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► **To cite this version:**

Marie-Lise Pannier, Patrick Schalbart, Bruno Peuportier. Dealing with uncertainties in comparative building life cycle assessment. *Building and Environment*, 2023, pp.110543. 10.1016/j.buildenv.2023.110543 . hal-04140645

HAL Id: hal-04140645

<https://hal.science/hal-04140645v1>

Submitted on 26 Jun 2023

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--- Dealing with uncertainties in comparative building life cycle assessment ---

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Abstract

Building LCA aims at guiding designers towards more sustainable projects. Many sources of uncertainties affect environmental modelling. Therefore, the reliability of decisions based on building LCA is questioned. However, information on uncertainties can strengthen decisions, when properly addressed. In this study, seven statistical metrics are compared based on dependent samplings for sensitivity analyses (SA) and uncertainty analyses (UA). It allows to identify a set of indicators on which conclusions are more reliable. For the first time, this methodology is applied to comparative building LCA, considering three construction alternatives: a concrete, a concrete blocks and a wooden-framed house. A new SA method, based on Morris, helps identifying which of 153 uncertain factors are more likely to influence decisions. More precise data is then collected on these uncertain factors. In this case study, the Heijungs significativity metric and the distribution of relative differences were the most appropriate metrics to assess UA results. They allow to determine, for each indicator, which is the best alternative and how much better it performs. Consequently, the non-conclusive indicators are discarded. Applying this methodology, decision are enhanced by uncertainties and rely on a smaller set of indicators to select an alternative in terms of environmental performance.

Keywords:

Building design; Life cycle assessment; Comparison of alternatives; Uncertainty analysis; Sensitivity analysis.

1 **Acronyms:**

- 2 BAIA: Building Attribute to Impact Algorithm;
- 3 CDF: Cumulative Density Function;
- 4 CED: Cumulative Energy Demand;
- 5 CF: Characterisation Factors;
- 6 CompLCA: Comparative Life Cycle Assessment
- 7 DA: Discernibility Analysis;
- 8 DBES: Dynamic Building Energy Simulation;
- 9 Dj: Distribution;
- 10 DoE: Design of Experiments;
- 11 DRD: Distribution of Relative Differences;
- 12 DW: Double-Wall;
- 13 EE: Elementary Effect;
- 14 EPD: Environmental Product Declaration;
- 15 EOL: End-Of-Life;
- 16 EV: Elementary Variance;
- 17 HSM: Heijungs Significativity Metric;
- 18 LCA: Life Cycle Assessment;
- 19 LCI: Life Cycle Inventory;
- 20 LCIA: Life Cycle Impact Assessment;
- 21 LSH: Latin Hypercube Sampling;
- 22 MC: Monte Carlo;
- 23 MQ: Means and Quantiles;
- 24 PDF: Probability Density Function;
- 25 RI: Relative Influence;
- 26 RP: Ranking Probability;
- 27 SA: Sensitivity Analysis;
- 28 SC: Shuttered Concrete;
- 29 SM: Supplementary Materials;
- 30 SMD: Standardised Mean Difference;
- 31 UA: Uncertainty Analysis;

1 WF: Wooden-Framed.

2 Symbols

3 a_1 : alternative 1

4 $a_{1,i}$: i -th sample of alternative 1

5 a_2 : alternative 2

6 $a_{2,i}$: i -th sample of alternative 2

7 \bar{c} : mean of the $a_{1,i}$ and $a_{2,i}$

8 d : standardized Mean Difference of Cohen's d

9 i : sample index

10 j : sample index

11 K : number of environmental indicators

12 K_4 : Heijungs significativity metric

13 K_{4,a_1} : superiority statistic for alternative 1

14 K_{4,a_2} : superiority statistic for alternative 2

15 M : number of characterisation factors

16 N : number of sub-processes in the inventory

17 n : sample size

18 std : standard deviation

19 X : set of background environmental data

20 Y : set of characterisation factors

21 λ : threshold to set an alternative preference

22 θ : Heaviside step function

23

1 Introduction

The building and construction sectors account for almost 40 % of the global energy consumption and of the greenhouse gases emissions worldwide [1]. In addition, they cause high resource consumption and waste production, as well as various pollution in air, water and soil [2–4]. The life cycle assessment (LCA) methodology [5,6] is recognised as a suitable eco-design tool to mitigate the building sector impacts. More than assessing the environmental impacts of one construction project, building LCA is useful to compare alternatives. It should therefore provide reliable and robust results in order to guide decision makers towards more sustainable projects. However, many sources of uncertainties and variabilities can affect the environmental modelling of products [7–11]. Tackling these uncertainties is one of the challenges of building LCA identified by Nwodo and Anumba [12], especially in the case of comparative LCA (CompLCA) and in the early design phase of a building project [13]. In this work, a methodology is proposed to deal with uncertainties in CompLCA of building design alternatives. It aims at informing on uncertainties to strengthen the reliability of the decision making.

1.1 Uncertainties in LCA

Uncertainties are discussed in LCA since the early 1990s [14]. The generic uncertainty terms generally encompasses the concepts of uncertainty i.e. lack of knowledge on the true value of a quantity, and variability i.e. natural stochastic variation of a quantity [7,8]. Uncertainties are linked to all steps of an LCA [10]: goal and scope definition, life cycle inventory (LCI), life cycle impact assessment (LCIA), and interpretation. In addition, they can be related to the representativeness of the LCA model (model uncertainties), the model input parameters (parameter uncertainties), or choices related to the context of the study (scenario uncertainties) [10]. Thus, LCA results may change significantly depending on assumptions made by LCA practitioners [15].

Since 2010, despite being increasingly mentioned in the LCA literature [10], uncertainties have not been taken into account in most articles on LCA. According to Bamber et al. [11], less than 20 % of the papers published between 2014 and 2018 quantified uncertainties. This can be explained by lack of information in some environmental databases [10,13], difficulties and lack of tools to address uncertainties (especially for correlated data) [16,17], or complexity of communicating and interpreting LCA results with uncertainties [9,18]. Heijungs et al. (2019) emphasised the need to tackle these challenges and recommended to stop producing LCA results without uncertainties.

1.1.1 Uncertainty and sensitivity analysis

Several statistical and analytical methods are available to deal with uncertainties in LCA. On the one hand, uncertainty analysis (UA) methods are applied to propagate uncertainties throughout the model, i.e. from input to output. Among available UA methods, the random Monte Carlo (MC) sampling is the most used in LCA [9] due to its availability in most LCA software [11]. On the other hand, sensitivity analysis (SA) methods are useful to identify the most influential uncertain factors on which model refinement should focus, and to sort the uncertain factors by influence [19,20]. In the following, the generic term “uncertainty” encompassed UA and SA. “UA” or “SA” terms are used to specifically discuss uncertainty propagation or factor influence quantification respectively.

1.1.2 Uncertainty quantification in CompLCA

LCA is often used to compared design alternatives. Given the numerous uncertainties in environmental modelling of products, robustness and reliability of CompLCA results are questioned. Decision makers who are familiar with uncertainties, fear that they change the conclusions of their

1 studies. Yet, taking uncertainties appropriately into account can help interpretation because trade-
2 offs between alternatives are better highlighted [21,18].

3 Appropriate management of uncertainty in CompLCA requires the use of adequate sampling
4 strategies and comparison metrics for UA and SA. Firstly, it involves using dependent sampling [22],
5 also called paired simulations or blocked simulations [23]. The basic idea behind dependent sampling
6 is to consider the same background data and the same choices in the foreground system when
7 comparing product alternatives [24]. More globally, it involves considering the correlation between
8 pairs of input and output variables [17], i.e. using the same sampling for uncertain factors affecting
9 the compared alternatives [10].

10 Secondly, once dependent sampling is applied, several metrics can be used for the UA. They were
11 discussed by Mendoza Beltran et al. [18] and Heijungs [25]. They all rely on pairwise comparison
12 between alternatives. A null hypothesis significance testing is applied to identify if the mean
13 environmental impact of an alternative a_1 is significantly different than the mean impact of an
14 alternative a_2 [22,26]. However, this approach is not appropriate in CompLCA based on Monte Carlo
15 simulations [23]. In addition, it does not answer the two main questions in CompLCA: how often and
16 how much a_1 is less impactfull than a_2 [25]. Overlap statistics [21] can be computed in order to
17 quantify the degree of overlap of output distributions of the compared alternatives. A large overlap
18 means that a_1 and a_2 leads to similar environmental impacts. An extension of this approach, the
19 stochastic multi-attribute analysis, can be applied to identify trade-off and to support decision
20 making when handling several environmental indicators [27,28]. Discernibility analysis (DA) [29] is
21 the most popular approach to compare UA results. It consists in counting how often a_1 performs
22 better than a_2 among all sampled values. But the DA does not inform on how much a_1 is less
23 impactfull than a_2 [25]. In order to fill this gap, Heijungs [25] proposed a new indicator, called
24 Heijungs Significativity Metric (HSM) in this article, able to quantify how often a_1 is significantly less
25 impactfull (with a given degree of significance) than a_2 , thus answering both meaningful questions in
26 CompLCA. A first application of this metric can be found in Michiels and Geeraerd [30]. The above-
27 mentioned metrics have some drawbacks: they should be computed for each pair of alternatives and
28 for each environmental indicator, increasing the computation and analysis time. Moreover,
29 thresholds needs to be defined to indicate an alternative preference.

30 Contrarily to UA, the comparison of SA results of pairs of alternatives has rarely been addressed in
31 the literature. Instead of identifying the most influential factors for each alternative separately, SA
32 performed in a CompLCA can highlight which uncertain factors are more likely to change the
33 conclusion [31]. Wei et al. [32] and Ravikumar et al. [33] applied respectively the FORM method from
34 the reliability theory, and moment-independent SA, in order to identify the most influential factors in
35 a decision context.

36 A global framework for UA and SA is still missing to our knowledge in CompLCA.

37 1.2 Uncertainties in the CompLCA of building alternatives

38 Buildings have specifically a very long lifetime, so that the impacts of the use stage are predominant
39 compared to those of the construction, renovation and end-of-life (EOL) stages [2,34]. Building LCA is
40 increasingly used, however, the results are mostly deterministic [13,35]. Among the papers on
41 building LCA published between 2000 and 2020, less than 10 % mentioned uncertainties and less
42 than 1 % applied uncertainty quantification methods [35].

1 Marsh et al. [13] summarised the sources of uncertainties in building LCA and sorted them by their
2 life cycle stage. Uncertain factors included in building LCA studies are mostly linked to the LCI and
3 correspond to parameters uncertainties (e.g. uncertainties in quantities or physical properties of
4 building materials or systems, or in the service lifetime). As pointed out by several authors, the
5 potential environmental gains are the largest in early design phase, but uncertainties are also higher
6 in this phase as many decisions have yet to be made [36–39,13].

7 Regarding the specific subject of uncertainties in CompLCA of buildings, the set of 14 studies listed in
8 Table 1 was found. Only studies performed at the building level were selected, thus stochastic
9 comparison of building materials [40,41,32,42,43] was not considered. Furthermore, the selected
10 articles compare building design or renovation alternatives in an uncertain context using LCA. The
11 studies focusing on the comparison of methodological choices are not included [44–48]. In the
12 14 articles, two to twelve alternatives were compared, mostly for residential buildings. In addition to
13 parameter uncertainties, other uncertain factors were taken into account, such as model uncertainty
14 (e.g. characterisation factors CF), scenario uncertainty (e.g. allocation rules or functional unit), spatial
15 variability (e.g. occupancy and climate) or temporal variability (e.g. future climates or energy mix).
16 Uncertainty propagation was performed in one study using an analytical method [49]. All other
17 articles used statistical methods, mostly the MC random sampling. This makes possible using
18 dependent sampling. However, dependent sampling was applied only in half of the listed papers, and
19 its application was not always clearly stated. When the samples from each alternative were not
20 dependent, the authors compared all alternatives using probability density functions (PDF) [50],
21 histograms with errors bars [51], boxplots [52,38,53], violin plots, or statistics on the distributions
22 such as mean or standard deviation [54]. This kind of visualisation may be misleading as correlations
23 between alternatives in foreground and background systems do not appear. The seven studies
24 considering dependent samplings used DA or similar methods in order to compare alternatives,
25 which were visually compared by plotting DA results in graphs [55] or in matrices [36]. Another
26 option was to plot the distribution of impact ratios [56,57], or the distribution of impact differences
27 [39,58,59] between pairs of alternatives. This is in line with the recommendations of Marsh et al. [13]
28 to use dependent sampling, and DA or HSM. No application of HSM was yet found in CompLCA of
29 buildings.

Table 1: Studies on comparative probabilistic building LCA.

Article	Alternative compared	Uncertain factors	UA	Dependent sampling	Method for ComplCA
Huijbregts et al., 2003 [56]	2 alt.: level of insulation for a house	Parameter: envelop, energy used Scenario: allocation, EOL, time horizon Model: spatial variability, CF	10000 MC runs	X	Distribution of $\frac{a_{1,i}}{a_{2,i}}$ * (similar to DA)
Blengini and Di Carlo, 2010 [51]	2 alt.: low energy and standard house	Fabrication, transportation and EOL of building envelop and systems, energy used	10000 MC runs		Histograms with error bars
Hoxha et al., 2014 [49]	2 alt.: reinforced concrete vs. wooden house	Material quantities and service life, EPD impact values	Analytical		Histograms with error bars
Heeren et al., 2015 [57]	2 alt.: massive vs. wooden house	Building size, material physical properties, service life, use scenarios, variability of climate and occupancy, electricity mix	4500 MC runs	X	Distribution of $\frac{a_{1,i}}{a_{2,i}}$ (similar to DA)
Favi et al., 2018 [52]	3 alt.: renovation options for a house	Materials quantities and physical properties, systems, service life, impact values, climate variability	Sobol sequences, 8192 runs		Boxplots
Hester et al., 2018 [36]	12 alt.: design variants for a house	Building geometry, systems, service life, climate variability	5000 MC runs BAIA	X For energy related input	DA: $\frac{1}{n} \sum_{i=1}^n \begin{cases} 1, & \frac{a_{1,i}}{a_{2,i}} < 1 \\ 0, & \frac{a_{1,i}}{a_{2,i}} \geq 1 \end{cases}$ Mean normalised difference: $\frac{\frac{1}{n} \sum_{i=1}^n (a_{1,i} - a_{2,i})}{\frac{1}{2n} \sum_{i=1}^n (a_{1,i} + a_{2,i})}$ Matrix of results to show pairwise comparison
Piroozfar et al., 2019 [54]	2 alt.: contemporary vs. traditional houses	Materials quantities	1000 MC runs		Mean, median, standard deviation, coefficient of variance
Harter et al., 2020 [38]	7 alt.: shapes for an office building	Building size and orientation, material physical properties, systems, use scenarios	500 LHS runs		Boxplots
Ylmén et al., 2020 [39]	2 alt.: wooden vs concrete framework for an office building	Question to answer with the LCA, decision rules, confidence level in the LCA results, rules to build future scenarios, functional unit	5000 MC runs	Not clearly stated	Distribution of: $a_{1,i} - a_{2,i}$ (similar to DA)
Zhang and Zheng, 2020 [58]	5 alt.: structures systems for a multi-storey building	Emission factors	10000 MC runs	Not clearly stated	Mean, median, standard deviation, variance, 90 % confidence interval CDF Distribution of: $a_{1,i} - a_{2,i}$: (similar to DA)
Famiglietti et al., 2021 [55]	2 alt.: heat pump vs. gas boiler for a house	Param: energy, system	2000 MC runs	Not clearly stated	DA
Galimshina et al., 2021 [53]	8 alt.: renovation options for a multifamily house	Systems, impact values, service life, variability of occupancy, variability of future climate, future electricity mix	MC runs on a surrogate model		Boxplots
Hart et al., 2021 [50]	3 alt.: wooden, steel and concrete structures	Structural frames related impacts	1000 MC runs		PDF Violin plot
Pannier et al., 2022 [59]	3 alternatives: smart vs. conventional multifamily house	Energy savings Variability of occupancy	1000 MC runs per occupancy scenarios	X	Distribution of: $\frac{a_{1,i} - a_{2,i}}{\max(a_{1,i}, a_{2,i})}$ (similar to DA)

* $a_{1,i}$ corresponds to the impact value of alternative a_1 at the i -th run in the sampling.

1 Contrary to UAs, SAs did not use dependent sampling for building LCA. However, it was done at the
2 component level in order to compare two insulation materials [32].

3 1.3 Aim of the study

4 Heijungs [25] provided recommendations to compare product alternatives “in a sea of uncertainties”
5 using UA. The present article aims at applying a global UA and SA framework to surf on the sea of
6 uncertainties in CompLCA of building. Therefore, the sampling strategy of a screening SA method is
7 adapted to a comparative context, and to handle all kinds of uncertain factors; which was not done
8 previously. After this SA stage, the uncertainty characterisation of the main uncertain factors is
9 improved before conducting an UA.

10 As highlighted in Table 1, even recent studies did not apply dependent sampling to compare building
11 design alternatives using LCA. Suitable UA in comparative context is thus performed. Different
12 metrics are investigated and presented using various data visualisation methods. This manner of
13 exploiting CompLCA results is new in building applications. In the next sections, the methodology
14 (§ 2) and the LCA model (§ 3) are described and applied to compare three building design
15 alternatives presented in § 4. In the results section (§ 5), SAs and UAs are run based on dependent
16 sampling and different comparison metrics are applied. Finally, the results and methodology are
17 discussed in § 6, before concluding in § 7 on the most appropriate metrics to address uncertainties,
18 and strengthen the decision making in building LCA.

19 2 Methodology to address uncertainties in building compLCA

20 The proposed methodology to address uncertainties in building compLCA is split in five stages, that
21 are discussed in the following subsections:

- 22 1. Selection of the alternatives and of the LCA model
- 23 2. Identification of uncertain factors and gross characterisation of uncertainties
- 24 3. Sensitivity analysis in a comparative context
- 25 4. Improvement of the uncertainty characterisation for the most influential factors
- 26 5. Uncertainty analysis in an alternatives-comparison context

27 2.1 Selection of the alternatives and of the LCA model

28 The first step consists in the definition of alternatives. A building designer may have to choose
29 between: levels of energy performance, architectural forms, construction types, technical solutions,
30 or refurbishment alternatives. After this goal and scope step, the LCA model is built to enable the
31 comparison of alternatives corresponding to the same functional unit.

32 Classical LCA is performed using averaged values regarding the background system. For instance if
33 electricity is consumed, constant average environmental impacts are considered all along the life
34 cycle. In the case of buildings, this assumption is no more valid due to the long life span (several
35 decades) during which the electricity production system is likely to change. Furthermore, electric
36 heating induces a high peak demand during cold days, when GHG emissions of electricity production

1 are higher than average. It is therefore essential to associate a dynamic building energy simulation
2 (DBES), yielding temporal evolution of buildings energy loads (hourly time-step) with a model or data
3 accounting for temporal variation of the electricity production mix and related impacts. In this way,
4 the impacts of building operation, that still represent the largest share of environmental impacts
5 [60,61] due to long buildings lifetimes, are more accurately calculated. This is a way to progress
6 towards a dynamic LCI modelling for buildings [62].

7 2.2 Identification of uncertain factors and uncertainty characterisation

8 Many input parameters are required to perform DBES and LCA. They are part of the uncertain factors
9 and can be listed by a designer, referring to the model. However, other sources of uncertainties exist
10 such as: model uncertainty; uncertainty due to choices; spatial, temporal and technological
11 variabilities; epistemic uncertainties; mistakes; or meta-uncertainties [7–9]. A non-exhaustive list of
12 uncertain factors in the context of building LCA is provided by Marsh et al. [13]. When data is
13 available, the different uncertainty types should be included in the analysis.

14 The first characterisation of uncertainty on the identified factors is based on expert knowledge or
15 available data from literature. Building designers may have experience to define variation ranges for
16 some parameters (e.g. conductivity of an insulation material), but do not necessarily know the
17 associated probability distribution. Therefore, we suggest the use of uniform distributions for a quick
18 uncertainty characterisation. The distributions will be updated in stage #4. For other sources with
19 which the designer is not familiar, data should be gathered (e.g. literature review) in order to
20 associate a probability distribution with continuous factors, or a set of possible values with discrete
21 factors. In order to facilitate this task, uncertainty databases for the building sector should be
22 developed, similarly to the work of Hoxha [63].

23 2.3 Sensitivity analysis (SA) for alternatives' comparison

24 An SA is conducted in order to identify the most influential factors. This step is important for a better
25 understanding of LCA modelling. Thus, decision makers become aware of aspects having a key
26 influence on LCA results. In addition, they can search for further information on sensitive factors.

27 2.3.1 SA method

28 The Morris method [64] adapted by Pannier et al [37,65] was used. It has the advantage to precisely
29 quantify the influence of uncertain factors with much less simulations than the variance-based Sobol
30 method [66], which is considered as a reference. An elementary variance (square of the elementary
31 effect) is calculated instead of an elementary effect. A sensitivity index similar to the expectancy of
32 the variance computed in the Sobol method is obtained [37]. It is named MA-Morris (for Multilevel
33 Adapted Morris) method in this article. Its performance was investigated for continuous factors as
34 well as categorical factors (i.e. discrete factors without logical order) with many levels¹ [65]. Some
35 categorical factors had 200 levels, previously generated with a stochastic model. This number of
36 levels allows to reach convergence on the mean for almost all environmental indicators. MA-Morris
37 was able to quantify the importance of all kinds of uncertain factors with small differences compared
38 to the Sobol method [65]. A sensitivity index S_j for the j -th uncertain factor, similar to the
39 expectancy of the variance computed for Sobol, is obtained using MA-Morris, as explained in [65].
40 Then, the influence of the factor j is quantified based on the relative influence RI_j indicator proposed

¹ In [65], the comparison between Sobol and MA-Morris was done for the same case studied than the one of this article.

1 in [37], and calculated as in (1). It is defined as the share of the sensitivity index of one factor
 2 relatively to the sum of the sensitivity indices of all factors.

$$RI_j = \frac{S_j}{\sum_j S_j} \quad (1)$$

3 2.3.2 Application to alternatives comparison

4 The distributions of uncertain factors are sampled following the design of experiments (DoE) of MA-
 5 Morris. As the aim is to compare alternatives, a dependent sampling is used: for uncertain factors
 6 appearing in several alternatives, the same DoE must be used for all alternatives, as pointed out by
 7 Henriksson et al. [22]. This means that for one given simulation, the values of the uncertain factors
 8 are the same for all alternatives. Thus, the alternatives can be compared by performing n simulations
 9 all things being equal otherwise. For one alternative, the results of the DoE can be summarized in a
 10 matrix consisting of n rows (one for each simulation performed) and of K columns (one for each
 11 environmental indicator considered).

12 The sensitivity indices are computed for each alternative separately as well as for a metric reflecting
 13 the alternatives comparison context: in our case the pairwise difference between alternatives. The
 14 following calculation is performed to get the pairwise difference; for each of the n simulations and
 15 for each of the K indicators, the impact value of a_2 is subtracted from that of a_1 :

$$\mathbf{a}_1 - \mathbf{a}_2 = \begin{pmatrix} a_{1,1,1} & \dots & a_{1,1,K} \\ \dots & \dots & \dots \\ a_{1,n,1} & \dots & a_{1,n,K} \end{pmatrix} - \begin{pmatrix} a_{2,1,1} & \dots & a_{2,1,K} \\ \dots & \dots & \dots \\ a_{2,n,1} & \dots & a_{2,n,K} \end{pmatrix} \quad (2)$$

16 with the matrices representing the results for alternative \mathbf{a}_1 (right matrix), and \mathbf{a}_2 (left matrix). In
 17 one row of the matrices, the coefficients are the value of the K indicators calculated during the same
 18 simulation. In columns, the coefficients are the n values calculated for the n simulations for a given
 19 indicator.

20 Performing SA in a comparative context is important before performing UA in a comparative context
 21 in order to improve the uncertainty characterisation on factors than can may change the ranking of
 22 alternatives.

23 2.4 Improvement of uncertainty characterisation

24 For the most influential factors identified using SA, uncertainty characterisation is refined in order to
 25 get more reliable UA results. Literature and technical review are more deeply investigated for these
 26 factors.

27 In order to determine for which factors characterisation should be improved, uncertain factors are
 28 ranked by increasing relative influence RI , for each alternative and each pairwise difference $\mathbf{a}_1 - \mathbf{a}_2$.
 29 This is done for all environmental indicators. The set of most influential factors can be defined as the
 30 set of factors covering at least a certain share of the total influence for all indicators and alternatives
 31 as suggested by Lacirignola et al. [67]. If many factors belong to this set, the building designer will
 32 spend too much time searching for additional information. A different approach is thus chosen here.
 33 A budget is set regarding the number of influential factors. The uncertainty characterisation is
 34 improved only for the 15 most influential factors, i.e. giving the 15 highest RI among all alternatives
 35 and indicators.

1 2.5 Uncertainty analysis (UA) for alternatives' comparison

2 The improved distributions of uncertain factors are sampled with Sobol sequences for a more
 3 efficient (higher convergence speed) exploration of the variation ranges [68]. As for SA, dependent
 4 sampling is used, allowing to obtain distributions of results for each alternative and each pairwise
 5 difference $a_1 - a_2$. Four types of analyses corresponding to seven methods (see Table 2) are tested.
 6 The key question is how often and how much one alternative performs better than another one, for
 7 each indicator.

8

Table 2: Alternatives' comparison methods and their notations.

Analysis type	Alternatives' comparison method	Notation
Distribution	Plot of distributions	Di
Alternative preference	Discernibility analysis	DA
	Probability of occurrence of rankings	RP
Impact gaps between alternatives	Computation of means and quantiles	MQ
	Standardised mean difference	SMD
Cross-analysis	Distribution of relative differences	DRD
	Heijungs significativity metric K_4	HSM

9

10 Firstly, impact distributions of each alternative are plotted for each indicator to get an overview of
 11 impact values and dispersions. This analysis is called Di.

12 Secondly, analyses are carried out to understand how often an alternative performs better:

- 13 • A discernibility analysis [29], called DA, is performed for all pairwise comparisons. It consists
 14 in counting the cases where $a_{1,i} - a_{2,i} > 0$ and dividing this number by the sample size. This
 15 gives the probability that a randomly sampled alternative $a_{2,i}$ performs better than the
 16 corresponding alternative $a_{1,i}$. A probability closed to 0 (respectively to 1) indicates that a_1
 17 (respectively to a_2) more often has the lowest impacts and thus performs better. When the
 18 probability is close to 0.5 for one indicator, both alternatives are undistinguished.
- 19 • An analysis of the most represented ranking is conducted. The ranking between all
 20 alternatives is assessed for all simulations. The probability of occurrence of each possible
 21 ranking is computed. For this analysis, the pairwise difference is not necessary. This analysis
 22 is called RP (ranking probability).

23 This kind of analysis can only be applied to dependent samplings; non-overlap statistics or other
 24 measures of superiority are available for independent samplings [25]. In addition, it does not indicate
 25 how much an alternative performs better.

26 Thirdly, impact gaps between alternatives are assessed:

- 27 • Statistics on distributions (e.g. means, medians, and quantiles) are computed to find how
 28 much better an alternative performs. This analysis is called MQ (means and quantiles).
- 29 • In addition, the standardised mean difference (SMD) also called Cohen's d [69] is calculated
 30 to find how many standard deviations separate the means for each pairwise comparison. For
 31 dependent samplings, d is the mean of the pairwise difference divided by the standard
 32 deviation of the pairwise difference, as in (3). A small difference between these statistics or
 33 a small d (i.e. small mean of the pairwise difference) indicate that the two products have
 34 similar environmental impacts.

$$d = \frac{\bar{c}}{std_c} \quad (3)$$

1 with d the SMD, \bar{c} the mean pairwise difference between \mathbf{a}_1 and \mathbf{a}_2 defined in (4) and std_c standard
 2 deviation of the pairwise difference defined in (5).

$$\bar{c} = \overline{\mathbf{a}_1 - \mathbf{a}_2} = \frac{1}{n} \sum_{i=1}^n a_{1,i} - a_{2,i} \quad (4)$$

$$std_c = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (\bar{c} - (a_{1,i} - a_{2,i}))^2} \quad (5)$$

3 with n the number of simulations and i the simulation index.

4 Lastly, instead of performing the second and third types analysis, we can compute at the same time
 5 how often and how much one alternative performs better than another using the following metrics:

- 6 • The distribution of the relative differences (noted DRD) is computed as described in equation
 7 (6) for each indicator similarly to Pannier et al. [70,59]. For each of the n simulations the
 8 impacts difference between alternatives is computed, and then normalised by the maximum
 9 impact value. This gives a dimensionless series of values, which is displayed as a boxplot.
 10 Visually, one can see how often one alternative performs better (part of the boxplot below
 11 the 0-axis). In addition, the shape of the boxplot indicates how much one alternative perfoms
 12 better. For a thick boxplot, the uncertain factors strongly affect the results, which are more
 13 likely to be questioned. For a flattened boxplot, whatever the values of uncertain factors, the
 14 impact difference between the two alternatives are always in the same order of magnitude.
 15 If the flattened boxplot is centred on the 0-axis (e.g. in a range of $\pm\lambda\%$ around the
 16 indifference line), both alternatives have similar impacts; otherwise, one alternative is clearly
 17 preferred.

$$\frac{a_{1,i} - a_{2,i}}{\max(a_{1,i}, a_{2,i})} \quad (6)$$

- 18 • The superiority statistic K_{4,a_1} (resp. K_{4,a_2}) introduced by Heijungs [25] is computed to find
 19 the probability that alternative \mathbf{a}_1 (resp. \mathbf{a}_2) performs at least $\lambda\%$ better than alternative \mathbf{a}_2
 20 (resp. \mathbf{a}_1). K_{4,a_1} represents the number of times where $a_{1,i}/a_{2,i}$ exceeds $1 + \frac{\lambda}{100}$, divided by
 21 the sample size N , as in (7). Heaviside step function θ (8) allowing for counting the
 22 occurrences. K_{4,a_1} is built symmetrically. Large values for the Heijungs significativity metric
 23 K_4 , called HSM, indicate a strong preference for one alternative. K_{4,a_1} is given by:

$$K_{4,a_1} = \frac{1}{n} \sum_{i=1}^n \theta \left(\frac{a_{1,i}}{a_{2,i}} - \left(1 + \frac{\lambda}{100} \right) \right) \quad (7)$$

24 with λ the threshold for defining a better alternative, and θ the Heaviside step function
 25 defined as in equation (8):

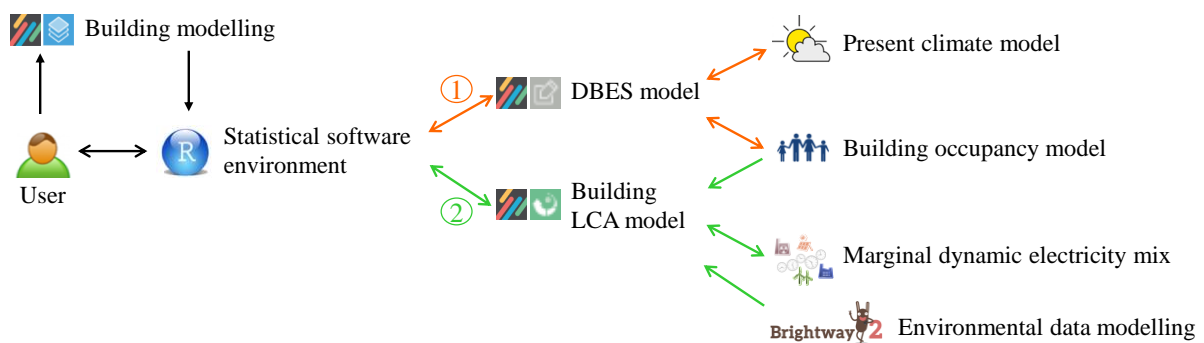
$$\theta(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases} \quad (8)$$

26 For each environmental indicator, the seven methods are applied and their results are compared. It
 27 is possible to identify indicators for which it is likely to get much lower impact for one alternative. An
 28 alternative ranking can be obtained for such indicators and decision makers can be more confident in

1 their choices. On the contrary, if for one indicator: i) the impact values of the two alternatives are
2 always close or ii) there is as much chance that one alternative or another performs better; the
3 results are debatable and the final decision should not rely on this indicator.

4 3 LCA model and framework to deal with uncertainties

5 Many energy and LCA simulations are required when running SA and UA. The building LCA
6 framework of Figure 1 is used for uncertainty quantification in a comparative context. Based on
7 modelled alternatives and uncertain factors defined by a user, the statistical programming
8 environment R manages the entire SA or UA process: creation of the DoE, launch of building
9 simulations, post-processing of results. The model framework used in this study is presented in the
10 next subsections.



11
12

Figure 1: Building LCA framework to perform sensitivity and uncertainty analysis.

13 3.1 DBES

14 Before performing LCA, DBES is run using the COMFIE model [71] of the software Pleiades². This is an
15 important step for a precise assessment of the temporal evolution of energy loads, that generally
16 account for a large part of buildings impacts. In this reduced multizone building model, the building is
17 split in thermal zones with homogenous operative temperature. Thermal zones are meshed using a
18 finite volume discretisation. Energy balance is applied in order to get zones operative temperatures
19 and eventually heating or cooling loads. The reliability of this DBES tool has been verified through
20 model intercomparison [72–75] and comparison with measurements [76,77].

21 The DBES takes as inputs the characteristics of the building site, envelope and equipment, and the
22 occupancy scenarios of each zone. These inputs are uncertain and the predefined values are
23 modified at each simulation based on the DoE. It has been shown that the variability of two of these
24 inputs, namely climate and occupancy, may lead to significant gaps in the building energy assessment
25 [78,79]. Specific models, described in the next two paragraphs, are used to account for these
26 variabilities. In both case, the approach consists in generating a diversity of realistic scenarios
27 (climates or occupancy), and randomly sampling from the generated scenarios for each simulation.

² <https://www.izuba.fr/logiciels/outils-logiciels/>

1 A sample of meteorological years is generated by applying the model of Ligier et al. [80,81]. The
2 temperature and radiation of a typical meteorological year are characterised into a mean trend and a
3 residual series, using a Fourier decomposition and a seasonal auto-regressive moving average model.
4 Then, new realistic series are produced based on the identified characteristics. The model is designed
5 to maintain the natural correlation between temperature and radiation. The obtained climate files
6 are representative of the present climate.

7 The stochastic occupancy model of Vorger [82,83] enables generating realistic occupancy scenarios.
8 Depending on the building type and location, occupants are generated for each run. Their presence
9 and activities over the simulated year are defined with a 10 min timestep using time-inhomogeneous
10 Markov chains calibrated on a French time use survey. Based on the sampled activities and
11 measurements campaigns data, energy for appliances and water consumptions are estimated. In
12 addition, adaptive actions can be set (e.g. window opening). The occupancy model gives as output
13 scenarios of presence, temperature setpoints, appliances and water consumptions, windows
14 shadings and openings.

15 After a DBES, the building loads are available for every hour of the simulated year and R launches the
16 associated LCA simulation.

17 3.2 LCA

18 LCA is performed using the LCA engine EQUER [84–86] of the software Pleiades. All life cycle stages
19 of the project are considered. Being developed as a decision support tool, a consequential-oriented
20 approach is implemented in Pleiades LCA through three main modelling choices. Firstly, the approach
21 proposed by Polster et al. [84] to account for benefits and burdens of recycled materials corresponds
22 to the 50/50 substitution method, also described in Schrijvers et al. [87]. Secondly, electricity
23 exported to the grid (e.g. with photovoltaics panels) results in avoided impacts. [Thirdly, for biogenic
24 carbon, the approach of Polster et al. \[84\] is followed.](#) It consist in accounting impacts separately at
25 construction and end-of-life stages. It corresponds to the -1/+1 approach, described in Hoxha et al.
26 [88], and has the advantage of differentiating origins (trees replanted or not after harvesting) and
27 end-of-life options (reuse, disposal, incineration with or without energy recovery) of bio-based
28 materials. The reliability of the tool has been investigated through models intercomparisons in
29 different projects: PRESCO, COIMBA, BENEFIS [89–91]. Despite methodological differences, the
30 compared models ranked building alternatives in the same way in most cases.

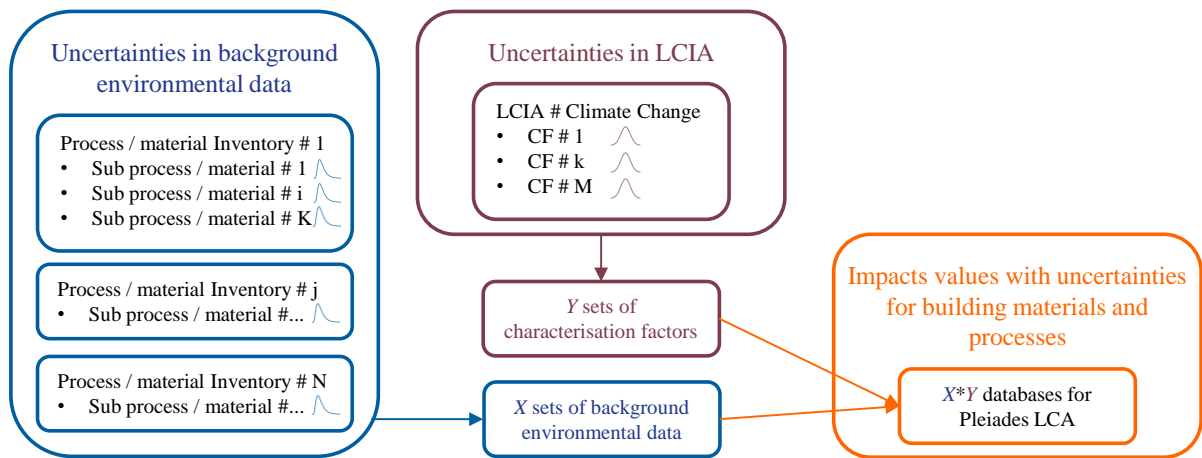
31 In countries with a large share of electrical heating such as France, the electricity consumption
32 fluctuates significantly over the year. Consequently, the electricity production mix adapts and the
33 related impacts vary. The hourly model of electricity production of Roux et al. [92]³ is linked with
34 Pleiades LCA to take temporal variation of impacts of electricity use into account. To be consistent
35 with the consequential-oriented approach of Pleiades LCA, the marginal version of the model [92] is
36 used. In this study, the electricity production allocated to the building project corresponds to the
37 production differences between i) the production required to supply the reference electricity
38 demand, and ii) the production required to supply the reference demand increased by the additional
39 electricity load for the project.

40 Pleiades LCA and the marginal dynamic electricity mix model take as an input the characteristics of
41 the building envelope (quantities of materials) and systems (equipment and energy sources), as well
42 as water use and energy loads. Environmental data from ecoinvent v3.2 [93] are used for fabrication

³ Their model will be integrated in Pleiades LCA soon.

1 and end-of-life of materials and components, energy, water and transport processes. All above-
 2 mentioned parameters are subject to uncertainties.

3 In addition, uncertainties in background environmental data and in LCIA are specifically modelled
 4 (see *Figure 2*). Brightway2 [94] is used to generate environmental databases for Pleiades LCA
 5 containing uncertainties. Regarding uncertainties on the background environmental data of the
 6 building project, X random samples are drawn from the uncertainty distributions provided by
 7 ecoinvent, resulting in X technosphere and biosphere matrices. In addition, for uncertainties on LCIA,
 8 uncertainty distributions are affected to characterisation factors (CF) using Brightway2: Y samplings
 9 are drawn to get Y sets of characterisation factors. Combining the X technosphere and biosphere
 10 matrices to the Y characterisation matrices, $X * Y$ lists of impact values of building materials and
 11 processes are obtained, corresponding to Z databases containing uncertainties for Pleiades LCA.
 12 Finally, for each simulation, Pleiades LCA uses one of the randomly sampled database.



13
 14 **Figure 2: Generation of the databases with uncertainties on the background data and on the characterisation factors.**
 15 At the end of an LCA simulation, 14 environmental indicators or fluxes listed in Table 3 are obtained.

16 **Table 3: Environmental indicators or fluxes.**

Indicator / flux	Legend	Unit	Reference
Climate change GWP100	Clim. Change	kg CO ₂ eq	IPCC 2013 [95]
Cumulative Energy Demand	CED	MJ	CED [96]
Abiotic Depletion of Minerals	Resources	kg Sb	CML [97]
Mass of Waste	Waste	kg	Flux from ecoinvent [93]
Water use	Water	litre	Flux from ecoinvent [93]
Fine particulate matter formation	Particulate M.	kg PM10 eq	ReCiPe [98]
Photochemical ozone formation	P. Ozone	kg NMVOC eq	ReCiPe [98]
Volume occupied by radioactive waste	Rad. Waste	m ³	Flux from ecoinvent [93]
Ionising radiation	Ioni. Rad.	kg ²³⁵ U eq	ReCiPe [98]
Human toxicity	Hum. Tox.	CTU _h	USEtox [99]
Eutrophication	Eutrop.	kg PO ₄ ³⁻ eq	CML [97]
Acidification	Acid.	kg SO ₂ eq	CML [97]
Ecotoxicity	Ecotox.	CTU _e	USEtox [99]
Land use	Land use	points	ReCiPe [98]

1 4 Case study

2 The methodology is applied to compare three houses located in the experimental platform INCAS (Le
3 Bourget-du-Lac, France), using the previously defined LCA framework. These buildings were studied
4 in many research projects; they are therefore precisely characterised. In this study, however, we
5 assume to be in the design phase when a designer or a customer wants to choose the construction
6 type having the lowest impacts.

7 4.1 Compared alternatives

8 The three building alternatives are two-storey single-family houses, whose performance corresponds
9 to the passive house standard [100]. They have the same geometry, area and orientation; only their
10 construction type differ. The first alternative is a shuttered concrete (SC) house with extruded
11 polystyrene external insulation , as described in Munaretto et al. [77]. The second alternative has a
12 double-wall (DW) type of construction: it consists in two rows of concrete blocks with glass wool in-
13 between [101,102]. The last alternative is a wooden-framed (WF) house, with wood wool inside OSB
14 panels and a concrete ground floor slab, as described by Brun et al. [103]. In this case study, the
15 insulation thickness in the walls of DW and WF were slightly modified to reach the same thermal
16 resistance as SC, enabling to compare the construction types, all things being equal otherwise. All
17 alternatives have an electric air heating system, an electric domestic hot water system, and a double-
18 flow mechanical ventilation system. The EOL assumptions are given in . The complete description of
19 the houses and the modelling assumptions can be found in Pannier [31].

20

Table 4: EOL assumptions.

Material type	EOL
Inert waste[104]	66 % material recovery
	34 % inert material landfill
Wooden material [105]	43 % material recovery
	34 % incineration with heat recovery
	23 % non-hazardous waste landfill ⁴
Other combustible materials [104]	31 % incineration with heat recovery
	69 % non-hazardous waste landfill
Plaster	100 % non-hazardous waste landfill
Glass wool	100 % non-hazardous waste landfill
Steel frame [106]	85 %recycled
	15 % inert material landfill

21

22 4.2 Functional unit

23 The single-family house of 90 m² net floor area is studied over its entire lifecycle, including
24 construction, use, renovation and EOL stages. The building lifetime is an uncertain factor taking
25 values between 40 and 200 years. Regarding the use stage, an occupancy scenario is randomly
26 sampled, but the same scenario is applied to all compared alternatives.

⁴ Impacts of non-hazardous waste landfill are assumed to be six times greater than the impacts of inert material landfill [84].

1

2

3 4.3 Uncertain factors and uncertainty characterisation

4 A list of 153 uncertain factors is considered. The categories of uncertain factors included in the study
5 can be found in Table 5 with the main assumptions regarding the variation ranges of their uniform
6 distributions. Many categories were considered in this study to reflect a wide variety of uncertainties
7 a designer can face, regarding the building site, materials, components, construction processes,
8 systems or use, as well as uncertainties related to background environmental data or LCIA...
9 However, no uncertainties were accounted for neither regarding the material EOL processes, nor on
10 the evolution of the building and its context along its long lifetime. The complete list of uncertain
11 factors is given in the Supplementary Materials (SM) with their detailed variation ranges and the
12 alternative to which they relate.

13 In this first step of uncertainty quantification, uniform distributions were chosen for all continuous
14 factors. In the case study, ranges are defined around a reference value; values and variation ranges
15 are found in the literature and reported in Table 5. Globally, low variation ranges were chosen for
16 uncertainties related to building materials. This reflects the case where a designer has already
17 selected suppliers for the materials of all alternatives to be compared. Quite large variation ranges
18 are defined for thermal bridges, as they can vary depending on the data sources: e.g. catalogues or
19 default values in simulation software [107,108].

20 Four factors are categorical: climate, occupancy, environmental background data, and choice of the
21 polystyrene extrusion process. A random sample is drawn among available levels.

1 **Table 5: Categories of uncertain factors included in the case study. Categorical factors are in bold. Uniform distribution**
 2 **truncations are given in the SM. A relative variation is expressed with a “%” sign, the variation is absolute otherwise.**

N°	Uncertain factors	Variation ranges and data sources
1-6	Site-related: <ul style="list-style-type: none"> • albedo • orientation • transportation distances of materials • water network efficiency • variability of climate 	+/- 0.05 as in Munaretto et al. [77] +/- 2° as in Munaretto et al. [77] [109–112,57] [113] 2 000 climate files, model of Ligier et al. [80,81]
7	Variability of occupancy	2 000 occupancy scenarios, model of Vorger [82,83]
8-11	Ventilation-related: <ul style="list-style-type: none"> • ventilation rate of unoccupied zones • double flow heat exchanger efficiency • fan consumptions 	+/- 50 % as in Munaretto et al. [77] +/- 5 % as in Spitz et al. [101] +/-0.37 Wh/m ³ as in Merzkirch et al. [114]
12-21	Windows transmittances (U value)	+/- 5 % as in Spitz et al. [101], Munaretto et al. [77]
13-30	Solar factors of windows	+/- 5 % as in Spitz et al. [101], Munaretto et al. [77]
31-35	Surfaces Emissivity	Ranges defined in Macdonald [115] for the available materials; +/- 5 % otherwise as in Munaretto et al. [77]
36-40	Surfaces Absorptivity	Ranges defined in [115] for the available materials ; +/- 15 % otherwise as in Munaretto et al. [77]
41-65	Materials Thickness	+/- 5 % for layers of less than 5 cm; +/- 0.25 cm for larger layers
66-86	Materials Conductivity	Ranges defined in [115] for the available materials; +/- 5 % otherwise as in [101]
87-108	Materials specific heat	Ranges defined in [115] for the available materials; +/- 10 % otherwise
109-124	Heat transfer coefficients	Based on the literature review of Munaretto [108]
125-133	Thermal bridges in each room	-75% to +25% as in [37]
134-144	Lifetime of: <ul style="list-style-type: none"> • building • components 	[116,2,4,57] [49,117]
145-149	Characterisation factor of gases contributing to climate change	+/- 2 σ around the values given by Myhre and Drew [118]
150	Environmental background data	2 000 uncertain databases from ecoinvent v3.2 generated with Brightway2 [94]
151-153	Specific construction processes: <ul style="list-style-type: none"> • construction material waste • polystyrene extrusion process • steel rate in concrete 	Based on an analysis of the INIES database [117] Choice between R134a and CO ₂ as a blowing agent 0.2 to 4.2 % as in Hoxha et al. [49]

3

5 Results

The three houses alternatives (SC, DW and WF) with uncertainties are compared by analysing the SA and UA results. For information purposes, the deterministic DBES and LCA results are in the SM.

5.1 Sensitivity analysis

5.1.1 Influential factors in a comparison context

For each of the three alternatives (SC, DW, WF), 22 h of calculation are required for the 15 400 simulations. The results are presented in Figure 3 for two environmental indicators and in the SM for all indicators. For each indicator, six bars are shown. The first three bars show the results of the building alternatives, and the next three correspond to the pairwise impact differences ($SC - DW$; $SC - WF$; $WF - DW$). The colours correspond to the relative influence RI_j of an uncertain factor. Only the most influential factors appear in the legend and the number in bracket corresponds to the uncertain factor number in Table 5 and SM.

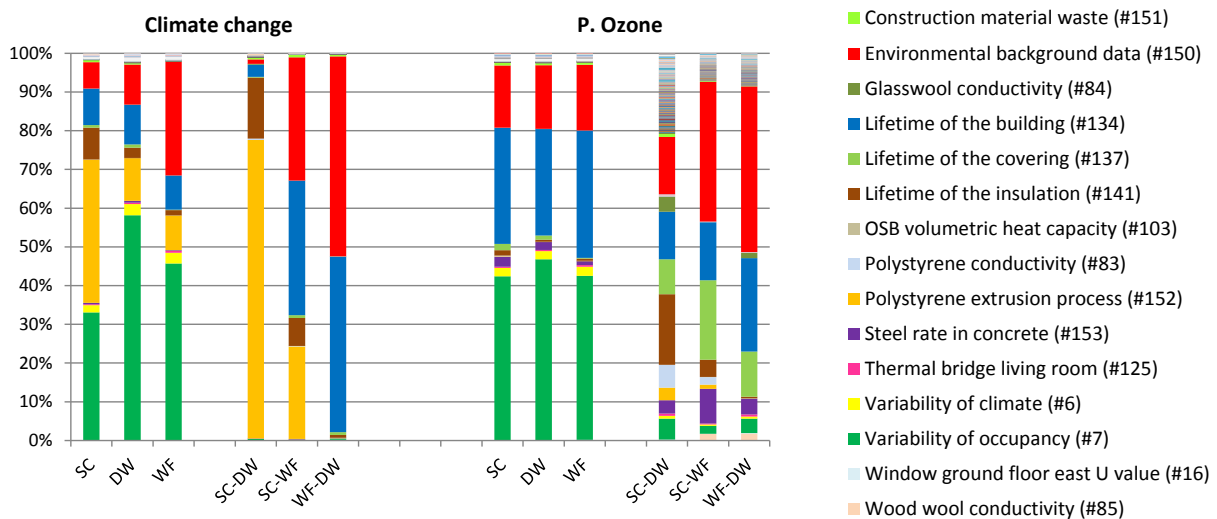


Figure 3: SA results on the comparison of the three design alternatives for two indicators.

The most influential factors identified when focusing on the individual alternatives are different from those selected in the comparison context. For example, the variability of occupancy, which has a large influence on the individual alternatives, has little influence on the pairwise impact differences. Depending on the objective of the study, we recommend to select the most influential factors among those having a high relative influence for either the individual alternatives (SC, DW, WF) or the comparison context (SC-DW, SC-WF, WF-DW). Both are illustrated in this article.

5.1.2 Improvement of the uncertainty characterisation

Many factors should be selected in order to reach a share of 90 % of relative influence for each indicator and for each pairwise difference: 113 factors in our case. Improving the uncertainty characterisation for so many factors would be time consuming for a building designer. Therefore, this task is performed for the shortlist of the 15 most influential factors, i.e. with the highest relative influence for all indicators, listed in the legend of Figure 3. The updated values are given in SM.

For instance regarding thermal bridges, the designer can use a thermal bridges simulation software to calculate the ψ -value instead of a catalogue. The distribution was therefore narrowed and modelled using a normal distribution. Regarding the polystyrene extrusion process, designers can ask their supplier which blowing agent is used. In this case study, this uncertainty factor has been

1 removed: CO₂ is chosen. The stochastic occupancy model of Vorger [82,83] can be used to generate
2 occupancy scenarios corresponding to the market target group of the house being designed. In this
3 case study, new scenarios are generated to correspond to first-time buyers with one child.

4 For other uncertain factors, designers can search additional information in scientific or technical
5 literature. For conductivities, specific heat and windows U-values, a normal distribution is used as in
6 Munaretto et al. [77] : the mean μ is the centre value of the previous uniform distribution, and the
7 truncations correspond to the boundary of the previous distribution. The standard deviation σ is
8 chosen to reflect the uncertainty found in the literature listed in Table 5. The same process is
9 followed for the steel ratio in concrete, waste of building construction, and building or components
10 lifetime, using normal distribution as in Hoxha et al. [49].

11 For the remaining uncertain factors, we assume that designers have no possibility to improve the
12 uncertainty characterisation, which is therefore unchanged. In this case study, climate variability is
13 unchanged (although it would have been possible to refine the climate generation by feeding it with
14 local data). Environmental background data are also remained unchanged due to lack of expertise of
15 building designers. Another manner to update uncertain distribution is to follow a Bayesian approach
16 [119], but this is out of the scope of this article.

17 5.2 Uncertainty analysis

18 5,000 simulations of each alternative were performed using a Sobol sequence sampling. 21 h were
19 necessary to run the 15,000 simulations. A large sampling size was chosen in this study in order to
20 reach convergence. As shown in the SM, this number could have been reduced to 1,000 with
21 negligible differences on the results. Even with 100 simulations the rankings remain the same. The
22 results of the seven methods to interpret UA results in a comparative context are presented in the
23 next subsections.

24 5.2.1 Distributions (Di)

25 The UA results are given in Figure 4 for the climate change indicator through output distributions of
26 each construction type: SC, DW and WF. The distributions are given for all indicators in the SM. Many
27 outliers are observed in the distributions that can spread over wide ranges as unbounded
28 distributions were used for the generation of uncertain environmental databases.

29 As shown in the deterministic results in SM, the use stage, which has similar impacts for all
30 alternatives, is the most contributing life cycle stage. Therefore, the impact of the three alternatives
31 are close. Visually, the distributions of the three alternatives or at least of SC and DW display a large
32 overlap. Therefore, the DW alternative was removed in some of the graphs presented in the
33 following sections of this article; but the complete graphs can be found in SM.

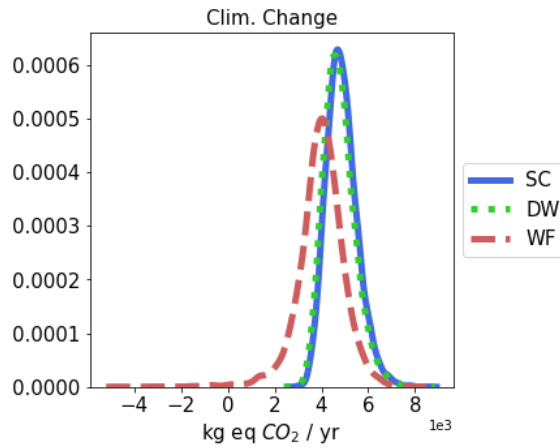


Figure 4: Output distributions of the alternatives for the climate change indicator.

A summary of the advantages and disadvantages of Di to analyse UA results in a comparative context is provided in Table 6.

Table 6: Summary of the characteristics of the Di method.

Advantages	Disadvantages
<ul style="list-style-type: none"> • Easy to understand • No specific calculation to perform 	<ul style="list-style-type: none"> • No pairwise comparison • Qualitative results • Not possible to quantify how often an alternative performs better • Not possible to quantify how much an alternative performs better • Results difficult to interpret as the distributions overlap • Assumption on the level of overlap up to which an alternative ranking is possible

5.2.2 Alternative preference

5.2.2.1 Discernibility analysis (DA)

The results of the DA are given in Table 7; each line standing for a pairwise comparison result. The colour code indicates which alternative has lower impacts.

Table 7: Probability that the impacts of one alternative are lower.

SC is better than WF	0.0038	0.989	0.166	0.992	0.302	0.134	0.398	0.965	0.967	0.015	0.281	0.38	0.67	0.968
DW is better than WF	0.0138	0.999	0.277	0.996	0.48	0.518	0.874	0.912	0.908	0.0298	0.447	0.68	0.786	0.967
SC is better than DW	0.017	0.103	0.499	0.0396	0.239	0.0126	0.0032	0.885	0.916	0.0398	0.161	0.0742	0.306	0.665
	Clim. Change	CED	Resources	Waste	Water	Particulate M.	P. Ozone	Rad. Waste	Ioniz. Rad.	Hum. Tox.	Eutrop.	Acid.	Ecotox.	Land use

For indicators having probabilities close to 0 (yellow) or 1 (dark green), a best performing alternative can easily be identified. Thus for climate change, WF is better than SC and than DW in most cases; in addition, DW is better than SC. It can be concluded that the construction type WF is the best alternative for this indicator, while SC is the worst one. Ranking can be established for cumulative

1 energy demand, mass of waste, volume occupied by radioactive waste, ionising radiation, and human
 2 toxicity.

3 For three indicators (fine particulate matter formation, photochemical ozone formation and land
 4 use), only a best or a worst alternative can be identified, but the full ranking cannot be established.
 5 For instance, WF is the worst alternative for the land use, but it is not possible to clearly state that SC
 6 beats DW as the probability reaches 66.5 %.

7 For the remaining indicators, it is not possible to establish an unequivocal ranking.

8 Table 8 summarises the rankings or partial rankings obtained with the discernibility analysis when the
 9 probability of occurrence exceeds 80 %. However, as previously mentioned, it is not visible from this
 10 analysis how much one alternative performs better than the two others.

11 **Table 8: Alternative ranking based on the discernibility analysis.**

Indicator	Best	Intermediate	Worst
Clim. Change	WF	DW	SC
CED	DW	SC	WF
Resources	-	-	-
Waste	DW	SC	WF
Water	-	-	-
Particulate M.	-	-	SC
P. Ozone	DW	-	-
Rad. Waste	SC	DW	WF
Ioni. Rad.	SC	DW	WF
Hum. Tox.	WF	DW	SC
Eutrop.	-	-	-
Acid.	-	-	-
Ecotox.	-	-	-
Land use	-	-	WF

12
 13 Note that, in this case study, the WF alternative is the worst option due to the EOL assumptions (that
 14 were not considered as uncertain factors). The share of not recovered wood is sent to non-hazardous
 15 waste landfill, whereas for the other two houses, the share of non-recovered heavy materials is sent
 16 to inert material landfill, which was assumed to have impacts six times lower (see).

17 A summary of the advantages and disadvantages of DA is provided in Table 9.

18 **Table 9: Summary of the characteristics of the DA method.**

Advantages	Disadvantages
<ul style="list-style-type: none"> Quantification of how often an alternative performs better (contrarily to Di) 	<ul style="list-style-type: none"> Not possible to quantify how much an alternative performs better Results more complex to understand than for Di in presence of more than two alternatives: probabilities obtained for each pair of alternatives Assumption on the probability up to which an alternative performs significantly better than the other (set at 80 % here) Post-processing necessary to find the alternative ranking based on the pairwise probabilities

19

1 5.2.2.2 Ranking probabilities (RP)

2 The results of the ranking analysis are given in Table 10. In each line, a possible ranking is shown. For
 3 climate change, WF is the best alternative while SC is the worst in 97 % of the simulations. In
 4 addition, for photochemical ozone formation, DW is the best alternative in 88 % (40%+48%) of the
 5 cases. The ranking is the same as in Table 8 when considering a probability of occurrence of a ranking
 6 that exceeds 80 %. However, with three alternatives, rankings are easier to obtain with RP than with
 7 DA.

8 **Table 10: Probability of occurrence of each ranking.**



9
 10 A summary of the advantages and disadvantages of RP is provided in Table 11.

11 **Table 11: Summary of characteristics of the RP method.**

Advantages	Disadvantages
<ul style="list-style-type: none"> Quantification of how often an alternative performs better (contrarily to Di) Ranking of alternatives directly obtained (contrarily to Di and DA) Most and less frequent rankings easily found for each indicator 	<ul style="list-style-type: none"> Not possible to quantify how much an alternative performs better Results more complex to understand than for Di in presence of more than two alternatives: probabilities obtained of each ranking Assumption on the probability up to which a partial or full ranking is significant

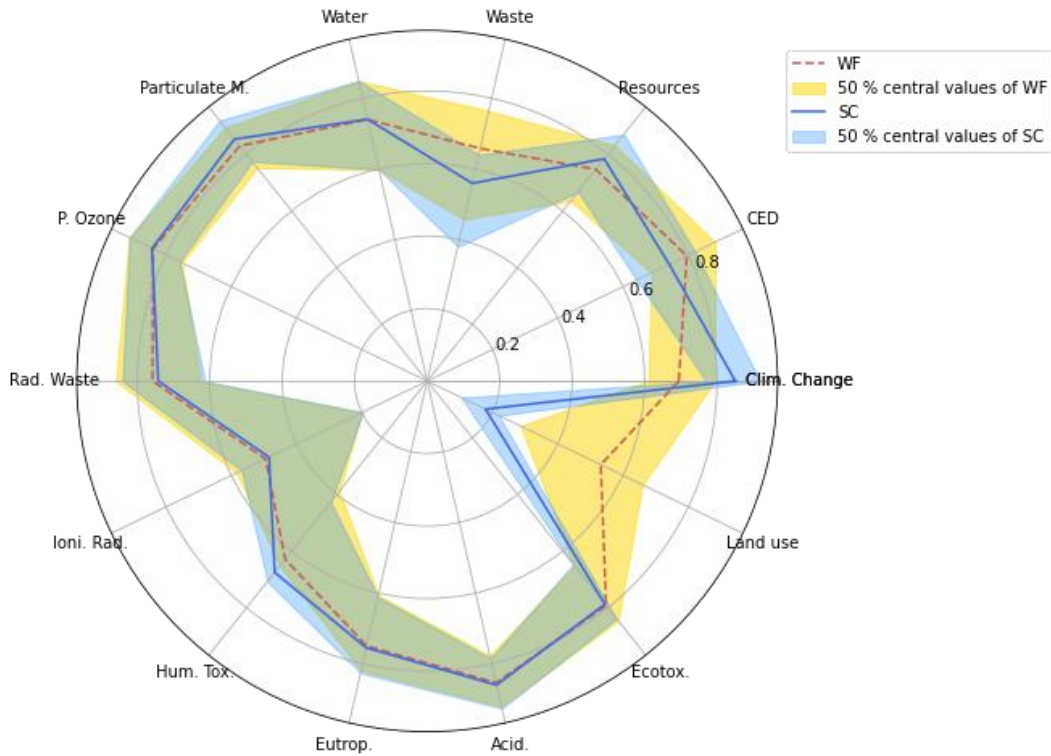
12
 13 5.2.3 Impact gaps between alternatives

14 5.2.3.1 Computation of means and quantiles (MQ)

15 In order to identify how much one alternative performs better than another one, statistics on the
 16 distributions are collected in SM. Some statistics are presented for SC and WF in Figure 5 for all
 17 indicators through a radar chart. The central line is the mean of the distribution. The coloured area
 18 contains 50 % of the central values.

19 From Figure 5, it is difficult to take a decision for most of the indicators. For only four indicators
 20 (climate change, mass of waste, human toxicity, and land use), the mean value of one alternative
 21 does not overlap with the 50 % central values of another alternative. A full or a partial ranking was
 22 established previously for these indicators. For three indicators (cumulative energy demand, volume

1 occupied by radioactive waste and ionising radiation) a large overlap is observed in Figure 5, while a
 2 ranking was possible based on the DA and the RP. The figure has a tendency to temper the
 3 distinction between alternatives because their uncertainty propagation results are plotted
 4 independently. It should be complemented by additional analyses, such as pairwise comparison.



5 **Figure 5: Output distributions of the alternatives SC and WF for all indicators.**

6 A summary of the advantages and disadvantages of MQ is provided in Table 11.

7 **Table 12: Summary of the characteristics of the MQ method.**

Advantages	Disadvantages
<ul style="list-style-type: none"> • Easy to understand • Quantitative results based on the distribution analysis 	<ul style="list-style-type: none"> • No pairwise comparison • Not possible to quantify how often an alternative performs better • Not possible to quantify how much an alternative performs better • Results more complex to interpret than for Di in presence of more than two alternatives: metrics to be analysed for each alternative • Assumption on the level of overlap up to which an alternative ranking is possible

8

9

10 **5.2.3.2 Standardised mean difference (SMD)**

11 The SMD was calculated to find how many standard deviations separate the means for each pairwise
 12 comparison (cf. Table 13). According to Cohen [69] *d* values are small around 0.2 (white values),
 13 medium around 0.5 (yellow values) and high around 0.8 (green values). In our case, environmental
 14 impacts of alternatives are significantly different for climate change, cumulative energy demand,
 15 mass of waste, fine particulate matter formation, photochemical ozone formation, volume occupied
 16 by radioactive waste, human toxicity and land use. A full or a partial ranking was established
 17 previously with DA and RP for these indicators. However, for ionising radiation, a ranking was found
 18 but the Cohen's *d* value indicated medium impact differences between the alternatives.

1

Table 13: Cohen's d for each pairwise comparison and each indicators.

	SC - WF	DW - WF	SC - DW
Clim. Change	1.168	1.029	2.174
CED	-1.190	-1.407	1.214
Resources	0.635	0.348	0.215
Waste	-1.585	-1.625	1.319
Water	0.366	-0.008	0.615
Particulate M.	0.970	-0.002	1.529
P. Ozone	0.113	-0.897	2.669
Rad. Waste	-1.218	-1.101	-0.899
Ioni. Rad.	-0.579	-0.572	-0.500
Hum. Tox.	1.217	0.947	0.903
Eutrop.	0.147	0.012	0.686
Acid.	0.309	-0.294	1.366
Ecotox.	-0.232	-0.468	0.265
Land use	-1.052	-1.029	-0.294

2

3 A summary of the advantages and disadvantages of SMD is provided in Table 14.

4

Table 14: Summary of the characteristics of the SMD method.

Advantages	Disadvantages
<ul style="list-style-type: none"> Quantification of how much an alternative performs better (contrarily to Di, DA, RP and MQ) 	<ul style="list-style-type: none"> Not possible to quantify how often an alternative performs better contrarily to DA and RP Not possible to obtain the ranking of alternatives contrarily to DA and RP Results more complex to interpret than for Di in presence of more than two alternatives: metrics to be analysed for each alternative Assumption on the Cohen's <i>d</i> value up to which pairs of alternatives are distinguishable

5

6 DA and RP quantify how often an alternative performs better, while SMD quantifies on how much
7 criteria an alternative performs better. Combining the two analyses gives a broader view on the
8 results in a comparative context. The combination is shown in Table 15 which corresponds to Table 8
9 with the background colours of Table 13. For instance, for an indicator, if the Cohen's *d* has low
10 values for at least two pairwise comparisons, then a white background is applied to the line
11 corresponding to this indicator in Table 15 to show that the impact values are often close to each
12 other. It is thus possible to read in Table 15 the alternative ranking and to identify if the impact
13 differences are large enough to distinguish alternatives. Generally, when impact differences are too
14 small according to SMD, no ranking is possible according to DA or RP. Relying on the life cycle stage
15 contribution analysis presented for the deterministic results in SM, the indicators for which a
16 decision can be made are, in this case study where the construction type is compared, those for
17 which the contribution of the construction and end-of-life stages are higher. A post-processing of
18 these two analyses is necessary to obtain this broader view, making the results more complex to
19 obtain.

1

Table 15: Alternative ranking and impact differences.

Indicator	Best	Intermediate	Worst
Clim. Change	WF	DW	SC
CED	DW	SC	WF
Resources	-	-	-
Waste	DW	SC	WF
Water	-	-	-
Particulate M.	-	-	SC
P. Ozone	DW	-	-
Rad. Waste	SC	DW	WF
Ioni. Rad.	SC	DW	WF
Hum. Tox.	WF	DW	SC
Eutrop.	-	-	-
Acid.	-	-	-
Ecotox.	-	-	-
Land use	-	-	WF

2

3 5.2.4 Cross-analyses

4 5.2.4.1 Distribution of relative differences (DRD)

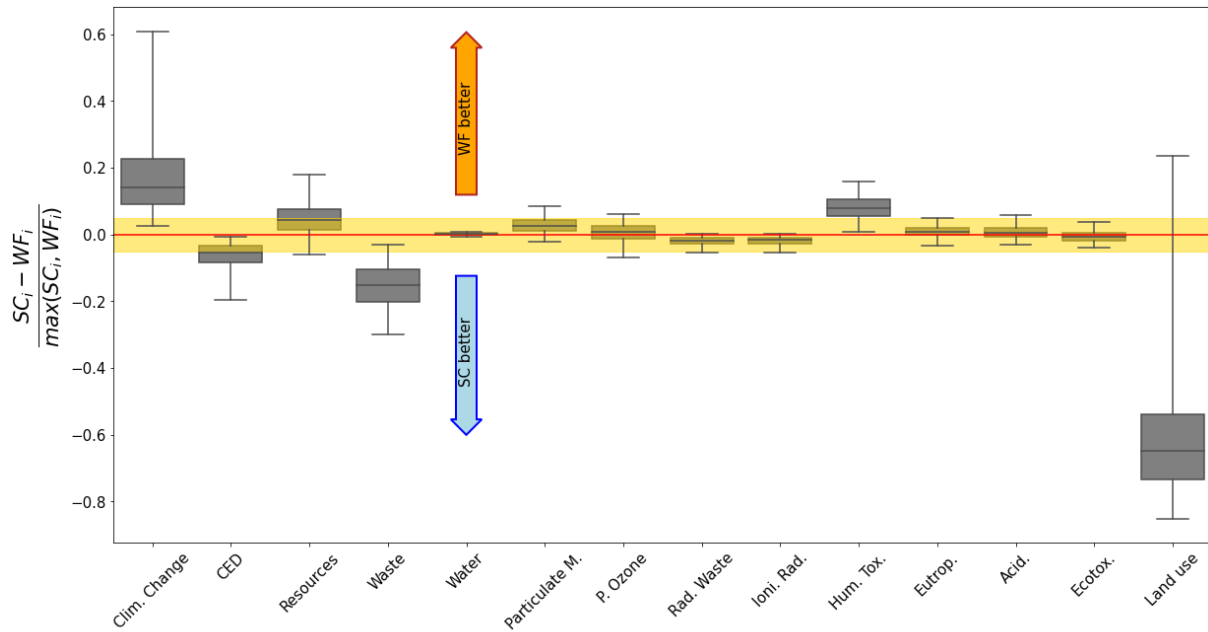
5 The DRD are given in Figure 6 for the pairwise comparison between SC and WF, and in SM for the
6 other pairs. In these graphs, boxplots are used to represent the distributions: they show the median
7 value, the first and third quartile, while the whiskers are the 2.5 and 97.5 centiles. The indifference
8 line (0-axis), where the impacts of both alternatives are equal, is plotted in red. The indifference zone
9 (yellow zone on the figure) around the indifference line represents the zone where the impact
10 difference between alternatives ranges between +5 and -5 %.

11 For some indicators (climate change, mass of waste, human toxicity and land use), more than three
12 quarters of the values fall outside the yellow zone indicating that impact differences are generally
13 significant: an alternative can be chosen with a high confidence.

14 For cumulative energy demand, the impact difference between alternatives may be small in some
15 cases. However, SC is better in at least 97.5 % of the cases as the upper whisker of the boxplot do not
16 overlap the indifference line: an alternative can be chosen with a high confidence.

17 For abiotic depletion of minerals, fine particulate matter formation, volume occupied by radioactive
18 waste, and ionising radiation, impact differences are smaller. However, one alternative is always
19 slightly preferred (at least 75 % of the value are upper or lower the 0-axis).

20 Regarding the five remaining indicators (water, photochemical ozone formation, eutrophication,
21 acidification and ecotoxicity), impact differences are always small. The final decision should not rely
22 on these indicators that do not give clear decisive information.



1

2

Figure 6: Distribution of the relative differences between SC and WF.

3

Similar conclusions are made for the comparison between WF and DW. For the comparison between SC and DW however, all boxplots fall into this yellow zone: the two houses always have similar environmental impacts.

5

6

Using all three pairwise comparisons, the alternative ranking of Table 16 is obtained. A colour code is used to depict the reliability in the choice: a green background corresponds to a choice with high reliability, while a yellow background stands for a choice with medium reliability. The following thresholds are set: i) the choice has high reliability if the mean impact difference is larger than 0.05 and the probability that an alternative performs better exceeds 90 %; ii) the choice has medium reliability if the mean impact difference is larger than 0.01 and the probability that an alternative performs better exceeds 75 %. Nine indicators are conclusive, as in the combination of RP and SMD (Table 15). Due to the thresholds settings, two main differences appear between Table 15 and Table 16. Firstly, the yellow background is more frequent in DRD (Table 16). Secondly, for the volume occupied by radioactive waste and ionising radiation, only a partial ranking is shown with DRD while a full ranking was shown in the combination of RP and SMD.

16

1

Table 16: Alternative ranking and impact differences based on DRD.

Indicator	Relative difference		
	Best	Intermediate	Worst
Clim. Change	WF	DW	SC
CED	DW	SC	WF
Resources	-	-	-
Waste	DW	SC	WF
Water	-	-	-
Particulate M.	-	-	SC
P. Ozone	DW	-	-
Rad. Waste	SC	-	-
Ioni. Rad.	SC	-	-
Hum. Tox.	WF	DW	SC
Eutrop.	-	-	-
Acid.	-	-	-
Ecotox.	-	-	-
Land use	-	-	WF

2

3 A summary of the advantages and disadvantages of DRD is provided in Table 9.

4

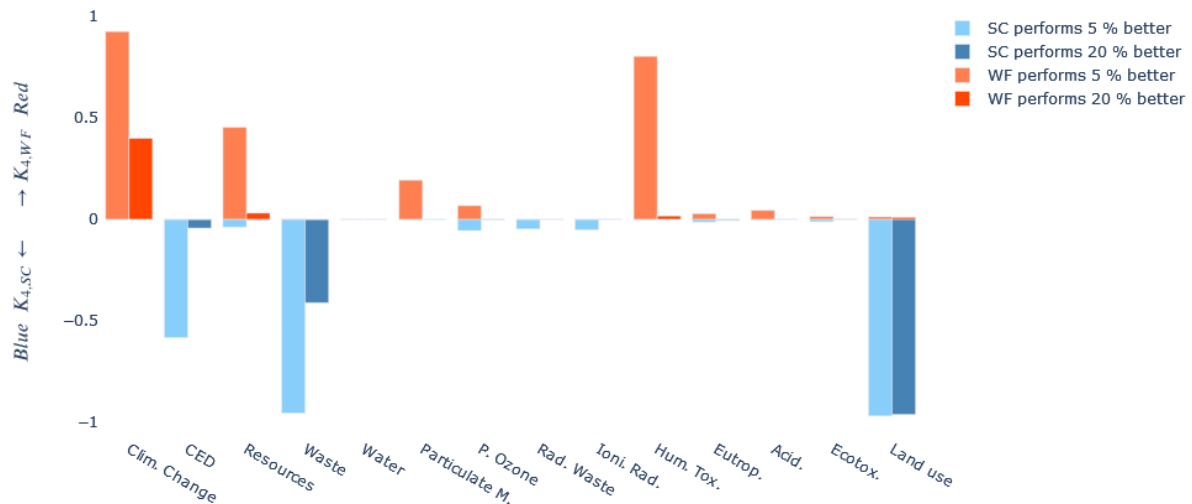
Table 17: Summary of the characteristics of the DRD method.

Advantages	Disadvantages
<ul style="list-style-type: none"> Quantification of how often an alternative performs better (contrarily to Di, MQ and SMD) Quantification of how much an alternative performs better (contrarily to Di, DA and RP) 	<ul style="list-style-type: none"> Results more complex to understand than for Di in presence of more than two alternatives: plots for each pair of alternatives Assumption on the probability that an alternative performs better than the other (visible on the boxplots lines) Assumption on the impact difference up to which an alternative performs significantly better than the other (set at +/- 5 % here) Post-processing necessary to find the alternatives ranking based on the pairwise plots

5

6 *5.2.4.2 Heijungs significativity metric (HSM) K_4*

7 The K_4 [25] are given in Figure 7 for the pairwise comparison between SC and WF for $\lambda = 5\%$ and
 8 $\lambda = 20\%$, and in SM for other pairs. In 93 % of the cases, WF outperforms SC by 5 % for climate
 9 change (first light red bar). However, WF performs at least 20 % better than SC in only 40 % of the
 10 cases (second dark red bar). For the CED, SC outperforms WF with at least 5 % (resp. 20 %) impact
 11 difference with a probability of 58 % (resp. 4 %).



1
2 **Figure 7: K_4 : Probability that the impact difference between SC and WF reaches at least 5 % or 20 %.**

3 From this analysis, it turns out that SC is better than WF for land use, and slightly better for
4 cumulative energy demand and mass of waste. WF slightly outperforms SC for climate change, and to
5 some extent for abiotic depletion of minerals and human toxicity. The photochemical ozone
6 formation indicator is one of the most uncertain: there is almost as much chance that SC
7 outperforms WF by 5 % than the reverse.

8 The conclusions are similar for the pairwise comparison between WF and DW. However, SC and DW
9 are not distinguishable: K_4 never exceed 25 % for $\lambda = 5 \%$. Using all three pairwise comparisons, the
10 alternative ranking of Table 18 is obtained. The same colour code is used as in Table 16, but with
11 different thresholds. The choice is reliable if K_4 exceeds 80 % for $\lambda = 5 \%$; a green background is
12 applied in this case. The choice is fairly reliable if K_4 exceeds 80 % for $\lambda = 1 \%$; a yellow background
13 is applied in this case. Due to the thresholds settings, only seven indicators are conclusive. In
14 addition, a partial ranking is available for cumulative energy demand, while a fully one is provided
15 with DRD and the combination of RP and SMD.

16 **Table 18: Alternative ranking and impact differences based on the cross-analyses.**

Indicator	K_4		
	Best	Intermediate	Worst
Clim. Change	WF	DW	SC
CED	-	-	WF
Resources	-	-	-
Waste	DW	SC	WF
Water	-	-	-
Particulate M.	-	-	SC
P. Ozone	DW	-	-
Rad. Waste	-	-	-
Ioni. Rad.	-	-	-
Hum. Tox.	WF	DW	SC
Eutrop.	-	-	-
Acid.	-	-	-
Ecotox.	-	-	-
Land use	-	-	WF

1 A summary of the advantages and disadvantages of HSM is provided in Table 9.

2 *Table 19: Summary of the characteristics of the DRD method.*

Advantages	Disadvantages
<ul style="list-style-type: none"> Quantification of how often an alternative performs better (contrarily to Di, MQ and SMD) Quantification of how much an alternative performs better (contrarily to Di, DA and RP) 	<ul style="list-style-type: none"> Results more complex to understand than for Di in presence of more than two alternatives: plots for each pair of alternatives Assumption on the probability that an alternative performs better than the other (set at 80 % here) Assumption on the impact difference significance between alternatives λ (set at 1, 5 and 20 % here) Post-processing necessary to find the alternatives ranking based on the pairwise plots

3

4 5.2.5 Comparison of the seven methods to interpret UA results in a comparative context

5 Table 20 summarises the characteristics of all seven methods to analyse UA results in a comparative
6 context. An additional line in Table 20 shows the characteristics of the combination of DA or RP with
7 SMD.

8 *Table 20: Comparison of the characteristics of the methods.*

Method	Type	Pairwise comparison	Ranking of alternatives	Impact difference	Assumptions required
Di	Qualitative	No	No	No	No
DA	Quantitative: how often	Yes	After post-processing	No	1 threshold
RP	Quantitative: how often	No	Yes	No	1 threshold
MQ	Quantitative: statistics	No	No	Yes	1 threshold
SMD	Quantitative: how much	Yes	No	Yes	1 threshold
SMD+DA / SMD+RP	Quantitative: how often + how much	Yes	Yes	Yes	2 thresholds
DRD	Quantitative: how often + how much	Yes	After post-processing	Yes	2 thresholds
HSM	Quantitative: how often + how much	Yes	After post-processing	Yes	2 thresholds

9

10 Di and MQ give first insight on the results. In addition, Di is the most suitable method to plot many
11 alternatives within one graph. Di and MQ have a tendency to temper the distinction between
12 alternatives: alternatives are handled independently and the strong overlap is difficult to interpret.
13 Yet, it should be noticed that the higher the overlap on an indicator in Di and MQ, the smaller the
14 pairwise impact difference obtained with SMD, DRD or HSM. For instance, for acidification, the
15 distributions of SC and WF have a large overlap in Figure 5 and Table 15; Table 16 and Table 18 have
16 a white background indicating a small impact difference. Furthermore, as Di and MQ are not based
17 upon pairwise comparisons, it is difficult to get a ranking for highly overlapping distributions.

18 DA and RP are easy to run. As they rely on the same concepts (counting number of occurrences),
19 they give the same results for the ranking which requires post-processing for DA; RP is more

1 convenient to analyse. SMD does not provide a ranking but highlights if the impact values of pairs of
 2 alternatives are close to each other. DA and SMD relying on pairwise comparison, the interpretation
 3 is more complex when the number of alternatives to be compared increases. All in all, provided that
 4 a threshold is set, DA, RP and SMD help answering either the *how much* or the *how often* questions,
 5 but not both.

6 The last three options (SMD+DA / SMD+RP, DRD and HSM) allow to extract the most information
 7 from the results. As a counterpart, two thresholds should be set: one related to the *how much*
 8 question, and the other related to the *how often* question as summarised in Table 21. As for all
 9 pairwise comparison based methods, the interpretation becomes more complex with an increasing
 10 number of alternatives. The results shown in Table 15 (SMD+DA / SMD+RP), Table 16 (DRD) and
 11 Table 18 (HSM) are very similar in terms of ranking and of impacts gaps between alternatives. The
 12 observed difference between the three methods (i.e. partial or full ranking for an indicator, or degree
 13 of reliability of the ranking) is linked to the choice of the thresholds: the mathematical indicators
 14 being different in the three analyses, the thresholds cannot be equivalent.

15 Applying DRD and HSM is more convenient than applying SMD+DA or SMD+RP as results are
 16 obtained within only one analysis. HSM has the advantage over DRD of precisely quantifying the
 17 impact gap between alternatives by setting the *how-much*' threshold λ so that an alternative
 18 performs at least λ % better than the other. However, this is what makes the HSM at bit less flexible
 19 than DRD: if the decision maker wants to change the *how-much* threshold, a new calculation with a
 20 new λ value should be run with HSM, while the indifference zone just needs to be adjusted on the
 21 graph for DRD. Despite of the convenience of HSM, we suggest to use DRD for this flexibility reason.

22 **Table 21: Thresholds for SMD+DA / SMD+RP, DRD and HSM.**

Method	How-often threshold	How-much threshold
SMD+DA / SMD+RP	Probability that an alternative performs better / Probability that a ranking is more frequent	Cohen'd value
DRD	Share of the boxplot above the indifference line of Figure 6	Range of the indifference zone
HSM	Probability that an alternative performs better	λ value so that an alternative performs at least λ % better than the others

23 6 Discussion

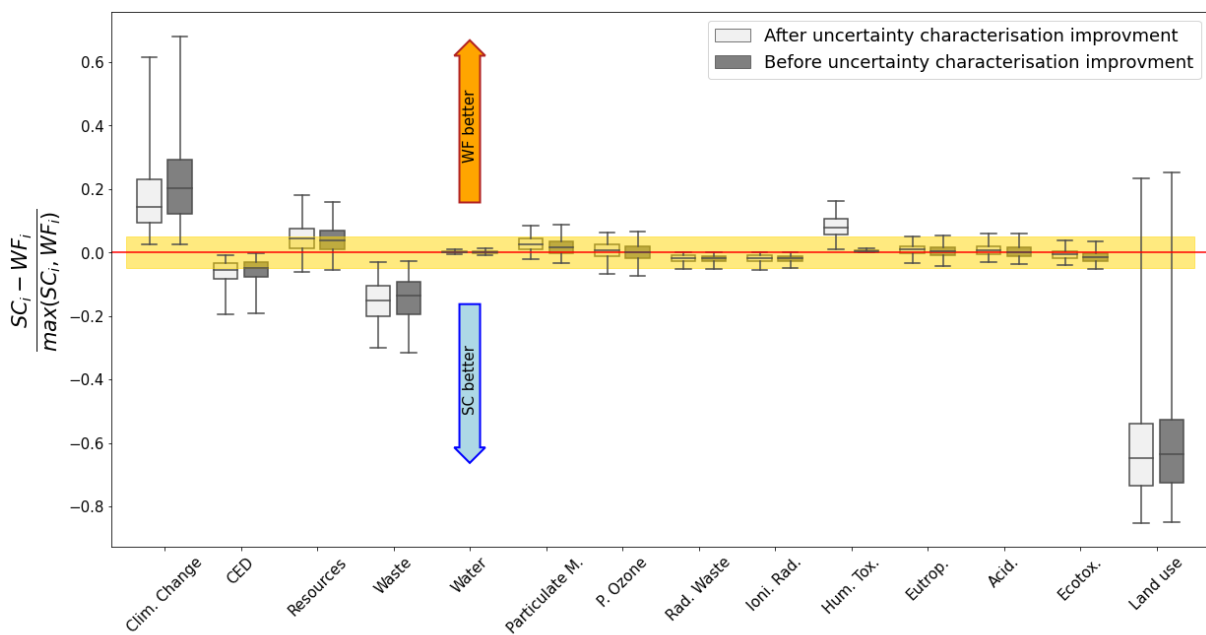
24 The proposed methodology can be applied by building designers in order to select environmental
 25 indicators for which a reliable alternatives ranking is possible. The final selection is easier as it bases
 26 upon a smaller set of indicators. Discussions with the building owner and other decision makers (e.g.
 27 urban planners), as well as multicriteria decision making methods [27,120,121] are then useful to
 28 select an alternative.

29 A wide range of uncertain factors that a designer faces were included in the study. However, the list
 30 is not comprehensive. For instance, uncertainties regarding the evolution of the building (e.g.

1 material degradation) and its context (climate, grid content, recycling processes...) along its long
 2 lifetime were not considered. The development of prospective scenarios is complex but when
 3 available, these uncertain scenarios can easily be included in the scope without modifying the
 4 methodology.

5 The simulation time required to performed the 15,000 simulations of the three alternatives was quite
 6 large is this study (21 h), making it difficult to replicate in real practice. However, it was shown that
 7 the number of simulations (and thus the calculation) could be divided by five for this case study,
 8 making such calculation feasible. Another option to decrease the computation time could be using
 9 surrogate models.

10 UA results depend on assumptions, for instance regarding uncertainty characterisation of the most
 11 influential factors. Yet, uncertainty distributions of input factors often rely on a few real observed
 12 data (much less than the sampling size) potentially leading to inaccurate decisions in a CompLCA
 13 [122]. Uncertainty in the definition of uncertainty, called meta-uncertainty, can be assessed. The
 14 effect of this uncertainty improvement on UA results are shown in Figure 8. For most indicators, the
 15 results interpretation remains the same. Nothing could be concluded for human toxicity without this
 16 step, while this indicator became decisive after improvement.



17
 18 **Figure 8: Distribution of the relative differences before and after improvement in the uncertainty characterisation.**

19 Other meta-analyses can be carried out. For instance, several uncertainty characterisations can be
 20 tested for the most influential factors, as done by Pomponi et al. [123]. The results robustness to the
 21 baseline can then be checked to identify if uncertainty characterisation modifies the conclusions. In
 22 the SM, several mean values and distribution types were investigated for the building lifetime. In this
 23 case, whatever the distributions for the building lifetime, the conclusions and alternatives ranking
 24 remains unchanged for all indicators. For a holistic meta-analysis, a complete DoE can be generated
 25 as in Lacirignola et al. [67], who analysed their results sensitivity to the distribution types of each
 26 uncertain factors of their model.

27 In order to further investigate the results and improve uncertainty characterisation, an SA can be
 28 performed on the alternative ranking change. In this additional step, the UA results are used to find
 29 out which uncertain factors lead to a ranking change. Regression, or the COSI or EASI methods

1 [124,125] can be used in that sense provided that a specific DoE is used for UA. Otherwise, a regional
2 SA can be applied: the distribution of each uncertain factor is split into two parts, one corresponding
3 to the cases where \mathbf{a}_1 is better, and the other where \mathbf{a}_2 are better. A Kolmogorov-Smirnov test is
4 then run to compare the two distributions: if they are distinct, the factor is influential in the ranking
5 change. However, these methods are not compatible with categorical variables having many possible
6 levels.

7 In this study, three alternatives are compared, leading to $\binom{3}{2} = 3$ pairwise comparisons and $3! = 6$
8 possible alternative rankings. The conclusions remain easily interpretable. Yet, increasing the number
9 of alternatives compared would make the results interpretation much more complex due to the
10 significant increase of pairwise comparisons. As suggested by Henriksson et al. [22] statistical tests
11 can be applied in such cases to group alternatives having similar environmental impacts. The UA
12 results analysis would then be performed on the groups instead of on the alternatives.

13 The case study presented in this article is only an illustration of the application of SA and UA
14 methods. Results regarding the comparison of wood versus concrete structures depend on many
15 assumptions, e.g. on the EOL processes like the recycling percentage of materials, which was not
16 considered, in this study, in the list of uncertain factors. The selected indicators would probably be
17 quite different if other alternatives were compared, e.g. gas, electric or wood fuel heating.

18 7 Conclusion

19 Uncertainties remain rarely addressed in the comparison of building design alternatives using LCA.
20 However, studying the effect of uncertainties can help building designers and stakeholders choosing
21 one alternative: they become able to understand which factors mostly affect results, and to focus on
22 environmental indicators for which a reliable choice is possible.

23 An uncertainty quantification approach for comparative LCA combining SA and UA was proposed. It
24 was applied to compare three construction types for a passive house. The particularities of this
25 article relies: i) in the wide variety of uncertainties and variabilities included in the scope; ii) in the
26 adaptation of SA methods to an alternative comparison context; and iii) in the assessment of several
27 metrics to interpret UA results.

28 The most influential factors for each individual alternative were not the same as in the comparison
29 context. In this case, uncertainty on background environmental data, climate variability, and lifetimes
30 of the building and some of its components were highly influential. After having improved the
31 uncertainty characterisation for the 15 most influential factors, a UA was performed. Results were
32 analysed in order to assess if and how much an alternative performs better than another one.
33 Gathering only one information (if or how much) can be misleading. In addition, it is preferable to
34 use metrics assessing pairwise comparison of alternatives, than metrics analysing individual
35 alternatives separately.

36 Cross-analysis answering both questions at the same time, such as DRD or HSM demonstrated their
37 ability to give results that are consistent with more common analyses, and to reduce the analysis

1 time. In this study, five indicators were conclusive with a high level of confidence regarding the
2 identification of alternatives performing significantly better or worse than others. According to these
3 results and assumptions regarding e.g. end of life processes, the wooden-framed house was the best
4 alternative for climate change and human toxicity, but the worst option for cumulative energy
5 demand, mass of waste, and land use. The alternative selection is thus based on five indicators
6 instead of fourteen. Building owners or decision makers can rely on this smaller set of indicators to
7 make the final decision, with the help of multicriteria decision making methods.

8 Further application of the methodology is needed in order to better define thresholds that are used
9 to assess the reliability of the obtained alternative ranking.

10 8 Acknowledgments

11 This work was supported by the research Chair ParisTech VINCI “Eco-design of buildings and
12 infrastructure”.

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