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Probabilistic LCA and LCC to identify robust and reliable renovation strategies

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Abstract. Buildings are one of the largest energy consumers and greenhouse gas emitters in the world. As the largest part of the energy consumed by the existing non-insulated buildings occurs during the operation stage, retrofitting the building stock is crucial to reduce the environmental impact. To guarantee that the retrofit measures provide economic and environmental benefits, the whole life cycle should be assessed. However, the identification of environmental and at the same time cost-effective solutions is difficult due to the complexity and the uncertainty involved. Currently, simplified approaches based on limited assumptions are used that can lead to inaccurate results. This paper proposes a method for identifying robust renovation scenarios for residential buildings in Switzerland. The method and the developed tool use 47 uncertain parameters and Sobol' indices to identify the most influential parameters. As such, robust renovation strategies can be identified in the early design stage.

1. Introduction

Buildings are the largest energy consumers in the world [1]. The largest part of the energy consumption of existing buildings occurs during the operation stage. Therefore, retrofitting buildings is crucial to reduce environmental impacts and meet the United Nations (UN) climate action goals. In order to assess the environmental impacts holistically, it is vital to assess the whole life cycle. *Life Cycle Costing* (LCC) and *Life Cycle Assessment* (LCA) are two well-known approaches for assessing the economic and environmental impacts of buildings. However, the conventional LCA and LCC approaches apply deterministic assumptions for many parameters. These assumptions are taken for the input model parameters (e.g. material properties, selected material costs and environmental impacts) as well as exogenous parameters, which cannot be affected by the designer but directly impact the model response (e.g. room temperature, external climate, discount rates, price growth rates). These assumptions are highly uncertain and the consequent inaccuracy might lead to the big performance gap between the



computed model and real result. Therefore, the question of uncertainty and data reliability has to be addressed to apply LCA and LCC as a practical and robust tool to assist policy decisions. Data quality and sensitivity of the results to the input data and the taken assumptions have been discussed in the field of LCA [2], [3]. Recent studies have shown that there is a balance point when the renovation can still be cost-effective and environmentally-friendly [4]. However, studies also highlighted the fact that the resulting uncertainties of LCC and LCA might be higher than the difference between two solutions [5]. Therefore, to achieve the robust renovation scenario in terms of LCC and LCA, the uncertainty sources need to be identified and quantified through rigorous statistical treatment. The current paper proposes a method to define the renovation scenario depending on the level of knowledge of the building. It is based on preliminary investigations in the field of historic building renovation [6]. The aim is to identify a robust renovation scenario by combining advanced statistical methods with the LCA and LCC methodologies. The proposed method is applied to an existing residential building located in Switzerland. The results show how to prioritize renovation strategies and at the same time determining the key parameters influencing the renovation using Sobol' indices [7].

2. Methodology

The methodology of the paper is shown in the Figure 1. First, the model for LCA and LCC calculations is created. After that, all possible renovation measures are selected and uncertain parameters for each measure are identified. Each uncertain parameter is described by a possible variability range and a distribution, which are selected according to literature sources or expert interviews. Then, the sensitivity analysis for all the measures is performed to understand the priorities for the renovation strategy. Finally, the uncertainty quantification on the selected strategy is applied to see the influence on the total LCC and LCA results. These steps are explained in further detail in the following.

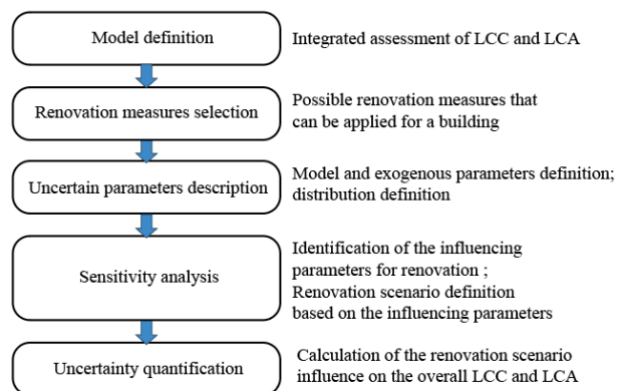


Figure 1. Methodology steps.

2.1. Integrated calculation for LCA and LCC.

The model includes three steps – heating demand calculation, LCC and LCA. The overall objective is to create an integrated workflow for LCC and LCA. The metrics of interest for the integrated assessment are the total costs and environmental impacts. For both, LCA and LCC, the functional unit refers to the use of the building over its lifetime. A period of 60 years is used as a reference study period of the building at the year of renovation according to the Swiss standard SIA 2032 [8]. The whole calculation process is conducted using python programming language.

Heating demand. The first step of the process includes the operational energy demand calculation which is performed according to the Swiss standard SIA 380/1 [9]. The calculation is performed using a quasi-steady state approach based on monthly values in order to achieve low computational costs.

Life cycle cost. The heating demand results are used for the LCC analysis. The stages for LCC include initial costs, operation, replacement and demolition. The net present value approach is selected for this study as a well-recognized and broadly used approach [10]. The cost data is taken from the Swiss Federal Office of Statistics [11].

Life cycle assessment. In parallel with LCC, an LCA is applied. The conventional life cycle stages according to SN EN 15978 with the modules A1-A3 (production), B4 (replacement), B6 (operational energy use) and C1-C4 (end of life) are used as system boundaries for this study. KBOB "Ökobilanzdaten im Baubereich", a Swiss database is used for the life cycle impact assessment of the building materials and technical systems [12]. The greenhouse gas emissions (GHGe) are used as an

indicator for climate change, (unit expressed in kg CO₂-eq) and calculated based on the IPCC Global Warming Potential (GWP) characterizations factors [13].

After the initial model is set, the validation of the heating demand results is performed using the Lesosai software which also complies with SIA 380/1 standard [14]. After the model is set, the possible renovation measures are applied in the model.

2.2. Renovation measures selection

Renovation strategies can be characterized differently depending on the design stage as well as different stakeholders. For instance, the priorities in renovation strategies for the whole Swiss building stock is likely to be different from the renovation priorities for one specific construction period or for an individual building as the level of details and knowledge about the initial model might vary highly. In case of different stakeholders, portfolio managers might have different perspective on renovation strategies and therefore, different goals compared to real estate managers or building owners. Therefore, a strategy that is able to cover all possible renovation scenarios is needed.

The model is able to cover different levels of details. This allows modelling the input parameters and seeing their influence on the total LCA and LCC results. The method allows to assess different renovation strategies and understanding the most influential parameters using Sobol indices.

The range of design parameters is selected to include all possible solutions, i.e. from the current state of the building to renovation solutions that comply or even outperform the requirements according to Swiss standards (e.g., the SIA 380/1 for the heating demand). Initially, the sensitivity analysis is performed to understand the influential parameters for the renovation in terms of LCA and LCC. Afterwards, the uncertainty quantification using polynomial chaos expansion (PCE) is used to see the influence of the input parameters' range on the results.

2.3. Uncertainty quantification

Uncertainty quantification (UQ) aims at identifying all sources of uncertainty in the parameters of a model and assessing how they affect the model response. Sensitivity analysis is an important tool in UQ and allows to identify which input parameters, and combination thereof, influence the model output the most. The analysis is often carried out by propagating the uncertainty throughout the model, *e.g.* using Monte Carlo simulation. However, the resulting computational cost is prohibitive, as it would require thousands to millions of calls to the computational model. In this work, the computational model described above is approximated by a surrogate model, *i.e.* an easy-to-evaluate proxy. More specifically, *polynomial chaos expansions* (PCE) are used as a surrogate model as they allow efficient representation of the model response and can further be used for sensitivity analysis.

Polynomial chaos expansion. A finite variance computational model is considered $Y = \mathcal{M}(\mathbf{X})$ that allows to compute some quantity of interest (herein, heating demand, LCA or LCC) and which takes as input an M -dimensional random vector $\mathbf{X} \sim f_{\mathbf{X}}(\mathbf{x})$ whose marginals are assumed to be independent. PCE allows for a spectral decomposition of the random variable Y onto a set of orthonormal polynomials [15]:

$$Y = \sum_{\alpha \in \mathbb{N}^M} y_{\alpha} \psi_{\alpha}(\mathbf{X}) \quad (1)$$

where $\psi_{\alpha}(\mathbf{X}) = \prod_{i=1}^M \psi_{\alpha_i}(X_i)$ are a set of multivariate orthonormal polynomials obtained by the tensor product of univariate polynomials. These polynomials are selected according to the marginal distribution of the random variables X , α alpha are a set of indices and y_{α} are coefficients to be computed.

In practice, this infinite series is truncated into a finite set of polynomials, thus leading to an approximation. The surrogate model is obtained by calibrating the coefficients y_{α} for a given set of polynomials. This can be achieved using different methods, among which are least-squares techniques. This requires first generating an *experimental design* (ED) $\{\mathcal{X}, \mathcal{Y}\}$, where $\mathcal{X} = \{\mathbf{x}^{(i)}, i = 1, \dots, N\}$ correspond to uniformly sampled input points and \mathcal{Y} are the corresponding model evaluations, *i.e.* $\mathcal{Y} = \{\mathcal{M}(\mathbf{x}^{(1)}), \dots, \mathcal{M}(\mathbf{x}^{(N)})\}$. N is the ED size and typically ranges from tens to a few hundreds. Given the

ED, the coefficients are computed using least-squares minimization or other advanced techniques. Details on practical computation of PCE can be found in Gratiet *et.al*[16].

Global sensitivity analysis. Global sensitivity analysis [7] aims at quantifying the importance of each random input in the variability of a model output. Many methods found in the literature are based on the decomposition of the output variance [17]. Sobol' indices are a popular technique that belong to this category of methods [7]. Assuming that the input \mathbf{X} are independent, the Sobol' decomposition of the model \mathcal{M} reads [18]:

$$\mathcal{M}(\mathbf{x}) = \mathcal{M}_0 + \sum_{i=0}^M \mathcal{M}_i(x_i) + \sum_{1 \leq i \leq j \leq M} \mathcal{M}_{ij}(x_i, x_j) + \dots + \mathcal{M}_{1,2,\dots,M}(x_1, \dots, x_M), \quad (2)$$

where M_0 is a constant and the other summands satisfy the following orthogonality condition:

$$\int_{D_{\mathbf{x}}} \mathcal{M}_{i_1, \dots, i_s}(x_{i_1}, \dots, x_{i_s}) f_{x_{i_1}}(x_{i_1}) \dots f_{x_{i_s}}(x_{i_s}) dx_{i_1} \dots dx_{i_s} = 0, \quad 1 \leq i_1 \leq \dots \leq i_s \leq M, \quad (3)$$

It can then be shown that the output variance can be decomposed as follows [7]:

$$D = \text{Var}[\mathcal{M}(\mathbf{X})] = \sum_{i=1}^M D_i + \sum_{1 \leq i \leq j \leq M} D_{ij} + \dots + D_{1,2,\dots,M} \quad (4)$$

where

$$D_{i_1, \dots, i_s} = \int_{D_{\mathbf{x}}} \mathcal{M}_{i_1, \dots, i_s}(x_{i_1}, \dots, x_{i_s}) f_{x_{i_1}}(x_{i_1}) \dots f_{x_{i_s}}(x_{i_s}) dx_{i_1} \dots dx_{i_s} \quad (5)$$

The Sobol' indices are eventually obtained by normalizing the partial variances and read:

$$S_{i_1, \dots, i_s} = \frac{D_{i_1, \dots, i_s}}{D} \quad (6)$$

The first-order Sobol' indices relate to the univariate term and express the additive effect of each input taken separately. Higher-order Sobol' indices (combination of two or more variables) represent the interaction effects. Finally, the total order index for a given variable represents its own effect together with any interaction. A small value typically means that the parameter has very little effect on the output variability. As a consequence, setting the corresponding variable to a constant value would not affect the distribution of the quantity of interest. On the contrary, a large value means that the analyst should focus on reducing the corresponding parameter uncertainty.

Sobol' indices in the general case are computed using Monte Carlo simulation. However in this paper, we consider PCE-based Sobol' indices as developed by B.Sudret [19]. Sobol' indices can be obtained at no additional cost by simply post-processing the PCE coefficients. Further details on the computational aspects of sensitivity analysis can be found in the corresponding UQLab users manuals[20].

3. Case study

The chosen case study is located near Lausanne, Switzerland. The building was constructed in 1972 and has a total energy reference area of 1440 m². The ground floor is partly occupied by the commercial space of 50 m². The initial properties of the building can be seen in the Table 1.

Table 1. Initial building properties before renovation

Element	Existing state of the building
Ext.wall (Residential)	4cm mineral wool, U = 0.56 W/(m ² K)
Ext.wall (Shop)	4cm mineral wool, U = 0.71 W/(m ² K)
Ground floor	2cm cork in the shop, U = 1.4 et 3.2 W/(m ² K)
Ceiling against attic	6cm mineral wool, U = 0.5 W/(m ² K)

Windows	Double glazing (low-E layer, PVC frame, $U=1.91 \text{ W/(m}^2\text{K)}$, $g_p = 0.55$
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The current case study was selected from the eRen building models, because they cover different construction periods and were already characterised for their initial states i.e. before any renovation [21]. The construction period for this building was selected to be 1970s as it represents the majority of the Swiss building stock (32.5% of the entire building stock, [22]). Different goal and scope and settings for the model parameters can be chosen for the renovation measures of this building. They are presented in Table 2 for the three scopes of the assessment which are described below in separate sub-sections.

Table 2. Parameters' setting for the renovation of the building envelope in the three assessments

	1 st assessment	2 nd assessment		3 rd assessment	
<i>Goal of the study</i>	<i>Screening assessment of all possible measures</i>	<i>Comparative LCA & LCC of two heating system replacement with a distribution of the U-values for the renovation of the envelope</i>		<i>Comparative LCA & LCC of two heating system replacement with specific U-value and materials for the renovation of the envelope</i>	
Element		Solution 1	Solution 2	Solution 1	Solution 2
Heating source and system	Random heating systems (oil, gas, coal, wood pellets boilers) floor and radiators heating	Wood pellets boiler, floor heating	Gas boiler, floor heating	Wood pellets boiler, floor heating	Gas boiler, floor heating
Roof insulation thickness	Random values between the existing state and an improved U-value of $0.15 \text{ W/m}^2\text{K}$			0.2 m	0.1 m
Windows	Random values between the existing state and an improved U-value of $0.6 \text{ W/m}^2\text{K}$			Triple glazed, wooden frame, U-value $-1.2 \text{ W/m}^2\text{K}$	Double glazed, PVC, U-value $-1.4 \text{ W/m}^2\text{K}$
External walls	Random values between the existing state and an improved U-value of $0.2 \text{ W/m}^2\text{K}$			No insulation	No insulation
Floor insulation thickness	Random values between the existing state and an improved U-value of $0.2 \text{ W/m}^2\text{K}$			0.15 m	0.1 m

3.1 Variability of all possible measures (screening assessment)

In the first screening assessment, we assume the user of the tool does not know which scenarios to apply for the replacement of heating systems and for the renovation of the envelope. The idea is first to describe all possible renovation measures with different U-value requirements for the elements from no renovation up to very low U-values and different heating system types. For example, each building element can be kept either in its current state (uninsulated) or renovated according to different U-values (e.g., 0.25, 0.20, 0.10 [$\text{W/m}^2\text{K}$], etc.). The U-values after renovation were varied using continuous variables for the thicknesses and thermal conductivities values to ease the probabilistic assessment.

Similarly, we also take into account the expected variations of the exogenous parameters, which can be seen in the Table 3. These parameters cannot be influenced by the designer and therefore, this uncertainty cannot be reduced during the design stages. The values were fixed based on variations around the conventional values defined in the SIA 380/1 standard and in the CRB (for costs' parameters).

Table 3. Exogenous parameters in the screening assessment and in the two comparative LCA & LCC

Parameter	Distribution	Range, moments
Room temperature	Uniform	19 - 23 °C
Discount rate	Uniform	1 - 3 %
Price growth for heating	Uniform	3.5 - 5.5%

Thermal bridge	Gaussian	Mean – 10%, Std – 5%
Airflow	Uniform	0.7-0.9 m ³ /(m ² *h)

After the ranges of model and exogenous parameters are defined, the sensitivity analysis is conducted to identify the most sensitive parameters for this level of knowledge (screening assessment). To understand how the selected levels of performance for the envelope and technical systems influence the total LCA and LCC results, the uncertainty quantification using PCE method is applied in UQlab [23].

3.2 Comparison of two renovation scenarios

Following the screening assessment, in a second step, comparative LCA and LCC are conducted. Two solutions of replacement of the heating system are chosen and compared (cf. Table 2). We assume the replacement of the old oil boiler by a new gas boiler (baseline case) and the replacement of a new wood pellet boiler (“environmental friendly” alternative). Each scenario is coupled with different renovation measures for the envelope (roof, external walls, windows and floor). For each scenario, the renovation measures of the building elements take random values for the insulation thickness, the thermal conductivity, the associated environmental impacts, and the investment costs between the existing state and an improved energy-efficient renovation as already introduced in section 3.1.

In the third assessment (i.e., in the second comparative LCA & LCC analysis), a specific renovation scenario is applied for the building envelope (with a given U-value for each element after renovation). Assumptions for this scenario are presented in Table 2. This scenario represents the one defined in the eRen project. The same range for exogenous parameters as the ones presented in Table 3 were considered in these two comparative assessments.

4. Results

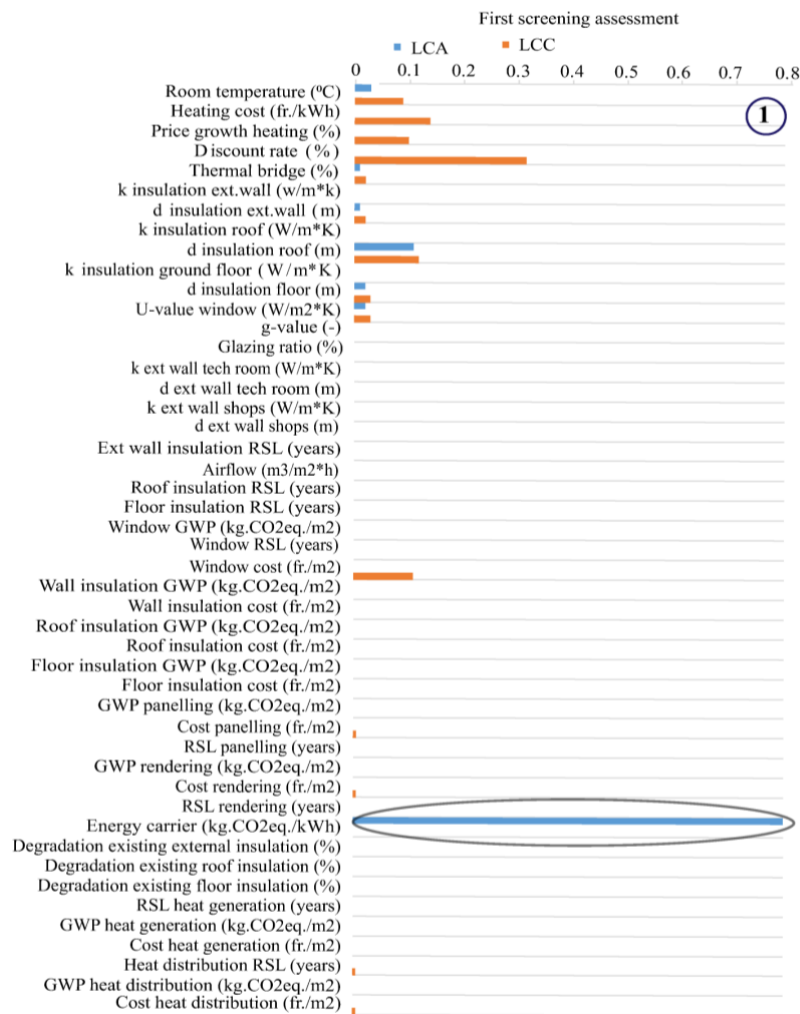


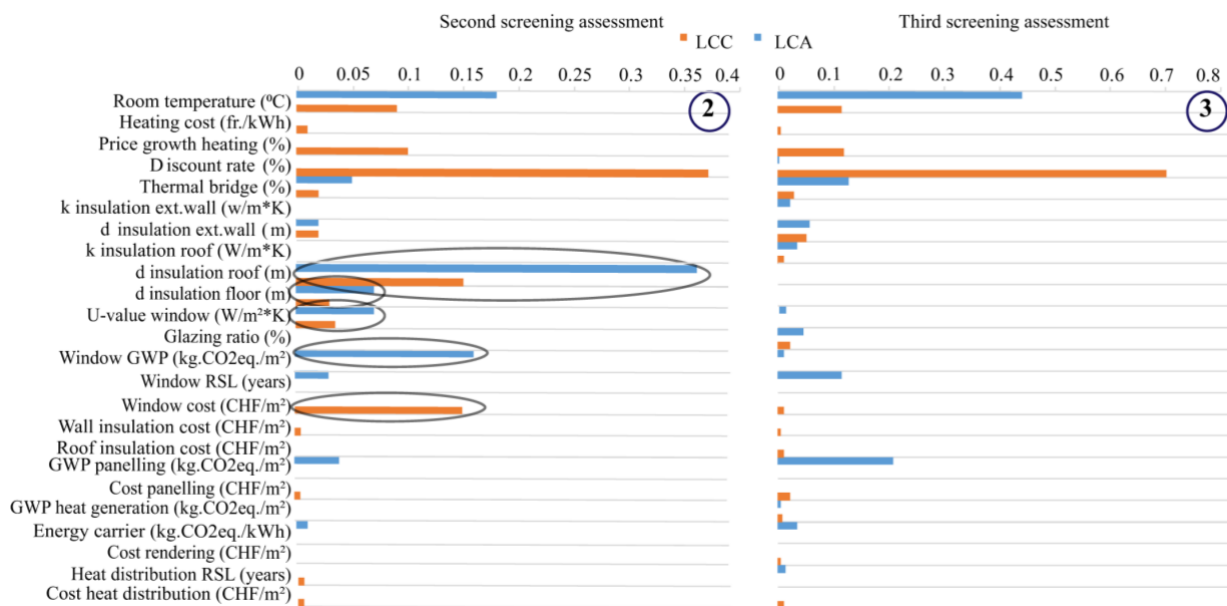
Figure 2 (1). Sensitivity analysis using Sobol indices for the screening assessment when the variability of all the measures was applied.

As it was mentioned in section 3, 47 model and exogenous parameters used for the building heating demand, LCA and LCC calculations are considered. The first screening assessment includes a range for all of them. The second and third assessments only include a range for the parameters that have an influence on the total LCA and LCC results.

As it can be seen in Figure 2(1), when the variability of all measures is applied (using assumptions from section 3.1), we notice that from the 47 parameters defined with a range, only about 8 of them present a sensitivity index of more than 0.05. Looking at the LCA, the variance of the output GHG emissions is only driven by the uncertainty on the choice of the energy carrier. In terms of life cycle costs, more parameters are sensitive: model parameters (the heating costs, windows costs, the density of the insulation for the roof) and exogenous ones (room temperature, price growth heating, discount heating). Interestingly, the heating cost is comparatively less sensitive to the output result than the heating environmental costs (energy carrier GHG emissions). This can be explained by the higher variance of the energy carriers GHG emissions directly influencing the output results (GHG emissions of the building, see Figure 3).

In the second and third comparative LCA & LCC, when the energy carrier is selected for each scenario using assumptions from Table 2, there is no more variability on the energy carrier GHG emissions. So the Sobol index becomes zero for this “known” parameter. In this case (Figure 2(2)), other

model parameters become sensitive in each scenario of heating system replacement (according to Sobol) e.g., the roof insulation and windows. In terms of exogenous parameters, for LCA, modelling parameters are prevailing in the first and second screening assessment, and once the roof insulation, windows and heating system are renovated, the exogenous parameters become of highest importance. In terms of LCC, it can be seen that the exogenous parameters appear to have high importance already in the first screening assessment (e.g. discount rate and price growth rate for heating).



Figures 2(2) and 2(3). Sensitivity analysis for the second and third assessment (for specific heating systems' choice)

After the sensitivity analysis is conducted, uncertainty quantification for the selected renovation scenario is performed. As is was mentioned earlier, sensitivity analysis is helpful to identify the most sensitive parameters of the renovation measures. It goes along with the uncertainty quantification of different renovation scenarios but it cannot provide the optimal solution for the renovation. Therefore, at the current stage, two options were selected as possible renovation strategies.

Figure 3 presents the probabilistic LCA and LCC results when all renovation measures are considered. The results show an important variability of both GHG emissions and total costs in CHF.

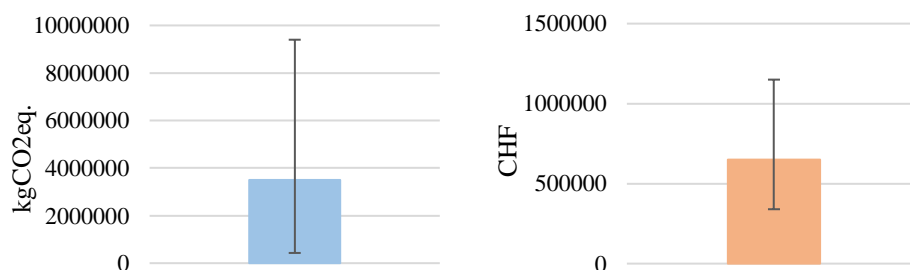


Figure 3. LCA and LCC results for the uncertainty quantification on the screening assessment of the building (variability of all possible measures).

The results for the probabilistic LCA and LCC for the second and third assessment are presented in Figures 4-5.

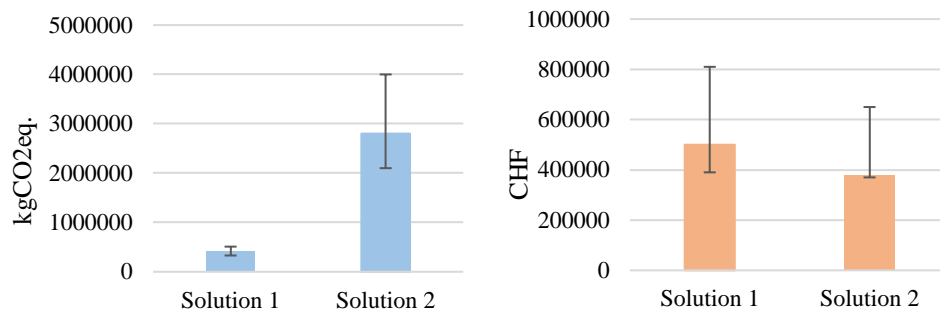


Figure 4. Comparative LCA and LCC results for solutions 1 and 2 using the applied measures of the second assessment.

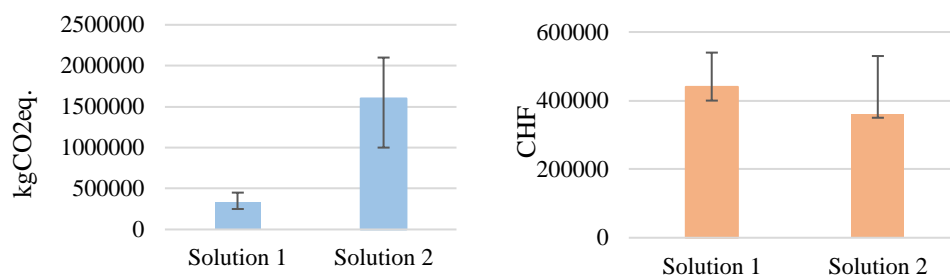


Figure 5. Comparative LCA and LCC results for solutions 1 and 2 using the applied measures of the third assessment

While the first sensitive parameter in the screening assessment is fixed (in the second and third assessment) using low-GHG emissions heating systems' solutions (wood pellets and heat pump), an important decrease in the mean value as well as uncertainty for both LCC and LCA can be observed. It can also be seen from two solutions that the decrease of the mean value for LCC does not occur with the same proportion as for LCA, which means that low GWP renovation measures do not necessarily yield low NPV. Therefore, an optimal solution that is both cost-effective and environmentally friendly still needs to be found. This can be potentially achieved by using multi-objective robust optimization under uncertainties.

Interestingly, Figure 4 shows that solution 1 is a robust solution for lowering the GHG emissions compared to the solution 2 (as the error bars do not merge between the two). In contrast, we cannot distinguish the two solutions in terms of life cycle costs. This shows the usefulness of such combined statistical approach with usual LCA and LCC methodologies.

5. Discussion

The current study shows how to identify the influential parameters for the renovation using a sensitivity analysis. This approach allows understanding the focus of the renovation at the early design stage. At the current stage, the method is able to handle stochastic calculations of LCA and LCC of building renovation scenarios. The renovation scenarios definition can be more or less detailed (see section 4 with a first screening assessment to a very specific third assessment). However, proper optimization process is needed to identify the best renovation strategy.

So further development will include the optimization under uncertainty, which allows understanding the renovation priorities as well as finding the optimal solutions in terms of LCA and LCC.

In this paper, the approach was applied for one residential building in Switzerland. In the future, the aim is to analyse the applicability of this method for the Swiss building stock. In order to find an optimal robust solution for the renovation of the building stock, building archetypes for different construction periods will be analysed.

The current method also shows that there is a non-negligible influence of the exogenous parameters on LCC and LCA, which means that even with identification of a precise renovation scenario with powerful statistical treatment, there are still many uncertainties in the building's life cycle. Therefore, it is crucial to consider parameters like occupants' behaviour, possible degradation rates for the building materials and economical parameters like price growth rates and inflation. The associated exogenous parameters shall also be considered with their uncertainty (including climate change trends) for a more realistic analysis. In the current study, climate data from SIA was used and the modelling of the relevant climate data for this type of analysis is currently in progress.

6. Conclusion

A statistical method combined with existing LCA and LCC methodologies was applied to the renovation scenarios of one residential building in Switzerland. The proposed framework is able to compute probabilistic LCA and LCC to compare different renovation strategies for different levels of knowledge of the existing building. It also identifies the most influential parameters for each type of assessment (screening or detailed). First results show the range of impacts and costs for all possible renovation measures when the energy carrier and heating system are not chosen or known. Once the heating system is fixed, the level of uncertainty on LCA and LCC is much reduced allowing to focus on the renovation of the building envelope. A first comparative LCA and LCC on two renovation scenarios shows that the choice of the best scenario is robust for the LCA while it is not possible to conclude on the LCC part. It can also be observed from the results of uncertainty quantification that the minimum value is always closer to the mean than the maximum value, which means that without uncertainty consideration the values at risk for both LCC and LCA are high. This highlights the necessity of uncertainty propagation when LCA and LCC are used during the decision-making process.

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