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Towards a probabilistic approach in LCA of building retrofit measures

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Abstract

This paper proposes an approach of sensitivity analysis for LCA of building retrofit measures aiming to establish the impact of input data uncertainties on the output variance. The approach includes the quantification of data input uncertainties in terms of their Probability Distribution Functions (PDFs), their sampling and the uncertainty propagation through Monte Carlo (MC) methods. A sensitivity analysis through Variance based decomposition (Sobol' method) techniques are used to point out the key parameters uncertainties that mostly affect the LCA results distributions. The paper presents a building case-study where the MC-based uncertainty and sensitivity analysis method is applied considering different design options (XPS and Cork internal insulation measures) and different scenarios for the assessment of the building energy need (use phase). Results obtained highlight that the differences on the Climate change environmental impact between the two design options is quite limited (about 12%) and this is mainly due to the use phase which is the more relevant input parameter on the overall result. Concerning the Sensitivity Analysis, when the building energy need is considered as a "deterministic" input in the LCA assessment, the unitary impacts of the design options materials uncertainties are the most influential parameters. On the other hands, when the building energy need is represented by a PDF, the quantity of energy carrier consumed and its unitary environmental impact are the most influential parameters on the output variance.

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1. Introduction

The building sector accounts for 40% of the energy use within Europe. Energy efficiency and the use of sustainable materials are then key aspects to be considered to meet the European climate change and energy objectives for the 2020 [1]. The 2010 Energy Performance of Buildings Directive (EPBD recast) [2] clearly established that all new buildings must be nearly Zero Energy Buildings (nZEB) by 31 December 2020 (public buildings by 31 December 2018), with great benefits in energy and environmental terms during the building use phase. Nevertheless, European buildings turnover rate is quite low (annually estimated at around 1-1,5% of the housing stock [1]), and 30% of actual buildings are historical buildings that ought to last for decades. Consequently, there is a great potential to reduce energy use and greenhouse gas emissions related to building renovation sector [3][4] and retrofit into Nearly Zero-Energy level is more and more recommended by European Commission [5].

In this context, building environmental performances need to be deeply evaluated taking into account a lifecycle perspective, considering not only building use energy needs but also the environmental aspects related to renovation design choices [6].

2. Background on LCA probabilistic approaches in building sector

Life cycle assessment (LCA) is a consolidated methodology for evaluating the environmental loads of products and services and it addresses the potential environmental impacts over the life cycle [7][8]. LCA has been used in the building sector from early '90s and it is an important tool for assessing environmental buildings performances [9][10]. However, the practical application of LCA methodologies is often carried out with many simplifications related to data inputs and forecasting, that could increase the result uncertainty [11]. For this reason, LCA could have practical limitations as a decision-making tool in the analysis of the retrofitting measures, if the user is not aware of these inherent limitations and does not have proper tools to assess them [12].

In the last decades, several works have been issued on the characterization of uncertainties for LCA. In general, uncertainties can be categorized as either aleatory or epistemic. Epistemic uncertainties can be reduced by gathering more data or by refining the model. Uncertainties categorized as aleatory do not foresee the possibility to be reduced [13]. From an engineering point of view, only epistemic sources can be managed as LCA data input. According to Chouquet et al. uncertainty sources in building LCA models can be defined as follows: (i) environmental data quality (incomplete, inaccurate, obsolete), (ii) building description (incomplete, inaccurate), (iii) building lifespan and components service life (assumptions on lifespan, degree of refurbishment) and (iv) building operation (performance of heating equipment, long term evolution of costs and resource depletion, etc.) [14].

Environmental data quality is generally estimated using the pedigree matrix approach [15][16][11], introduced into LCA repositories (e.g. Eco-invent). Other than that, statistical methods have been used to a limited extent in LCAs to characterize the data quality [17][18]. Amongst them, Monte Carlo simulation have been included into commercial LCA software (e.g. SimaPro) [19]. Building context and description uncertainties are related to the amount of data available for the project under evaluation. Service life of materials and components used in buildings is usually shorter than the building lifespan [20][21]. The effective service life of these elements and the related uncertainty are affected by many factors and operative condition (e.g. humidity, UV, temperature, etc.) and for these reasons maintenance and/or complete substitution is necessary in most of the cases. Data collection can be performed by a critical literature review of materials typically used in building and their service life [22]. Building operations are affected by a huge uncertainty. Building Performance Simulation software's provide relevant design information by indicating the primary energy consumptions [23][24], but it also deals with a large variety of parameters and complexity of factors affected to uncertainties themselves. Furthermore, during the use phase, the advent of new technologies, the nature of energy carriers and their associated environmental impact can drastically change [25][26]. This topic is particularly relevant for existing buildings, whose energy performance is more affected to uncertainties related to existing building features, equipment, use. The above-described uncertain data, identified in a typical LCA building model, affect the result in different way. Sensitivity analysis (SA) is a systematic procedure which aids to assess the effects of the chosen methods and data on the outcome of a study [27]. It can be used in LCA to provide a meaningfulness of uncertainties and their impact on the result.

This paper proposes an approach to conduct a sensitivity analysis in the case of LCA analysis of building retrofit measures aiming to establish the impact of input data uncertainties on the output variance. The approach includes the quantification of data input uncertainties in terms of their Probability Distribution Functions (PDFs), their sampling and propagation through Monte Carlo (MC) methods and finally a sensitivity analysis through Variance based decomposition (Sobol' method) techniques to point out the key parameters uncertainties that mostly affect the LCA results distributions.

The paper presents a building case-study where the MC-based uncertainty and sensitivity analysis method is applied considering different approaches for the uncertainties on the building energy performance. Specific results obtained are shown and debated, underlining the potentials of the approach.

3. Methodology

3.1. Building case-study and retrofit measures

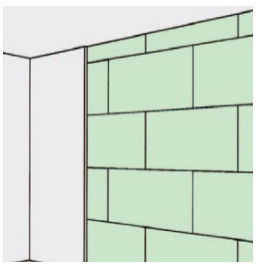
The case study is a single-family detached house with two floors and an attic of early 1900s, located in Cattolica, a coastal town in the centre of Italy (average heating degree days: 2165). The gross volume of the building is about 467 [m3], the net floor area 178 [m2], for a surface/volume ratio of 0.82. The original walls are made by plastered brick masonry (29 [cm] thickness, U-value of 1.76 [W/m2K]), while floors and roof structure consist of the wooden joists with respectively pavements (U-value 1.29 [W/m2K]) or clay tiles (U-value 1.68 [W/m2K]). In this exemplary case, two alternative internal insulation solutions for the building walls are selected as energy efficiency measures:

Design option A (Table 1): 11 [cm] XPS coupled with plasterboard, without vapour barrier, directly fixed to the wall through a specific mortar;

Design option B (Table 2): 12 [cm] Cork coupled with plasterboard, with vapour barrier, fixed to the wall through a metallic frame.

Table 1 Design option A

Materials	Thickness [m]	Density [kg/m3]	Thermal conductivity [W/mK]	Mass [Kg]
Skim coat and Paint	-	1200	0.7	27.6
Stucco	-	1970	0.9	64.4
Plasterboard	0.0125	760	0.20	1748
XPS insulating mat.	0.11	30	0.035	608
Fixing screws	-	7800	-	25.4



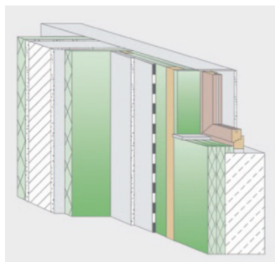
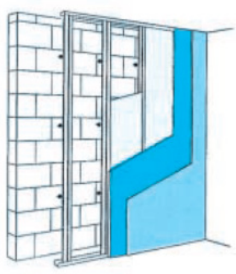
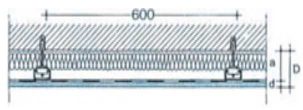


Table 2 Design option B

Materials	Thickness [m]	Density [kg/m3]	Thermal conductivity [W/mK]	Mass [Kg]
Skim coat and Paint	-	1200	0.7	27.6
Stucco	-	1970	0.9	64.4
Plasterboard	0.0125	760	0.20	1748
Vapour barrier	-	2700	204	74.6
Cork insulating mat.	0.12	100	0.039	2229.5
Metal frame and fixing screws	-	7800	36	236.7





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The two internal insulation measures allow to reach almost the same U-value for the wall based on the actual requirements (U ≤ 0.30 [W/m^{2}K] imposed by Italian Ministerial Decree 26/06/2015 for second level renovation interventions in the Italian climatic zone "E (the most widespread in Italy). In particular, 0.28 [W/m^{2}K] for design option A and 0.29 [W/m^{2}K] for design option B. The slight different values depend on the commercial insulation thicknesses available in the market. The building energy performance for heating has been assessed according to national technical standard UNI TS 11300 [28] (that implemented at national level the European standard EN 13790). The assessment has been performed with the following assumptions: ventilation rate at 0.5 [h-1], simplified approach for the calculation of internal heat gains, building internal heat capacity, temperature of unconditioned spaces, and thermal bridge effects (percentage increase of the transmission heat transfer), global heating efficiency 0.8, conversion coefficient to primary energy fixed at 1.05 for fossil fuels.

3.2. LCA model and PDFs of calculation inputs

Principles and guidelines provided by the UNI EN ISO 14040 and 14044 have been used for the definition of the proposed LCA calculation method. Specifically, the European standard EN 15978 has been followed for the consistency in terminology and specificity in building sector.

The functional equivalent is defined as the insulation intervention needed to cover an area of 184 m^2 providing an average thermal transmittance of 0,30 [W/m^{2}K] for a service life of 30 years. The definition of this functional unit covers both design options previously described and fits with the Italian Ministerial Decree 26/06/2015.

The system boundaries are limited to the production stage (A1-3), transportation (A4) and operational energy use stage (B6) in accordance with the EN 15978 [29]. The construction-installation process (A5) and end-of-life stage (C1-4) fall outside the system boundaries according to [12]. Maintenance, replacement and refurbishment (B1-5) have not been considered in reference to the components service lives [30].

The LCI (Life Cycle Inventory) have been carried out using primary data for the LCA analysis whenever available and secondary data from EcoInvent 3.1 database.

The following LCIA (Life Cycle Impact Assessment) methods have been used for the calculation of the environmental impacts:

- ReCiPe mid-point - Hierarchist (H) version - Europe [31].
- Cumulative Energy Demand (CED) [32].

Since this study is addressed to building retrofit measures, energy and natural resources are of primary importance. To address these perspectives, this study uses Human Health (HH) and Resources (RA) mid-point impact categories from the internationally accepted method ReCiPe (H) [31]. The climate change impact category within the ReCiPe mid-point (H) method includes all greenhouse gases specified in the Kyoto Protocol using global warming potentials from the IPCC Fourth Assessment Report with a 100-year time horizon [33]. The cumulative energy demand (CED) method [32] is used, additionally, as a single-issue indicator to evaluate energy demand associated with a product's life cycle. The default ReCiPe mid-point method perspective used is the Hierarchist (H) version referred to the normalisation values of Europe. Perspective H is based on the most common policy principles with regards to 100 [year] timeframe (as referenced in the ISO 14044 standard).

The LCA approach proposed in this work is based on an uncertainty and sensitivity analysis (UA and SA) through Monte-Carlo method, to build the output probability density function and to assess global uncertainty and sensitivity [34]. The output distribution is obtained running the LCA model N times, where N is the dimension of the vectors obtained by drawing samples from the LCA input distributions. Once the UA is performed, SA allow to determine which of the input parameters influence more the model output uncertainty. In order to perform UA and SA, it is therefore necessary to define the PDFs for the model inputs, assumed here to be independent, which will be propagated to obtain the probability density of the output variable [22]. PDFs are defined based on different sources: literature analysis, existing database, time series from national and international organizations, etc.

In stage A1-3, the parameters considered as stochastics are the mass of the material and the unitary environmental impacts. For the components mass used in the insulation measures, a triangular PDF has been assumed with a min = -5% and a max = +10% based on [22]. For the unitary environmental impacts (materials, transport, and natural gas energy), the Eco-Invent DB 3.1 has been used to characterize the uncertainties of the secondary data [35].

Table 3 Probabilistic input parameters for the case study

LCA Phase	LCA parameter	Design Option A	Design Option B	Quantity PDF*	Quantity Reference for PDF	Impact PDF	Impact Reference for PDF
A1-A3	Plasterboard	X	X	Tri (1662.9; 1925.5; 1750.5) [kg]	[22] [35]	Nor (0.401;0.055) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	XPS	X		Tri (577.6; 668.8; 608.1) [kg]	[22] [35]	Nor (3.98; 0.489) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	Cork		X	Tri (2118.1; 2452.5; 2229,5) [kg]	[22] [35]	Nor (1.59; 0.168) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	Vapour barriers		X	Tri (70.9; 82.1; 74.6) [kg]	[22] [35]	Nor (5.02; 0.913) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	Fixing screw (carbon steel)	X	X	Tri (45.2; 52.3; 47,5) [kg]	[22] [35]	Nor (2.01; 0.412) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	Hook (carbon steel)		X	Tri (13.13; 15.20; 13.82) [kg]	[22] [35]	Nor (2.01; 0.412) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	C-shape frame (carbon steel)		X	Tri (131.9, 152.8, 138.9) [kg]	[22] [35]	Nor (2.01;0.412) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	U-shape frame (carbon steel)		X	Tri (34.6; 40.1; 36,5) [kg]	[22] [35]	Nor (2.01;0.412) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	Stucco	X	X	Tri (61.27; 70.94; 64.49) [kg]	[22] [35]	Nor (0.104; 0.0117) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	Skim coat	X	X	Tri (26.26; 30.40; 27,64) [kg]	[22] [35]	Nor (2.23; 0.518) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
	Paint	X	X	Tri (26.26; 30.40; 27,64) [kg]	[22] [35]	Nor (6.02; 7.97) [CO2 eq/kg]	Eco-Invent DB3.1 with MC analysis
A4	Transport	X	X	Tri (50; 300; 120) [km]	[12]	Nor (0.00017; 0.000013) [kg CO2 eq/kmkg]	Eco-Invent DB3.1 with MC analysis
B6	Energy needs for heating (natural gas)	X	X	A: Det (921.14) [m3/year] B: Det (975.09) [m3/year]	Energy Building Simulation	A-B: Nor (0.539,0.0825) [kgCO2 eq/m3]	Eco-Invent DB3.1 with MC analysis
				A: Nor (921.14; 149.14) [m3/year] B: Nor (975.09; 158.71) [m3/year]	[36][37] [36][37]	A-B: Nor (0.539,0.0825) [kgCO2 eq/m3]	Eco-Invent DB3.1 with MC analysis
				A: Uni (736.9; 1105.4) [m3/year] B: Uni (780.1; 1170.1) [m3/year]	[36][37][38] [36][37][38]	A-B: Nor (0.539,0.0825) [kgCO2 eq/m3]	Eco-Invent DB3.1 with MC analysis

* Uni (a,b): uniform distribution between a and b. Nor (μ,σ): normal distribution with mean value μ and standard deviation σ. Tri (a,b,c): triangular distribution with lower limit a, upper limit b and mode c, where a < b and a ≤ c ≤ b. Det (a): deterministic value a.

The ReCiPe LCIA method has been adopted using a MC analysis with 500 runs for the definition of each PDF. In stage A4, the uncertainty on the distance covered by lorry to bring the insulation materials to the building site has been assumed based on literature analysis [12].

Concerning the use stage (B6), the amount of energy consumed for building heating was considered in 3 different ways, leading to three alternative assessment scenarios. In the first scenario (1), energy was fixed at its "deterministic" value, coming from the building energy simulation performed according to technical standard UNI TS 11300 [28], then in scenarios 2 and 3, specific PDFs were considered according to author judgment and expertise and literature suggestions [36][37][38]. The related environmental impact to the Italian energy grid mix is represented by a normal distribution in the 3 scenarios (according to Eco-Invent DB3.1 with MC analysis approach). All other input parameters required for the analysis are considered deterministic and fixed in single value.

The material quantities and a summary of the PDFs of the LCA input distributions considered in this study are reported in Table 3. Concerning the unitary impacts, for simplicity, it has been reported only the Climate Change indicator [kg CO2 eq.] but all the indicators in the ReCiPe method were considered and assessed.

3.3. Uncertainty propagation and Sensitivity Analysis

The distributions of the LCA input variables are then propagated through MC methods considering this specific LCA model to assess the global environmental impact. As a consequence of this procedure, the resulting impact is evaluated based on its probability distribution.

The quality of the output PDF is dependent on the number of simulations performed. Generally, in MC methods, a high number of runs is necessary to ensure the accuracy of the result. A minimisation of this number can be obtained through an efficient sampling strategy [39]. Therefore, in this study, Sobol's sequences are used as quasi-random sampling technique in order to generate samples as uniformly as possible. The sample size needed depends on the number of input variables and was calculated as $n(2k+2)$ [40], where n takes the value of 16, 32, 64, etc…; k is the number of variables. The efficiency of the sampling strategy was assessed by comparing the deviations of the outcome at increasing runs (until approx. 6912 runs) compared to a reference solution with MC Basic Random samples (BRS) at 20000 runs.

Finally, Sensitivity Analysis through Variance based decomposition (Sobol' method) techniques was performed to obtain the sensitivity indices, which allow to establish which input uncertainties are more influential on output result. Through this method, it is possible to obtain two sets of indices: the "first-order" and the "total-order" indices. The "first-order" sensitivity index (Si) represents the main contribution of each input factor to the variance of the output. The "total-order" index measures the contribution to the output variance due to each input, including all variance caused by its interactions with any other input variables. The higher the value of the sensitivity indices, the most influential are the related parameters of the model. Therefore, since SA allow establishing which parameters need accurate distributions and which parameter variations can be neglected, the model can then be updated to improve the calculation efficiency or limit data gathering activities. The probabilistic methodology developed has been implemented in R, a free software environment for statistical computing.

4. Results and discussion

The LCA output PDFs of the two design options, A (XPS) and B (cork), in the three energy scenarios for the Climate change indicator [kg CO2 eq.] are reported in Fig. 1. They have been calculated using 6912 model runs, once assessed that this was to minimum sample size to guarantee the quality of the outcome. As example, looking at the design option A, scenario 2 (compared to the BRS simulation at 20000 runs) the normalized mean and standard deviation of the output sample are respectively: 0.03% and 0.4%. In the Fig. 1, the red line represents the PDF of the output coming from the BRS simulation.

For design option A (black lines – XPS), the median value of the impact is respectively 23079.7 [kg CO2 eq.] for scenario 1 (with a standard deviation of 397.3), 22836.4 [kg CO2 eq.] for scenario 2 (with a standard deviation of 4394.9) and 22872.6 [kg CO2 eq.] for scenario 3 (with a standard deviation of 3780.3). Similarly, for design option B (gray lines – Cork), the median value of the impact is respectively 26231.7 [kg CO2 eq.] for scenario 1 (with a standard deviation of 478.7), 25952.8 [kg CO2 eq.] for scenario 2 (with a standard deviation of 4685.4) and 26004.3 [kg CO2 eq.] for scenario 3 (with a standard deviation of 4010.6).

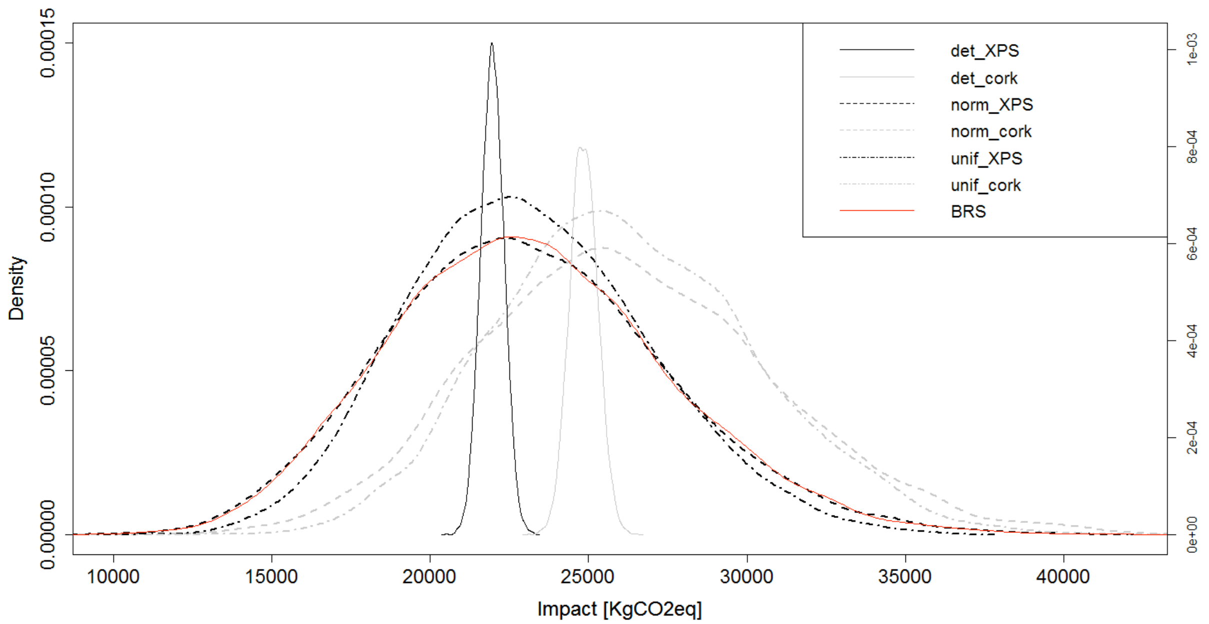

Fig. 1 PDFs of the environmental impact for the design options A and B in the energy scenarios 1-2-3 and convergence assessment.

Results obtained highlight that the differences on the Climate change environmental impact among the two design options is quite limited (about 12%) and this is mainly due to the use phase (B6) which is the more relevant input parameter on the overall result. Furthermore, focusing on the outcomes of the assessment performed in the alternative energy scenarios (within the same design option), it is evident how the differences among the median values are quite low, while the standard deviations vary widely. This is mainly due to the higher uncertainty range that characterizes the energy PDFs (both normal and uniform) compared to the deterministic case, considering also that the major contribution to the global impact mainly comes from the use phase. Finally, the shape of the output PDFs is only slightly influenced by the energy distributions shapes of scenarios 2 and 3: the results obtained with normal and uniform distributions are similar.

Concerning the Sensitivity Analysis, the first-order indices (Si), calculated through Sobol method, are reported in Fig. 2 for design option A and in Fig. 3 for the design option B. These graphs provide an idea on the input ranking and an estimate of their influence on the output variance. For both design options, the ranking based on the Si in the three energy scenarios is similar. In particular, when the building energy need is fixed in its “deterministic” value obtained by the energy simulation and the related impact is also considered deterministic (scenario 1), the unitary impacts of the design options materials uncertainties are the most influential parameters.

The contribution of insulation and painting impacts uncertainties on the variance of the output is about 89% for design option A (XPS) and 85% for design option B (cork), as obtaining by summing the related Si. On the contrary, when we consider the energy need represented by PDFs with wide uncertainty margins (normal or uniform distributions), the Si related to the use phase (B6) are much higher. Therefore, in scenarios 2 and 3, the quantity of natural gas consumed and its unitary environmental impact are the most influential parameters on the output variance. In both scenarios and for both design options, the related Si contribute until 98% on the outcome. Consequently, the other parameter uncertainties (concerning material and transport phases) in scenarios 2 and 3 are never influential. These results highlight the importance of the correct characterization of the input PDFs, since their influence on the output variance can be noteworthy.

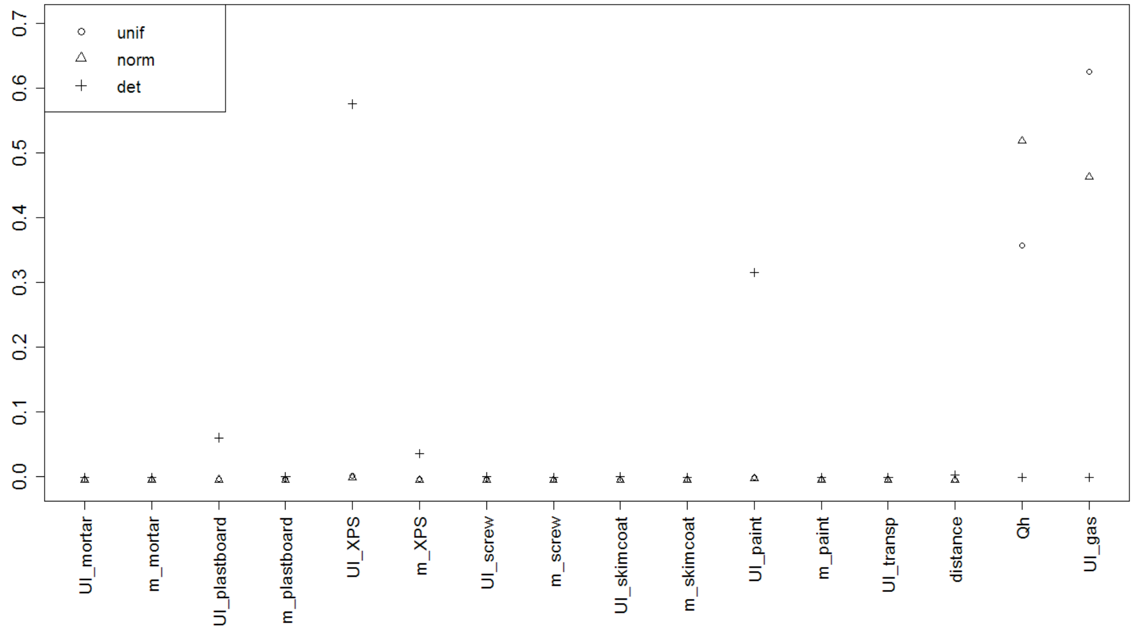

Fig. 2 Results of SA for design option A (scenarios 1-2-3)

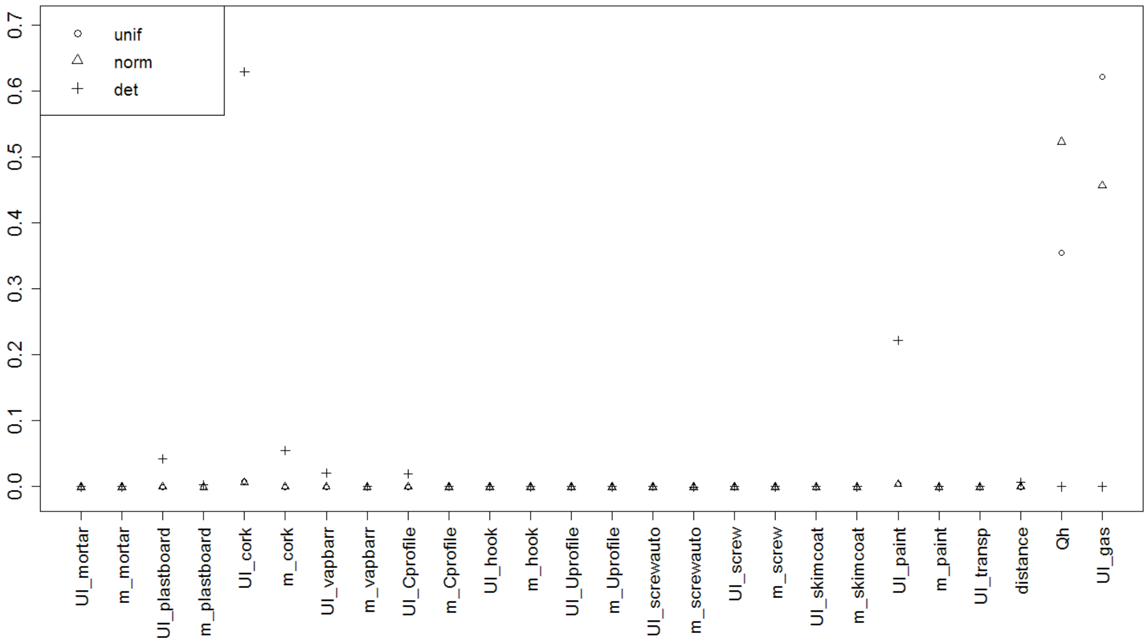

Fig. 3 Results of SA for design option B (scenarios 1-2-3)

5. Conclusions

LCA is a consolidated methodology in the building sector. Nevertheless, especially in building refurbishments interventions, LCA is often carried out with many simplifications and assumptions on data inputs -as the building energy-needs that actually increase the result uncertainty, even if this aspect is not highlighted by the results, usually presented as "deterministic" single values. LCA could be a more effective decision-making tool in the analysis of retrofitting measures, if the user is more aware of these inherent limitations and has the possibility to quantify them. Coupling together LCA and LCC probabilistic approaches, it will be possible to providing a more robust decision support about energy efficiency projects, including building retrofitting measures. Indeed, the same potential has been demonstrated for the life cycle cost analysis using a probabilistic LCC approach [41].

The paper proposes a Monte Carlo-based approach applied to an LCA analysis of building retrofit measures, including the characterisation of data inputs as probability distributions, the uncertainty propagation and a sensitivity analysis through variance based decomposition methods to establish the impact of input data uncertainties on the output distribution. The probabilistic methodology is applied to a building case-study refurbished through two alternative internal insulation solutions (XPS and Cork), also considering several scenarios for the characterisation of the building energy needs.

Results obtained highlighted a quite limited difference on the environmental impact distributions due to the two design options considered, mainly because the impact of the use phase is the same for the two measures and this phase is the most relevant on the overall impact result. Nevertheless, the study outcomes point out how the model inputs deeply influence the output variance depending on the specific assumptions made on their PDFs. In particular, in this study we addressed the building energy need, which represents the most impacting phase in usual building refurbishment projects, underlying how fixing it at its deterministic value as obtained by energy simulation software on characterizing it through PDFs could have a strong impact on result uncertainty.

Future work on this research context will be the investigation of other insulation materials using the same methodology to address if other insulation materials highly affect the final result compared with the two analysed measures (XPS and Cork). The SA conducted on a wide range of insulation measures will provide the evidence of the most important input parameters which affect the result and to consider only these latter for the definition of a robust standardized methodology. In addition, it is of interest, in this context, the investigation of other lifecycle phases, which have been neglected in this study such as maintenance, replacement, end-of-life, etc. Indeed, these phases are affected by high uncertainties, which can propagate on the final result.

Therefore, the development of a standardized methodology will be useful to analyse different case studies and to support engineers and architects in the decision making process for the selection of the most sustainable internal insulation measure in building retrofit.

Acknowledgements

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