





Article

A Stochastic Approach to LCA of Internal Insulation Solutions for Historic Buildings

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Abstract: Internal insulation is a typical renovation solution in historic buildings with valuable façades. However, it entails moisture-related risks, which affect the durability and life-cycle environmental performance. In this context, the EU project *RIBuild* developed a risk assessment method for both hygrothermal and life-cycle performance of internal insulation, to support decision-making. This paper presents the stochastic Life Cycle Assessment method developed, which couples the LCA model to a Monte-Carlo simulation, providing results expressed by probability distributions. It is applied to five insulation solutions, considering different uncertain input parameters and building heating scenarios. In addition, the influence of data variability and quality on the result is analyzed, by using input data from two sources: distributions derived from a generic Life Cycle Inventory database and “deterministic” data from Environmental Product Declarations. The outcomes highlight remarkable differences between the two datasets that lead to substantial variations on the systems performance ranking at the production stage. Looking at the life-cycle impact, the general trend of the output distributions is quite similar among simulation groups and insulation systems. Hence, while a ranking of the solutions based on a “deterministic” approach provides misleading information, the stochastic approach provides more realistic results in the context of decision-making.

Keywords: historic building; energy efficiency; internal insulation; LCA; Monte-Carlo simulation; uncertainty analysis; EPD

1. Introduction

The building sector is the single largest energy consumer and responsible for approximately 42% of energy consumption, 35% to 40% of CO₂ emissions, 20% of all waste and 40% of all materials used in Europe [1]. It is estimated that almost 75% of the building stock is energy inefficient, while only 0.4% to 1.2% of it is renovated each year [2]. Among existing buildings, the historical ones—about 30% of all European buildings [3]—have a significant potential to improve EU energy efficiency.

The thermal insulation of such inefficient building is thus a necessary step to meet the European energy efficiency objectives. In the case of historic buildings, however, external thermal insulation is often not suitable due to the need of preserving the façades along with their aesthetical, heritage,

and cultural values. For this reason, internal insulation is generally considered as a valid alternative to external insulation in order to improve the buildings' thermal performance. However, its design and application could be technically complex entailing several risks [4,5]. For instance, the risks of internal dampness, mold growth, interstitial condensation, and freeze-thaw damage may further lead to structural deterioration, aesthetical damages, and eventually a reduced service life for the whole renovation intervention. At present, there is a lack of knowledge on how to apply correctly internal insulations and handle the inherent risks. The EU project RIBuild (Robust Internal Thermal Insulation of Historic Buildings) aims to fill this gap, by investigating how and under which conditions internal insulation can be safely used [6].

Regarding insulation materials and systems for historical buildings, there is a large number of products available in the market, including natural materials (e.g., cellulose, cork), conventional materials (e.g., mineral wool, glass wool, polyurethane, expanded polystyrene, insulating plaster) and other advanced materials (e.g., calcium silicate, aerated concrete) [7,8]. According to Vereecken, internal insulation systems can be categorized into three types: (i) condensate-preventing insulation systems, based on vapor-tight insulation materials or metal foil; (ii) condensate-limiting insulation systems with normal or smart vapor barrier; (iii) condensate-tolerating insulation systems with capillary active materials [9].

However, when selecting the most appropriate insulation system, multiple key performance indicators must be considered, not only related to the energy performance but also to the hygrothermal risk, the life cycle environmental impacts, and costs.

The environmental performance of internal insulation must be evaluated through a consolidated, comprehensive, and systematic method, in order to provide real decision support during the design stage. Life Cycle Assessment (LCA) is a standardized and internationally recognized method to quantify resource consumption, environmental impacts, and emissions linked to a product or service through its whole life cycle. Part of the RIBuild project includes the development of a stochastic approach for the assessment of the internal insulation hygrothermal performance [5], life-cycle costs (LCC) [10,11], and life cycle environmental impacts (LCA) [12], by coupling specific calculation models to Monte-Carlo (MC) simulation and Probability Density Functions (PDFs) for data inputs.

In the past, several EU projects already focused on energy efficiency measures for historic buildings. For instance, the EFFESUS project focused on the development of a holistic assessment methodology, including economic, environmental, and cultural aspects, in order to choose the best retrofit solutions for historic buildings [13]. Exemplary environmental and economic assessments of internal insulation solutions have been carried out for some building case studies [14].

The 3encult project developed passive and active solutions aimed at combining both the instance of conservation and of energy retrofit [15]. The NEW4OLD project was aimed at facilitating the integration of renewable energy and energy efficiency technologies into historic buildings and at contributing to their protection [16].

In the context of these projects, innovative insulation materials have been also developed and tested to verify their thermal performance and suitability for historic buildings, in terms of easy application, reversibility, and material compatibility [17,18]. However, none of these projects was especially focused on internal insulation solutions, also aiming at developing "probabilistic" approaches for the assessment of their performance from energy, economic and environmental points of view, as made in the RIBuild project.

With the growing demand in the energy and climate mitigation targets, the number of LCA studies in the building field increased significantly, as shown by the recent reviews reported in [19–21]. Several authors focused on the LCA of various types of building internal insulation systems [22–24], even if the LCA application of internal insulation solutions for historic buildings is limited to fewer studies [1,25,26].

Moreover, there is an increasing trend to develop and apply "probabilistic" approaches to LCA analysis, in order to fully capture the inherent uncertainties related to data quality and calculation

methods [27–30]. Indeed, neglecting uncertainties and variabilities of various life cycle parameters and scenarios may affect the results' reliability and robustness for final decisions.

In the state of the art, several studies in the building field deal with “probabilistic” approaches to LCA [31–34]. Some works especially focus on materials or structural components, mainly addressing parameter uncertainties, which can be traced from more than one source, such as material quantities, the unitary environmental impact of materials, heat transmission losses, service life (SL) estimation, etc.

For instance, Hoxha et al. investigated the impact of construction materials uncertainties on LCA reliability in few works [35–37]. In [37], the authors used the statistical method to identify parameters having the greatest contribution to the uncertainty of the final result. They focused on the service life of the building component, the environmental impact of building component's production, and the amount of material used within the building. In [35], by evaluating the impact of 30 residential projects situated in France, the authors identified the building materials that have the largest relative contribution to buildings' impacts and uncertainties and found insulation materials as the key building materials controlling this uncertainty. Moreover, Häfliger et al. aimed to assess the sensitivity of construction materials to the different modeling choices (database choices, system boundary definitions, and replacement scenarios) in order to highlight their consequences at the building scale. Results clearly show the importance of these choices, especially for some materials as thermal insulation [38].

Among uncertainty analysis methods, Monte-Carlo simulation is one of the most used techniques, even if other approaches are also available, such as the fuzzy set theory [39,40], Taylor series expansions [35,36], Bayesian theorem [41], and Markov Chain modeling [42]. However, their applications in the building sector are limited in comparison to other fields. Pomponi et al. used primary data for embodied energy collected from European manufacturers as inputs for the stochastic modeling of uncertainty, considering two alternative distributions (data normally or uniformly distributed) [43]. Results showed that the hypothesis on the data no longer influences the results after a high enough number of random samplings in the MC simulation.

An example of a Monte-Carlo simulation application to assess uncertainty on building insulation LCA is provided by Su et al., which compared the life cycle performance of eight types of insulation materials [24]. The authors transformed the inventory analysis results into a probability distribution around a mean value and propagate data uncertainty using MC iterations. Results revealed that physical parameters, as density and thermal conductivity, have a significant contribution to the uncertainty of LCA results [24]. In a preliminary work of the same authors of this work, Favi et al. extended this approach considering several uncertainty sources for the LCA of a historic building renovation based on internal insulation and performed an MC-based global sensitivity analysis [26].

This paper provides a further contribution in this context, by presenting the stochastic LCA approach developed within the RIBuild project for internal insulation of historical buildings and the illustration of its application on five internal insulation solutions. When performing a building LCA, different backgrounds for life cycle inventory (aggregated data or industry data) can be adopted. Aggregated data is available through commercial databases where datasets are defined based on available statistics and sources of literature and usually associated with a high degree of uncertainty. Over the past three decades, LCA databases (such as ecoinvent) have been developed, trying to cluster general information [44]. At the same time, European environmental policies are pushing the use of Environmental Product Declarations (EPDs) for building materials [45]. EPDs are based on the actual production data from a specific manufacturer and reviewed by an independent third party prior to publication. In this respect, the LCA data refer to the specific product. However, for the same product, generic datasets from commercial databases and EPD's data may be not directly comparable, due to the different data sources [46].

Based on the stochastic LCA approach developed by the authors, this work analyses the environmental performance of five insulation solutions and, in addition, investigates the impact of data availability and data quality on the variability of LCA results, by using input data from different sources (i.e., a generic international database and EPDs). Indeed, when a building designer

wants to assess the environmental performance of several design alternatives, he may have to deal with different data sources. In the early design stage, a designer may not have identified yet the specific products to use and therefore uses data from generic databases for the product category. However, data are not always available, especially for specific and new materials and products that the building market is developing ever more rapidly. Even for these products, EPDs may be available or not. As these two types of sources (i.e., a generic international database and EPDs) refer to different background data, this paper aims to understand whether the use of generic data or of EPD for the materials composing internal systems leads to substantial differences, starting from the point of view of a building designer/consultant.

The results of the stochastic LCA of the insulation systems are presented both as probability distributions (defining the range and likelihood of impacts) and using a traditional “deterministic way”, representing the ranking of their environmental profiles based on the mean values of the distributions, in order to compare results’ effectiveness and representativeness.

The paper is outlined in the following structure: Section 2 presents the developed stochastic LCA methodology, while Section 3 illustrates its application on five internal insulation solutions. Section 4 reports the obtained results. A discussion of results including future developments in the field of historic building renovation is finally drawn in Section 5 and complemented by conclusions in Section 6.

2. The Stochastic LCA Methodology for Internal Insulation

This section briefly describes the stochastic LCA methodology developed for the evaluation of the environmental impacts of internal insulation solutions of historic buildings, which has been developed within the RIBuild project [12].

The stochastic LCA approach couples the calculation model of the environmental impacts to Monte-Carlo simulations. Based on data inputs PDFs, the output probability distribution is thus obtained for the analysis of global uncertainty and sensitivity. The uncertainty analysis aims at representing the range of possible environmental impacts for the various scenarios. The sensitivity analysis aims at identifying which parameters contribute the most to the overall uncertainty.

The methodology has been implemented in a software tool accessible through the RIBuild project web page [6], using R, an open-source programming language and software environment for statistical computing and graphics [47], and Shiny, an R package addressed to build interactive and user-friendly web apps straight from R. This “LCA/LCC probabilistic tool” includes both the stochastic LCA and LCC methodologies developed during the project, allowing a real-time calculation of the economic and environmental impacts of internal insulation systems applied to wall case studies under several possible scenarios.

2.1. Overview

The stochastic LCA methodology follows the typical steps used by analytical methods to treat uncertainty [29,30], and which are described in detail in the next sections (Figure 1):

1. Definition of the LCA model. The LCA model to assess the environmental performance of internal insulation solutions is established according to relevant international standards.
2. Uncertainty characterization. The uncertain data inputs of the LCA model are identified, and specific procedures for their characterization through PDFs are proposed.
3. Uncertainty propagation. The MC method is applied to propagate input distributions and obtain the output PDF.
4. Uncertainty and Sensitivity Analysis. The output distribution is represented and interpreted. Sensitivity indices can be calculated to establish which parameters’ uncertainties are most influential on the output variance.

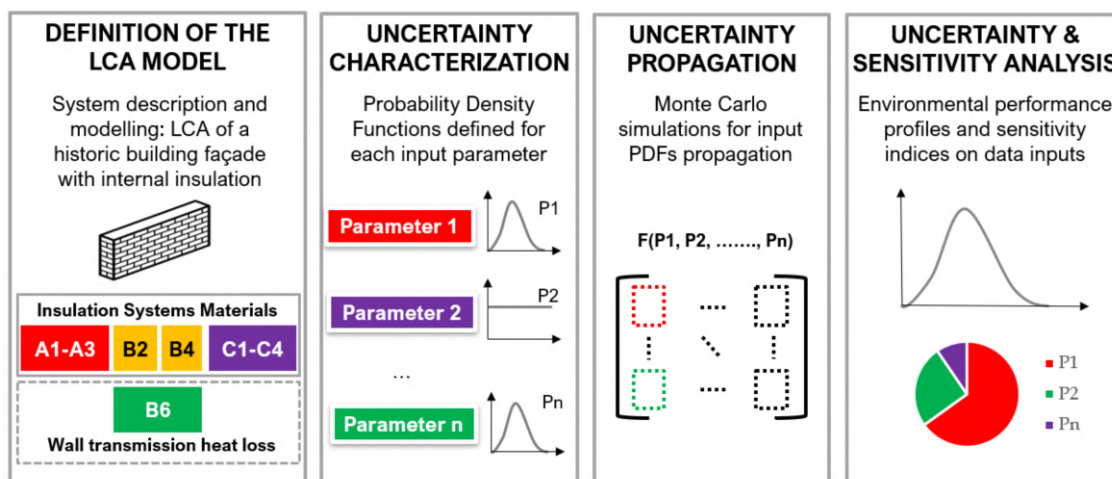


Figure 1. Overview of RIBuild stochastic Life Cycle Assessment (LCA) methodology to assess internal insulation solutions environmental performance.

2.2. LCA Model

The probabilistic LCA is performed at “component level” (insulated wall) and is based on the procedures defined in ISO 14040, ISO 14044, EN 15804, and EN 15978 standards [48–51].

2.2.1. Goal and Scope Definition

The goal of the study is to assess the environmental impacts of internal insulation measures installed on historic building facades. The functional unit (FU) is defined as “the insulation measure performed by several possible internal insulation systems and technologies required to cover 1 m² of historical building façade, to reach a given thermal transmittance [W/m²K], for a reference study period expressed in years”. The FU for the LCA of a building component can use different thermal transmittance values and reference study period depending on the goal of the study. The reference flows that accomplish the FU are reached through the insulation thickness compliant to a given thermal transmittance (based on renovation standards or other factors). Other functions, as the need to have a “safe” solution from a hygrothermal point of view, can be added, requiring a preliminary assessment of this aspect before the LCA.

The scope of the study comprises the environmental impact assessment of installing the new internal insulation systems assuming a given “building heating system scenario”, i.e. a heat source to convert the heat transmission losses into final energy. The impacts of the new internal insulation systems after renovation cover the material manufacture, the use phase impacts related to the building heating energy needs and the possible repair and replacement of material layers, as well as the dismantling at the end-of-life. As a result, the following life cycle stages are considered: (i) the production stage (modules A1–A3), (ii) the use stage (modules B2 maintenance, B4 replacement, and B6 operational energy use), and (iii) the End of Life (EoL) stage (modules C1–C4). Based on the literature survey and reports of LCA practitioners, the construction processes are less relevant in the LCA of building components than the operational ones [37,52–54]. The distinction between modules B2 (maintenance), B3 (repair), B4 (replacement) is considered according to EeBGuide guidance recommendations [55]. Hence, the maintenance is considered as the periodic wall re-painting; while replacement involves the whole insulation system, according to its estimated service life.

Several design options (internal insulation measures, comprising different layers of materials) and scenarios (original wall typologies, building heating systems, reference study periods) can be defined. In the following, a “case-study” is set when a certain insulation system is applied in a certain original wall configuration under certain climatic conditions. The same case study can be assessed in several building heating systems scenarios and reference study periods.

2.2.2. Life Cycle Inventory (LCI)

Life cycle inventory requires the definition of each parameter referred to the reference flow for each system covered by the functional unit. It encompasses all the life cycle stages covered within the functional unit. The LCA data used to model the environmental impacts of an internal insulation renovation can be collected from different sources. As illustrated later, within Section 3 (case study), LCA data are collected from two sources and used for two alternative simulations sets: (i) the Environmental Products Declarations (EPD) provided by the manufacturers of the materials composing the insulation systems and (ii) data from an LCI generic database (i.e., ecoinvent).

2.2.3. Life Cycle Impact Assessment (LCIA)

Several life cycle impact assessment (LCIA) methodologies have been applied in the building sector (e.g., CML, ReCiPe, CED, etc.) Standard EN 15978 leaves to LCA practitioners the possibility to choose the most suitable LCIA method (usually based on geographic location or type of measures). In the case study reported in Section 3, the unitary environmental impacts are calculated according to the CML LCIA method [56]. In particular, the CML-2001 baseline V3.02/EU25 LCIA method is chosen, as it is widely applied in the building sector [21,57] and, above all, as it is referenced in most of the EPDs found for the materials composing the insulation systems. Midpoint impact categories from the CML-2001 baseline method are reported in Table 1 [56].

Table 1. Impact categories for the CML-2001 baseline life cycle impact assessment (LCIA) method.

Impact Category Extended Name	Impact Category Abbreviation	Unit
Global warming (GWP100a)	GWP	kgCO ₂ eq.
Abiotic depletion	ADPe	kgSb eq.
Abiotic depletion (fossil fuels)	ADPf	MJ
Acidification	AP	kgSO ₂ eq.
Eutrophication	EP	kgPO ₄ eq.
Ozone layer depletion	ODP	kgR-11 eq.
Photochemical oxidation	POCP	kgC ₂ H ₄ eq.
Freshwater aquatic ecotoxicity	FAETP	kg1,4-DB eq.
Human toxicity	HTP	kg1,4-DB eq.
Marine aquatic ecotoxicity	MAETP	kg1,4-DB eq.
Terrestrial ecotoxicity	TETP	kg1,4-DB eq.

Wall Transmission Heat Loss Calculation Method

The LCA requires information on the operational energy use (module B6 of EN 15978) before and after the application of the internal insulation, in order to account for the use phase and determine the environmental burden savings. The LCA is performed at the “component level”; this means that the operational energy use (module B6 according to EN 15978) is considered as the annual heat transmission through the building facade.

The heat losses and gains through the façade do not cover the entire heating or cooling demand of a building, which depends on several factors, such as solar gains, ventilation losses, thermal bridges, etc. Considering that the internal insulation especially affects the heat transmission losses and gains through the facade, while the other factors remain almost unchanged, for the sake of simplicity these factors are not taken into account in the LCA methodology developed.

The annual heat transmission through the building facade can be obtained in different ways such as (i) through coupled heat and mass transfer numerical models based on hourly climate data, (ii) monthly calculation between the internal temperature and the average monthly temperature, and (iii) annual calculation based on Heating and Cooling Degree Days.

Concerning the first two methods, within the RIBuild project, a “probabilistic” approach to the hygrothermal performance assessment of interior insulation is developed, based on heat and mass transfer numerical models coupled to MC simulations [5,58]. Furthermore, a stochastic monthly calculation is developed [12]. Based on these choices, wall heat transmission can be defined through accurate PDFs [12].

Within the exemplary case illustrated in Section 3, for the sake of brevity and simplicity, the third method is presented, limited to the heat transmission loss through the wall during the heating season. It is based on the Heating Degree Days (HDD) method according to the following Equation (1):

$$Q_h = \frac{U}{1000} \cdot HDD \cdot HH \quad (1)$$

where

- Q_h is the annual heat transmission loss through the wall [kWh/m²]. Q_h can refer to the heat losses before (Q_{hpre}) or after (Q_{hpost}) the insulation intervention;
- U is the wall thermal transmittance (U -value) [W/m²K];
- HH is the heating hours a day [h] (set at 24 h);
- HDD are the annual heating degree-days [K].

The U -value of the wall is calculated with the following Equation (2):

$$U = \frac{1}{(R_{si} + R_{se} + R_w + R_{is})} \quad (2)$$

where

- R_{si} and R_{se} are the internal and external surface resistances, $R_{si} = 0.13$ m²K/W and $R_{se} = 0.04$ m²K/W defined for vertical walls in EN 6946 [59];
- R_w is the original wall surface-to-surface thermal resistance [m²K/W];
- R_{is} is the insulation system surface-to-surface thermal resistance [m²K/W].

Life Cycle Impacts Calculation Method

The environmental impact of the j -th insulation system, composed by several materials k , for a given LCA indicator is calculated, considering the previously defined life cycle phases and during a certain calculation period cp , through the following Equation (3):

$$IG_j = \left\{ sI_j + sI_j \cdot s_j + EoLI_j + EoLI_j \cdot s_j + \sum_{i=1}^{cp} (Q_h \cdot EI_i) + smI_j \right\} \quad (3)$$

where

- IG is the Global Impact for a given indicator;
- i is the year of the calculation period;
- sI_j is the j -th system environmental impact related to production phase;
- $EoLI_j$ is the j -th system environmental impact related to the End of Life phase;
- s_j is the number of replacements of the j -th system within cp ;
- EI_i is the unitary impact of the energy vector at year i ;
- smI_j is the environmental impact related to the system periodic maintenance.

sI_j is defined in the following Equation (4):

$$sI_j = \sum_{k=1}^n UI_k \cdot m_k \quad (4)$$

where

- UI_k is the unitary production impact of the k -th material composing the j -th system;

- m_k is the mass of the k -th material [kg].

s_j , the number of replacements of the j -th system within cp , considering its Service Life SL_j [years], is defined in the following Equation (5):

$$s_j = \text{int}\left(\frac{cp - 1}{SL_j}\right) \quad (5)$$

$EoLI_j$ is defined in the following Equation (6), where EoL_k is the unitary End of Life impact of the k -th material composing the j -th system:

$$EoLI_j = \sum_{k=1}^n EoL_k \cdot m_k \quad (6)$$

smI_j is defined in the following Equation (7):

$$smI_j = \sum_{k=1}^n UI_k \cdot m_k \cdot s_k \quad (7)$$

where s_k is the number of replacements of the k -th material within the calculation period cp , calculated considering the k -th material Service Life sl_k [years] through the following Equation (8):

$$s_k = \text{int}\left(\frac{cp - 1}{sl_k}\right) \quad (8)$$

2.2.4. Interpretation

Life cycle interpretation is the last phase identified within the ISO 14040 and 14044 standards [48,49]. Both standards specify that interpretation comprises the following elements: (i) an identification of the significant issues (hotspots); (ii) an evaluation that considers completeness, sensitivity, and consistency checks; and (iii) conclusions, limitations, and recommendations for end-users and stakeholders. ISO 14044 defines uncertainty analysis as a systematic procedure to quantify the uncertainty introduced in the results. Since the stochastic LCA approach developed within the *RIBuild* project is oriented to the characterization of uncertainties in data input and sensitivity analysis of the results, this phase is in the critical path and serves to: (i) better understand the obtained results, (ii) increase the level of confidence in the decision-making process, and (iii) support the robustness and applicability of the study results.

2.3. Uncertainty Characterization

The stochastic approach couples MC simulations to the wall transmission heat loss calculation (Equations (1) and (2)) and to the LCA model (Equation (3) to Equation (8)). Thus, the method requires defining the PDFs of all data input, identifying the uncertainty sources, and characterizing them based on available information. In general, the uncertainty characterization of input parameters entails data collection based on literature and commercial databases for each uncertainty source identified and eventually depending on the national context. A quantitative approach based on parameter estimation techniques and goodness-of-fit test can be used to fit distributions when sufficient data is available. When limited data are available or uncertainty is subjective, experts' judgment can help to define the proper PDF. As previously stated, in this work, the heat transmission losses through the wall are obtained through a stochastic annual HDD method, thus the following input parameters are characterized with PDFs for each case study:

- The thermal resistance of the historic wall [$\text{m}^2\text{K/W}$];
- The thermal resistance of the insulation system [$\text{m}^2\text{K/W}$];
- Annual heating degree-days HDD [K].

Regarding the LCA model, two levels of uncertainty can be identified for the input parameters: (i) the one related to the LCI background data for material manufacturing, end of life and heating systems, and (ii) the one related to the design option under study (i.e., service life and mass of materials). The following input parameters are then considered as stochastic variables of the LCA assessment:

- Unitary environmental impact of each material layer;
- Unitary environmental impact of the building heating system;
- Masses of the material layers;
- The service life of the whole insulation system (influencing the number of replacements) and of the material layers (influencing the number of replacements of the internal finishing layer = re-painting (maintenance)).

When using manufacturer's information on the environmental impacts, i.e., EPDs, background PDFs for the unitary environmental impact of a specific dataset are replaced with "deterministic" values retrieved in EPDs.

Once the PDFs for the unitary environmental impact of the component materials are defined, it is necessary to calculate the unitary environmental impact at the whole insulation system level, considering the masses (and related uncertainties) of each material.

In Table 2, the uncertain parameters identified in the LCA model are reported for each LCA stage. In Section 3.2, the uncertainty characterization procedures of input data for the specific exemplary application are described.

Table 2. LCA model input parameters.

LCA Stage (EN 15978 Nomenclature)		LCA Parameter Description
Production stage	Material	Mass of the materials composing the insulation system [kg]
		Unitary environmental impact of the materials [Unit of indicator/kg]
Use stage	Maintenance	Materials' Service Life (which affects the need for periodic replacement of the finishing layer of the insulation system) [years]
	Replacement	Insulation System Service Life (which affects the whole insulation system replacement) [years]
	Energy consumption	Heat transmission losses through the wall before/after renovation [kWh/year]
	Energy impact	Unitary environmental impact of the heating system [Unit of indicator/kWh]
EoL stage	EoL material impact	Unitary environmental EoL impact of material [Unit of indicator/kg]

2.4. Uncertainty Propagation and Analysis, Sensitivity Analysis

MC method is used to propagate the heat losses and LCA parameter uncertainties into a distribution of the output variable, reflecting the combined parameter uncertainties. According to MC method, values from the input PDFs are drawn and inserted into the output equations for a given number of times—set based on convergence evaluation—to obtain the output parameters distributions. Minimization of iterations (required runs) can be obtained through a sampling strategy. In this study, Sobol's sequences are used as sampling technique, in order to generate samples as uniformly as possible and effectively perform the sensitivity analysis through a variance-based decomposition technique (Sobol's method) identifying the most influential parameters' uncertainty on the output variance [60,61].

The output sample can then be visually represented by PDFs, Cumulative Distribution Functions (CDF), or box whiskers plots, which can be used to compare the performance of several design options under the same scenarios (or under several scenarios), as shown in the exemplary case presented in Section 3.

3. Case Study

The case study reported in this section shows the application of the stochastic LCA of internal insulation measures developed within the RIBuild project. The case study refers to the assessment

of five insulation systems applied to a historic building in the Italian context. The comparative LCA assessment of the five insulation systems is performed considering:

- 2 alternative datasets for the unitary environmental impacts of materials production: EPDs (simulation group 1) or ecoinvent v.3.1. (simulation group 2).
- 2 alternative “building heating systems scenarios”, characterized by 2 different building heating systems (a gas boiler and an air-to-water heat pump), among the most widespread in Italy for existing historic buildings.

As a result, 20 simulation cases have been obtained from the combination of all the insulation systems, heating scenarios, and data sets (5 insulation systems \times 2 heating scenarios \times 2 simulation groups).

3.1. Goal and Scope Definition

Five internal insulation systems typically used in Italy for historic building renovation were considered in this study: (i) Expanded Polystyrene (EPS), (ii) Calcium Silicate (CaSi), (iii) Autoclaved Aerated Concrete (AAC), (iv) Cork, and (v) Rockwool (RW) (Table 3). The internal insulation systems are applied to historic buildings located in the region Lombardia, belonging to the largest climatic zone of Italy (zone E). The building has a plastered solid bricks masonry, with an overall thickness of about 30 cm and an air-to-air heat transfer coefficient (U-value) of 1.760 W/m²K.

Table 3. Stratigraphy of the 5 internal insulation layers adopted in this study (outermost layer first), along with thermophysical properties of the most relevant materials (mass quantities obtained from the manufacturers) and wall U-values obtained after the application of each insulation system on the considered masonry wall (including surface thermal resistances according to ISO 6946:2008).

Layer	Material ID for LCA	Standard Thickness [m]	Density [kg/m ³]	Mass [kg]	Thermal Conductivity [W/mK]
“EPS” insulation system (Wall U-value = 0.349 W/m ² K) EPS insulating board fixed to the wall through an adhesive mortar, externally finished by plasterboard					
Gypsum adhesive mortar	101	0.006	1400	3.50	0.400
EPS boards	102	0.080	15	1.26	0.035
Gypsum plasterboard	103	0.0125	680	8.93	0.200
Stucco	101	-	-	0.40	-
Gypsum finishing	104	0.002	950	1.90	0.400
“CaSi” insulation system (Wall U-value = 0.359 W/m ² K) CaSi insulation board fixed to the wall through an adhesive mortar, externally finished with a reinforced multilayer rendering system					
Adhesive mortar for CaSi	105	0.006	1450	8.70	0.600
CaSi	106	0.130	184	23.92	0.059
Glass fiber mesh	107	-	-	0.08	-
Surface rendering for CaSi	105	0.004	1450	5.80	0.0680
“AAC” insulation system (Wall U-value = 0.333 W/m ² K) AAC insulation board fixed to the wall through an adhesive mortar, externally finished with a reinforced multilayer rendering system					
Adhesive mortar for AAC	105	0.006	1450	8.70	0.180
AAC	109	0.100	90	9.00	0.042

Table 3. Cont.

Layer	Material ID for LCA	Standard Thickness [m]	Density [kg/m ³]	Mass [kg]	Thermal Conductivity [W/mK]
Surface rendering for AAC	105	0.004	1450	5.80	0.180
“Cork” insulation system (Wall U-value = 0.339 W/m ² K) Cork insulation board fixed to the wall through an adhesive mortar, and plasterboard as an external layer					
Gypsum adhesive mortar	101	0.006	1400	3.50	0.400
Cork	110	0.090	150	10.80	0.039
Gypsum plasterboard	103	0.0125	680	8.93	0.200
Stucco	101	-	-	0.40	-
Gypsum finishing	104	0.002	950	1.90	0.400
“RW” insulation system (Wall U-value = 0.322 W/m ² K) Rockwool insulating board fixed to the wall through a metallic frame with vapor barrier and two plasterboards as an external layer					
Rockwool	111	0.08	18	1.44	0.035
Air gap	-	0.02	1.23	-	5.423 ¹
Steel C-profiles	112	-	7800	0.84	-
Steel U-profiles	112	-	7800	1.97	-
Gypsum plasterboards	103	0.025	680	17.86	0.200
Aluminum vapor barrier	113	-	-	0.08	-
Steel screws	112	-	-	0.08	-
Stucco	101	-	-	0.40	-
Gypsum finishing	104	0.002	950	1.90	0.400

¹ Conductance value [W/m²K].

The thicknesses of the different internal insulation layers have been computed in order to reach a wall U-value lower than 0.360 W/m²K, according to the actual Italian law requirements [62]. The slight differences in terms of U-values among insulation systems (for a maximum of 10%, see Table 3) are due to the commercial insulation thicknesses available in the market.

In this study, the following life cycle stages are included in the assessment: the production stage (modules A1–A3), the use stage (B6 operational energy use) and the EoL stage (modules C1–C4). For the sake of brevity and simplicity, the use stage was limited to the operational energy use, while components maintenance or replacement needs were neglected.

A calculation period of 30 years was taken into account. This timeframe is assumed to correspond to the service life of the insulation systems, assuming that no maintenance or replacement operations should occur during this time horizon. The functional unit is then defined as: “the insulation intervention (realized with insulation systems EPS, CaSi, AAC, Cork or RW) needed to cover a wall area of 1 m², providing an average thermal resistance $U \leq 0.36$ W/m²K for a building reference study period of 30 years”.

3.2. LCI and LCA Data Input Characterization

As previously introduced, the LCI is performed by adopting two different groups of datasets for the materials manufacturing stage, to obtain two alternative simulations sets: (i) data coming from EPDs (simulation group 1) and (ii) data coming from commercial LCI database ecoinvent v.3.1. (simulation group 2).

For the first group, the “deterministic” values from EPDs were used to characterize the unitary environmental impacts of materials adopted in the five insulation systems during the production stage. EPDs were retrieved from the websites of EPD program operators and all follow EN15804 standard, including life cycle stages A1 (raw material supply), A2 (transport), and A3 (manufacturing), i.e., cradle-to-factory gate. The unitary production impacts for all materials extracted from EPDs are reported in Appendix A, Table A1. Only for three materials (glass fiber mesh, steel elements and vapor barrier), EPD data were not available, thus the ecoinvent datasets were used.

In the second group, data from the ecoinvent v.3.1 database were used to characterize the unitary environmental impacts of materials used in the five insulation systems during the production stage.

Table 4 summarizes the data sources used for the materials' unitary environmental impact in the two simulation groups.

Table 4. Material datasets used in the two simulation groups.

Material ID-Name	Environmental Product Declaration (EPD) Number	Ecoinvent Dataset
101-Stucco	EPD-BVG-KNG-20140072-IAG1-EN	Stucco {RoW} production Alloc Rec, U
102-EPS boards	EPD-EUM-20160269-IBG1-EN	Polystyrene, extruded {RER} polystyrene production, extruded, CO ₂ blown Alloc Rec, U
103-Gypsum Plasterboard	EPD-KNA-20160140-IAG1-EN	Gypsum plasterboard {RoW} production Alloc Rec, U
104-Gypsum finishing	EPD-BVG-KNG-20140073-IAG1-EN	Stucco {RoW} production Alloc Rec, U
105-Mortar for CaSi/AAC	S-P-01012	Adhesive mortar {RoW} production Alloc Rec, U
106-CaSi	EPD-CSP-20180010-IBC1-EN	Calcium Silicate Board (dataset modeled with the tool based on literature, see EPD).
107-Glass fiber mesh	Not available	Glass fiber {RER} production Alloc Rec, U
109-AAC	EPD-XEL-20140218-CAD2-EN	Autoclaved aerated concrete block {GLO} market for Alloc Rec, U
110-Cork	DAP 002:2016	Cork slab {RER} production Alloc Rec, U
111-Rockwool	EPD-KNI-20160050-CBB1-EN	Rock wool, packed {RoW} production Alloc Rec, U
112-Metallic elements	Not available	Steel, low-alloyed, hot rolled {RER} production Alloc Rec, U
113-Aluminum vapor barrier	Not available	Aluminum alloy, AlMg3 {RER} production Alloc Rec, U

Concerning the two alternative building energy system scenarios, the following datasets were selected from ecoinvent V.3.1 to model the heating systems:

- Heat, central or small-scale, natural gas IT | heat production, natural gas, at boiler modulating <100kW | Alloc Rec, U;
- Heat, air-water heat pump 10kW IT| production | Alloc Rec, U.

Finally, the following dataset was selected from ecoinvent V.3.1 to model the EoL phase for all the materials used in both simulation groups: “Municipal solid waste (waste scenario) {RoW}| Treatment of municipal solid waste, landfill | Alloc Rec, U”. Table 5 summarizes the LCA input parameters PDFs, while the characterization procedure is described in the next paragraphs.

Table 5. Probability Density Functions (PDFs) of the parameters included in the LCA.

LCA Stage (EN 15978)	LCA Parameter Description	PDF (Simulation Group 1)	PDF (Simulation Group 2)
Production Stage	Mass of the materials composing the insulation system [kg]	Triangular distribution	
	Unitary environmental impact of material [Unit of indicator/kg]	Deterministic value from EPDs	Lognormal distribution
Use Stage	Energy Consumption	Normal distribution	
	Energy Impact	Lognormal distribution	
EoL Stage	EoL Material Impact	Lognormal distribution	

Within the ecoinvent database, the uncertainty of the unitary environmental impact for LCI background data is quantified by using the qualitative assessment of data quality indicators based on the pedigree matrix approach [63]. For each specific dataset (material production and EoL, heating

systems), MC analysis was performed using SimaPro software v8.1 (10.000 runs) and a data-fitting procedure was followed to identify and characterize the related PDF. The PDFs obtained are all lognormal with an R^2 equal to or higher than 0.99.

For the sake of brevity, only three indicators of the CML-2001 baseline method were reported in this work, i.e., global warming (GWP), acidification (AP), and eutrophication (EP). These indicators were chosen as the most significant indicators according to [64] and in compliance with most of the EPDs retrieved by insulation materials manufacturers.

Parameters of the distributions obtained are reported in Appendix A Table A2 (materials' production), Table A3 (heating systems), and Table A4 (Materials' EoL). Moreover, Figure 2 shows the lognormal cumulative density functions (CDF) retrieved for the GWP, AP, and EP impact indicators of the two datasets used for heat production (gas boiler and heat pump).

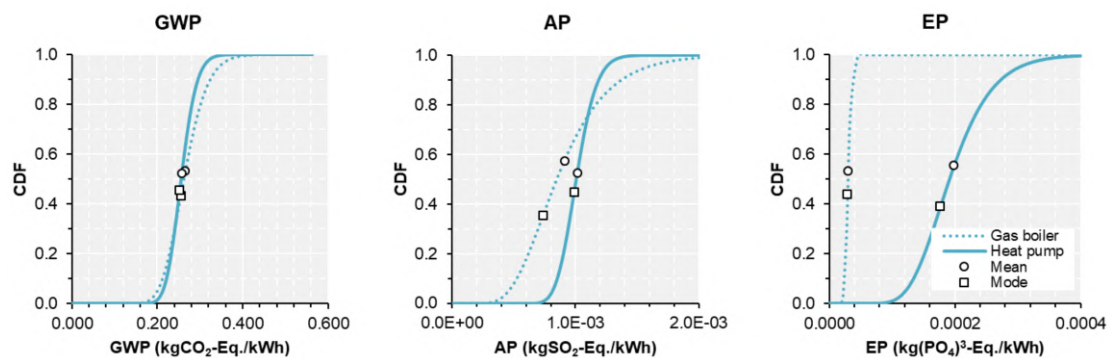


Figure 2. Lognormal cumulative density functions for the two datasets (gas boiler and heat pump) extracted from ecoinvent, according to global warming (GWP), acidification (AP), and eutrophication (EP) midpoint impact categories.

Concerning the masses of all materials composing the insulation systems (reported in Table 3), it is assumed that they are subject to uncertainty due to the possible differences among provisional and real quantities installed during the renovation. According to [30], a triangular distribution is assigned to the material mass, where the mode value is the quantity of material mass defined in the project, calculated based on the density and volume of each material or technical sheets, while minimum and maximum values are defined considering a variation from the mode by -5% to $+10\%$.

Once the deterministic values (simulation group 1) or the PDFs (simulation group 2) for each unitary environmental impact of component materials were defined, the unitary environmental impact at the whole insulation system level was calculated, considering the masses (and related uncertainties) of each material. This assessment was done through a basic random MC process with 10,000 runs, and lognormal distributions were estimated through a data-fitting test (Log-likelihood). This procedure is implemented and automatically performed in the RIBuild LCA/LCC software (Figure 3).

Normal distributions for the heat transmission losses pre- and post-renovation were obtained based on the annual HDD method described (Equation (1)), considering variable HDD data of the Italian region Lombardy from 2000 to 2016, extracted from Eurostat database [65]. In this study, the thermal transmittance values of the original wall and of the insulation systems were considered deterministic and are those previously reported (see Table 3). The PDFs values and parameters for Q_{hpre} and Q_{hpost} are reported in Appendix A, Table A5.

3.3. LCA and Uncertainty Analysis

After the uncertainty characterization of input parameters, Sobol's sequences technique is used to generate samples from the input PDFs and propagate the uncertainties according to the methodology developed. 50,000 simulation runs have been performed through the RIBuild LCA/LCC software, and finally, the probability distributions of the resulting environmental impacts were obtained.

Figure 3 represents the flowchart of the calculations performed with the RiBuild LCA/LCC software and previously illustrated. Once the data inputs of materials' impacts are retrieved for simulation groups 1 or 2 (step 1 in Figure 3) and the masses of the materials are defined for each insulation system (step 2), the MC simulation is performed in the software to calculate the PDFs of unitary environmental impact at the whole insulation system level, both for production and for EoL stage. Then, once defined the energy source (step 3) and the case study (step 4) with related data inputs of the use stage, the software performs the MC simulation to get the life-cycle impacts.

The LCA results of the five insulation systems related to the production stage are reported in Section 4.2, while those related to the whole life cycle in Section 4.3.

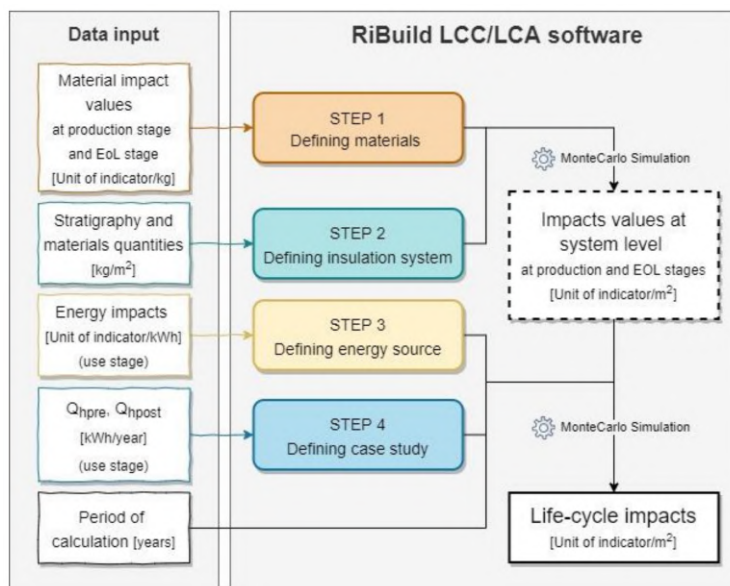


Figure 3. Flowchart depicting the operation of the RiBuild LCA/LCC software.

4. Results

4.1. Preliminary Comparison between EPD and Ecoinvent Data Sets

In order to understand whether the use of generic data or of EPD for the materials composing internal systems leads to substantial differences in terms of insulation systems LCA—and quantify these differences—a preliminary comparison between the “deterministic” (EPD) and “stochastic” (ecoinvent) data sets of the unitary environmental production impact of the component materials was carried out. At this aim, the percentile ranks of the EPD data related to the lognormal ecoinvent distributions were computed (see Table 6). It is worth noting that the declared unit in the EPDs has been scaled to 1 kg for each construction product to allow the comparison with the ecoinvent database.

Concerning the percentile ranks, it is assumed that the two datasets can be considered as “close” if the EPDs values fall between the 5th and 95th percentiles of the stochastic distributions, i.e., if the percentile rank associated with each deterministic value falls within the 5–95 range. Accordingly, several ranks are out of the 5–95 range, denoting a remarkable difference between the two datasets. Moreover, even when the percentile ranks fall within the 5–95 range, the differences observed between the mean values can still be quite high (even higher than 100% in some cases).

Table 6. For each material and impact category, these are percentile ranks of the material EPD values within the ecoinvent lognormal distribution. The values lower than 5 or higher than 95 are underscored. Insulation materials in bold.

Material ID-Name	GWP	AP	EP
101-Stucco	99.9	3.7	0.0
102-EPS boards	<u>4.3</u>	<u>0.0</u>	<u>0.0</u>
103-Gypsum Plasterboard	0.0	0.0	0.0
104-Gypsum finishing	100.0	40.5	0.0
105-Mortar for CaSi/AAC	0.0	0.0	0.0
106-CaSi	48.0	0.0	0.0
109-AAC	99.9	74.5	4.6
110-Cork	0.0	69.4	86.7
111-Rockwool	0.0	2.7	30.3

4.2. LCA Results of Production Stage (System Level)

The environmental performance of the five insulation systems, limited to the material production phase, is reported in this section with the aim of highlighting the outcomes and the differences at this stage. The analysis was performed by using: (i) EPD or ecoinvent data (respectively simulation groups 1 and 2) and (ii) the RIBuild stochastic approach or a “traditional” deterministic approach. At this aim, Figure 4 reports the Cumulative Density Functions (CDFs) of the insulation system impacts at the production stage obtained following the stochastic LCA for the simulation group 1 and 2. The parameters of the CDFs and the sample geometric coefficient of variation (gCV) are fully reported in Appendix A, Tables A6 and A7. Table 7, instead, presents the ranking of the environmental performance of the systems, computed by considering the mean values of the obtained distributions according to a traditional “deterministic” approach.

Concerning the CDFs, as expected, a low scattering has been obtained for the simulation group 1 (EPDs data) (Figure 4a), with gCV of about 2% to 3%, excepting for the RW case (gCV ranging from 11% to 28%, due to the adoption of the ecoinvent dataset for steel elements; see Section 3.2). This is mainly due to the absence of uncertainties on material impact values, drawn from EPD and to the low uncertainties related to the material quantities. Due to this aspect, the production impact of the insulation systems can be still ranked with good approximation by using mean values, as made in the “deterministic” approach (Table 7).

In particular, in the GWP case, the CaSi-based system is the worst performing solution, mainly due to the high insulation mass. Conversely, the Cork-based system is the best-performing one (see Figure 4b and Table 7), mainly due to the quite null and negative deterministic impact value from EPD adopted for the Cork material (-1.72×10^{-4} kgCO₂ eq./kg). The EPD of the Cork material, in fact, considers the CO₂ captured during cork oak tree growth, which leads to a negative balance of CO₂ eq. per cubic meter of cork insulation material [66].

This benefit is particularly relevant for the GWP indicator but not for the AP and EP indicators. In fact, when AP and EP indicators are concerned, the Cork-based system turns out to be the worst-performing solution, despite the insulation mass lower than that of CaSi (see Figure 4b and Table 7), while EPS and AAC based solutions are the best-performing ones. Once again, this can be ascribable to the higher order of magnitude of the impact values of the Cork insulation (1.00×10^{-2} kgSO₂ eq./kg and 3.19×10^{-3} kg(PO₄)³ eq./kg for AP and EP, respectively) respect to the other impact values of insulation materials from EPD (for CaSi insulation 2.40×10^{-3} kgSO₂ eq./kg and 4.90×10^{-4} kg(PO₄)³ eq./kg for AP and EP, respectively).

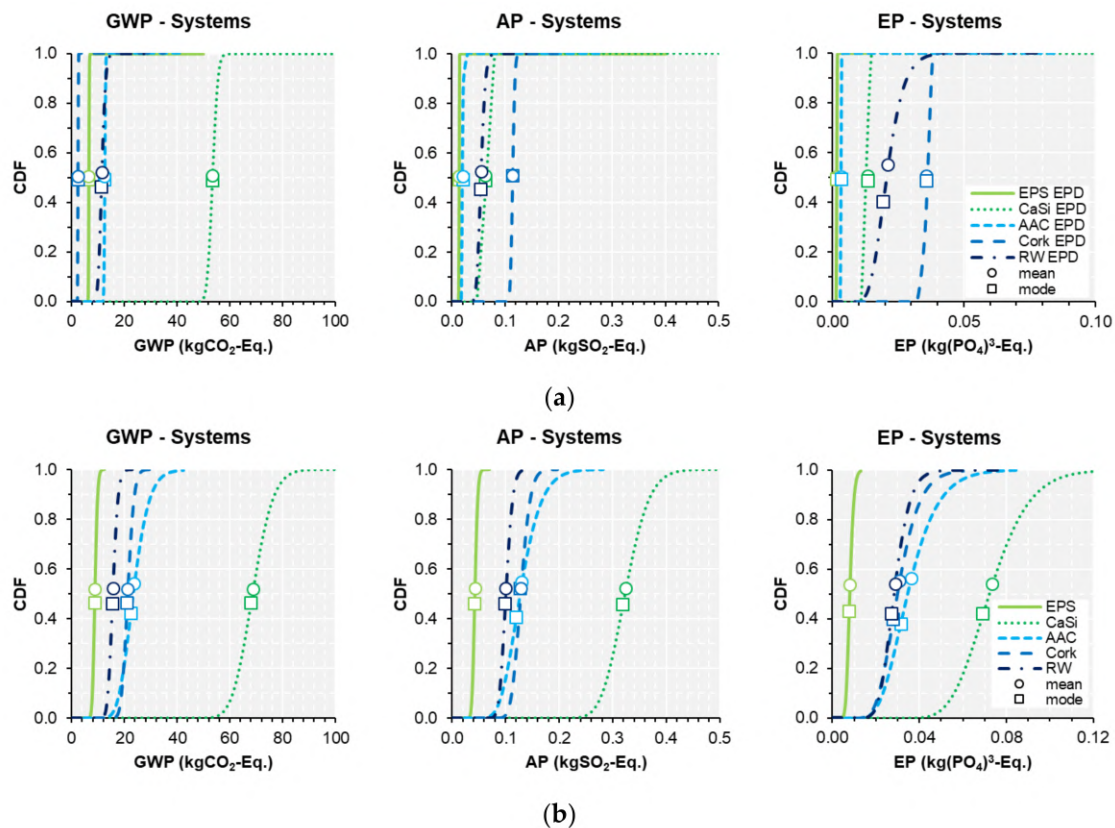


Figure 4. CDF of production impacts GWP, AP, and EP for the five insulation systems, computed for simulation group 1 (EPDs data) (a) and simulation group 2 (ecoinvent data) (b).

Table 7. Ranking of the production impacts (according to GWP, AP, and EP) for the insulation systems, calculated based on EPDs' data (group 1) and ecoinvent mean values (group 2) with a “deterministic” approach. Mean values in round brackets.

Systems	GWP (kgCO ₂ -Eq.)		AP (kgSO ₂ -Eq. 10 ⁻¹)		EP (kg(PO ₄) ³ -Eq. 10 ⁻²)	
	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
EPS	2 (6.6)	1 (9.0)	1 (0.1)	1 (0.4)	1 (0.2)	1 (0.8)
CaSi	5 (53.5)	5 (69.0)	4 (0.6)	5 (3.2)	3 (1.4)	5 (7.4)
AAC	4 (12.7)	4 (23.8)	2 (0.2)	4 (1.3)	2 (0.3)	4 (3.6)
Cork	1 (2.6)	3 (21.4)	5 (1.1)	3 (1.3)	5 (3.6)	3 (3.1)
RW	3 (11.5)	2 (15.7)	3 (0.6)	2 (1.0)	4 (2.1)	2 (2.9)

When ecoinvent datasets are used (simulation group 2, Figure 4b), a higher scattering is obtained (gCV ranging from 9% to 36%) due to the uncertainties on material impact values. In this case, a ranking of the material impact can be nontrivial. In fact, while the EPS and CaSi systems are certainly the best and worst-performing solutions for all the considered indicators (mainly ascribable to the different mass of the insulation materials, which is the lowest in the EPS case and the highest for the CaSi case; see Table 3), some issues arise by ranking AAC, Cork, and RW, whose CDFs overlap (see Figure 4b). It is also worth noting that the dataset for cork insulation material retrieved by the ecoinvent database does not include CO₂ capture during cork oak tree growth (as for EPD); hence, in this case, the dataset assumes a positive value. This higher uncertainty and difficulty in ranking the insulation systems of simulation group 2 does not emerge if results are read from a merely “deterministic” point of view (Table 7). With a “deterministic” approach, the analyst categorically and with certainty classify the performance of the solutions. However, he is not aware of the uncertainties that could affect the ranking.

The high differences obtained among the two simulation groups in terms of material production phase datasets (see Section 4.2.), significantly affect the production phase impacts. A comparison between the two simulation groups output is carried out in terms of percentage differences of mean values (adopting the simulation group 2 as reference) and fully reported in Appendix A, Table A8. In particular, for the GWP case, the percentage difference ranges from −22% (CaSi) to 88% (Cork) for the GWP case, from 12% (Cork) to 84% (AAC) for the AAC case and from 16% (Cork) to 91% (AAC) for the AAC. Materials with the highest share on the total insulation systems' impact at the production stage are also evaluated to establish individual responsibilities (for the sake of brevity results are reported in Table 8). In general, as expected, the insulation materials (and in some cases the finishing materials) have the greatest impact weight for all the systems. The only exception is the RW system, where the metallic frame and the plasterboard provide the highest impact. This result is obviously influenced by the masses of the materials involved.

Table 8. LCA shares at system level computed on mean values.

Layers	Mat. ID	Mass [kg]	Simulation Group 1			Simulation Group 2		
			GWP	AP	EP	GWP	AP	EP
"EPS" insulation system								
Gypsum adhesive mortar/stucco	101	3.90	3%	2%	3%	7%	4%	5%
EPS boards	102	1.26	55%	41%	42%	61%	72%	52%
Gypsum plasterboard	103	8.93	40%	56%	54%	29%	21%	40%
Gypsum finishing	104	1.90	2%	1%	1%	3%	3%	3%
"CaSi" insulation system								
Adhesive mortar/rendering	105	14.50	28%	36%	46%	8%	7%	10%
CaSi	106	23.92	71%	63%	54%	91%	91%	88%
Glass fiber mesh	107	0.08	1%	1%	0%	1%	2%	2%
"AAC" insulation system								
Adhesive mortar/rendering	105	14.50	80%	90%	92%	35%	25%	46%
AAC	109	9.00	20%	10%	8%	65%	75%	54%
"Cork" insulation system								
Gypsum adhesive mortar/stucco	101	3.90	1%	1%	2%	17%	1%	0%
Cork	110	10.80	81%	80%	84%	0%	96%	98%
Gypsum plasterboard	103	8.93	17%	19%	14%	73%	3%	2%
Gypsum finishing	104	1.90	1%	0%	0%	10%	0%	0%
"RW" insulation system								
Rockwool	111	1.44	14%	17%	12%	10%	26%	14%
Steel elements	112	2.89	37%	31%	55%	50%	57%	75%
Gypsum plasterboards	103	17.86	46%	48%	30%	33%	11%	7%
Aluminum vapor barrier	113	0.08	3%	3%	2%	0%	0%	0%
Stucco	101	0.40	0%	0%	0%	2%	1%	0%
Gypsum finishing	104	1.90	0%	1%	1%	4%	6%	3%

4.3. LCA Results of the Overall Life Cycle

LCA results are presented in this section considering the overall life cycle of the five insulation systems. Figures 5–7, according to the stochastic approach, show the CDFs of the global GWP, AP, and EP impacts in the two building heating system scenarios (gas boiler and air-to-water heat pump) and for both simulation groups. The parameters of all the CDFs, along with the related sample coefficient of variations (CV), are fully reported in Appendix A, from Table A9, Table A10, Table A11 to Table A12.

The most important outcome is that the general trend of CDFs (CV and mean values of distributions) is quite similar among both simulation groups, i.e., LCA results for this case study are similar when input datasets are retrieved from ecoinvent or from EPDs. The similarity in the results obtained in the two simulations groups occurs with the only exception of the AP and EP impacts of the CaSi system, which more clearly differs from group 1 to group 2 due to the higher share of the material production phase in this case on the LCA (Tables A13 and A14). For example, in the "gas boiler" scenario, the percentage differences between the two simulation groups, computed on the mean values, are approximately between 0% and −10% for the GWP case, from about −2% to −18% for AP, excepting for the CaSi system (30%), and between −5% and −10% for EP excepting for the CaSi case (33%, see also Table A15). Similar results have been obtained for the "heat pump" scenario.

The environmental performance of all insulation systems according to GWP and AP indicators are quite similar in both simulation groups. For instance, in the “gas boiler” scenario and the simulation group 1, the mean impact values of the insulation systems range from 163 to 170 kgCO₂ eq. for GWP (with the exception of CaSi that reaches 230 kgCO₂ eq.) and from 5.21 to 6.25 kgSO₂ eq. (AP, see Table 9). Similarly, in the simulation group 2, they range from 168 to 182 kgCO₂ eq. for GWP (excepting for CaSi that reaches 245 kgCO₂ eq.) and from 5.67 to 6.40 kgSO₂ eq. for AP (excepting for CaSi that reaches 8.67 kgSO₂ eq., see Table 10). Concerning EP indicator, the results are more uneven, and the environmental performance of the solutions differs most, with mean values ranging from about 0.60 to 2.70 kg(PO₄)³ eq for both simulation groups (see Tables 9 and 10). In particular, the AAC emerges as the worst-performing solution.

Table 9. Global ranking of the insulation systems based on their environmental impacts mean values (according to GWP, AP, and EP): simulation group 1 (EPD data). Mean values in round brackets.

Systems	GWP (kgCO ₂ -Eq.)		AP (kgSO ₂ -Eq. 10 ⁻¹)		EP (kg(PO ₄) ³ -Eq. 10 ⁻¹)	
	Gas Boiler	Heat Pump	Gas Boiler	Heat Pump	Gas Boiler	Heat Pump
EPS	3 (167)	3 (162)	3 (5.38)	3 (5.98)	1 (0.61)	1 (1.58)
CaSi	5 (230)	5 (225)	4 (6.07)	4 (6.68)	4 (1.23)	4 (2.22)
AAC	4 (170)	4 (166)	1 (5.21)	1 (5.78)	5 (2.44)	5 (3.36)
Cork	2 (164)	2 (159)	5 (6.25)	5 (6.83)	3 (1.14)	3 (2.08)
RW	1 (163)	1 (159)	2 (5.41)	2 (5.95)	2 (0.89)	2 (1.78)

Table 10. Global ranking of the insulation systems based on their environmental impacts mean values (according to GWP, AP, and EP): simulation group 2 (ecoinvent data). Mean values in round brackets.

Systems	GWP (kgCO ₂ -Eq.)		AP (kgSO ₂ -Eq. 10 ⁻¹)		EP (kg(PO ₄) ³ -Eq. 10 ⁻¹)	
	Gas Boiler	Heat Pump	Gas Boiler	Heat Pump	Gas Boiler	Heat Pump
EPS	2 (169)	2 (164)	1 (5.67)	1 (6.27)	1 (0.67)	1 (1.64)
CaSi	5 (245)	5 (240)	5 (8.67)	5 (9.28)	4 (1.83)	4 (2.83)
AAC	3 (181)	3 (177)	3 (6.33)	3 (6.90)	5 (2.73)	5 (3.65)
Cork	4 (182)	4 (178)	4 (6.40)	4 (6.98)	3 (1.09)	3 (2.02)
RW	1 (168)	1 (163)	2 (5.86)	2 (6.41)	2 (0.97)	2 (1.86)

These results are widely justified looking at the impact shares due to the different life-cycle stages (materials, energy, EoL) on the overall life-cycle, reported in Tables 11 and 12. The energy-related impact generally has the highest share on the global one. Concerning the GWP and AP indicators, it is generally higher than 80% of the global impact, thus reducing the effect of the material and EoL stages on the whole result. The only exceptions to this general rule occur in the case of insulating systems composed of high impact materials in the production phase (e.g., GWP of CaSi) or for the EP indicator, where the EoL and material phases assume an increasing influence.

It is worth noting that the operational energy use phase in this case study is assumed to be the same for all simulated cases, except for minor differences due to the choice of commercial insulation thicknesses, leading to slightly different wall U-values (for a maximum of 10%). Moreover, the same EoL scenario is assumed to be the same in the two simulation groups. This means that the environmental performance differences among solutions at the production phase, due to materials' impact and eventually to the different input datasets, highlighted in previous Section 4.2, are now relatively “flattened” due to the high impact of the use phase.

Concerning the CDFs trends, regardless of the simulation group and heating scenario, a scattering of the samples higher than that obtained in Section 4.2 at system level can be noted, with more scattered results for the “gas boiler” scenario. In particular, for the latter, the sample coefficient of variations (CV) ranges between 12% and 16% for the GWP indicator, from 31% to 38% for the AP indicator, and from 15% to 26% for the EP indicator (excepting for AAC that reaches a CV equal to 61% for EP). For the “heat pump” scenario, instead, the sample coefficient of variations (CV) ranges between 9% and 11% for the GWP indicator, from 12% to 14% for the AP indicator, and from 17% to 22% for the EP indicator (excepting for AAC that reaches a CV equal to 45% for EP).

For this reason, and due to the overlap of distributions in many cases, a ranking of the solutions based on the mean values, according to a “deterministic” approach, cannot be considered a viable solution for both the simulation groups. For instance, if we look at the “deterministic” ranking of solutions, reported in Tables 9 and 10, the RW and EPS based systems seem always among the best performing solutions. However, looking at the CDFs trend, it clearly emerges that the relative differences among these systems performances are quite limited, compared to those highlighted at the production stage, except for the CaSi or the AAC depending on the impact indicator as previously stated. Hence, a clear ranking among these solutions is not straightforward.

Finally, LCA results obtained in the two alternative heating scenarios only slightly differ according to the differences detected between the heating systems at the dataset level (see Figure 2). In particular, as seen in Figure 2, no significant differences can be noted for the GWP impact, while slight and noticeable differences can be appreciated for the AP case and the EP case, respectively (see mean values in Tables 9 and 10). More in detail, regardless the simulation group, the percentage differences between the two heating scenarios, computed on the mean values, range between -2% and -3% for the GWP case, from 7% to 11% for AP and from 34% to 159% for EP (see Table A16).

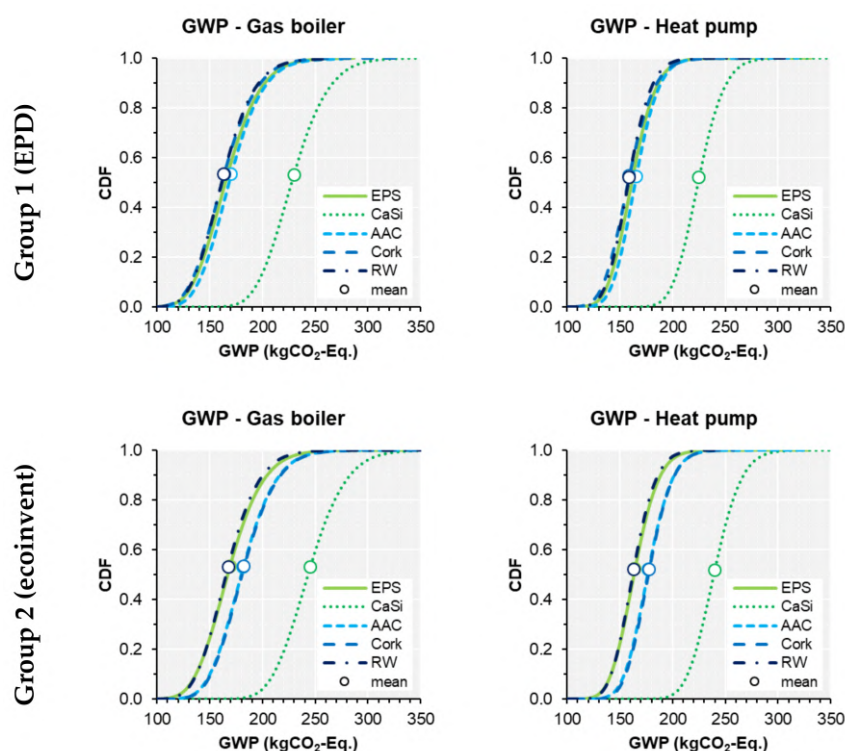


Figure 5. Life-cycle GWP of the five insulation solutions in the two building heating scenarios (different columns) and obtained by considering different data sources (in lines).

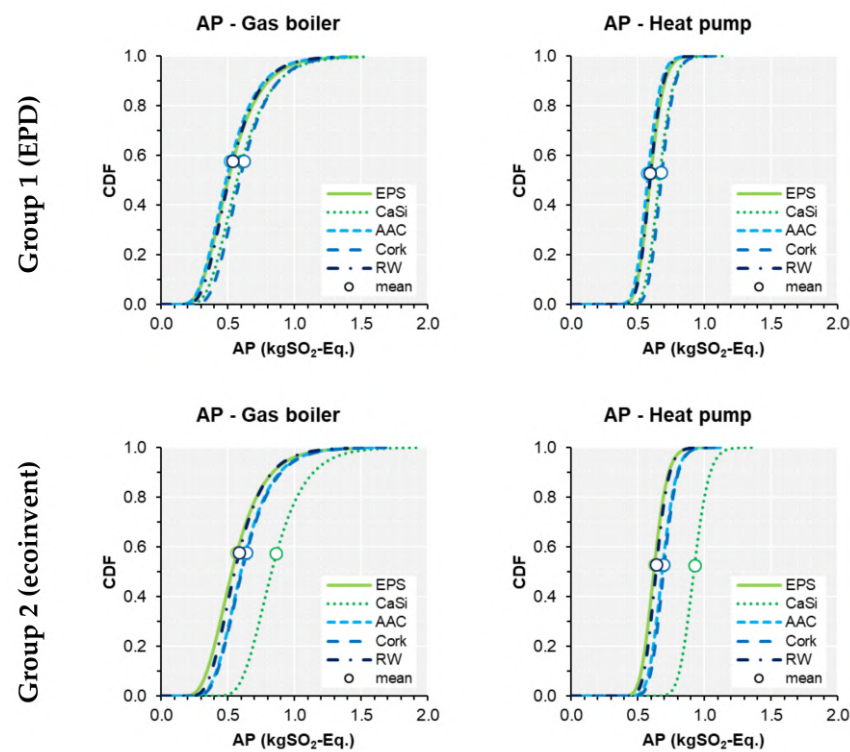


Figure 6. Life-cycle AP of the five insulation solutions in the two building heating scenarios (different columns) and obtained by considering different data sources (in lines).

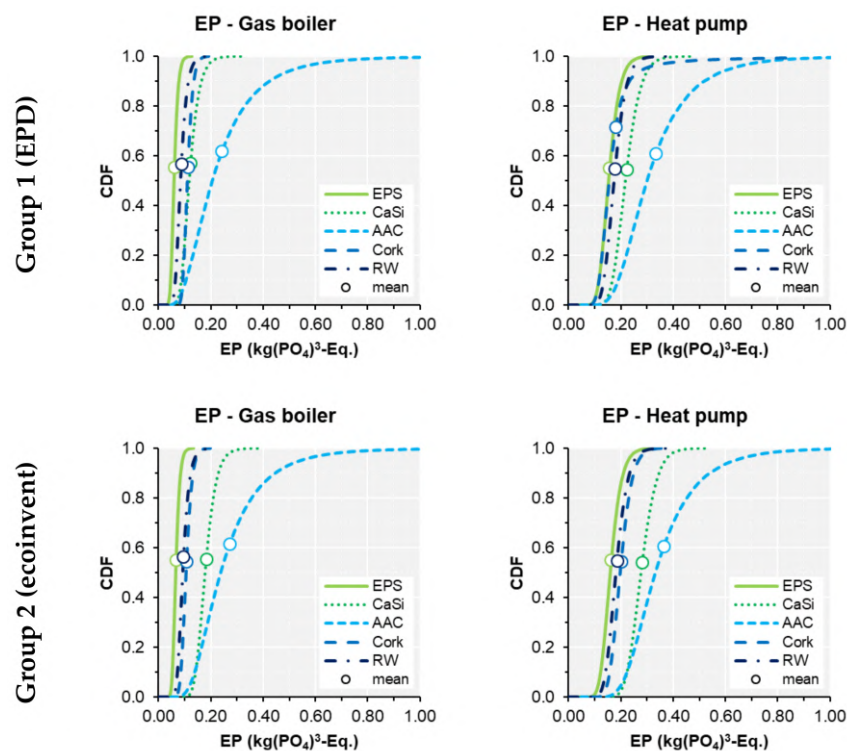


Figure 7. Life-cycle EP of the five insulation solutions in the two building heating scenarios (different columns) and obtained by considering different data sources (in lines).

Table 11. LCA shares computed on mean values (Simulation group 1, data from EPD).

Impact category	Insulation system	Gas Boiler			Heat Pump		
		Materials	EoL	Energy	Materials	EoL	Energy
GWP	EPS	4.0%	4.6%	91.4%	4.1%	4.7%	91.2%
	CaSi	23.3%	8.6%	68.2%	23.8%	8.7%	67.5%
	AAC	7.5%	7.0%	85.5%	7.7%	7.2%	85.1%
	Cork	1.6%	7.8%	90.6%	1.6%	8.1%	90.3%
	RW	7.1%	6.6%	86.4%	7.3%	6.7%	86.0%
AP	EPS	2.6%	0.2%	97.2%	2.4%	0.2%	97.5%
	CaSi	10.5%	0.5%	89.0%	9.6%	0.4%	90.0%
	AAC	4.1%	0.4%	95.5%	3.7%	0.3%	96.0%
	Cork	18.3%	0.3%	81.4%	16.7%	0.3%	83.0%
	RW	10.3%	0.2%	89.6%	9.3%	0.2%	90.5%
EP	EPS	2.9%	40.7%	56.4%	1.1%	15.7%	83.1%
	CaSi	11.0%	50.2%	38.8%	6.1%	27.7%	66.2%
	AAC	1.4%	18.2%	80.4%	1.0%	13.2%	85.8%
	Cork	31.5%	30.6%	37.9%	17.2%	16.7%	66.0%
	RW	24.0%	29.1%	46.9%	12.0%	14.5%	73.5%

Table 12. LCA shares computed on mean values (Simulation group 2, data from ecoinvent).

Impact category	Insulation system	Gas Boiler			Heat Pump		
		Materials	EoL	Energy	Materials	EoL	Energy
GWP	EPS	5.3%	4.5%	90.2%	5.5%	4.7%	89.9%
	CaSi	28.1%	8.0%	63.8%	28.7%	8.2%	63.1%
	AAC	13.1%	6.6%	80.3%	13.5%	6.8%	79.8%
	Cork	11.7%	7.0%	81.2%	12.0%	7.2%	80.7%
	RW	9.4%	6.4%	84.2%	9.6%	6.6%	83.8%
AP	EPS	7.6%	0.2%	92.2%	6.9%	0.2%	93.0%
	CaSi	37.5%	0.3%	62.2%	35.0%	0.3%	64.7%
	AAC	20.7%	0.3%	79.0%	19.0%	0.3%	80.7%
	Cork	20.2%	0.3%	79.5%	18.6%	0.3%	81.2%
	RW	17.2%	0.2%	82.6%	15.7%	0.1%	84.1%
EP	EPS	12.1%	36.8%	51.1%	4.9%	15.1%	79.9%
	CaSi	40.1%	33.6%	26.3%	26.0%	21.8%	52.2%
	AAC	13.4%	16.3%	70.4%	10.0%	12.1%	77.9%
	Cork	28.5%	32.0%	39.5%	15.3%	17.2%	67.6%
	RW	30.1%	26.7%	43.2%	15.6%	13.9%	70.5%

Finally, Figure 8 represents the CDFs of the global impact savings for the gas boiler scenario obtained thanks to the internal insulation measures, considering the reduced operational energy use compared to that of the original uninsulated building. Once again, CDFs are reported for both simulation groups. While confirming the solution performance ranking, this representation provides evidence on the environmental advantage to undertake the renovation intervention. The average payback time ranges from 1 to 5 years, depending on the insulation system, considering GWP and AP indicators, while it varies between 20 and 110 years considering EP. Results then highlight that according to the EP indicator, the internal insulation could even be counterproductive from an environmental point of view. In this sense, the stochastic representation is useful to assess the “probability” that a renovation measure leads to environmental advantages.

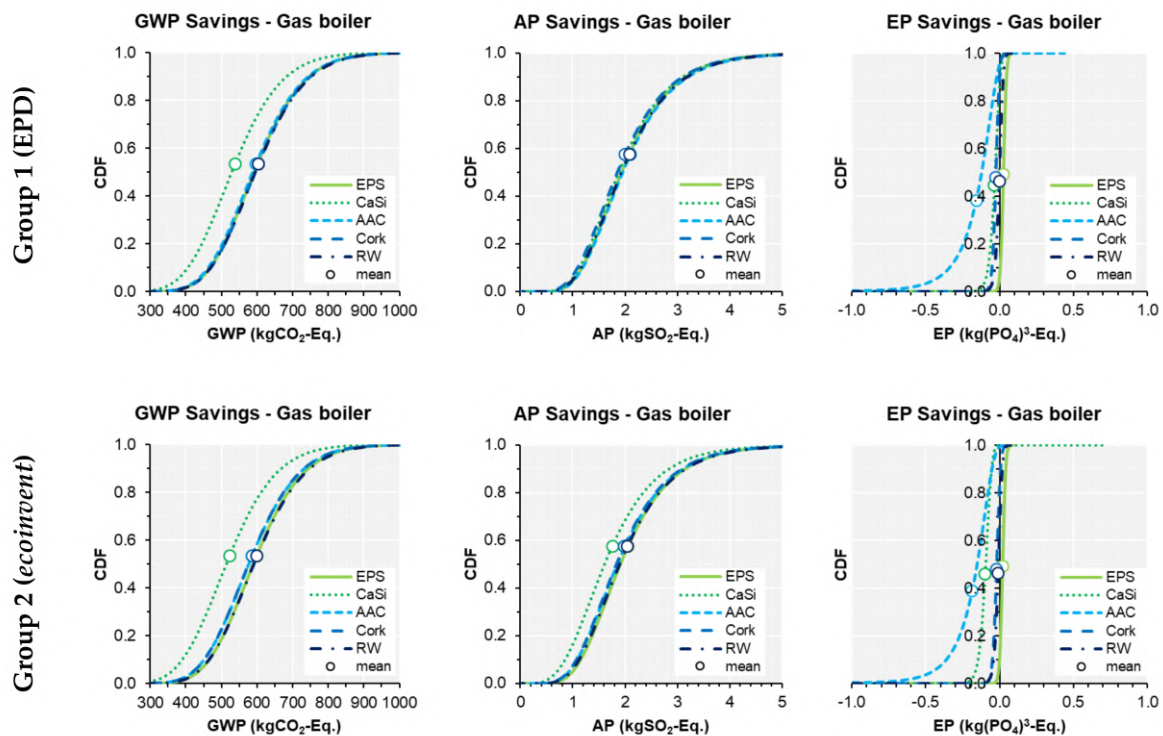


Figure 8. Impact savings for the impact categories considered in this study in the gas boiler energy scenarios (in columns) and obtained by considering different data sources (in lines).

5. Discussion

At the early design stage of a building renovation project, the building designers could evaluate to use alternative internal insulation solutions that may be functionally equivalent, but differ in their environmental performances. With the increasing climate challenges and public concerns, designers and decision-makers are urged to choose an optimal solution to mitigate the environmental burdens.

However, when performing an LCA, they may deal with different LCI data sources. If specific products are not identified and for common materials used in insulation systems (e.g., common plasters, insulation materials, etc.), they may acquire data from generic databases. At the same time, in such databases, they may not find datasets for specific and new products in the building market, e.g., “vapor-open capillary active insulation materials”, specific mortars with advanced hygrothermal properties, “smart” vapor barriers, etc. In this case, if available, they may be forced to use EPDs.

Based on the stochastic LCA approach developed by the authors during the EU project RIBuild, presented in Section 2 of the paper, this work investigates the impact of data availability and quality on the variability of the results of an LCA of five internal insulation systems applied to a historic building in Italy. The LCI data for materials’ manufacturing has been collected from two sources: a commercial LCI database or the EPDs of specific products selected among the most widespread in the Italian market. This led to two different simulation groups, which have been conducted under two different building heating systems scenarios.

The environmental performance of the insulation solutions has been analyzed both considering the whole impacts distributions ranges (as provided by the stochastic assessment) and the mean values (thus following a standard “deterministic” approach). At first, the environmental performance is analyzed only considering the material production phase, to highlight the outcomes differences obtained using EPD or ecoinvent data (respectively simulation groups 1 and 2); then, the whole life-cycle performance, including building use phase and EoL, was assessed.

The following points summarize the main findings obtained:

1. From a preliminary screening of the datasets on the unitary environmental production impact of the component materials, a remarkable difference between the deterministic (EPD) and stochastic (ecoinvent) data is ascertainable. This finding is in line with previous studies [24,38,46]. All the considered materials present at least one impact value from EPD “out” of the Ecoinvent PDF 5–95 percentile rank range. Even for those values within the range, high percentage differences are observed between EPD values and the mean values of the Ecoinvent lognormal distributions, ranging between 0% and 110%. Even if generic and EPD’s data are not directly comparable, as they refer to different background data, this analysis highlights that the starting points for an LCA of internal insulation, based on generic or specific datasets depending on the available information for the real products on the market, could be quite different.
2. At the production stage, an insulation systems’ environmental ranking can be quite easily performed for the simulation group 1 (EPDs data), as results present low uncertainties (generally gCV of 2% to 3%). However, the ranking is highly dependent on the environmental indicator selected. On the contrary, a clear ranking for group 2 (ecoinvent data) is not straightforward: A high distributions’ scattering is detected, with gCV ranging from 9% to 36%, due to the uncertainties on materials’ impact values. A similar amplitude of the coefficients of variation was obtained by Su et al. in their study [24]. Moreover, in group 2, while the EPS and CaSi systems are clearly respectively the best and worst-performing solutions, for all the indicators, the CDFs of the other insulation systems overlap. It is also worth noting that the environmental performance of solutions in simulation group 1 is better than that of group 2. Although previous studies, e.g., in [1,22–26], carried out an LCA of different insulation materials, a direct comparison of the results is not possible, due to the different preconditions of the studies (e.g., assumptions, database, functional units) and to the innovative insulation materials addressed in this study (CaSi, AAC).
3. Looking at the overall life cycle impact assessment, what primarily emerges is that the general trend of CDFs is quite similar among simulation groups and insulation systems. This means that the environmental performance differences among solutions at the production phase, due to materials’ impact and eventually to the different input datasets, are relatively “flattened”. This result is due to the operational energy use phase that in this case study accounts for more than 80% of the global impacts for the majority of simulated cases and which is assumed the same for all systems (with minor deviations due to slightly different wall U-values). As a result, the insulation thickness needed to reach the U-value of 0.36 W/m²K remains relatively low compared to the “optimal insulation thickness” from a life cycle impact assessment point of view for which the energy savings would compensate only the manufacturing impacts. In other words, in the current building energy norms, in the renovation, the influential parameter remains the heat demand and the energy carrier type.
4. The average environmental payback time of the five insulation systems is quite low, ranging from 1 to 5 years (depending on the specific system) considering GWP and AP indicators, while it is extremely high considering EP (between 20 and 110 years). Hence, it can be concluded that insulating is a good option in general, but the choice among different systems should be made by analyzing several indicators.
5. The LCA results obtained for all insulations systems, in both simulation groups and building heating systems scenarios, are affected by high uncertainty (with a maximum CV of 16% for the GWP indicator, ranging from 10% to 36% for the AP indicator, and from 15% to 61% for the EP indicator). For this reason, and due to the overlap of distributions in many cases, a ranking of the solutions based on the mean values, according to a “deterministic” approach, risks to provide misleading information.

The implications of the results obtained in this work are twofold. Firstly, they highlight the urgent need for consistent databases and to push for the development of accurate EPDs, especially for new and specific building materials with advanced properties, which are spreading more and more in the

market. Secondly, it demonstrates the potential of the use of stochastic LCA approaches in building decision making, which needs to be encouraged. Indeed, the information provided by the stochastic approach—estimates of the range and likelihood of impacts, rather than deterministic values—is more realistic and useful in the context of decision-making.

It should be considered that the work presents some limitations due to the specific assumptions made for the case study. Firstly, the stochastic LCA method within the *RIBuild* project was developed “at component level”. Even if this facilitates the immediate comparison between different solutions, it neglects the complexity and uncertainty sources present at the whole building level.

The use phase was limited to the operational energy use, while components maintenance or replacement needs were neglected. The EoL scenario was assumed to be the same for all systems. Further developments of the study could extend the range of validity of the results including and/or differentiating further the LCA phases.

In addition, the operational energy use was considered to be almost the same for all systems (except for slight differences due to the thickness of the insulation) and relatively high, thus reducing the influence of the other life stages on the overall impact. Moreover, it was calculated based on a simplified HDD method, neglecting the cooling behavior and how systems’ real hygrothermal performance could affect the life cycle performance, i.e., influencing the annual energy consumption and the periodical maintenance and replacement tasks.

Indeed, the high potential of the stochastic LCA developed for the evaluation of internal insulation is that it could be joined to a “probabilistic” hygrothermal performance assessment, in order to fully capture the real—different—life cycle behavior of alternative insulation measures, in this way effectively supporting decision-making. By doing so, outputs coming from the stochastic hygrothermal simulations and risk damage assessments could be used as inputs for the stochastic LCA, delivering more substantial results.

Using this approach could even overturn the ranking among the insulation systems obtained in the case study presented in this work, supporting solutions with higher production impact but safer from a hygrothermal point of view. This constitutes a future research direction.

6. Conclusions

Internal insulation of historic buildings is a widespread and effective solution to improve their energy efficiency while preserving their façades. However, the environmental benefit should not be limited to the evaluation of the energy-saving but rather be assessed in a life-cycle perspective, in order to take into the different environmental impacts account all possible risks that affect the whole performance, e.g., the risks of internal dampness and mold growth, the need for wall maintenance and system replacement.

The decision-making process before installing internal insulation should then address both hygrothermal performance and life cycle—environmental impacts and costs—analysis. At this aim, “probabilistic” methodologies in both fields, as those investigated and developed under *RIBuild* project, can better support risk management and decision-making, by addressing the issue of data uncertainty and providing results that are more reliable.

This paper presented the stochastic approach to the LCA of internal insulation solutions for historic buildings developed under the *RIBuild* project and its application to an exemplary case study. The example was intended to illustrate the potential of the method and to demonstrate how data input uncertainties—especially related to LCI background data for material manufacturing—could affect results. Those outcomes are important feedbacks for engineers and architects that are looking for decision-making support tools for the internal insulation of historical buildings. Even if specific assumptions are made for the probabilistic LCA of internal insulations, the methodology developed is an example of a probabilistic LCA approach that could be iterated with additional inputs and could find also other relevant applications in the building refurbishment sector.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Unitary production impacts for all materials extracted from EPDs.

Material ID-Name	GWP100 [kgCO ₂ eq/kg]	AP [kgSO ₂ eq/kg]	EP [kg(PO ₄) ³ eq/kg]
101-Stucco (EPD)	1.10×10^{-1}	1.51×10^{-4}	2.01×10^{-5}
102-EPS boards (EPD)	3.14	7.93×10^{-3}	7.33×10^{-4}
103-Gypsum Plasterboard (EPD)	2.09×10^{-1}	3.24×10^{-4}	7.96×10^{-5}
104-Gypsum finishing (EPD)	1.40×10^{-1}	2.04×10^{-4}	2.65×10^{-5}
105-Mortar for CaSi/AAC (EPD)	3.00×10^{-1}	2.88×10^{-4}	9.50×10^{-5}
106-CaSi (EPD)	2.01	2.40×10^{-3}	4.90×10^{-4}
109-AAC (EPD)	8.78×10^{-1}	1.62×10^{-3}	2.01×10^{-4}
110-Cork (EPD)	-1.72×10^{-4}	1.00×10^{-2}	3.19×10^{-3}
111-Rockwool (EPD)	8.05×10^{-1}	9.79×10^{-3}	2.04×10^{-3}

Table A2. Logarithmic mean (μ_{\log}), logarithmic standard deviation (σ_{\log}), mean (μ), and geometrical coefficient of variation (gCV) of the lognormal distributions for the unitary production impacts of all material samples extracted from ecoinvent database.

Material ID-Name	GWP100 [kgCO ₂ eq./kg]			gCV GWP [%]	AP [kgSO ₂ eq./kg]			gCV AP [%]	EP [kg(PO ₄) ³ eq./kg]			gCV EP [%]
	μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ	
101-Stucco	−2.72	1.65×10^{-1}	6.67×10^{-2}	18	−8.45	1.94×10^{-1}	2.18×10^{-4}	21	−9.68	2.12×10^{-1}	6.41×10^{-5}	24
102-EPS boards	1.35	1.18×10^{-1}	3.87	12	−4.29	1.12×10^{-1}	1.38×10^{-2}	12	−5.96	2.33×10^{-1}	2.66×10^{-3}	26
103-Gypsum Plasterboard	-9.36×10^{-1}	1.33×10^{-1}	3.96×10^{-1}	14	−5.95	1.65×10^{-1}	2.64×10^{-3}	18	−7.68	2.83×10^{-1}	4.80×10^{-4}	33
104-Gypsum finishing	−2.72	1.65×10^{-1}	6.67×10^{-2}	18	−8.45	1.94×10^{-1}	2.18×10^{-4}	21	−9.68	2.12×10^{-1}	6.41×10^{-5}	24
105-Mortar for CaSi/AAC	2.35×10^{-1}	2.41×10^{-1}	1.30	27	−4.87	2.68×10^{-1}	7.99×10^{-3}	31	−6.15	3.45×10^{-1}	2.27×10^{-3}	41
106-CaSi	7.02×10^{-1}	8.44×10^{-2}	2.03	9	−4.79	8.78×10^{-2}	8.38×10^{-3}	9	−6.43	2.08×10^{-1}	1.64×10^{-3}	23
107-Glass fiber mesh	8.70×10^{-1}	1.04×10^{-1}	2.40	11	−4.14	1.46×10^{-1}	1.61×10^{-2}	16	−5.66	2.69×10^{-1}	3.60×10^{-3}	31
109-AAC	-6.86×10^{-1}	1.81×10^{-1}	5.12×10^{-1}	20	−6.53	1.57×10^{-1}	1.48×10^{-3}	17	−8.07	2.62×10^{-1}	3.23×10^{-4}	30
110-Cork	4.51×10^{-1}	9.97×10^{-2}	1.58	10	−4.67	1.31×10^{-1}	9.44×10^{-3}	14	−6.09	3.08×10^{-1}	2.38×10^{-3}	36
111-Rockwool	3.68×10^{-1}	9.59×10^{-2}	1.45	10	−4.44	9.69×10^{-2}	1.19×10^{-2}	10	−6.07	2.49×10^{-1}	2.39×10^{-3}	28
112-Metallic elements	6.65×10^{-1}	2.00×10^{-1}	1.98	22	−4.55	2.10×10^{-1}	1.08×10^{-2}	23	−5.27	3.32×10^{-1}	5.45×10^{-3}	39
113-Aluminum vapor barrier	1.59	1.80×10^{-1}	4.99	20	−3.27	2.22×10^{-1}	3.90×10^{-2}	25	−4.76	2.92×10^{-1}	8.90×10^{-3}	34

Table A3. Logarithmic mean (μ_{\log}), logarithmic standard deviation (σ_{\log}), mean (μ), and geometrical coefficient of variation (gCV) of the lognormal distributions for the energy vector impacts extracted from ecoinvent database.

Heating System	GWP100 [kgCO ₂ eq./kWh]			gCV GWP [%]	AP [kgSO ₂ eq./kWh]			gCV AP [%]	EP [kg(PO ₄) ³ eq./ kWh]			gCV EP [%]
	μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ	
Gas boiler	−1.34	0.17	2.66×10^{-1}	18	−7.07	0.38	9.10×10^{-4}	46	−10.43	0.16	2.99×10^{-5}	17
Heat pump	−1.36	0.11	2.58×10^{-1}	12	−6.90	0.13	1.01×10^{-3}	14	−8.56	0.28	1.98×10^{-4}	32

Table A4. Logarithmic mean (μ_{\log}), logarithmic standard deviation (σ_{\log}), mean (μ), and geometrical coefficient of variation (gCV) of the lognormal distributions of the EoL phase dataset for all the materials extracted fromecoinvent database.

Material ID-Name	GWP100 [kgCO ₂ eq./kg]			gCV GWP [%]	AP kgSO ₂ eq./kg]			gCV AP [%]	EP [kg(PO ₄) ³ eq./kg]			gCV EP [%]
	μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ	
101-Stucco	-7.69×10^{-1}	3.94×10^{-1}	5.01×10^{-1}	48	-8.75	2.15×10^{-1}	1.62×10^{-4}	24	-6.18	4.84×10^{-1}	2.32×10^{-3}	62
102-EPS boards	-2.31	4.60×10^{-1}	1.11×10^{-1}	58	-9.51	2.65×10^{-1}	7.71×10^{-5}	30	-5.42	6.56×10^{-1}	5.51×10^{-3}	93
103-Gypsum Plasterboard	-7.71×10^{-1}	3.97×10^{-1}	5.01×10^{-1}	49	-8.74	2.18×10^{-1}	1.63×10^{-4}	24	-6.16	4.56×10^{-1}	2.35×10^{-3}	58
104-Gypsum finishing	-7.69×10^{-1}	3.94×10^{-1}	5.01×10^{-1}	48	-8.75	2.15×10^{-1}	1.62×10^{-4}	24	-6.18	4.84×10^{-1}	2.32×10^{-3}	62
105-Mortar for CaSi/AAC	-7.67×10^{-1}	3.96×10^{-1}	5.02×10^{-1}	49	-8.74	2.17×10^{-1}	1.64×10^{-4}	24	-6.15	4.57×10^{-1}	2.36×10^{-3}	58
106-CaSi	-7.69×10^{-1}	3.89×10^{-1}	5.00×10^{-1}	48	-8.74	2.20×10^{-1}	1.64×10^{-4}	25	-6.15	4.55×10^{-1}	2.37×10^{-3}	58
107-Glass fiber mesh	-5.27	2.84×10^{-1}	5.35×10^{-3}	33	-1.02 × 10	3.11×10^{-1}	4.09×10^{-5}	36	-1.17 × 10	3.11×10^{-1}	8.44×10^{-6}	37
109-AAC	-7.64×10^{-1}	4.00×10^{-1}	5.05×10^{-1}	49	-8.74	2.19×10^{-1}	1.63×10^{-4}	25	-4.14	7.26×10^{-1}	2.07×10^{-2}	107
110-Cork	-7.78×10^{-1}	3.94×10^{-1}	4.96×10^{-1}	48	-8.75	2.17×10^{-1}	1.63×10^{-4}	24	-6.14	4.59×10^{-1}	2.38×10^{-3}	58
111-Rockwool	-7.66×10^{-1}	3.93×10^{-1}	5.02×10^{-1}	48	-8.74	2.17×10^{-1}	1.63×10^{-4}	24	-6.16	4.83×10^{-1}	2.36×10^{-3}	62
112-Metallic elements	-5.26	2.76×10^{-1}	5.38×10^{-3}	32	-1.01 × 10	3.05×10^{-1}	4.10×10^{-5}	36	-1.17 × 10	3.08×10^{-1}	8.46×10^{-6}	36
113-Aluminum vapor barrier	-7.72×10^{-1}	3.96×10^{-1}	5.00×10^{-1}	49%	-8.74	2.20×10^{-1}	1.63×10^{-4}	25%	-6.15	4.58×10^{-1}	2.36×10^{-3}	58

Table A5. Mean (μ), standard deviation (σ), and coefficient of variation (CV) of the normal distributions of Q_{hpre} and Q_{hpost} related to the five insulation interventions.

System ID-Name	Q _{hpre} [kWh/year]		CV [%]	Q _{hpost} [kWh/year]		CV [%]
	μ	σ		μ	σ	
CS1-EPS				19.12	1.00	5.2
CS2-CaSi				19.67	1.03	5.2
CS3-AAC	96.19	5.02	5.2	18.25	0.95	5.2
CS4-Cork				18.57	0.97	5.2
CS5-Rockwool				17.64	0.92	5.2

Table A6. Logarithmic mean (μ_{\log}), logarithmic standard deviation (σ_{\log}), mean (μ), and geometrical coefficient of variation (gCV) of the lognormal distributions of the whole insulation system production impacts obtained through MC simulation, based on EPDs data (simulation group 1).

System ID-Name	GWP100 [kgCO ₂ eq.]			Gcv GWP [%]	AP [kgSO ₂ eq.]			gCV AP [%]	EP [kg (PO ₄) ³ eq.]			gCV EP [%]
	μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ	
CS1-EPS (EPD)	1.89	0.02	6.63	2	-4.26	0.02	1.41×10^{-2}	2	-6.32	0.02	1.79×10^{-3}	2
CS2-CaSi (EPD)	3.98	0.03	53.54	3	-2.75	0.03	6.40×10^{-2}	3	-4.30	0.03	1.36×10^{-2}	3
CS3-AAC (EPD)	2.54	0.02	12.68	2	-3.84	0.02	2.15×10^{-2}	2	-5.68	0.02	3.41×10^{-3}	2
CS4-Cork (EPD)	0.96	0.02	2.61	2	-2.17	0.03	1.14×10^{-1}	3	-3.33	0.03	3.58×10^{-2}	3
CS5-Rockwool (EPD)	2.44	0.10	11.53	11	-2.90	0.12	5.54×10^{-2}	13	-3.88	0.25	2.13×10^{-2}	28

Table A7. Logarithmic mean (μ_{\log}), logarithmic standard deviation (σ_{\log}), mean (μ), and geometrical coefficient of variation (gCV) of the lognormal distributions for the whole insulation system production impacts obtained through MC simulation, based on ecoinvent data (simulation group 2).

System ID-Name	GWP100 [kgCO ₂ eq.]			Gcv GWP [%]	AP [kgSO ₂ eq.]			gCV AP [%]	EP [kg (PO ₄) ³ eq.]			gCV EP [%]
	μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ		μ_{\log}	σ_{\log}	μ	
CS1-EPS	2.19	0.09	8.97	9	−3.15	0.10	4.31×10^{-2}	11	−4.83	0.18	8.12×10^{-3}	20
CS2-CaSi	4.23	0.09	69.00	9	−1.13	0.11	3.25×10^{-1}	12	−2.63	0.20	7.35×10^{-2}	22
CS3-AAC	3.15	0.20	23.81	22	−2.06	0.24	1.31×10^{-1}	27	−3.36	0.31	3.64×10^{-2}	36
CS4-Cork	3.06	0.09	21.41	9	−2.05	0.11	1.30×10^{-1}	12	−3.51	0.26	3.09×10^{-2}	30
CS5-Rockwool	2.75	0.10	15.72	11	−2.30	0.10	1.01×10^{-1}	11	−3.56	0.20	2.90×10^{-2}	22

Table A8. Percentage differences between the impact at systems level between mean values obtained in simulation group 1 (EPD) and mean values from simulation group 2 (ecoinvent). Simulation group 2 is taken as reference. Negative values mean ecoinvent impacts higher than EPD ones.

System ID-Name	GWP100	AP	EP
CS1-EPS	−26%	−67%	−78%
CS2-CaSi	−22%	−80%	−82%
CS3-AAC	−47%	−84%	−91%
CS4-Cork	−88%	12%	16%
CS5-Rockwool	−27%	−45%	−27%

Table A9. LCA results of the overall life cycle in terms of mean (μ), standard deviation (σ), and Coefficient of Variation (CV) of the obtained samples from MC simulation for the GWP impact category, based on EPD data (simulation group 1).

System ID-Name	GWP100/Gas [kgCO ₂ eq.]		CV Gas [%]	GWP100/HP [kgCO ₂ eq.]		CV HP [%]
	μ	σ		μ	σ	
CS1-EPS (EPD)	166.91	26.72	16	162.04	18.50	11
CS2-CaSi (EPD)	229.98	28.03	12	224.97	19.80	9
CS3-AAC (EPD)	170.15	25.67	15	165.50	17.89	11
CS4-Cork (EPD)	163.74	26.05	16	159.01	18.10	11
CS5-Rockwool (EPD)	163.36	24.87	15	158.87	17.39	11

Table A10. LCA results of the overall life cycle in terms of mean (μ), standard deviation (σ), and Coefficient of Variation (CV) of the obtained samples from MC simulation for the AP impact category, based on EPD data (simulation group 1).

System ID-Name	AP/Gas [kgSO ₂ eq.]		CV Gas [%]	AP/HP [kgSO ₂ eq.]		CV HP [%]
	μ	σ		μ	σ	
CS1-EPS (EPD)	5.38×10^{-1}	2.05×10^{-1}	38	5.98×10^{-1}	8.15×10^{-2}	14
CS2-CaSi (EPD)	6.07×10^{-1}	2.11×10^{-1}	35	6.68×10^{-1}	8.29×10^{-2}	13
CS3-AAC (EPD)	5.21×10^{-1}	1.96×10^{-1}	38	5.78×10^{-1}	7.78×10^{-2}	13
CS4-Cork (EPD)	6.25×10^{-1}	2.00×10^{-1}	32	6.83×10^{-1}	7.92×10^{-2}	12
CS5-Rockwool (EPD)	5.41×10^{-1}	1.90×10^{-1}	35	5.95×10^{-1}	7.55×10^{-2}	13

Table A11. LCA results of the overall life cycle in terms of mean (μ), standard deviation (σ), and Coefficient of Variation (CV) of the obtained samples from MC simulation for the EP impact category, based on EPD data (simulation group 1).

System ID-Name	EP/Gas [kg (PO ₄) ³ eq.]		CV Gas [%]	EP/HP [kg(PO ₄) ³ eq.]		CV HP [%]
	μ	σ		μ	σ	
CS1-EPS (EPD)	6.10×10^{-2}	1.27×10^{-2}	21	1.58×10^{-1}	3.51×10^{-2}	22
CS2-CaSi (EPD)	1.23×10^{-1}	3.17×10^{-2}	26	2.22×10^{-1}	4.63×10^{-2}	21
CS3-AAC (EPD)	2.44×10^{-1}	1.48×10^{-1}	61	3.36×10^{-1}	1.51×10^{-1}	45
CS4-Cork (EPD)	1.14×10^{-1}	1.71×10^{-2}	15	2.08×10^{-1}	3.61×10^{-2}	17
CS5-Rockwool (EPD)	8.87×10^{-2}	2.09×10^{-2}	24	1.78×10^{-1}	3.67×10^{-2}	21

Table A12. LCA results of the overall life cycle in terms of mean (μ), standard deviation (σ), and Coefficient of Variation (CV) of the obtained samples from MC simulation for the GWP impact category, based on ecoinvent data (simulation group 2).

System ID-Name	GWP100/Gas [kgCO ₂ eq.]		CV Gas [%]	GWP100/HP [kgCO ₂ eq.]		CV HP [%]
	μ	σ		μ	σ	
CS1-EPS	169.21	26.73	16	164.34	18.51	11
CS2-CaSi	245.20	28.74	12	240.19	20.79	9
CS3-AAC	181.63	26.12	14	176.98	18.54	10
CS4-Cork	182.50	26.12	14	177.77	18.21	10
CS5-Rockwool	167.53	24.90	15	163.04	17.43	11

Table A13. LCA results of the overall life cycle in terms of mean (μ), standard deviation (σ), and Coefficient of Variation (CV) of the obtained samples from MC simulation for the AP impact category, based on ecoinvent data (simulation group 2).

System ID-Name	AP/Gas [kgSO ₂ eq.]		CV Gas [%]	AP/HP [kgSO ₂ eq.]		CV HP [%]
	μ	σ		μ	σ	
CS1-EPS	5.67×10^{-1}	2.05×10^{-1}	36	6.27×10^{-1}	8.16×10^{-2}	13
CS2-CaSi	8.67×10^{-1}	2.14×10^{-1}	25	9.28×10^{-1}	9.15×10^{-2}	10
CS3-AAC	6.33×10^{-1}	1.99×10^{-1}	31	6.90×10^{-1}	8.41×10^{-2}	12
CS4-Cork	6.40×10^{-1}	2.00×10^{-1}	31	6.98×10^{-1}	8.05×10^{-2}	12
CS5-Rockwool	5.86×10^{-1}	1.90×10^{-1}	32	6.41×10^{-1}	7.59×10^{-2}	12

Table A14. LCA results of the overall life cycle in terms of mean (μ), standard deviation (σ), and Coefficient of Variation (CV) of the obtained samples from MC simulation for the EP impact category, based on ecoinvent data (simulation group 2).

System ID-Name	EP/Gas [kg (PO ₄) ³ eq.]		CV Gas [%]	EP/HP [kg(PO ₄) ³ eq.]		CV HP [%]
	μ	σ		μ	σ	
CS1-EPS	6.73×10^{-2}	1.27×10^{-2}	19	1.64×10^{-1}	3.51×10^{-2}	21
CS2-CaSi	1.83×10^{-1}	3.54×10^{-2}	19	2.83×10^{-1}	4.88×10^{-2}	17
CS3-AAC	2.73×10^{-1}	1.41×10^{-1}	52	3.65×10^{-1}	1.44×10^{-1}	40
CS4-Cork	1.09×10^{-1}	1.88×10^{-2}	17	2.02×10^{-1}	3.70×10^{-2}	18
CS5-Rockwool	9.65×10^{-2}	2.10×10^{-2}	22	1.86×10^{-1}	3.68×10^{-2}	20

Table A15. Percentage differences between the impact of the overall life cycle computed by considering the mean values obtained in simulation group 1 (EPD) and mean values from simulation group 2 (ecoinvent). Simulation group 2 is taken as reference; then, negative values mean ecoinvent impacts higher than EPD ones.

System ID-Name	GWP100		AP		EP	
	Gas	HP	Gas	HP	Gas	HP
CS1-EPS	−1.36%	−1.40%	−5.11%	−4.62%	−9.43%	−3.87%
CS2-CaSi	−6.21%	−6.34%	−29.96%	−27.99%	−32.96%	−21.36%
CS3-AAC	−6.32%	−6.49%	−17.66%	−16.21%	−10.65%	−7.96%
CS4-Cork	−10.28%	−10.55%	−2.36%	−2.17%	4.75%	2.55%
CS5-Rockwool	−2.49%	−2.55%	−7.71%	−7.05%	−8.12%	−4.22%

Table A16. Percentage differences between the impact of the overall life cycle computed on mean values obtained for the “gas boiler” and “heat pump” scenarios. “Gas boiler” scenario is taken as reference, then negative values mean that the “Gas boiler” scenario related impacts are higher than “heat pump” ones.

System ID-Name	Simulation Group 1			Simulation Group 2		
	GWP	AP	EP	Gas	AP	EP
CS1-EPS	−3%	11%	159%	−3%	11%	144%
CS2-CaSi	−2%	10%	80%	−2%	7%	55%
CS3-AAC	−3%	11%	38%	−3%	9%	34%
CS4-Cork	−3%	9%	82%	−3%	9%	85%
CS5-Rockwool	−3%	10%	101%	−3%	9%	93%

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