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Data Sheet

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Abstract

Building renovation is urgently required to decrease the energy consumption of the existing building stock and reduce greenhouse gas emissions coming from the building sector. Selecting an appropriate renovation strategy is challenging due to the long building service life and consequent uncertainties. In this paper, we propose a new framework for the robust assessment of renovation strategies in terms of environmental and economic performance of the buildings life cycle. First, we identify the possible renovation strategies and define the probability distributions for 74 uncertain parameters. Second, we create an integrated workflow for Life Cycle Assessment (LCA) and Life Cycle Cost analysis (LCC) and make use of Sobol indices to identify a prioritization strategy for the renovation. Finally, the selected renovation scenario is assessed by metamodeling techniques to calculate its robustness. The results of three case studies of residential buildings from different construction periods show that the priority in renovation should be given to the heating system replacement, which is followed by the exterior wall insulation and windows. This result is not in agreement with common renovation practices and this discrepancy is discussed at the end of the paper.

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1 Introduction

The built environment has a big impact on climate change (UN Environment and IEA, 2018). Construction of new buildings is responsible of 25% of global greenhouse gas (GHG) emissions and heating of the existing building stock contributes to another third of the emissions (Cabernard et al., 2019). Furthermore, buildings provide the biggest potential for cost-effective GHG emission reduction (UNEP SBCI, 2012). However, the current directives are still focused mainly on new construction despite a growing attention in the field of renovation (EU, 2010). Within the European building stock, 90% was constructed before 1990 and the annual growth of new buildings in the residential sector is estimated to be about 1% (Economidou et al., 2011). Achieving simultaneously a low energy standard while being cost-efficient in the existing building is challenging (Lasvaux et al., 2017) as it is crucial to assess the whole life cycle. Life cycle cost analysis (LCC) and life cycle assessment (LCA) are two well-known approaches to analyse the economic and environmental performance of a building. An integrated approach of LCC and LCA has previously been applied in building renovation studies (Ott et al., 2015; Conci et al., 2019; Olsson et al., 2016). Several studies have shown that there is a balanced point where the renovation strategy is environment-friendly and cost-effective (IEA, 2017; Almeida and Ferreira, 2015).

However, due to the long service life of a building and the associated uncertainties, the decision made in favour of one renovation strategy or another might be highly inaccurate or uncertain. These uncertainties affect parameters, which can be divided into design and exogenous parameters. The former represent the possible decisions the designer can make while the later represent the social and economic parameters such as external climate, human behavior and future evolution of energy costs. For buildings, which are long lasting systems, it has been shown that uncertainties related with building operation, components reference service lives, evolution of climate and energy mixes or economic situation highly affect the output of the LCA and LCC (Burhenne et al., 2013; Macdonald, 2002; Favi et al., 2018; Häfliger et al., 2017). In fact, it has been shown that the difference in resulting values of two distinct solutions might be lower than the level of uncertainties within each solution (Fawcett et al., 2012). The topic of uncertainty quantification has been discussed within the LCA community for many years. Several studies were conducted to summarize different approaches to treat uncertainties in LCA (Lloyd and Ries, 2007; Mendoza Beltran et al., 2018; Zhang et al., 2019; Heijungs and Huijbregts, 2004). These approaches include stochastic modelling (Heeren et al., 2015), data quality indicators (DQI)

(Coulon et al., 1997), fuzzy data sets (Egilmez et al., 2016), scenario analysis (Gregory et al., 2016), Taylor series expansion (Hoxha et al., 2014), expert judgement and the combination of several approaches. Some studies focus on the uncertainties in the methodology of LCA itself, e.g. goal and scope definition, life cycle inventory, impact assessment and interpretation (Huijbregts et al., 2003; Hellweg and Milà i Canals, 2014). Other studies specifically deal with uncertainties of building life cycle assessment (Heeren et al., 2015; Favi et al., 2018; Hoxha et al., 2017; Su and Zhang, 2016) and life cycle costs (Burhenne et al., 2013; Sharif and Hammad, 2019; Buyle et al., 2019; Giuseppe et al., 2017). Monte Carlo Simulation (MCS) is the most frequently-used method to evaluate the LCA output probabilistically (Lloyd and Ries, 2007). Many studies have used this method to evaluate the output uncertainty in building LCA or LCC, for example Burhenne et al. (2013); Heeren et al. (2015); Ross and Cheah (2017); Favi et al. (2017); Eckelman et al. (2018); Robati et al. (2019). The popularity of this method can be explained by its easy applicability and the straightforward procedure. MCS also allows representing the model output visually in a histogram or cumulative distribution function (CDF), which is crucial in uncertainty analysis. However, this method is limited as the number of model evaluations required to achieve an acceptable degree of accuracy is relatively large, especially when dealing with complex computational models (Groen et al., 2014). Besides the uncertainty analysis, it is vital for a designer to know, which parameters within the model input have the biggest contribution to the variability of the model output. To do this, global sensitivity analysis can be used (Saltelli, 2004). Sensitivity analysis has also been applied in different studies to identify the influential parameters or to simplify the model (Hoxha et al., 2014; Padey et al., 2013; Pannier et al., 2018; Nault et al., 2020; Das et al., 2014). Many techniques are currently available in literature (Groen et al., 2017; Mara et al., 2015; Lacirignola et al., 2017), some of which are based on the decomposition of the output variance (Iooss and Lemaître, 2015). Sobol indices are one such popular technique. They are based on the decomposition of the total output variance into the fractions related to the input parameters. These parameters are considered to be independent. It has been shown that the contribution to the variance for large input uncertainties in LCA is best performed by Sobol' indices or Spearman correlation coefficient (Groen et al., 2014). While MCS remains the most widely used method to propagate uncertainties and compute Sobol indices within the LCA community, it faces numerous hurdles, which are mainly associated to its relatively large computational cost (Pannier et al., 2018). For instance, to calculate the MCS-based Sobol indices, the computational cost is $N \times (k+2)$ model evaluations where N is a sample size defined by the analyst, usually in the order of thousands, and k is the number of the parameters (Saltelli et al., 2008). Other methods have been developed to specifically address such issues related to high-dimensionality and complex computational models. One of these methods is surrogate modelling where the original, potentially time-

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consuming, model is replaced by a less computationally expensive statistical model. Surrogate modelling techniques have been applied in many fields (Yang et al., 2015; Hover and Triantafyllou, 2006; Sun et al., 2017; O'Neill and Niu, 2017). However, to the authors best knowledge, they have not been applied in environmental and economic assessment of building renovation. In this paper, we use surrogate modelling, more specifically polynomial chaos expansions (PCE), as a method to propagate the uncertainties in LCA and LCC. The same PCE model is also used for the estimation of Sobol indices following (Sudret, 2008). In fact, it has been shown that Sobol indices can be analytically obtained by post-processing the PCE coefficients (Blatman and Sudret, 2010), hence no additional cost is incurred after the PCE model has been built. The goal of the study is to identify robust renovation scenarios for residential buildings in Switzerland using reference buildings. We define the critical parameters that need to be considered for robust environmental and economic renovation. Through a rigorous statistical treatment, we apply all possible uncertain design and exogenous parameters from the integrated assessment of LCA and LCC and perform global sensitivity analysis (GSA) to estimate Sobol indices by post-processing a PCE model. The novelty of this method is the possibility of a combined LCC and LCA with holistic integration of all sources of uncertainties using surrogate modelling, which allows us to quickly estimate, otherwise computationally expensive, Sobol indices.

2   Methodology

The methodology of the paper is outlined in Figure 1. First, the heating demand of the building and a combined LCC and LCA is conducted. Second, possible renovation measures are selected. Third, the uncertain parameters are identified and described. This is followed by the GSA, which is performed in several screening assessments to define the most influential parameters for the renovation. Finally, the uncertainties are propagated for the selected renovation measures and the solution robustness is compared to that of the non-renovated baseline case. Each of these steps is described in detail in the remainder of this chapter.
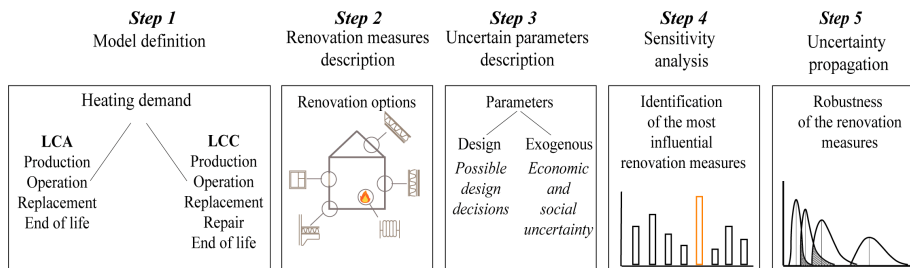

Figure 1: Proposed methodology

2.1 Model definition - Integrated analysis of environmental and cost performance

2.1.1 Heating demand

The first step of the method includes the heating demand calculation for the building. This step is done following the procedure of the Swiss standard for the energy demand analysis SIA 380/1:2016 (SIA 380/1, 2016), which includes quasi-steady monthly calculations. The validation of the calculations is made by comparison with the established commercial Lesosai software (Lesosai, 2020), which also complies with SIA 380/1:2016 (SIA 380/1, 2016). The calculations are performed using the python programming language, the code itself is open source and can be found on GitHub, the description of the code can be seen in the Supporting information 1. The heating demand is an intermediate result as it is used for the life cycle module B6 (operation) and to account for the operational costs.

2.1.2 Life cycle assessment

To assess the environmental impact of a renovated building, an LCA is performed. The life cycle modules A1-A3 (production), B4 (replacement), B6 (operation) and C3-C4 (end of life) are used as system boundaries for this study according to the standard for assessing the environmental performance of buildings SN EN 15978. The module A4 (transport to the construction site) is not included, because it has a relatively small effect on the overall life cycle assessment (Kellenberger and Althaus, 2009). The module A5 (construction process) is also not included as data is very rare. It has also been shown that the preparatory works on site can be neglected due to the low contribution to the LCA results (John, 2012). Detailed studies can be found from Indian construction processes (Devi and Palaniappan, 2017) and show that construction processes represent 2 to 3% of the total environmental impact of the building over its life cycle (Devi and Palaniappan, 2014). However translation from Southern India to Swiss context is difficult. Finally, the module B3 (repair) was excluded as well due to the limited data availability. The functional unit refers to the use of the building over a reference study period (RSP) of 60 years. It also includes the impact of the renovation activity as stated by Swiss standard SIA 2032 (SIA, 2010). The global warming potential (GWP), expressed in $kgCO_2eq.$, is used as an indicator for climate change based on IPCC characterization factors (IPCC, 2018) and is the only indicator considered in this study. The life cycle environmental impact (LCEI) refers in this study to the total $kgCO_2eq.$, which is the sum of GHG emissions over the life cycle of a building. LCEI is composed of the environmental impacts (EI) associated with production of all building components (Module A1-A3), their replacement (module B4) and end of life (modules C3 and C4) as well as the environmental impacts related with building operation (B6). This is

translated by the following equation:

$$LCEI = \sum_{i=1}^{b} k_{production,i} + k_{EoL,i} (n_i + 1) + Q_{F,a} k_{op.} RSP ERA \tag{1}$$

where $k_{production,i}$ [kg.CO$_2$ eq.] is the environmental impact of the production of the component i, $k_{EoL,i}$ [kg.CO$_2$ eq.] is the impact associated with the end of life of the component i, $n_i = \lceil RSP/RSL_i \rceil - 1$ [-] is the number of times the component i has to be replaced during the building's service life, RSP [years] is the reference study period (building life), RSL_i [years] is the component's reference service life, b is the number of the components. $Q_{F,a}$ [kWh/(m^2,a)] is the final yearly energy need of the building, which is calculated as $Q_{F,a} = Q_{H,a}/PF$, where $Q_{H,a}$ is the annual heating demand, PF is the performance factor, which depends on the energy system in a building (see more explanation in SI 1), $k_{op.}$ [(kg. CO$_2$ eq.)/kWh] is the operational impact factor, which represents the average value of CO$_2$ eq. emissions associated with the use of the specific energy system of the building, ERA [m^2] is the energy reference area, which refers to the heated floor area of a building.

2.1.3 Life cycle cost analysis

Simultaneously with the LCA, an LCC is performed. The net present value (NPV) methodology is used to evaluate the total costs of the renovated building under the renovation scenario. Similarly to LCA, the stages of production, replacement, operation, and end of life are included. In addition, costs related to repair as part of the maintenance is included in the calculations as a fixed percentage of the initial costs as stated by the Swiss Centre for buildings rationalization (CRB) [64]. The demolition costs are included in the analysis, however, it must be noted that due to the long building life span and applied discount rate, the NPV of a demolition cost becomes negligible. Labor cost is included in the analysis. The functional unit is the same as for LCA. The procedure of CRB is used during the analysis as follows (CRB, 2012):

$$\begin{aligned} LCC = &\sum_{i=1}^{b} C_{production,i} + \sum_{i=1}^{b} \sum_{l=1}^{n_i} \frac{C_{replacement,i}(1+r)^{lRSL_i}}{(1+d_{nominal})^{lRSL_i}} + \\ &\sum_{l=1}^{RSP} \sum_{i=1}^{b} \frac{C_{repair,i(1+r)^l}}{(1+d_{nominal})^l} + \sum_{l=1}^{RSP} \frac{Q_{F,a}m_{op}ERA(1+r)^l}{(1+d_{nominal})^l} + \sum_{i=1}^{b} \frac{C_{EoL,i}(1+r)^{RSP}}{(1+d_{nominal})^{RSP}} \end{aligned} \tag{2}$$

where $C_{production,i}$ [CHF] is the investment cost for the component i, $C_{replacement,i}$ [CHF] is the replacement cost for the component i, which is calculated as $C_{replacement,i} = C_{production,i} + C_{EoL,i}$, $C_{EoL,i}$ [CHF] is the demolition costs of the component i, b is the number of the components, $C_{repair,i}$ [CHF] is the repair cost of the component i, r [%] is the inflation rate, $d_{nominal}$ [%] is the nominal discount rate, m_{op} [CHF/kWh] is the operational costs for heating depending on the energy system of the building, and $Q_{F,a}$ is the final yearly energy need of the building,

and n_i is a number of times the component has to be replaced during the building's service life, RSP [years] is the reference study period (building life) and RSL_i [years] is the component's reference service life.

The analysis of LCC and LCA are run in parallel and share the operational consumption $Q_{F,a}$, the database for the costs and environmental impacts used in this study can be found in Supporting information 2. The code used for the calculations of $Q_{F,a}$, $LCEI$ and LCC as well as the parameters description can be found in Supporting information 1.

2.2 Renovation measures description and data collection

The possible renovation measures are defined by renovation of the envelope and replacement of the heating system. The envelope is represented by the exterior wall, roof, ground slab, windows and surfaces facing unheated areas (*e.g.* slab against unheated basement). The heating system can be chosen among a boiler (oil, gas, wood pellet, electric), an air-to-water heat pump or district heating. The data for the analysis is taken from the Swiss database for construction components for renovation called *Bauteilkatalog* (Bauteilkatalog, 2002). The structure of the database follows the e-BKP-H SN 506 511 structure where each element is composed by a number of components (Cavalliere et al., 2019). Data for the available components can be found in the Supporting information 2.

2.3 Uncertain input parameters

The uncertain parameters are divided into the categories shown below. The parameters' designations in brackets refer to the parameters described in the model calculation procedure shown in Supporting information 1. It has to be noted that only uncertain parameters from the defined model in Chapter 1.1 are presented here. Some of the parameters cannot be seen in Eq. (1-2) however, they can be found in the detailed model formulation in Supporting information 1.

- *Components types*: they represent the possible renovation solutions for the building envelope. They are defined according to the Swiss national database *Bauteilkatalog* (Bauteilkatalog, 2002).

- *Embodied emissions and investment costs* ($k_{production}$, k_{EoL} and $C_{production}$, C_{EoL}): they represent the environmental impact related to the production and the end of life of the components, and the investment costs for the components.

- *Operational emissions and costs* ($k_{op.}$ and $m_{op.}$, r, $d_{nominal}$): they represent the costs related to the type of a heating system, *e.g.* heating costs expressed in CHF per kWh and greenhouse gas emissions associated with the use of the system expressed in kgCO$_2$eq. per kWh. The data is taken from the Swiss database KBOB and Heating System Comparison

Tool by WWF (World Wide Fund for Nature): *Heizungsvergleich Excel Tool* (KBOB, 2016; WWF, 2015). This group of components also includes the inflation (r) and nominal discount rate ($d_{nominal}$) to account for the fluctuation of the future prices for LCC.

- *Reference service life* (RSL) of components: they are taken from the DUREE database (Lasvaux et al., 2019). In this database, all available RSL values, which exist in Swiss and international standards are collected and summarized regarding the mean value and standard deviation. At this development stage of the method, the components are being replaced by the initial components when reaching the end of the RSL without considering the future evolution of the materials.

- *System performance* (U_{ex}, d_i, ϕ, PF): they represent the existing building performance, for example the U-values (U_{ex}), existing and new heating system efficiency (d_i), thermal bridges before and after renovation (ϕ), performance factor (PF), etc.

- *User-oriented parameters* (T_{in}, t_{occ}, q_{vent}): they express parameters related to occupants, which might have an influence on the total energy consumption of the building, namely operating temperature (T_{in}), occupation schedule (t_{occ}), airflow (q_{vent}).

The parameters ranges are chosen to cover all available solutions ranging from the possibility of non-renovation to the renovation solution. The renovation solutions comply with the Swiss standards for the energy performance SIA 380/1 (SIA 380/1, 2016) using punctual requirements for the U-values.

2.4   Uncertainty quantification

Uncertainty quantification aims at identifying all sources of uncertainty and propagating these uncertainties from the input factors to the outputs. Sensitivity analysis aims at identifying important parameters within the inputs of a model. This section explains how these two analyses are carried out in the context of this paper. In both analyses, surrogate models are used to alleviate the computational burden. We specifically use polynomial chaos expansions (PCE) as surrogate of the model to compute the LCEI and LCC introduced above. A detailed description of using PCE for surrogate modelling is provided in the work from Sudret (Sudret, 2007; Marelli and Sudret, 2019). The main features of PCE are introduced in the following section. The entire uncertainty quantification analysis presented in this chapter is carried out using UQLab, a Matlab-based framework for uncertainty quantification (Marelli and Sudret, 2014).

2.4.1 Polynomial chaos expansions in brief

The output of the integrated LCA or LCC can be considered as a finite variance random variable Y, which is a function of a random vector X, *i.e.* :

$$Y = \mathcal{M}(\boldsymbol{X}) \tag{3}$$

where $\mathcal{M}$ is a computational model used to compute $LCEI$ or LCC (see Chapter 1.1). The vector $\boldsymbol{X}$ represents the parameters described in Chapter 1.1 and which are listed in detail in Supporting information 1. Note that the generic variable Y is used in the remainder of this paper to refer either to $LCEI$ in Eq. (1) or LCC in Eq. (2) as the subsequent developments are similar for either of the quantities of interest. The PCE consists of two parts:

$$Y = \mathcal{M}(\boldsymbol{X}) = \sum_{\alpha \in \mathbb{N}^M} y_\alpha \Psi_\alpha(\boldsymbol{X}) \tag{4}$$

where $\Psi_\alpha = \prod_{i=1}^{M} \Psi_{\alpha_i}(X_i)$ are a set of multivariate orthonormal polynomials obtained by the tensor product of univariate polynomials, y_α are coefficients to be computed, α are a set of indices, which define the degree of a polynomial and M is the number of input uncertain parameters. Depending on the case study, a total $M = 73$ to 75 input parameters are considered in this paper. Each univariate polynomial belongs to a classical family of polynomials defined according to the distribution of the corresponding input. For instance, Legendre polynomials are associated to uniform distribution while Hermite correspond to the Gaussian one. All the families of polynomials are presented in detail by Xiu and co-authors (Xiu and Karniadakis, 2002). The expansion in Eq. (4) is an infinite series. In practice, this series is truncated into a finite sum as follows:

$$\widehat{Y} = \mathcal{M}^{\mathrm{PC}}(\boldsymbol{X}) = \sum_{\alpha \in \mathcal{A}} y_\alpha \Psi_\alpha(\boldsymbol{X}) \tag{5}$$

where $\mathcal{A} \subset \mathbb{N}^M$. As the number of coefficients y_α grows exponentially with both the dimension and the degree, this truncation allows to cut off this number and thus, reduce the computational cost. In this paper, hyperbolic truncation is used as proposed by Blatman and Sudret (2011). The optimal PCE is sought within a $1 - 10$ degree range. We use the least square minimization method to estimate coefficients of the expansion Berveiller et al. (2007). This method is non-intrusive, *i.e.* the coefficients are obtained by post-processing a number of model evaluations, which form a so-called experimental design. Latin hypercube design is selected as sampling strategy for the analysis. The goal of the method is to minimize the mean square error Berveiller et al. (2007):

$$\widehat{y}_\alpha = \arg \min_{y_\alpha \in \mathbb{R}^{\mathrm{card}\mathcal{A}}} \frac{1}{N} \sum_{i=1}^{N} \left(\mathcal{M}\left(\boldsymbol{x}^{(i)}\right) - \sum_{\alpha \in \mathcal{A}} y_\alpha \Psi_\alpha\left(\boldsymbol{x}^{(i)}\right) \right)^2 \tag{6}$$

where $\mathcal{X} = \{\boldsymbol{x}^{(i)}, i = 1, \ldots, N\}$ is a set of realizations of the random parameters defined in Chapter 1.1 and of size N, which usually ranges between tens and several hundreds and $\mathcal{Y} =$

$\left\{ \mathcal{M} \left(\boldsymbol{x}^{(i)} \right), i = 1, \ldots, N \right\}$ is a set of the corresponding model evaluations (LCC or $LCEI$).

In order to estimate the accuracy of the constructed surrogate model, the calculation of the possible errors must be performed. The Leave-One-Out (LOO) error is then calculated following a cross-validation procedure. The idea is to create N different PCE models $\mathcal{M}^{\mathrm{PC}\backslash i}$ where each model is created using an experimental design excluding the i-th sample. The left-out point is then predicted by the built PCE and compared with the real output $\mathcal{M} \left(\boldsymbol{x}^{(i)} \right)$. This procedure is repeated for all the training points and the LOO error is then calculated as follows (Blatman and Sudret, 2010):

$$\varepsilon_{LOO} = \frac{\sum_{i=1}^{N} \left(\mathcal{M} \left(\boldsymbol{x}^{(i)} \right) - \mathcal{M}^{\mathrm{PC}\backslash i} \left(\boldsymbol{x}^{(i)} \right) \right)^2}{\sum_{i=1}^{N} \left(\mathcal{M} \left(\boldsymbol{x}^{(i)} \right) - \widehat{\mu}_Y \right)^2} \tag{7}$$

where $\widehat{\mu}_Y$ is the sample mean of the experimental design response. In practice, one does not need to construct N different PCE models to evaluate ε_{LOO} in Eq.(7): it is available as a post-processing of a single PCE model built using the entire experimental design (Le Gratiet et al., 2017).

$$\varepsilon_{LOO} = \frac{\sum_{i=1}^{N} \left(\frac{\mathcal{M}\left(\boldsymbol{x}^{(i)} \right) - \mathcal{M}^{\mathrm{PC}\left(\boldsymbol{x}^{(i)} \right)}}{1 - h_i} \right)^2}{\sum_{i=1}^{N} \left(\mathcal{M} \left(\boldsymbol{x}^{(i)} \right) - \widehat{\mu}_Y \right)^2} \tag{8}$$

Further details on the practical computation of a PCE model can be found in the UQLAB PCE manual (Marelli and Sudret, 2019).

2.4.2 Sensitivity analysis

Global sensitivity analysis aims at identifying the most influential parameters within the model inputs to the model output (Saltelli et al., 2008). Sobol' indices are a popular analysis of variance technique where the total output variance is decomposed into smaller fractions related to each input variable and combinations thereof. Sobol' indices of the first order represent the influence of each parameter taken separately while second order Sobol' indices show the possible interactions within the input parameters. The procedure of variance decomposition can be seen in Supporting information 1. In practice, a large Sobol' indice for a given variable implies a high contribution to the output uncertainty. On the contrary, if a parameter has a very low Sobol' indice value, it may be considered negligible to the output uncertainty and can therefore be taken out in order to simplify the model and reduce the computational cost. Computationally, the Sobol' indices can be obtained using Monte Carlo simulation. However in this paper, we rely on the built PCE models for this task. More specifically, the Sobol' indices are obtained analytically by simply post-processing the coefficients (y_α) of the PCE models (Marelli and Sudret, 2014).

Sensitivity analysis is used in this paper to help the designer identify the most influential parameters for the renovation. Initially, GSA using Sobol' indices is performed for the entire

range of possible renovation measures where the solutions vary within the available database simultaneously with other sources of uncertainties during the building life cycle.

After the first results are achieved, the most influential parameter is found and defined as a first renovation measure. Focusing on this parameter allows the designer increasing the robustness of the output regarding economic and environmental performance of a building over its lifetime. To be able to find the second priority in the renovation, the first most influential renovation measure is defined by selecting the deterministically optimal solution within the available database of renovation measures. To identify the optimal solution, the LCEI and LCC of all possible solutions are calculated deterministically.

The sensitivity analysis procedure continues until the exogenous parameters become the most influential ones. In this case, we stop the analysis and move on to the uncertainty quantification of the identified renovation solutions. Any additional renovation measure will not significantly improve the robustness of the LCEI and the LCC as they are controlled by parameters out of range for the designer (*e.g.* user behavior, economic evolution).

2.4.3   Uncertainty propagation

The defined solutions for the renovations, which are identified using sensitivity analysis are considered for uncertainty propagation and compared with the non-renovated case in terms of robustness. In practice, Monte Carlo simulation is carried out using the PCE models which are proxies of the original models defined in Section 2.1. The comparison is first made visually in terms of probability distributions which are obtained by kernel smoothing density. A numeric assessment on the improvement brought by each design choice is also carried out using the same Monte Carlo simulations.

3   Case studies

To evaluate the applicability of the method, three buildings from different construction periods are selected. The case studies are taken from eRen building models as the energy demand of these buildings was already calculated (Schwab et al., 2015). This allows us to validate the results using the created tool shown in Section 2.1. Three construction periods are chosen as representatives of the majority of the building stock in Switzerland. A brief description of the case studies can be seen in the Table 1.

The parameters of uncertainty selected for this study are shown in the Table 2. The parameters designation refers to the parameters from the calculation procedure shown in the Supporting information 1. The insulation thickness for all the component types is set to vary within the range [00.5] m. The uncertainty for the embodied impacts and investment costs is set respec-

Table 1: Description of the case studies

Year	1939	1960	1972
Year of renovation	Not renovated	Not renovated	Renovated in 2018
ERA	$2,445$ m^2	$1,475$ m^2	$1,446$ m^2
Walls	Cement bricks, not insulated	Hollow bricks	Double brick wall
Slabs	Hollow core clay slabs	Concrete & hollow core clay slabs	Reinforced concrete
Windows	Double glazing, PVC frame	Double glazing, wooden frame	Double glazing with low-E layer, PVC frame
Energy consumption (heating)	95.4 kWh/m^2,a	110 kWh/m^2,a	91.1 kWh/m^2,a

tively to $\pm 30\%$ (expert point of view and previous studies (Gomes et al., 2013; Chen et al., 2010)) and $\pm 20\%$ (SIA 480, 2016). The value of 0 in the moments for the component types always represents the non-renovated case, *i.e.* when no action is taken by the designer. For the variability of component types, each number within the range represents one system, *e.g.* for the heat production, 1 represents an oil boiler, 2 a gas boiler, 3 a district heating, 4 an air-to-water heat pump, 5 a wood pellets boiler and 6 an electric boiler. Detailed information about the envelope systems can be found in the Supporting information 2. The distribution of the parameters is mainly selected based on the available data. Uniform distribution is assumed for all parameters whose only knowledge available is the upper and lower limits. Finally, the distribution of the RSL for the components is chosen as discussed in Lasvaux et al. (2019).

Table 2: Parameters of uncertainty used in the case study. The parameters column refers to the distributions parameters and corresponds to the upper and lower bounds when using the uniform distribution. The moments represent the variable mean and standard deviation. $^{cat.}$ refers to a categorical variable

Model parameter	Parameters	Moments	Distribution	Source
Component types variability				
Exterior wall [-]	$[0, 44]^{cat.}$		uniform	
Roof [-]	$[0, 12]^{cat.}$		uniform	
Ground slab [-]	$[0, 26]^{cat.}$		uniform	
Wall against unheated surface [-]	$[0, 5]^{cat.}$		uniform	
Slab against unheated surface [-]	$[0, 6]^{cat.}$		uniform	[65]
Roof against unheated [-]	$[0, 11]^{cat.}$		uniform	
Windows [-]	$[0, 16]^{cat.}$		uniform	
Heat production[-]	$[0, 6]^{cat.}$		uniform	
Embodied LCEI ($m_{production}$) and investment costs ($C_{investment}$)				
Embodied impact heating system (heat distribution + heat diffusion) kgCO$_2$-eq./ERA)	[0.685, 0.729]		uniform	[67]
Cost oil boiler [CHF/ERA]	[34.2, 51.3]		uniform	
Cost gas boiler [CHF/ERA]	[30.1, 45.2]		uniform	
Cost wood pellets boiler [CHF/ERA]	[37.7, 56.5]		uniform	[68],[81]
Cost heat pump [CHF/ERA]	[40.7, 61]		uniform	
Cost electric heater [CHF/ERA]	[32.5, 48.8]		uniform	
Embodied impact components- [%]	[-30, 30]		uniform	Assumption, [80], [79]
Investment cost components [%]	[-20, 20]		uniform	[81]
Operational environmental and cost inputs				
Thermal energy generation $k_{op.}$ [kgCO$_2$-eq./kWh]				
Oil	[0.319, 0.322]		uniform	

[67],[68]

Gas	[0.248, 0.249]	uniform	
Wood pellets	[0.038, 0.048]	uniform	
Heat pump	[0.036, 0.039]	uniform	
Electricity	[0.102, 0.108]	uniform	
Operational cost for heating [CHF/kWh] m_{op}			
Oil	[0.093, 0.111, 0.128]	triangular	
Gas	[0.101, 0.111, 0.127]	triangular	[68],[82]
Wood pellets	[0.095, 0.107, 0.13]	triangular	
Heat pump	[0.064, 0.079, 0.093]	uniform	
Electricity	[0.192, 0.222, 0.259]	triangular	[83]
Inflation rate r [%]	[0.5,2]	uniform	[84]
Discount rate (real) $d_{nominal}$ [%]	[2.5,4.5]	uniform	[81]
Components reference service life RSL [years]			
Exterior wall [years]	[40.6, 11.6]	lognormal	
Roof [years]	[30.4, 9.6]	lognormal	
Slab [years]	[33.7, 14.2]	lognormal	
Wall against unheated surface [years]	[40.6, 11.6]	lognormal	
Windows [years]	[27.5, 12.2]	lognormal	
Oil boiler [years]	[19.4, 3.1]	lognormal	
Gas boiler [years]	[18.8, 3.3]	lognormal	[85]
Wood pellets boiler [years]	[18.3, 2.8]	lognormal	
Heat pump [years]	[17.1, 6.4]	lognormal	
Electric boiler [years]	[19.8, 5]	lognormal	
Slab against unheated surface [years]	[33.7, 14.2]	lognormal	
Roof against unheated surface [years]	[30.4, 9.6]	lognormal	
System performance			
Existing windows U-value	[2.9, 0.58]	lognormal	Assumption, [86]

U_{ex} [W/m2*K]

Parameter			Distribution	Source
Existing exterior wall degradation d_i [%]		[10, 3]	gumbel	Assumption, [87]
Existing roof insulation degradation d_i [%]		[20, 5]	lognormal	Assumption, [87]
Thermal bridge renovation φ [%]		[18, 5]	gaussian	Assumption
Efficiency loss of the existing system [%]	[0.15, 0.25]		uniform	Assumption [88]
Efficiency loss of a new system PF [%]		[0.15, 0.05]	gaussian	Dependent on the heating system, shown in SI1.
Existing slab against unheated surf., degradation [%] d_i		[10, 5]	lognormal	Assumption, [89]
User-oriented parameters				
Operating temperature inside T_{in} [°C]	[20,23]		uniform	[90]
Building occupation schedule t_{occ} [h/day]	[8, 16]		uniform	+/- 4 hours to the suggested 12 h value by [56]
Airflow existing building q_{vent} [m3h/m2]	[0.7, 1]		uniform	[90]

The assumption for the uncertainty on the U-value of the existing windows with wooden frame is roughly estimated to be 20% due to the age of the building (degradation level D) as discussed in Fernandes et al. (2019). The uncertainty on the performance of the insulation is based on a study by Domnguez-Muoz et al. [87], which focused on the uncertainties of the conductivity of insulation materials while taking into account the deterioration due to the building age. The performance loss of the existing system values are set depending on the heating system type and in accordance with European commission directorate (comission directorate-general for energy, 2016). The building structures deterioration rates are assumed according to Gharehbaghi et al. (2020).

4 Results

The results of the case study from the 1960 building (see Table 1) are presented in this section. The results of other studies can be found in the Supplementary information 1.

4.1 Sensitivity analysis

The results of the sensitivity analysis are presented in Figure 2. Several parameters (e.g. exterior wall insulation thickness, environmental impact and cost uncertainties) were summarized to one macro parameter (e.g. Exterior wall) for a more visual results' representation. The analysis of each separate parameter from Table 2 is shown in Supporting information 1. The parameters are distinguished between the design parameters and the exogenous ones. As it can be seen from the first screening assessment (the top graph), the heating replacement is the most influential parameter for the renovation. Therefore, we set the heating system as the first renovation measure and apply it to the model. As sensitivity analysis is helpful in identifying the influential parameters but not the actual practical solution, the applied measures are selected according to the deterministically optimal solution in terms of LCEI and LCC within the available options in the database. In this case, it is an air-to-water heat pump, with a coefficient of performance (COP) of 2.8. The results of the calculations can be found in the supplementary information 1. The summary of the applied solutions according to the sensitivity analysis is shown in Table 3.

After the heating system is selected, the sensitivity analysis is conducted again to identify the second priority for the renovation. It has to be noted that both model outcomes are treated equally. Thus, a combined sensitivity index is considered. In the second assessment, the Sobol index is different for LCEI and LCC but when considering the combination, the exterior wall insulation appears as the most important parameter. The impact of the exogenous parameters is growing with each step of the analysis. Eventually, these parameters are becoming the most crucial ones for the assessment and therefore, it is not possible to improve the robustness by applying more renovation measures. At this point, the assessment of the sensitivity analysis is stopped and the second phase, i.e. the uncertainty quantification on the applied measures, is initiated. In this case study, this point is reached during the fourth step of the procedure (See Table 3).

4.2 Uncertainty quantification

Uncertainty propagation is carried out along each iteration of sensitivity analysis, i.e. once a renovation measure is selected, distributions of the corresponding LCEI and LCC are obtained using crude MCS as shown in Figures 3 and 4. The shown densities are obtained by kernel smoothing using, in each case, 10^6 samples evaluated through the surrogate model. The LCEI and LCC distributions of the non-renovated building lie on the right side of the figure. As renovation measures are applied, the curves gradually shift towards the left, which indicates a reduction in the mean values. The spread of the density curves is also getting smaller as renovation measures are applied, thus indicating an overall increase in robustness. It has to be noted that the renovation scenarios are being applied cumulatively, for instance, once the

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Table 3: Measures applied following each iteration of the sensitivity analysis.

Measure	Description
Step 1: Heating system	Heat pump, air-to-water, COP 2.8
Step 2: Exterior wall	12 cm rockwool insulation and plaster, U 0.25 W/mK
Step 3: Windows	Wooden-aluminum window triple pane, frame part 10 %, U 0.8 W/mK
Step 4: Slab against unheated area	10 cm rockwool insulation and solid wood, U 0.25 W/mK

heating system is adapted, the exterior wall is applied additionally. It can be clearly seen that the application of the heating system and other applied measures has a higher impact on the environmental performance LCEI than on the economic performance LCC. This can be explained by discount and inflation rates, which are controlling the operational costs. Therefore, the application of the renovation measures is less influential for LCC than for the LCEI.

The results show that uncertainty quantification is a crucial element due to the big overlap of the various distributions in Figures 3-4. We therefore analyze the overlapping areas and introduce a risk index, which is the probability of the renovation measure to be ineffective with regards to environmental and economic performance compared to the previous measures or the non-renovated case. This probability of ineffective renovation has a scale from 0 to 1. The higher the number, the higher the chance of the renovation measure to be inefficient. This index indicates the probability that, due to various uncertainties, the environmental or economic performance over the life cycle after applying a renovation measure is worse than it would be without that renovation. This probability is calculated by MCS using 10^6 random independent samples.

As it can be seen from Table 4, when comparing with the non-renovated case, the index increases with the additional renovation measures for both, environmental and economic performance. However, if we compare the further renovation measures, the picture is less clear. For example, in terms of LCC, when comparing windows and exterior wall renovation, the probability of the renovation measure being ineffective is close 50%, and decreases if more measures are applied. This result shows that to be able to perform a robust cost-efficient renovation, the full building renovation should be performed while in terms of LCEI, only a replacement of the heating system is enough.
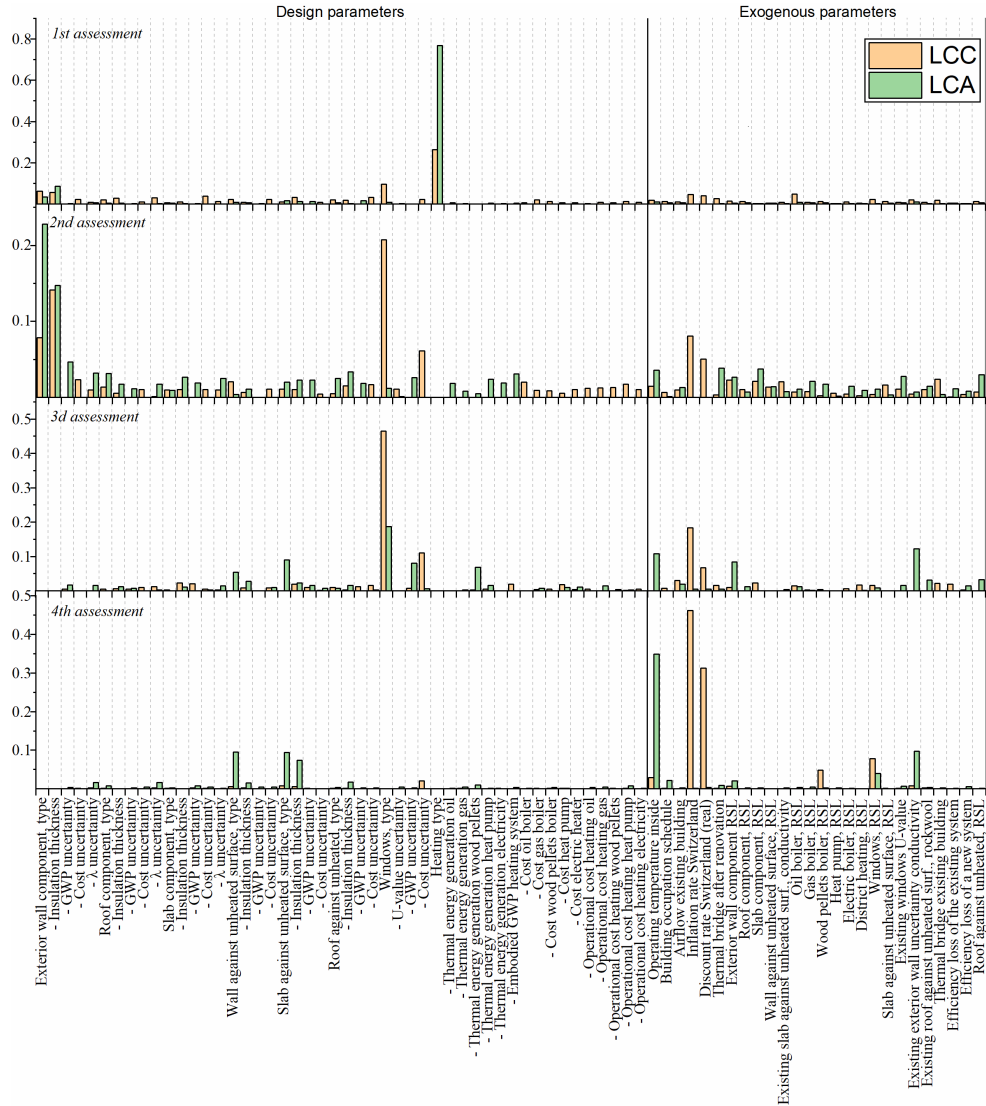
Figure 2: Sensitivity analysis results: the 1st assessment shows the total Sobol indices for the variability of all measures, the 2nd assessment shows the result once the heating system was applied as a renovation measure, 3rd and 4th assessments show the analysis after exterior wall and windows were applied respectively

5 Discussion

Three case studies from different construction periods were used to apply the proposed methodology based on GSA. The first results show that during the first screening assessment with all the possible renovation scenarios, the most influential parameter for both LCEI and LCC is the heating system replacement, which is followed by the exterior wall insulation and windows replacement for the LCEI. It can also be seen that the exogenous parameters become of highest
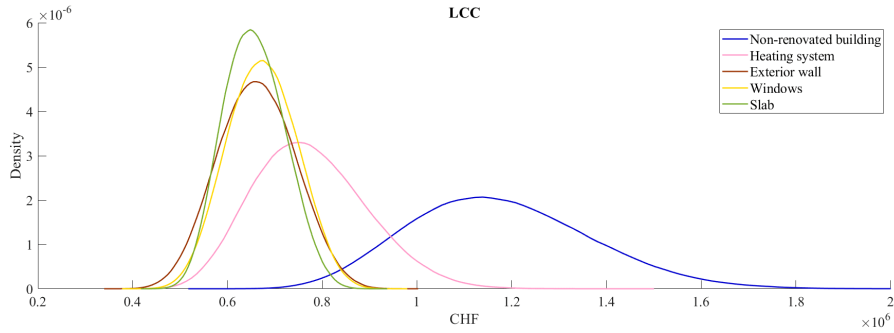
18

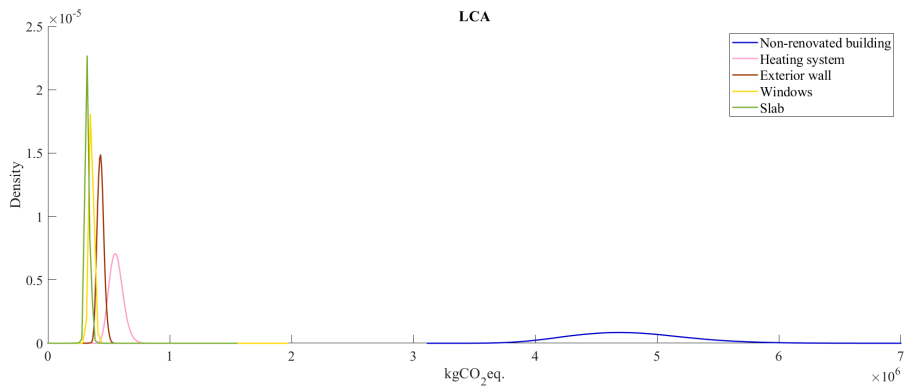Figure 3: Results of uncertainty quantification for LCC in total CHF

Figure 4: Results of uncertainty quantification for LCEI in total kg.CO2eq.

Table 4: Risk index results for economic performance - LCC

LCC	No renovation	Heating system	Exterior wall	Windows	Slab against unheated surface
No renovation	-	0.08	0.0019	0.0018	0.0004
Heating system		-	0.22	0.24	0.1949
Exterior wall			-	0.5427	0.48
Windows				-	0.4308

importance already after three renovation measures are applied. This highlights the importance of such parameters to be included and properly examined during the probabilistic assessment. It also shows that even when more renovation measures are applied, there are still a lot of

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Table 5: Risk index results for environmental performance - LCEI

LCC	No renovation	Heating system	Exterior wall	Windows	Slab against unheated surface
No renovation	-	0	0	0	0
Heating system		-	0.0129	0.001	0.0003
Exterior wall			-	0.01	0.008
Windows				-	0.1144

uncertainties during the life cycle, which need to be identified and described in a probabilistic context.

Limitations

For some of the parameters, it was not possible to find a defined distribution for uncertainties in the literature. Therefore, assumptions were made by the authors for some of the parameters. For example, the RSL was considered as an exogenous parameter, which cannot be affected by the designer. However, one can argue that the proper design and planned maintenance can increase the RSL of the components and therefore, can be considered as a design parameter.

The motivation in this study was to cover as many parameters as possible in the baseline building LCA & LCC models according to the current standards. However, the normative calculation rules remain a simplification of the reality. Some phenomena such as the evolution of parameters over the building lifetime (climate change scenarios, future energy mix) are currently not considered. Such an approach refers to a dynamic LCA where parameters evolve across time. Other phenomena are taken into account but are currently modelled using the normative approach (occupancy behaviour, monthly heat balance, etc.). The refinement of the current models and parameters should be included in future studies.

The results presented in this paper are highly sensitive to the input parameters uncertainty. The results of the case study for our methodology were achieved by using the described parameters ranges presented in the Table 2. Some variations can be discussed and might be found to be too extreme. The intention was to avoid an underestimation of some parameters without a proper description. The fact that even when considering extremely large range, these parameters do not seem significant confirms that the identified parameters (heating system, walls, windows,

slabs) are indeed the main parameters to consider in building LCA & LCC renovation studies.

The only indicator for the LCA considered in this study was GWP. Considering other impact categories might change the results. However, renovation of the existing building stock is a key priority due to climate change and therefore it should be the first focus, while paying attention not to have pollution transfer to other environmental impact categories.

Finally, only the available Swiss open source data for materials and components was considered in this study, which might be limited and has to be extended to cover all the possible renovation solutions.

Implications

The study demonstrates the significant difference between LCA and LCC when considering the robustness of the renovation scenario. Any renovation is significantly reducing the environmental impact while it is less clear from the economic perspective. This illustrates a known aspect of the reluctance to renovate as the economic incentives are not obvious [91]. Our results still show that from an economic point of view, it makes sense to go for deep renovation, while from the environmental perspective a medium renovation would not provide necessarily more robust results than a deep one. From an economic perspective, only an intense renovation will provide significant improvement compared to the no renovation scenario. This result would be in favour of deep renovation policy, if the objective is to reduce LCC. It is in contradiction with previous studies that would argue for lower investment to secure an environmental and economic benefit (Jones et al., 2013; La Fleur et al., 2019). Thanks to the use of uncertainties in LCC, the results presented here push for new economic solutions that would allow reducing initial investment costs to moderate renovation, which is beneficial for environmental impact and still secure a long term economic benefit.

Discrepancy with practice

The renovation measures prioritized by this paper (and their combination) may be different from the ones usually applied in practice. The heating system is often replaced as the last step of the renovation. The argument being that from an economic point of view, we first need to reduce the heating demand by insulating the envelope and then design a smaller heating system that can fulfil the reduced heating demand. Another reason to insulate a building first is to use a renewable source of energy (e.g. heat pump) with the highest possible efficiency. However, according to the results of the current study, the heating system is the most influential parameter controlling LCEI and LCC and as a consequence has to be dealt in priority in order to achieve a robust renovation.

In order to further explore this discrepancy between the current results and the common practice, results of the full envelope renovation with different heating systems are presented in

the Figures 5-6. They confirm the fact that changing only the heating system can be more efficient than doing a full renovation without changing the heating system. From the economic point of view, the heating system replacement provides 0.08 risk index of not improving the output while the full envelope renovation without a heating system replacement provides of higher risk of not improving the total costs (0.13).

From the environmental perspective, the renovation of only the heating system is more beneficial (5.4 kgCO2eq./m2,a) (See figure 4) than a full envelope renovation (21.25 kgCO2eq./m2,a) and is closer to the Swiss target of 5 kgCO2eq./m2,a (SIA 2040:2017, 2017).
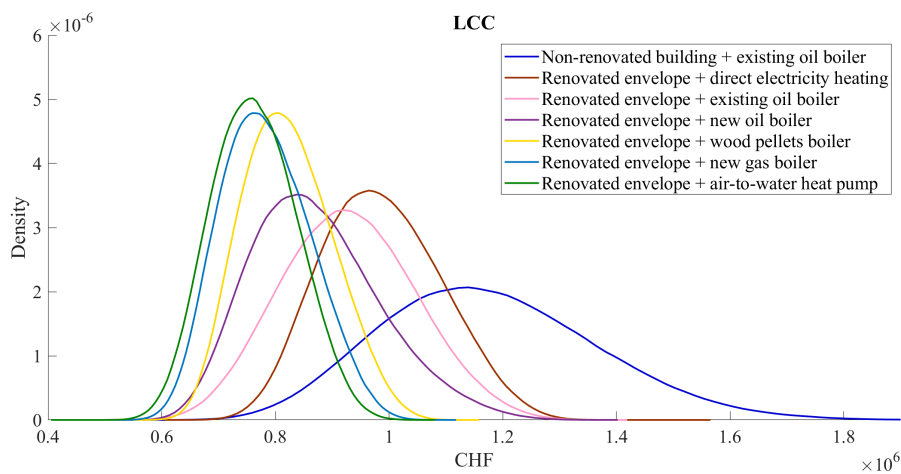

Figure 5: Applied envelope renovation measures with different heating systems - LCC
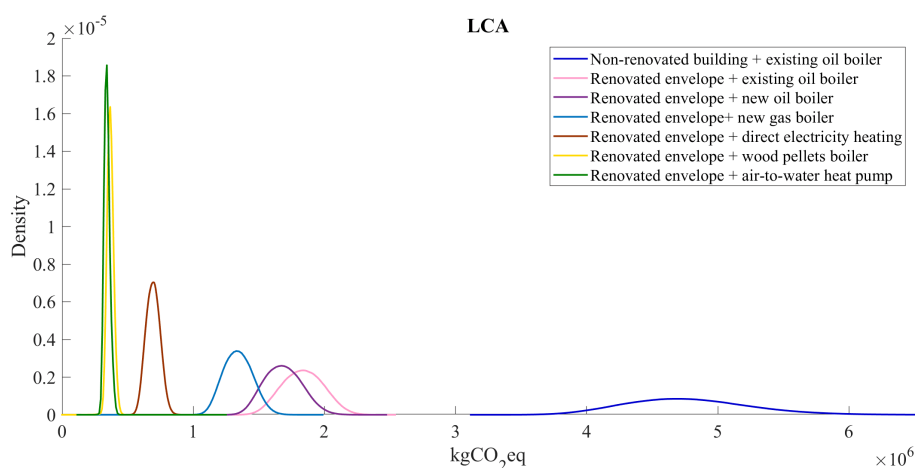

Figure 6: Applied envelope renovation measures with different heating systems - LCEI

The method proposed in this study gives a new insight in common renovation practices and questions the usual renovation policies that provide subsidies for envelope renovation or photo-

voltaics installation and taxes on oil boiler. European Union renovation policies will subsidize new heating systems when integrated in a deep renovation program, but not as a stand-alone measure (of economic affairs and communications, 2017). Actually, a change of heating system is included in deep renovation scenario while moderate renovation includes only the improvement of the envelope. As the framing of renovation scenario influences macro-economic calculation, one can imagine that introducing the possibility of changing only the heating system could drastically reduce renovation costs currently estimated at more than 100 Billion Euros for the EU market (Artola et al., 2016). Changing an oil or gas boiler to a renewable-based heating system does not require changing pipes and radiators in the buildings, so the investment is minimal.

Further studies are required to better constrain the robustness of renovation scenarios and target the most effective measures that would significantly improve the environmental and economic performance of existing buildings. In particular, the technical feasibility of a heating system change should be carefully addressed. This study shows the crucial importance of integrating multiple parameters uncertainty studies in LCA and LCC in order to be able to provide robust results to future decision makers.

Supporting information

The supporting information 1 provides additional results on the sensitivity analysis and the results on defined deterministically optimal solutions in terms of LCC and LCA within the available database. It also includes the procedure for the model evaluation and Sobol' decomposition. The supporting information 2 provides data for the available renovation components.

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