next most influential variable. Regression results are documented in Table S.7 in the SI. Figure 3 shows the eco-efficiency indicator results for three specification levels for RIT. Based on these results, the high-level specification presents the best eco-efficiency average.



	Step 3	Step 5		
$\bar{X}$	0.2496	**0.2567**	0.2475	0.2447
EWIM W/m.K	0-0.0500	**Low: 0**	Medium: 0-0.0354	High: 0.0354-0.0500
DMUs	3000	**1000**	1000	1000

Notes: In all figures, $\bar{X}$ denote the arithmetic average.; Exterior wall insulation material value equal to zero means a "no insulation" option.

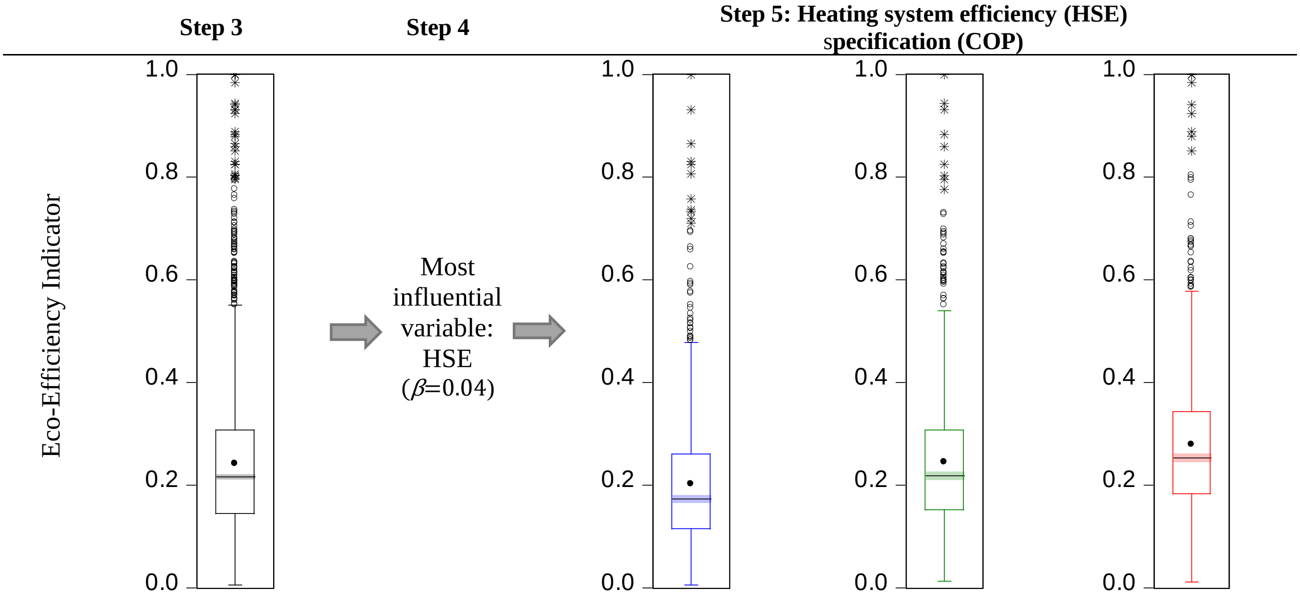
Figure 2. Eco-efficiency results of the first iteration for the short-term scenario (30 years and 8% discount rate with 3 occupants)



	Step 3	Step 5		
$\bar{X}$	0.1871	0.1809	0.1887	**0.1918**
RIT mm	**10-200**	Low: 10-80	Medium: 80-130	**High: 130-200**
DMUs	3000	1000	1000	**1000**

Figure 3. Eco-efficiency results of the second iteration for the short-term scenario (30 years and 8% discount rate with 3 occupants)

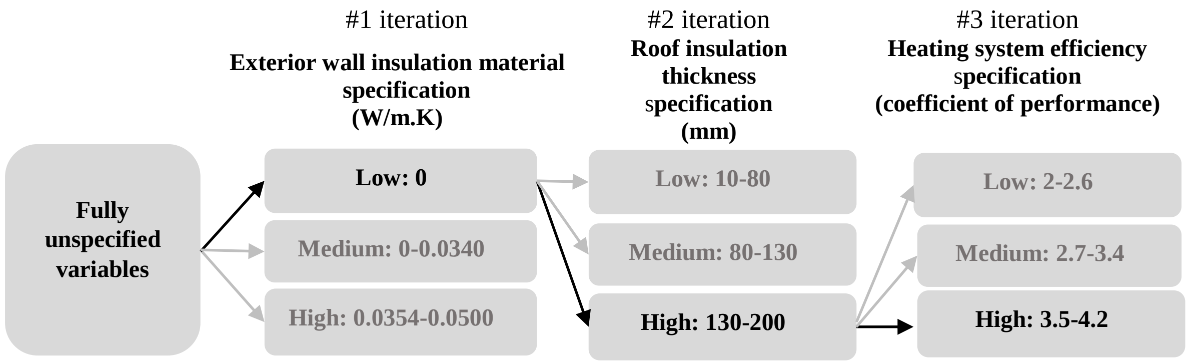
The analysis can be repeated until a significant number of variables are identified and/or an optimal resolution level (low uncertainty) is obtained. We exemplify one more iteration to identify the third most influential variable. Figure 4 presents the eco-efficiency results of the third iteration for the short-term scenario, after repeating steps 3-5. The regression analysis (Table S.8 in SI) suggests the choice of the HSE (Heating System Efficiency) variable. At this point, the High-level specification (COP: 3.5-4.2) presents the best eco-efficiency average 0.279.



	Step 3	Step 4	Low	Medium	High
$\bar{X}$	0.2424		0.2023	0.2455	**0.2793**
HSE COP	2-4.2		Low: 2-2.6	Medium: 2.7-3.4	**High: 3.5-4.2**
DMUs	3000		1000	1000	**1000**

Figure 4. Eco-efficiency results of the third iteration for the short-term scenario (30 years and 8% discount rate with 3 occupants)

Given the purpose of illustrating the methodology, the decision process can be completed after the third specification. Figure 5 summarizes the decision process and the options selected so far. The process can be repeated until a satisfactory resolution (number of selected variables or level of uncertainty) is achieved.



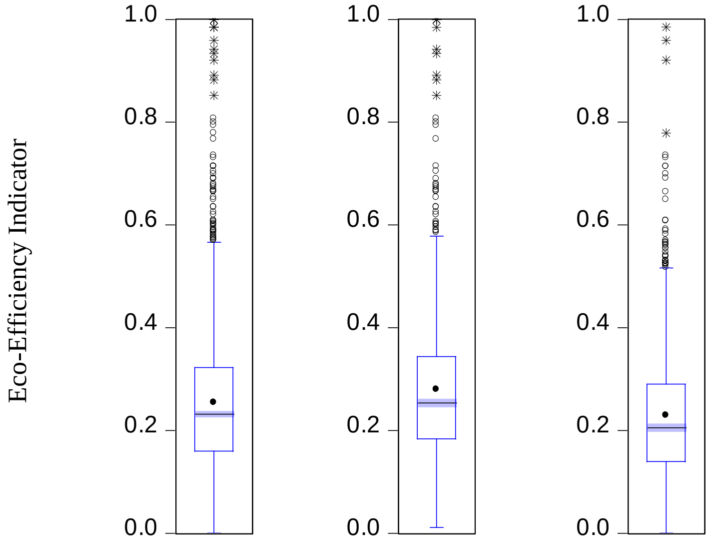
Notes: Each iteration selects a parameter, for which three specification intervals (low, medium and high) are analyzed, and then the interval leading to the highest average eco-efficiency is selected; Exterior wall insulation material value equal to zero means a "no insulation" option.

Figure 5. Variable specification levels after the third iteration for the short-term scenario (30 years and 8% discount rate with 3 occupants)

These results show the importance of exterior wall and roof insulation specification and heating system efficiency in early design stages of the retrofit process of buildings in Southern Europe in short-term.

To assess the evolution of the metrics after three iterations, the DEA model needs to be run once more. Indeed, the efficiencies reported in Figure 2 cannot be compared with those in Figure 3 or 4 because they are relative to the sample. Thus, to obtain comparable efficiencies, we sample 1000 DMUs with the final specification (low EWIM, high RIT, high HSE) and sample 1000 DMUs with no variable specified (from iteration 1), some of which may coincide with the final specification. Then, the efficiency of the DMUs in each set was computed relatively to all DMUs (2000) resulting from joining the two sets. The comparison is presented in Figure 6. The results show that the set of DMUs with the three specified variables is on average more efficient than without any specification (0. 2804 vs. 0. 2296, i.e., an increase of 22%).

Table A.1 in the Appendix presents the evolution of the averages for the different metrics throughout the three iterations. The results of the streamlined LCA-LCCA model (comparing the first and the last iterations) show a positive variation for the NPV, which increased 7%. The other metrics, reflecting impacts to minimize, show a reduction in impact ranging from -4.6% to -14%. Thus, further variable specification results in higher future savings and lower environmental impacts.



$\bar{X}$	0.2549	**0.2804**	0.2296
	Random #1 iteration + #3 iteration	#3 iteration	Random #1 iteration
DMUs	2000	1000	1000

Notes: The first box-plot presents the DEA results with 2000 DMUs (1000 random DMUs prior to any specification and 1000 DMUs after the 3rd iteration); The second box-plot focuses on the 1000 DMUs specified after the 3rd iteration; The third box-plot focuses on the 1000 unspecified DMUs.

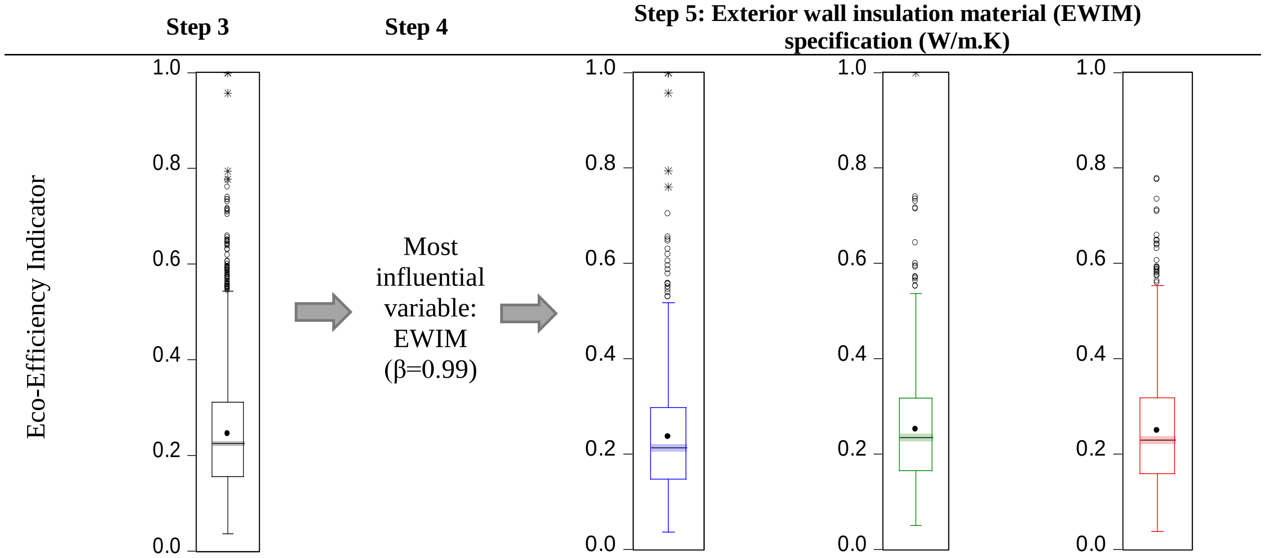
Figure 6. Eco-efficiency of the third iteration of the decision support tool compared with the first iteration (30 years, 8% discount rate and 3 occupants)

A sensitivity analysis on the decarbonization of the electricity mix performed on the short-term scenario was conducted using the same iterative process. All prospective scenarios present the same first two most influential variables (EWIM and RIM). The exterior wall without insulation and the roof insulation with higher thermal conductivities present the best eco-efficient options (as in the reference scenario). However, in the 90% GHG reduction scenario, incorporating insulation in the exterior wall with low thermal conductivities and thicknesses leads to better eco-efficiencies (high performance insulation material with low thickness). In all prospective scenarios, RIM is also an influential variable with higher thermal conductivities leading to higher eco-efficiencies. It is worth noting that, as the GHG emissions due to energy use during use phase decrease, HSE is no longer one of the most influential variables, i.e., the most influential variables may change as we approach carbon neutrality (nearly 100% renewables share).

As occurred in the base scenario, the set of DMUs with the three specified variables is on average more efficient than without any specification. The average efficiency increased 8% in the scenario of reducing the GHG emissions of the electricity system by 90% and increased 15% in the other two decarbonization scenarios after the third variable is specified. Detailed information on the results of the sensitivity analysis is documented in the SI (Tables S.9 to S.35 and Figures S.1 to S.16).

Long-term scenario (50 years, 1% discount rate and 3 occupants) results

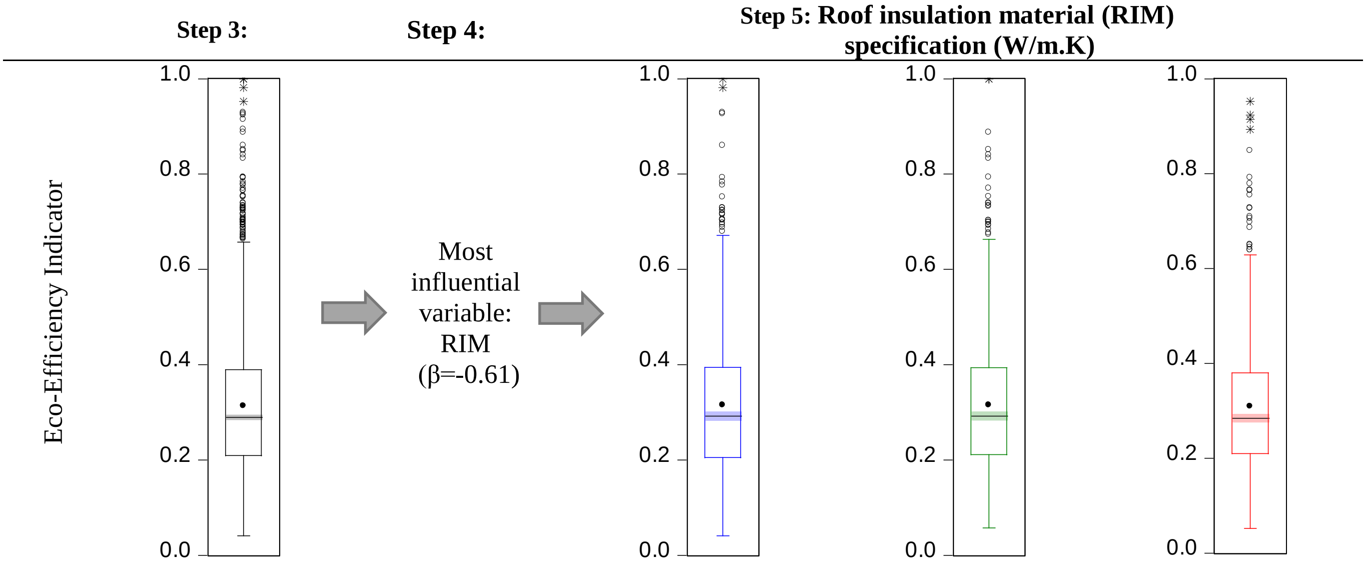
This scenario represents a long-term perspective by considering a relatively long service life of the building and a relatively low discounting of future impacts. As in the previous scenario, for the first iteration, steps 1 to 5 were performed. The eco-efficiency indicator results for the long-term scenario (with 3 occupants) are presented in Figure 7. The results for the regression analysis (Step 4) show that the EWIM variable has the highest impact on eco-efficiency. After steps 5 and 6, the medium specification was selected. However, when reiterating through Step 4, the new regression indicated that the EWIM variable should again be further specified, either a narrower interval or a single-value, as it continues to be the one that most impacts the eco-efficiency indicator. For the purpose of this demonstration, the EWIM variable was set to 0.035 (which corresponds to the thermal conductivity for extruded polystyrene (XPS), one of the most common in the market). Regression analysis results are presented in Table S.36 of the SI. Tests and diagnostic statistics were performed and are detailed in the SI (Tables S.37, S.38, S.39, S.40, and S.41).



$\bar{X}$	0.2455		0.2358	**0.2517**	0.2489
EWIM W/m.K	0-0.0500		Low: 0-	**Medium: 0.0280-0.0369**	High: 0.0369-0.0500
DMUs	3000		1000	**1000**	1000

Figure 7. Eco-efficiency results of the first iteration for the long-term scenario (50 years, 1% discount rate and 3 occupants)

The process then continues to identify the next variable. After performing steps 3 and 4, the results indicated that the RIM variable has the coefficient with the most significant impact (details are presented in Table S.42 in the SI). The eco-efficiency results for the second iteration are presented in Figure 8.

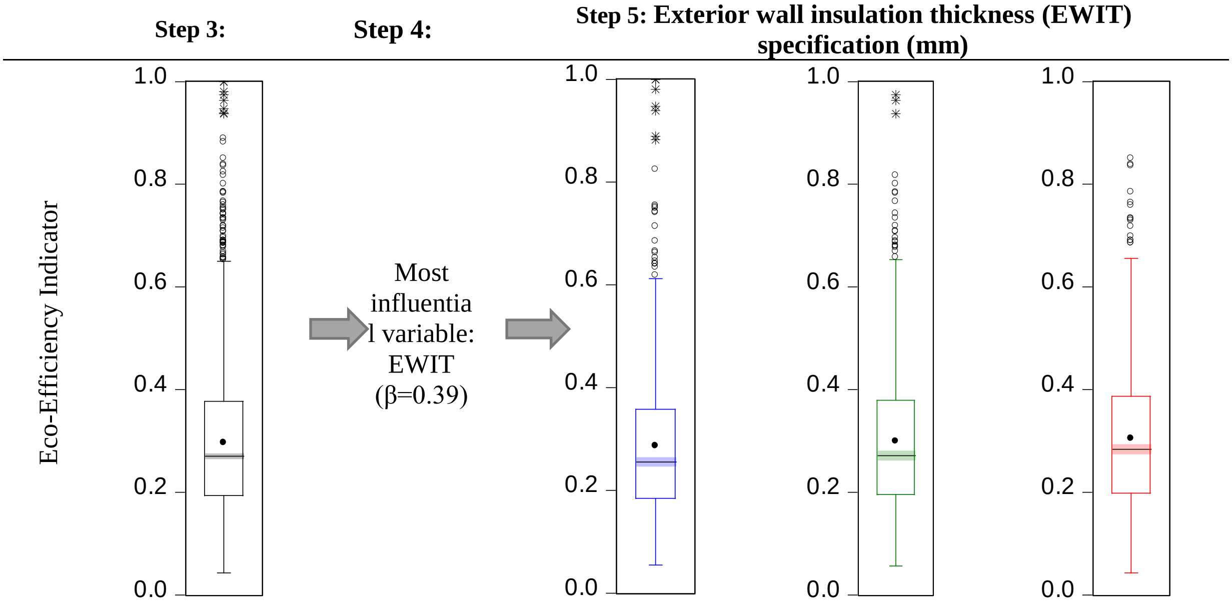


$\bar{X}$	0.3134	**0.3155**	0.3157	0.3091
RIM W/m.K	0.0280-0.0500	**Low: 0.0280-0.035**	Medium: 0.035-0.037	High: 0.037-0.0500
DMUs	3000	**1000**	1000	1000

Figure 8. Eco-efficiency results of the second iteration for the long-term scenario (50 years, 1% discount rate and 3 occupants)

This iteration illustrates the situation of a tie, as the low and medium levels of specification present very similar values for the eco-efficiency indicator average. So, another criterion was defined to select the level of specification with best eco-efficiency performance. The 75th percentile (third quartile) was selected as a tie breaker in favor of the low level (even though values are close: 0.395 for low vs. 0.394 for medium). The DM could also choose to follow other selection criteria. The results for two additional tie breaker options are presented in the Appendix (Tables A.2 and A.3). The first option is to select both the low and medium intervals; the second option is to select the second variable that most impacts eco-efficiency.

Figure 9 presents the eco-efficiency results of the third iteration for the long-term scenario (50 years, 1% discount rate and 3 occupants). EWIT is the selected variable with the high-level specification presenting the best eco-efficiency average, 0.316. The regression analysis results are presented in Table S.43 of the SI.



	Step 3	Step 4	Step 5		
$\bar{X}$	0.2970		0.2867	0.2993	**0.3049**
EWI Tmm	10-100		Low: 10-40	Medium: 40-70	**High: 70-100**
DMUs	3000		1000	1000	**1000**

Figure 9. Eco-efficiency results of the third iteration for the long-term scenario (50 years, 1% discount rate and 3 occupants)

The illustration for this scenario is completed here, but the analysis could continue to specify other variables as far as deemed necessary by the DM. Figure 10 summarizes the decision process and the options selected so far. Again, these results show the importance of exterior wall and roof insulation specification in early design stages of the retrofit process.

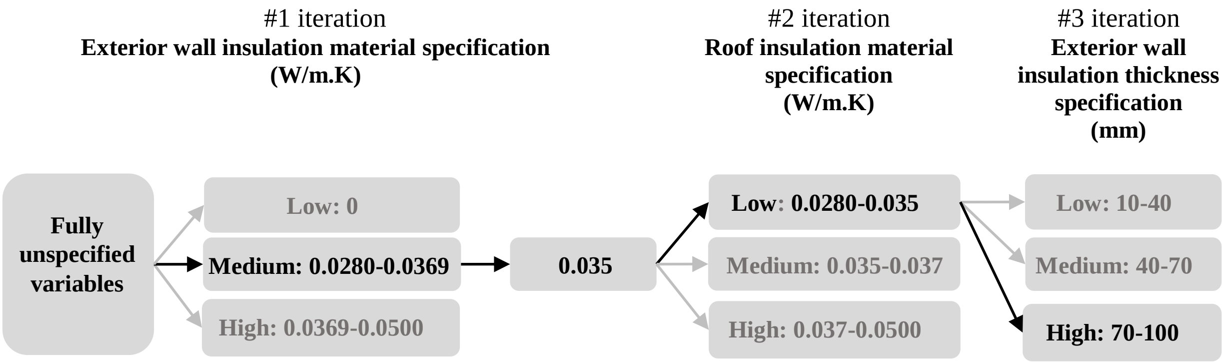
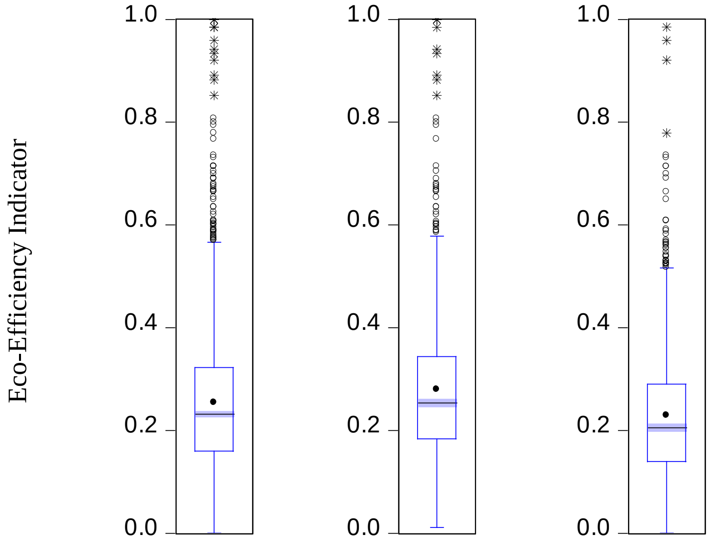


Figure 10. Variable specification after the third iteration for the long-term scenario (50 years, 1% discount rate and 3 occupants)

The results of the streamlined LCA-LCCA model (comparing the first and the last iteration) show a positive percentage variation for the NPV (0.5%), while the other metrics show an impact reduction ranging from -7.3% to -12.4%. These results are documented in the Appendix (Table A.4). To conclude the analysis of this scenario (50 years, 1% discount rate and 3 occupants), Figure 11 presents the efficiency score distributions of the set of DMUs with the best eco-efficiency identified by the methodology and a random set of DMUs without specifications (1000 DMUs of the first iteration). The results show that the average eco-efficiency of the set of DMUs identified by the methodology is 22% higher compared to unspecified DMUs.



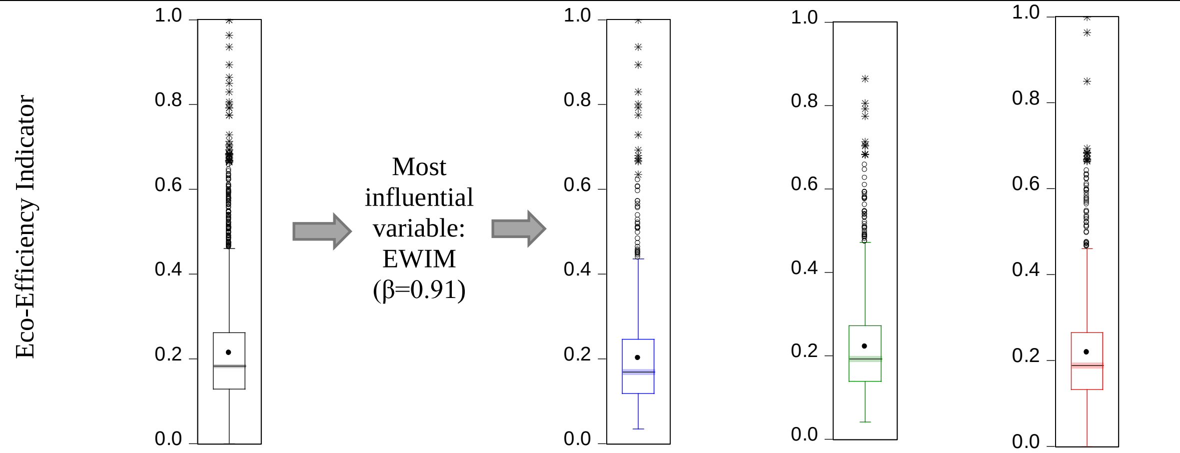
$\bar{X}$	**0.2549**	**0.2802**	**0.2296**
	Random #1 iteration + #3 iteration	#3 iteration	Random #1 iteration
DMUs	2000	1000	1000

Figure 11. Eco-efficiency of the third iteration of the decision support tool compared with the first iteration (50 years, 1% discount rate and 3 occupants)

Long-term scenario (50 years, 1% discount rate and five occupants) results

A second long-term scenario with five occupants was also analysed in order to assess the influence of occupancy in eco-efficiency. Once again, the first iteration of the multimethodology approach starts with all decision variables unspecified (Step 1) and calculates the streamlined LCA and LCCA results (Step 2). Figure 12 (left) presents the eco-efficiency indicator results from the DEA (Step 3). The results of the OLS regression (Step 4 of iterative process) show that the EWIM variable presents the greatest influence on the results with a very high statistical significance (p-value of 1%). These results are documented in Table S.44 of the SI. Tests and diagnostic statistics were performed and are detailed in the SI (Tables S.45, S.46, S.47, S.48 and S.49). Then, steps 5 (Figure 12, right) and 6 were performed and the medium specification level was selected. When reiterating, the EWIM variable was again selected, and a single-value (0.035, corresponding to XPS) was specified to continue the analysis.

	Step 3:	Step 4:	**Step 5:** Exterior wall insulation material (EWIM) specification (W/m.K)		

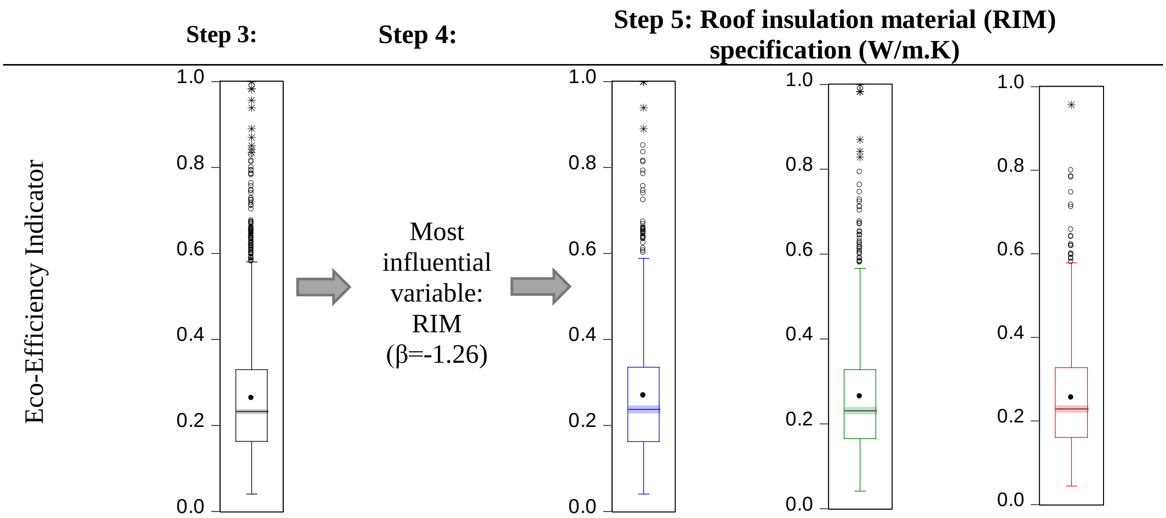


$\bar{X}$	0.2142		0.2017	**0.2221**	0.2188
EWIM W/m.K	0-0.0500		Low: 0-0.0280	**Medium: 0.0280-0.0369**	High: 0.0369-0.0500
DMUs	3000		1000	1000	1000

Figure 12. Eco-efficiency results of the first iteration for the long-term scenario (50 years, 1% discount rate and 5 occupants)

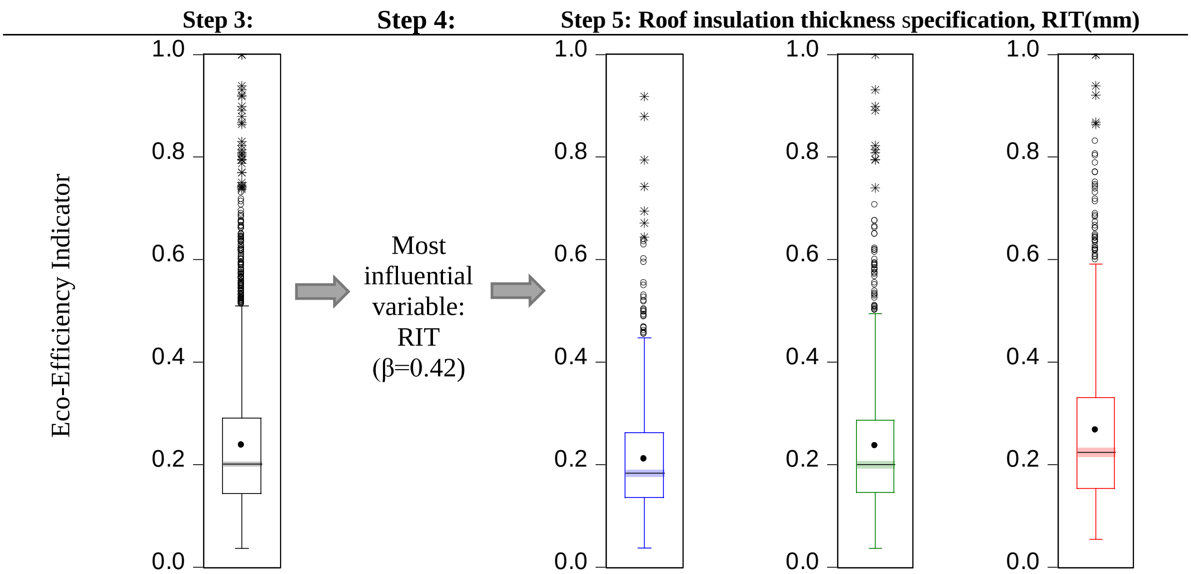
Figure 13 presents the results in the second iteration, RIM is the most influential variable and the low level of specification presents the best eco-efficiency indicator average. Therefore, this interval was selected to execute the new DEA and regression (Steps 3 and 4), showing that RIM is the next most influential variable (Table S.50 (SI)). To finalize the selection of variables, steps 5 (Figure 13, right) and 6 were performed.

In the final iteration (Figure 14), the results indicate that RIT is the most influential variable, as detailed in Table S.51 of the SI, and the high specification level for this variable is chosen to complete this illustration (again, the process could continue as far as needed to obtain further information to make a well-informed decision).



$\bar{X}$	0.2636		**0.2699**	0.2645	0.2565
RIM W/m.K	0.0280-0.0500		**Low: 0.0280-0.035**	Medium: 0.035-0.037	High: 0.037-0.0500
DMUs	3000		1000	1000	1000

Figure 13. Eco-efficiency results of the second iteration for the long-term scenario (50 years, 1% discount rate and 5 occupants)



$\bar{X}$	0.2383		0.2113	0.2367	**0.2669**
RIT (mm)	10-200		Low: 10-70	Medium: 80-130	**High: 140-200**
DMUs	3000 DMUs		1000 DMUs	1000 DMUs	1000 DMUs

Figure 14. Eco-efficiency results of the third iteration for the long-term scenario (50 years, 1% discount rate and 5 occupants)

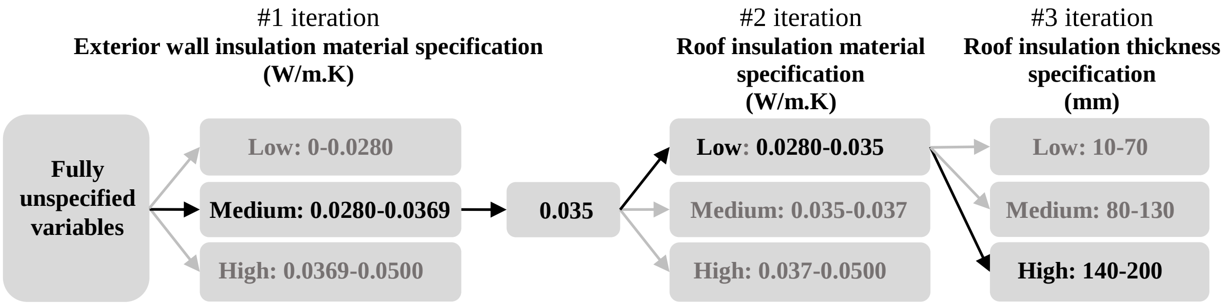
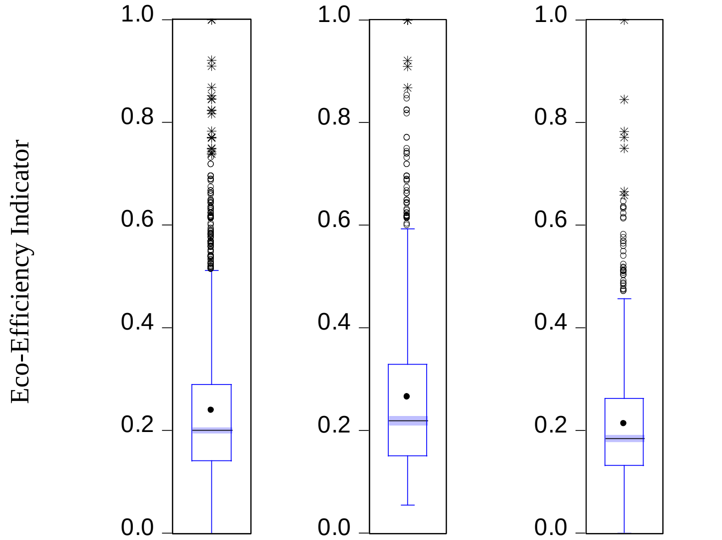


Figure 15. Variable specification after the third iteration for the long-term scenario (50 years, 1% discount rate and 5 occupants)

Figure 15 summarizes the decision process and the options selected so far. These results show again the importance of exterior wall and roof insulation specification in early design stages of the retrofit process. These results are in line with other studies in the literature that assess environmental impacts and costs of building retrofits using conventional LCA and LCCA approaches (Curado and de Freitas, 2019; Rodrigues and Freire, 2017b; Vilches et al., 2017).

The results of the streamlined LCA-LCCA model (comparing the first and the last iteration) show an improvement (2.9%) of the NPV, while the other metrics show an impact reduction ranging from -10.2% to -20.5% (more details in the appendix, Table A.5). Figure 16 presents the comparison of the DMU set with the specifications identified by the methodology with a random set of DMUs without specifications. The results reveal that the average eco-efficiency of the set of DMUs identified by the methodology is almost 25% higher compared with the unspecified DMUs.



$\bar{X}$	**0.2388**	**0.2651**	**0.2124**
	Random #1 iteration + #3 iteration	#3 iteration	Random #1 iteration
DMUs	2000	1000	1000

Figure 16. Eco-efficiency of the third iteration of the decision support tool compared with the first iteration (50 years, 1% discount rate and 5 occupants)

5. CONCLUSIONS

This article proposes a novel multimethodology decision-support approach to promote eco-efficiency, encompassing environmental impacts and costs at early design stages of products and services. This approach combines streamlined LCA, DEA and linear regression to address the lack of information inherent in early stage evaluations, permitting the identification of the most influential variables for further specification seeking eco-efficiency. This kind of analysis is usually performed in late design stages when a significant reduction in environmental impacts is costly or very difficult to achieve. The aim is to allow DM to rapidly evaluate the many options available to improve the eco-efficiency performance of their selections, in order to improve the current design process.

The multimethodology proved to be effective by presenting robust results to support decision-making in the retrofit process of residential buildings. The results show that, for Southern European building retrofits, both exterior wall and roof insulation are the most influential building parameters (decision variables). The first variable selected by the multimethodology is the same in all scenarios (exterior wall insulation material). However, the recommendation changed from the short to the long-term scenarios. In long-term scenarios, the recommendation is stronger insulation, as in these scenarios savings become more important than the initial costs.

Roof insulation appears as the second most influential component, either thickness, in the short-term scenario, or material, in both long-term scenarios. Heating system efficiency appears to be more influential in the short-term scenario than in the long-term, being the third most influential variable. The short-term scenario presented higher future savings (NPV) than both long-term scenarios after three iterations, while the long-term scenario with 5 occupants presented higher environmental impact reduction. Additionally, as the number of occupants increased, the environmental impact reduction also increased. The results indicate that, for more occupants, there is less need for heating and vice-versa. The external wall insulation and the roof insulation are more relevant in the long run, for 3 and 5 occupants, respectively. The sensitivity analysis on the decabornization of the electricity mix shows the most influential variables and the recommended choices may change when GHG emissions are significantly decreased. It is worth noting that very low GHG emissions (scenario with 90% reduction) lead to a shift in the most influential variables, as incorporating insulation in the exterior walls leads to better eco-efficiency results. Lower thermal conductivity (higher performance) and thickness leads to higher eco-efficiencies, as a result of an overall environmental impact reduction, both in the operational impacts (less energy needs) as well as in the embodied impacts (less quantity of material), and an increase in NPV.

The eco-efficiency indicator average is always higher (22-25% more) after three iterations (further variable selection) in all scenarios assessed with the current electricity mix, when compared to the initial situation prior to specification. Considering a progressively less carbon intensive electricity mix, the average efficiency increased by 8-15% after specifying the third variable. The potential gains of the recommended retrofits, therefore, tend to be higher for scenarios in which the GHG emissions of the grid are higher.

This application demonstrates how this multimethodology approach can provide robust results for the decision process at early development stages when limited information is available and design changes are still feasible.

This multimethodology approach can be used in future research to support eco-design of wide-ranging types of systems. In accumulating additional experience in using this approach in different fields, it will also be possible to discover which choices regarding some of the multimethodology components (e.g., regression method) and parameters (e.g., number of DMUs, number of specification levels) are better suited for specific applications. Additionally, as the purpose of this approach is to support, rather than substitute, the DM, another stream of research is to study to which extent it could be used to define some design variables (as an artificial expert), when the DM (e.g., a building owner) does not have the requisite expertise to make choices alone.

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REFERENCES

Álvarez-Rodríguez, C., Martín-Gamboa, M., Iribarren, D., 2019. Combined use of Data Envelopment Analysis and Life Cycle Assessment for operational and environmental benchmarking in the service sector: A case study of grocery stores. Sci. Total Environ. 667, 799–808. https://doi.org/10.1016/j.scitotenv.2019.02.433

Ariosto, T., Memari, A.M., Solnosky, R.L., 2019. Development of designer aids for energy efficient residential window retrofit solutions. Sustain. Energy Technol. Assessments 33, 1–13. https://doi.org/10.1016/j.seta.2019.02.007

Assiego de Larriva, R., Calleja Rodríguez, G., Cejudo López, J.M., Raugei, M., Fullana i Palmer, P., 2014. A decision-making LCA for energy refurbishment of buildings: Conditions of comfort. Energy Build. 70, 333–342. https://doi.org/10.1016/j.enbuild.2013.11.049

Asteriou, D., Hall, S.G., 2011. Applied Econometrics, Second Edi. ed. Palgrave Macmillan, Macmillan Publishers Limited., Basingstoke, Hampshire.

Beccali, M., Cellura, M., Fontana, M., Longo, S., Mistretta, M., 2013. Energy retrofit of a single-family house: Life cycle net energy saving and environmental benefits. Renew. Sustain. Energy Rev. 27, 283–293. https://doi.org/10.1016/j.rser.2013.05.040

Beltrán-Esteve, M., Reig-Martínez, E., Estruch-Guitart, V., 2017. Assessing eco-efficiency: A metafrontier directional distance function approach using life cycle analysis. Environ. Impact Assess. Rev. 63, 116–127. https://doi.org/10.1016/j.eiar.2017.01.001

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chiang, Y.H., Li, J., Zhou, L., Wong, F.K.W., Lam, P.T.I., 2015. The nexus among employment opportunities, life-cycle costs, and carbon emissions: A case study of sustainable building maintenance in Hong Kong. J. Clean. Prod. 109, 326–335. https://doi.org/10.1016/j.jclepro.2014.07.069

Curado, A., de Freitas, V.P., 2019. Influence of thermal insulation of facades on the performance of retrofitted social housing buildings in Southern European countries. Sustain. Cities Soc. 48, 101534. https://doi.org/10.1016/j.scs.2019.101534

Eurostat, 2020. Household composition statistics [WWW Document]. URL https://ec.europa.eu/eurostat/statistics-explained/index.php/Household_composition_statistics

Ewertowska, A., Pozo, C., Gavaldà, J., Jiménez, L., Guillén-Gosálbez, G., 2017. Combined use of life cycle assessment, data envelopment analysis and Monte Carlo simulation for quantifying environmental efficiencies under uncertainty. J. Clean. Prod. 166, 771–783. https://doi.org/10.1016/j.jclepro.2017.07.215

Ferrández-García, A., Ibáñez-Forés, V., Bovea, M.D., 2016. Eco-efficiency analysis of the life cycle of interior partition walls: a comparison of alternative solutions. J. Clean. Prod. 112, 649–665. https://doi.org/10.1016/j.jclepro.2015.07.136

Galindro, B.M., Bey, N., Olsen, S.I., Fries, C.E., Soares, S.R., 2019. Use of data envelopment analysis to benchmark environmental product declarations—a suggested framework. Int. J. Life Cycle Assess. https://doi.org/10.1007/s11367-019-01639-1

Garcia, R., Marques, P., Freire, F., 2014. Life-cycle assessment of electricity in Portugal. Appl. Energy 134, 563–572. https://doi.org/10.1016/j.apenergy.2014.08.067

Gidion, D.K., Hong, J., Adams, M.Z.A., Khoveyni, M., 2019. Network DEA models for assessing urban water utility efficiency. Util. Policy 57, 48–58. https://doi.org/10.1016/j.jup.2019.02.001

Gluch, P., Baumann, H., 2004. The life cycle costing (LCC) approach: a conceptual discussion of its usefulness for environmental decision-making. Build. Environ. 39, 571–580. https://doi.org/10.1016/j.buildenv.2003.10.008

Goedkoop, M., Heijungs, R., Huijbregts, M., Schryver, A. De, Struijs, J., Zelm, R. van, 2013. ReCiPe 2008 - A life cycle assessment method which comprises harmonised category indicators at the midpoint and the endpoint level. , Netherlands.

Gómez-Calvet, R., Conesa, D., Gómez-Calvet, A.R., Tortosa-Ausina, E., 2016. On the dynamics of eco-efficiency performance in the European Union. Comput. Oper. Res. 66, 336–350. https://doi.org/10.1016/j.cor.2015.07.018

Gouveia, M.C., Dias, L.C., Antunes, C.H., 2013. Super-efficiency and stability intervals in additive DEA. J. Oper. Res. Soc. 64, 86–96. https://doi.org/1057/jors.2012.19

Gouveia, M.C., Dias, L.C., Antunes, C.H., 2008. Additive DEA based on MCDA with imprecise information. J. Oper. Res. Soc. 59, 54–63. https://doi.org/10.1057/palgrave.jors.2602317

Gouveia, M.C., Dias, L.C., Antunes, C.H., Boucinha, J., Inácio, C.F., 2015. Benchmarking of maintenance and outage repair in an electricity distribution company using the value-based DEA method. Omega (United Kingdom) 53, 104–114. https://doi.org/10.1016/j.omega.2014.12.003

Hellweg, S., Canals, L.M.I., 2014. Emerging approaches, challenges and opportunities in life cycle assessment. Science (80-.). 344, 1109–1113. https://doi.org/10.1126/science.1248361

Hester, J., Gregory, J., Kirchain, R., 2017. Sequential Early-Design Guidance for Residential Single-Family Buildings Using a Probabilistic Metamodel of Energy Consumption. Energy Build. 134, 202–211. https://doi.org/10.1016/j.enbuild.2016.10.047

Hester, J., Miller, T.R., Gregory, J., Kirchain, R., 2018. Actionable insights with less data: guiding early building design decisions with streamlined probabilistic life cycle assessment. Int. J. Life Cycle Assess. https://doi.org/10.1007/s11367-017-1431-7

Huijbregts, M.A., Gilijamse, W., Ragas, A.M., Reijnders, L., 2003. Evaluating uncertainty in environmental life-cycle assessment. A case study comparing two insulation options for a Dutch one-family dwelling. Environ. Sci. Technol. 37, 2600–8.

Huppes, H., Ishikawa, M. (Eds.), 2007. Quantified Eco-Efficiency, An Introduction with Applications. Springer. https://doi.org/10.1007/1-4020-5399-1

Ibáñez-Forés, V., Bovea, M.D., Azapagic, A., 2013. Assessing the sustainability of Best Available Techniques (BAT): Methodology and application in the ceramic tiles industry. J. Clean. Prod. 51, 162–176.

https://doi.org/10.1016/j.jclepro.2013.01.020
Ibn-Mohammed, T., Greenough, R., Taylor, S., Ozawa-Meida, L., Acquaye, a., 2014. Integrating economic considerations with operational and embodied emissions into a decision support system for the optimal ranking of building retrofit options. Build. Environ. 72, 82–101. https://doi.org/10.1016/j.buildenv.2013.10.018
Ingrao, C., Messineo, A., Beltramo, R., Yigitcanlar, T., Ioppolo, G., 2018. How can life cycle thinking support sustainability of buildings? Investigating life cycle assessment applications for energy efficiency and environmental performance. J. Clean. Prod. 201, 556–569. https://doi.org/10.1016/j.jclepro.2018.08.080
International Energy Agency, 2017. Towards a zero-emission, efficient, and resilient buildings and construction sector, Global Status Report.
Iribarren, D., Marvuglia, A., Hild, P., Guiton, M., Popovici, E., Benetto, E., 2015. Life cycle assessment and data envelopment analysis approach for the selection of building components according to their environmental impact efficiency: A case study for external walls. J. Clean. Prod. 87, 707–716. https://doi.org/10.1016/j.jclepro.2014.10.073
Jafari, A., Valentin, V., 2018. Selection of optimization objectives for decision-making in building energy retrofits. Build. Environ. 130, 94–103. https://doi.org/10.1016/j.buildenv.2017.12.027
Kabayo, J., Marques, P., Garcia, R., Freire, F., 2019. Life-cycle sustainability assessment of key electricity generation systems in Portugal. Energy 176, 131–142. https://doi.org/10.1016/j.energy.2019.03.166
Klimberg, R.K., Lawrence, K.D., Yermish, I., Lai, T., Mrazik, D., 2009. Using regression and data envelopment analysis (DEA) to forecast bank performance over time, in: Applications of Management Science. pp. 133–142. https://doi.org/10.1108/S0276-8976(2009)0000013010
Kohler, N., Hassler, U., 2012. Alternative scenarios for energy conservation in the building stock. Build. Res. Inf. 40, 401–416. https://doi.org/10.1080/09613218.2012.675714
Kuosmanen, T., 2006. Data Envelopment Analysis as Least-Squares Regression (No. MTT Dicussion Paper, 3).
Laso, J., Vázquez-Rowe, I., Margallo, M., Irabien, Á., Aldaco, R., 2018. Revisiting the LCA+DEA method in fishing fleets. How should we be measuring efficiency? Mar. Policy 91, 34–40. https://doi.org/10.1016/j.marpol.2018.01.030
Lollini, Barozzi, Fasano, Meroni, Zinzi, 2006. Optimisation of opaque components of the building envelope. Energy, economic and environmental issues. Build. Environ. 41, 1001–1013. https://doi.org/10.1016/j.buildenv.2005.11.011
Madlener, R., Antunes, C.H., Dias, L.C., 2009. Assessing the performance of biogas plants with multi-criteria and data envelopment analysis. Eur. J. Oper. Res. 197, 1084–1094. https://doi.org/10.1016/j.ejor.2007.12.051
Mariani, M.M., Visani, F., 2019. Embedding eWOM into efficiency DEA modelling: An application to the hospitality sector. Int. J. Hosp. Manag. 80, 1–12. https://doi.org/10.1016/j.ijhm.2019.01.002
Martín-Gamboa, M., Iribarren, D., García-Gusano, D., Dufour, J., 2017. A review of life-cycle approaches coupled with data envelopment analysis within multi-criteria decision analysis for sustainability assessment of energy systems. J. Clean. Prod. 150, 164–174. https://doi.org/10.1016/j.jclepro.2017.03.017
Mingers, J., Brocklesby, J., 1997. Multimethodology: Towards a framework for mixing methodologies. Omega 25, 489–509. https://doi.org/10.1016/S0305-0483(97)00018-2
Monteiro, H., Freire, F., 2012. Life-cycle assessment of a house with alternative exterior walls : comparison of three impact assessment methods. Energy Build. 47, 572–583. https://doi.org/10.1016/j.enbuild.2011.12.032
Moutinho, V., Fuinhas, J.A., Marques, A.C., Santiago, R., 2018. Assessing eco-efficiency through the DEA analysis and decoupling index in the Latin America countries. J. Clean. Prod. 205, 512–524. https://doi.org/10.1016/j.jclepro.2018.08.322
Nemry, F., Uihlein, A., Makishi Colodel, C., Wittstock, B., Braune, A., Wetzel, C., Hasan, I., Niemeier, S., Frech, Y., Kreißig, J., Gallon, N., 2008. Environmental Improvement Potentials of Residential Buildings (IMPRO-Building), EUR – Scientific and Technical Research series. https://doi.org/10.2791/38942
Ortiz-Rodríguez, O., Castells, F., Sonnemann, G., 2010. Life cycle assessment of two dwellings: one in Spain, a developed country, and one in Colombia, a country under development. Sci. Total Environ. 408, 2435–43. https://doi.org/10.1016/j.scitotenv.2010.02.021
Patiño-Cambeiro, F., Armesto, J., Bastos, G., Prieto-López, J.I., Patiño-Barbeito, F., 2019. Economic appraisal of energy efficiency renovations in tertiary buildings. Sustain. Cities Soc. 47. https://doi.org/10.1016/j.scs.2019.101503
Pombo, O., Rivela, B., Neila, J., 2016. The challenge of sustainable building renovation: assessment of current criteria and future outlook. J. Clean. Prod. 123, 88–100. https://doi.org/10.1016/j.jclepro.2015.06.137
Poveda, A.C., 2011. Economic development and growth in Colombia: An empirical analysis with super-efficiency DEA and panel data models. Socioecon. Plann. Sci. 45, 154–164. https://doi.org/10.1016/j.seps.2011.07.003

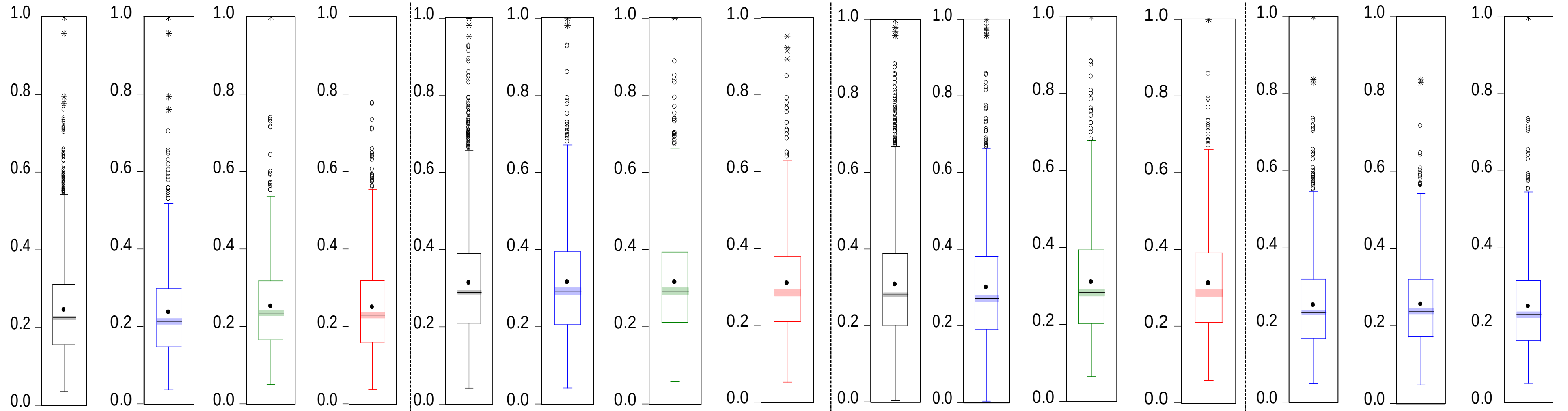
Rodrigues, C., Freire, F., 2017a. Building retrofit addressing occupancy: an integrated cost and environmental life-cycle analysis. Energy Build. 140, 388–398. https://doi.org/10.1016/j.enbuild.2017.01.084
Rodrigues, C., Freire, F., 2017b. Environmental impact trade-offs in building envelope retrofit strategies. Int. J. Life Cycle Assess. 22, 557–570. https://doi.org/10.1007/s11367-016-1064-2
Rodrigues, C., Freire, F., 2014. Integrated life-cycle assessment and thermal dynamic simulation of alternative scenarios for the roof retrofit of a house. Build. Environ. 81, 204–215. https://doi.org/10.1016/j.buildenv.2014.07.001
Rodrigues, C., Kirchain, R., Freire, F., Gregory, J., 2018. Streamlined environmental and cost life-cycle approach for building thermal retrofits: A case of residential buildings in South European climates. J. Clean. Prod. 172, 2625–2635. https://doi.org/10.1016/j.jclepro.2017.11.148
Tadeu, S., Rodrigues, C., Tadeu, A., Freire, F., Simões, N., 2015. Energy retrofit of historic buildings: Environmental assessment of cost-optimal solutions. J. Build. Eng. 4, 167–176. https://doi.org/10.1016/j.jobe.2015.09.009
Tatari, O., Kucukvar, M., 2012. Eco-Efficiency of Construction Materials : Data Envelopment Analysis. J. Constr. Eng. Manag. 138, 733–741. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000484.
The World Bank, 2019. Inflation, consumer prices (annual %) - European Union, Portugal [WWW Document]. URL https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG?end=2019&locations=EU-PT&start=1990
Thibodeau, C., Bataille, A., Sié, M., 2019. Building rehabilitation life cycle assessment methodology–state of the art. Renew. Sustain. Energy Rev. 103, 408–422. https://doi.org/10.1016/j.rser.2018.12.037
Torregrossa, D., Marvuglia, A., Leopold, U., 2018. A novel methodology based on LCA + DEA to detect eco-efficiency shifts in wastewater treatment plants. Ecol. Indic. 94, 7–15. https://doi.org/10.1016/j.ecolind.2018.06.031
Vásquez-Ibarra, L., Rebolledo-Leiva, R., Angulo-Meza, L., González-Araya, M.C., Iriarte, A., 2020. The joint use of life cycle assessment and data envelopment analysis methodologies for eco-efficiency assessment: A critical review, taxonomy and future research. Sci. Total Environ. 738, 139538. https://doi.org/10.1016/j.scitotenv.2020.139538
Vázquez-Rowe, I., Iribarren, D., 2015. Review of Life-Cycle Approaches Coupled with Data Envelopment Analysis: Launching the CFP. Sci. World J. 2015, 1–10.
Verfaillie, H., Bidwell, R., 2000. Measuring eco-efficiency — a guide to reporting company performance.
Vilches, A., Garcia-Martinez, A., Sanchez-Montañes, B., 2017. Life Cycle Assessment (LCA) of Building Refurbishment: a Literature Review. Energy Build. 135, 286–301. https://doi.org/10.1016/j.enbuild.2016.11.042
Zabalza Bribián, I., Valero Capilla, A., Aranda Usón, A., 2011. Life cycle assessment of building materials: Comparative analysis of energy and environmental impacts and evaluation of the eco-efficiency improvement potential. Build. Environ. 46, 1133–1140. https://doi.org/10.1016/j.buildenv.2010.12.002

APPENDIX

Table A.1. Streamlined LCA-LCCA results for the short-term scenario

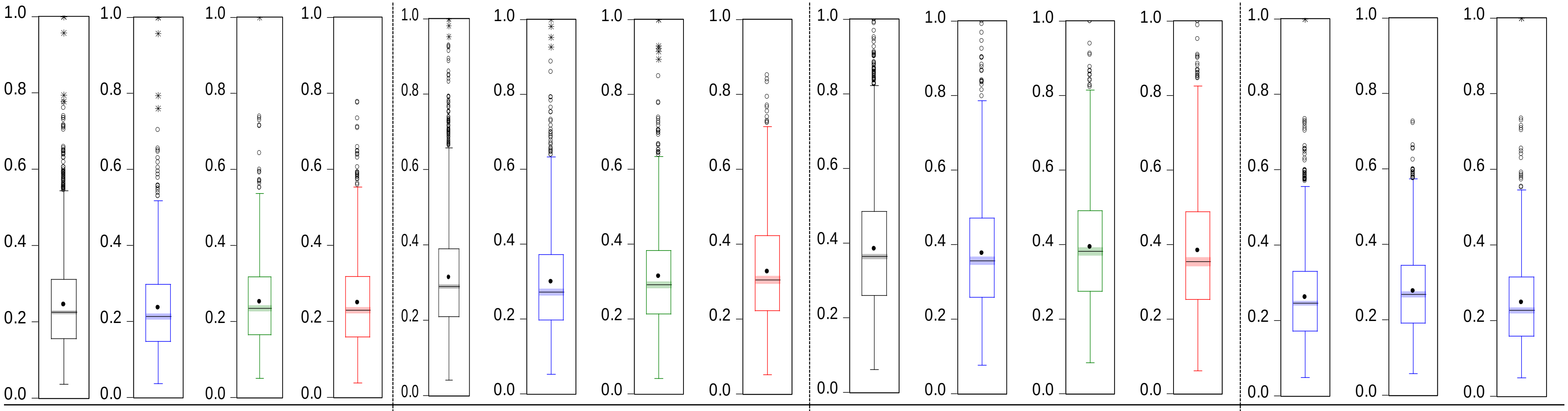
NPV	110615	120586	104825	106432	122929	125677	122715	120395	116084	112554	117292	118404	7%
CC	137201	148067	129252	134284	147028	154328	145681	141075	142320	169411	138805	118743	-13.5%
FE	50.5	55.6	46.9	49.1	55.1	58.3	54.5	52.5	53.2	64.3	51.7	43.5	-13.9%
ME	49.8	52.5	48.1	48.8	53.0	54.7	52.5	51.7	52.4	58.0	51.7	47.5	-4.6%
NRPE	2170769	2322603	2051281	2138422	2314902	2425112	2296532	2223063	2268439	2654676	2217749	1932892	-11%
TA	1004.1	1098.9	938.9	974.4	1095.3	1157.7	1085.5	1042.6	1052.0	1269.3	1023.6	863.2	-14%
		Low: 0	Medium: 0-0.0340	High: 0.0354-0.0500		Low: 10-80	Medium: 80-130	High: 130-200		Low: 2-2.6	Medium: 2.7-3.4	High: 3.5-4.2	
	3000 DMUs	1000 DMUs			3000 DMUs	1000 DMUs			3000 DMUs	1000 DMUs			
Exterior wall insulation material (W/m.K) #1 iteration					**Roof insulation thickness (mm) #2 iteration**				**Heating system efficiency (COP) #3 iteration**				Δ%

Table A.2. Eco-efficiency results 50 years, 1% and 3 occupants (Low and Medium intervals combined after second iteration)



0.2455	0.2358	**0.2517**	0.2487	0.3134	**0.3155**	**0.3157**	0.3091	0.3073	0.3003	0.3097	**0.3118**	**0.2519**	**0.2561**	**0.2478**
	Low: 0	**Medium: 0.0280-0.0369**	High: 0.0369-0.0500		**Low: 0.0280-0.035**	**Medium: 0.035-0.037**	High: 0.037-0.0500		Low: 10-40	Med: 40-70	**High: 70-100**	Random #1 iteration + #3 iteration	#3 iteration	Random #1 iteration
3000 DMUs	1000 DMUs			3000 DMUs	1000 DMUs			3000 DMUs	1000 DMUs			2000 DMUs	1000 DMUs	
Exterior wall insulation material (W/m.K) #1 iteration				**Roof insulation material (W/m.K) #2 iteration**				**Exterior wall insulation thickness (mm) #3 iteration**						

Table A.3. Streamlined LCA-LCCA 50 years, 1% and 3 occupants (second variable that most impacted eco-efficiency in the second iteration)



0.2455	0.2358	**0.2517**	0.2487	0.3134	0.2994	0.3139	**0.3271**	0.3850	0.3768	**0.3942**	0.3839	0.2619	**0.2760**	0.2478
	Low: 0	**Medium: 0.0280-0.0369**	High: 0.0369-0.0500		Low: 0.01-0.04	Medium: 0.04-0.75	**High: 0.07-0.10**		Low: 0.01-0.07	**Medium: 0.07-0.14**	High: 0.14-0.20	Random #1 iteration + #3 iteration	#3 iteration	Random #1 iteration
3000 DMUs	1000 DMUs			3000 DMUs	1000 DMUs			3000 DMUs	1000 DMUs			2000 DMUs	1000 DMUs	
Exterior wall insulation material (W/m.K) #1 iteration				**Exterior wall insulation thickness (mm) #2 iteration**				**Roof insulation thickness (mm) #3 iteration**						

Table A.4. Streamlined LCA-LCCA results for the long-term scenario (3 occupants)

NPV	560520	678805	553759	556890	568328	563575	572623	568786	568432	571988	569989	563319	0.5%
CC	222962	241202	211224	216461	208499	207403	208252	209843	208259	219920	206831	198024	-11.2%
FE	83.2	91.4	78.0	80.2	77.1	76.9	76.8	77.7	77.3	82.3	76.6	72.9	-12.4%
ME	77.2	81.1	75.1	75.3	73.8	73.9	73.2	74.4	73.5	75.9	72.9	71.6	-7.3%
NRPE	3470150	3715742	3315596	3379110	3272029	3256769	3270393	3288926	3273796	3433694	3233376	3154319	-9.1%
TA	1637.8	1792.2	1537.1	1584.1	1516.0	1511.7	1509.5	1526.9	1518.0	1617.7	1501.8	1434.4	-12.4%
		Low: 0.0280-0.0369	Medium: 0.0340-0.0380	High: 0.037-0.0500		Low: 0.0280-0.0369	Medium: 0.0340-0.0380	High: 0.037-0.0500		Low: 10-50	Medium: 40-70	High: 60-100	
	3000 DMUs	1000 DMUs			3000 DMUs	1000 DMUs			3000 DMUs	1000 DMUs			
	Exterior wall insulation material (W/m.K) #1 iteration				**Roof insulation material (W/m.K) #2 iteration**				**Exterior wall insulation thickness (mm) #3 iteration**				Δ%

Table A.5. Streamlined LCA-LCCA results for the long-term scenario (5 occupants)

NPV	558697	563818	558197	554079	568087	566941	569038	568281	573022	569877	574447	574743	2.9%
CC	219088	242166	205135	209965	201903	200340	200778	204591	198756	218012	198895	179361	-18.1%
FE	81.6	91.8	75.5	77.5	74.4	74.0	73.7	75.5	73.1	81.2	73.2	64.9	-20.5%
ME	76.4	81.3	73.8	74.0	72.5	72.4	71.6	73.3	72.4	76.2	72.4	68.6	-10.2%
NRPE	3415432	3729190	3230310	3286797	3179415	3158548	3163154	3216542	3133778	3403875	3135980	2861479	-16.2%
TA	1607.0	1799.9	1488.8	1532.2	1463.1	1455.2	1449.2	1485.0	1437.6	1596.0	1438.9	1278.0	-20.5%
		Low: 0.0280-0.0369	Medium: 0.0340-0.0380	High: 0.037-0.0500		Low: 0.0280-0.0350	Medium: 0.0350-0.0370	High: 0.0370-0.0500		Low: 10-70	Medium: 80-130	High: 140-200	
	3000 DMUS	1000 DMUs			3000 DMUS	1000 DMUs			3000 DMUS	1000 DMUs			
	Exterior wall insulation material (W/m.K) #1 iteration				**Roof insulation material (W/m.K) #2 iteration**				**Roof insulation thickness (mm) #3 iteration**				Δ%