Uncertainty Analysis of Life Cycle Assessment Input Parameters on City Quarter Level

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Abstract

Life Cycle Assessments (LCA) are mandatory to extend the assessment of the ecological and energetic performance of buildings to a life-cycle based approach. At the district level, however, there are often data gaps in relation to relevant assessment input data. These gaps are closed by assumptions, which lead to uncertainties in the calculation and interpretation of results. In order to identify the parameters with the greatest influence on the results, an uncertainty analysis is carried out using a case study with 196 residential buildings. Parameters with the greatest influence on life cycle based embedded and operational energy/emissions of buildings are identified.

Key Innovations

- The uncertainty analysis performed in this study relates to a method for performing LCA of large building stocks with focus on technical building service (TBS) components.
- An entire city district is used as a case study.
- Both embedded and operational energies and emissions are considered within the scope of the study.

Practical Implications

For more precise LCA on the city quarter level, accurate information must be provided for:

1. Estimates of buildings service life, renovation status and structural condition,
2. Information about type and age of the heating system,
3. Information about all components of the TBS used and
4. A clear definition of sources from which the electricity is obtained (non-renewable)

Introduction

When talking about sustainable building or city development, it is mandatory to extend the assessment of the ecological and energetic performance of buildings to a life-cycle based approach (Chau, Leung, & Ng, 2015). Life Cycle Assessments (LCA) allow not only the use phase of buildings to be taken into account but also their manufacturing and end-of-life phases. As stricter regulations and ordinances steadily reduce the energy requirements and associated emissions of buildings in the use phase, the energy requirements and emissions of the manufacturing and end-of-life phases are increasing in relative terms (Cabeza, Rincón, Vilarinho, Pérez, & Castell, 2014). Among other things, this is due to the fact that, in order to save energy and emissions in the use phase, a more elaborate construction including more insulation material is necessary. This leads to more energy input and emissions in the manufacturing phase. LCAs can help to identify saving and optimization potentials alongside the building’s life cycle. Since the building sector is responsible for about 40% of final energy demand and 35% of emissions worldwide (International Energy Agency 2020), it is important not only to look at individual buildings but also to evaluate large building stocks using LCAs. In a previous study, a methodology for an automated, static LCA calculation of large residential building stocks has been developed and applied to a case study with over 115,000 buildings, using semantic 3D city models based on the CityGML-standard (Harter, Willenborg, Lang, & Kolbe, 2020). At the level of building stocks, however, there are often data gaps in relation to relevant input data for calculations (e.g., the proportion of window area in the exterior walls or the heat generator installed in the building for heating and domestic hot water) that are closed by making assumptions. These assumptions can theoretically fluctuate within a certain range of values. Such fluctuations may have an effect on the variance of the final result. Uncertainty analysis can be used to determine the effect of the fluctuation of the input parameters on the variance of the final result. In addition, the uncertainty analysis method used in this study will determine which parameters within the calculation method have the greatest parameter interaction. The obtained results allow not only a ranking of parameters in terms of their fluctuation and thus caused variance on the final result, but also the representation of higher-order effects represented by the parameter interaction. These results of the uncertainty analysis allow a fundamentally better understanding and interpretation of the LCA results and give impulses for methodological development and data provision for further work.

The following sections describe the methodology used to perform the uncertainty analysis based on a city quarter with 196 residential buildings and the results obtained.

Method

The parameters analysed in the uncertainty analysis represent the input parameters for the already mentioned...
method to perform LCA of large building stocks with a special focus on technical building services (TBS). The method consists of four parts: the calculation of the building heating load, the energy demand for heating and domestic hot water (DHW), the dimensioning of the TBS components and the calculation of the associated life cycle-based embedded energies and emissions. These parts are performed individually for each building under consideration in an iterative process.

**Simulation Tool**

On the programming side, the method is implemented in a tool called *urbi*+ and has several data interfaces as input for the calculations. An overview of the structure of *urbi*+ can be seen in the Figure 1.

![Image](https://doi.org/10.26868/25222708.2021.30672)

Figure 1: Overview structure *urbi*+

All building-related geometric information, as well as information on the type of use of buildings (e.g., residential building, office building, etc.) and the year of construction of the building are obtained by the method from a semantic 3D city model in CityGML format (Gröger, Kolbe, Nagel, & Häfele, 2012; Kolbe, 2009) at Level of Detail 2 (LoD 2). All other information required for the calculations is obtained from a graphical user interface (GUI) and a specially created database. The GUI is used to define information such as the percentage distribution of heat generators/energy systems over the building stock under consideration or primary energy factors for the primary energy sources used by the heat generators. The created LCA database contains, e.g., location-specific climate data (lowest temperature of the year and the annual average temperature) as well as LCA data sets e.g., the energy demand and the caused emissions for the production, the replacement and the end-of-life of a heat pump. These LCA data sets are based on values from the German database 'Oekobaudat' (Federal Ministry of the Interior, Building and Community, 2020).

**Energy Demand, Heating Load and Dimensioning TBS**

The basis for the static heating load calculation is the standard DIN EN 12831-1:2017-09 'Energy performance of buildings - Method for calculation of the design heat load - Part 1: Space heating load' (DIN EN 12831-1:2017-09, 2017) and for the static heating demand calculation the standard DIN V 4108-6:2003-06 'Thermal protection and energy economy in buildings – Part 6: Calculation of annual heat and energy use’ (DIN V 4108-6:2003-06, 2003). A one-zone model is assumed for both calculations, according to the respective standard. The results of the heating load and energy demand calculation are used to dimension the TBS components under consideration, and the energy demand calculation for heating and DHW reflects the operational energy demand of the building.

**Life Cycle Assessment**

The implementation of the LCA is based on the standards DIN EN ISO 14040:2009-11 (DIN EN ISO 14040:2009-11, 2009) and DIN EN ISO 14044:2018-05 (DIN EN ISO 14044:2018-05, 2018) as well as the standard DIN EN 15978:2012-10 (DIN EN 15978:2012-10, 2012) for the building-specific implementation of LCAs. The dimensioned TBS components are coupled with the LCA data sets, resulting in a total of embedded energies and emissions for the manufacturing, use (replacement and maintenance) and end-of-life of the considered TBS components. Thus, the calculated embedded energies and emissions always refer to the TBS components under consideration. Other structural elements are not taken into account here. Basically, the following components are considered: Heat generators, heat storage tanks, heat distribution networks and heat transfer to the one zone model (radiator and floor heating). Emissions are reported and assessed using the Global Warming Potential (GWP) indicator in kg CO₂ equivalents [kg CO₂-eq.]. Energy values are assessed using the primary energy demand from non-renewable sources (PENRT) and from renewable sources (PERT) in kilowatt-hours [kWh]. This applies to both operational and embedded energies and emissions. Results are not normalized but represent the energy demand and emissions over the defined study period, which may vary, of the entire city quarter.

When calculating the LCA of the residential building stock of an entire city quarter, renovation is assumed for all buildings over a varying development period. A total life cycle, which can vary in time, is then calculated for each renovated building. At the end of this life cycle, removal and disposal of all TBS components is assumed. No credits for possible recycling are taken into account. The values for PENRT, PERT and GWP calculated in this study therefore refer to the sum of the disposal of the TBS components installed in the status quo of all existing buildings and the production, use (replacement and maintenance) and end-of-life of the components installed after renovation. In addition, the values for PENRT, PERT and GWP resulting from the energy demand for building operation are added.
Uncertainty Analysis

A building LCA model is expected to include higher order effects and parameter interactions, which is also the case in the method used in this study. Therefore, a variance-based method is more suitable for the considered life cycle-based building energy and environmental assessment method (Singh & Geyer, 2020). The Sobol Sensitivity Analysis method developed by Saltelli et al. (Saltelli et al., 2010) has already been successfully applied in the investigation of building energy models in scientific work (Harter et al. 2020; Menberg, Heo, and Choudhary 2016; Schneider-Marin et al. 2020; Singh and Geyer 2020) and thus is also used in the context of this study.

In the Sobol Sensitivity Analysis method, two indices are evaluated. This means that the first-order effect $S_i$ represents the direct influence of the fluctuating input parameter on the model output or result. The first-order effect represents the expected variance of the output given by the defined range of fluctuation of an input parameter. The first-order effect is normalized to that by the minimum to the maximum range of values of the total variance (Saltelli et al., 2010), and thus results in a value between 0 and 1. To reduce the first-order effect requires reducing the range of fluctuation of the identified input parameters with the largest effect on the computational model (Menberg et al., 2016). The first-order effect is therefore suitable for identifying the parameters with direct significant influence on the model output variance (Saltelli et al., 2008; Saltelli & Tarantola, 2002). The higher the value of $S_i$ of an input parameter, the higher its influence on the variance of the model output/result. Individual input parameters can be ranked for comparison with all other input parameters.

The total effect $S^T_i$ represents the effect of the input parameters, including their interaction effects with other parameters, and thus represent a higher order effect. In contrast to the first-order effect $S_i$, the total effect $S^T_i$ describes the influence of an input parameter on the model output, taking into account the interaction effects with all other input parameters (Buckert, Bös, & Hanselka, 2011). $S_i$ and $S^T_i$ are thus comparative measures for evaluating the uncertainty of computational models and represent the effect of an individual parameter and the effect of a parameter with respect to the overall effect of all parameters on the model (Campolongo, Cariboni, & Saltelli, 2007).

It should be noted at the outset that the results of the uncertainty analysis do not identify the parameters that can be used, for example, to achieve the greatest absolute reduction in life-cycle based energy demand, but rather which parameters, relative to all other parameters, cause the greatest variance in the LCA result and the most parameter interactions due to their fluctuation as input parameters.

The uncertainty analysis is performed at a city quarter level and not at the building level, because the large variation of the buildings excludes the possibility of falsification of results due to very specific building parameters that could distort the result (e.g., high roof area percentage in relation to exterior wall area). On city quarter level official building-specific information from the city of Munich is only available regarding the geometry and location of the buildings and their year of construction and type of usage.

Input Parameters - Overview

To perform the uncertainty analysis, the first step is to identify all input parameters necessary for the LCA assessment and thereby conducted calculations. Here, a distinction is made between varying and fixed parameters. Varying parameters are parameters that can either be redefined and adjusted by the user via the GUI of urbi+, for each calculation step, or changed by an adjustment or update of values in the database. Fixed parameters are permanently programmed values that cannot be changed without actively intervening in the programming code. The list of all varying parameters includes 381 input parameters, divided into ten different groups (see Table 1). This division is made because previous studies have shown that a large number of the parameters have very little to no influence on the results of the uncertainty analysis. In addition, the grouping allows a much clearer presentation of the results. The result values of the indices are summed up per parameter group and presented comparatively. Minimum and maximum values or average values and fluctuation/sampling ranges are defined for all input parameters (variation of the input parameter) as a basis for the uncertainty analysis.

<table>
<thead>
<tr>
<th>Parameter Groups</th>
<th>Abbreviation (Number of Parameters)</th>
<th>Range of Sampling</th>
</tr>
</thead>
<tbody>
<tr>
<td>energy system distribution</td>
<td>ESD (18)</td>
<td>0 – 100%</td>
</tr>
<tr>
<td>primary energy factors</td>
<td>PEF (5)</td>
<td>Specific for each energy source</td>
</tr>
<tr>
<td>reference service life components</td>
<td>RSL (27)</td>
<td>15 – 50 years</td>
</tr>
<tr>
<td>heat transfer system distribution</td>
<td>HTS (2)</td>
<td>0 – 100%</td>
</tr>
<tr>
<td>share of renewables primary energy sources</td>
<td>SRP (10)</td>
<td>0 – 100%</td>
</tr>
<tr>
<td>average service life building and development period</td>
<td>ASL (2)</td>
<td>Specific</td>
</tr>
<tr>
<td>additional calculation factor</td>
<td>ACF (1)</td>
<td>0 – 80%</td>
</tr>
<tr>
<td>u-g-values</td>
<td>UGV (28)</td>
<td>Specific</td>
</tr>
<tr>
<td>climate data</td>
<td>CLD (2)</td>
<td>± 3°C</td>
</tr>
<tr>
<td>LCA values</td>
<td>LCA (286)</td>
<td>± 25%</td>
</tr>
</tbody>
</table>

Input Parameters - Definitions

1) The parameter group ‘energy system distribution’ describes the distribution of energy systems across the
city quarter level (e.g., 80% gas boilers and 20% oil boilers). The sum of the distribution is always 100%.

2) The ‘primary energy factors’ group consists of factors for oil, gas, wood, electricity and district heating, representing the ratio between primary energy and final energy demand. The primary energy factor of oil, for example, only varies between 1.0 and 1.1, whereas the primary energy factor of electricity varies between 0.5 and 1.8. These values represent possible energy supply scenarios in the future.

3) The parameters of the ‘reference service life components’ group fluctuate in a range of values between 15 and 50 years and thus represent the average service lives of TBS components.

4) The parameter group ‘heat transfer system distribution’ defines the percentage distribution to radiators and/or floor heating systems for heat transfer. The parameters always add up to 100%, since it is assumed that one of the two systems is installed in each building.

5) The parameters of the group ‘share of renewables primary energy sources’ define the non-renewable and renewable share of each primary energy source for heat generation, e.g., what percentage of the gas used for heating is biogas and what percentage is natural gas.

6) The parameters of the group ‘average service life building and development period’ define the average service life of all buildings under consideration, varying between 20 and 100 years, and the development period in which all buildings under consideration are renovated, which varies between 10 and 30 years.

7) The ‘additional calculation factor’ is a single parameter that varies between 0% and 80% and includes additional, not considered TBS components on the basis of a factor (e.g., ventilation systems, air conditioners, etc.).

8) The ‘u-/g-values’ group defines the thermal transmittance of all construction parts of the building (floor, wall, roof, window surfaces) and the energy transmittance of the window panes. These values can vary specifically between values for existing buildings and buildings renovated according to the passive house standard. The values of the existing buildings result from predefined values from literature (German Federal Ministry of Economy Affairs and Energy, 2013; Ornth, 2009; Thiel & Riedel, 2011). The CityGML-model used for the calculations does not provide any information on the renovation status of existing buildings. Therefore, the energy standard of the building is assumed in relation to the year of construction, i.e., uncertainties can arise in the calculations which are addressed here.

9) The parameters of the group ‘climate data’ define the lowest temperature and the average temperature of a reference year. The values vary between -16 and -13 °C and 8 and 11 °C.

10) The ‘LCA values’ group consists of parameters which define the energy-related (PENRT/PERT) and the emission-related (GWP) indicator values. These values are sourced from the LCA database Oekobaudat (Federal Ministry of the Interior, Building and Community, 2020) and describe the energy demand and emissions for each life cycle phase considered (production, use and end-of-life) and for each component as well as per kilowatt-hour of final energy consumed for building operation. If other databases were used, these values could fluctuate, so a range of ±25% from the baseline value of the Oekobaudat data is assumed for all parameters.

Input Parameters – Sampling and Analysis

For the data sampling and analysis within the uncertainty analysis, the programming language Python, with the Sensitivity Analysis Library SALib (Herman & Usher, n.d.), is used. When sampling or varying the input data within their defined ranges, so-called ‘sampling sets’ are created, within which the data are varied using a continuous uniform distribution. In total, 500 sampling sets are generated, since this number has been found to be the optimum between result precision and computation time (Singh & Geyer, 2020). If N is the number of sampling sets and p the number of parameters, then Equation 1 calculates the number of model or method runs n that must be calculated to generate results for the analysis.

\[ n = N(p + 2) \]  

Each sampling set contains, related to the example here, 383 rows, each containing all 381 input parameters for one calculation run (see Equation 2). Thus, one row means one entire calculation run of the method across all 196 residential buildings. In total, this results in a number of 191,500 calculation runs.

\[ X = \begin{pmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,p} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n,1} & X_{n,2} & \cdots & X_{n,p} \end{pmatrix} \]  

This results in 191,500 results each for the life cycle based operational and embedded GWP, PENRT, and PERT (see Equation 3).

\[ Y(X) = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix} \]

The result values are further evaluated using Sobol Sensitivity Analysis, which results in the indices S1 and S1 described above.

Results

The results are listed according to the indicators of the LCA, starting with the emission-related indicator GWP, followed by the energetic indicators PENRT and PERT. For each indicator, a graph for the first-order effect S1, and for the total effect S1 is shown. In each of the graphs, a distinction is made between the embedded and operational parts of the building’s life cycle. The
The operational part only focuses on the building operation and no replacement and substitution of TBS components.

**Indicator Results GWP**

The left part of Figure 2 (first order effect $S_1$) shows that the fluctuation of the parameter groups ‘average service life building and development period’ (ASL), ‘share of renewables primary energy sources’ (SRP) and ‘energy system distribution’ (ESD) have the greatest effect on the variance of the life cycle based operational GWP result. In the ASL parameter group, mainly the parameter that defines the average service life of the buildings under consideration has the highest influence on $S_1$ (97%). If buildings are used for a longer or shorter period of time (one-year steps), the sum of emissions emitted during heat generation increases or decreases by this time. This can have a major effect on the overall balance. Basically, an existing structure of a building should be used as long as possible without having to demolish and rebuild it. However, a longer service life also means more emissions. Therefore, in terms of sustainable development, it is extremely important to make building operation as emission-free as possible. For the parameter group SRP, two parameters are responsible for the value deviation with 99%, namely the two parameters that define the renewable and non-renewable share of primary energy in electricity. Even if renewable energy is used to provide heat for heating and DHW, electricity will be used as an auxiliary energy for heat distribution, storage, etc. and will therefore have an effect on every calculation, regardless of the type of heat generator.

In the parameter group ESD, with the third largest effect on the first-order effect, there are five parameters that account for 88% of $S_1$: Percentage of oil boilers (22%), air-water and water-water heat pumps (18% each), brine-water heat pumps in combination with borehole heat exchangers (16%) and electric heaters (14%). This is mainly due to the different efficiencies and the use of renewable energy sources (e.g., environmental heat, geothermal energy, etc.) of the heat generators, which can have a significant effect on the operational GWP.

In the parameter groups related to the embedded GWP, it is the parameter group ‘additional calculation factor’ (ACF) that has the greatest effect on the variance of the final result due to its fluctuation. If additional TBS components are taken into account by means of an additional calculation factor, then this is multiplied by the indicator and can thus have a high effect on the final result. For the parameter group ASL, it is the indicator that defines the average service life of the buildings under consideration with 95% of $S_1$, just like for the operational GWP. In the case of the embedded GWP, however, this parameter can influence the number of replacements of the TBS components that have exceeded their reference service life. The heat transfer system distribution (HTS) group has the third largest impact in terms of $S_1$. It is with 90% the parameter that defines how much of the floor space of the buildings under consideration has underfloor heating.

The right part of Figure 2 shows the values for the total effect $S^T$ related to the life cycle based GWP. It becomes clear that for both $S_1$ and $S^T$ the same parameter groups and also the same parameters within the groups are decisive for both the operational and embedded part. This means that the parameter groups or parameters that have caused the greatest variance in the final result due to their fluctuation are also responsible for the most parameter interactions.

**Indicator Results PENRT**

In the operational part of the PENRT indicator (see left side of Figure 3), there are four groups of parameters that play a significant role regarding $S_1$: ‘average service life building and development period’ (ASL), ‘primary energy factors’ (PEF), ‘energy system distribution’ (ESD) and ‘share of renewables primary energy sources’ (SRP). For ASL, the same explanation applies as for GWP, with the parameter defining the average service life of buildings also accounting for the largest share of the deflection. For PEF, the parameter that defines the primary energy factor for electricity is responsible for the largest share of the value (97%).

As with the explanation of SRP for the indicator GWP, this is due to the fact that electricity has an influence on the calculation model, regardless of the heating system used. In the parameter group ESD it is the parameters that define the percentage of oil boilers (27%), gas boilers and water-water heat pumps (15% each), brine-water heat pumps with geothermal probes (14%) and electric heaters (13%). Due to the fluctuation of the efficiencies, these heat generators in particular can have a high effect on the variance of PENRT. For the parameter group SRP, the same explanation applies as for GWP, whereby the parameter that defines the share of renewable and non-renewable primary energy in the electricity used also takes the largest share in the deflection of $S_1$ with 91%.
In the case of the embedded PENRT, it is mainly the categories ‘additional calculation factor’ (ACF), ASL and ESD that show the largest swing for $S_1$.

For the parameter groups ASL and ACF, the same explanations apply as for the indicator GWP. For ESD, the parameter that defines the percentage of brine-water heat pumps with geothermal probes has the highest impact on $S_1$ (88%). This is due to the fact that in addition to the heat pump geothermal probes are installed, which additionally have a high proportion of PENRT and can have a strong impact on the result.

The right side of Figure 3 shows the same effect for PENRT as for GWP, when comparing $S_1$ with $S^T$. Also, here, the parameter groups with the highest swing in $S_1$ account for the highest amount of $S^T$.

**Indicator Results PERT**

The left side of Figure 4 shows the operational and embedded values for $S_1$ with respect to the indicator PERT. For the operational part, it is basically the same indicators as for PENRT that are responsible for the largest deflection of $S_1$.

However, for PERT, the indicator group SRP has a greater influence than ESD. Again, the parameter that defines the primary energy factor for electricity is responsible for the largest share of the value (95%). In the ESD parameter group, it is the parameters that define the percentage of biomass boilers (57%) and electric heating (20%) for heat and DHW generation. These two have a large effect on the PERT due to their fluctuation, since electricity on the one hand and biomass (pellets and wood chips) on the other hand offer a large potential for the use of renewable energies. For the embedded part of the PERT, it is the parameter groups ACF, ASL and ESD that have the greatest influence on $S_1$, just as for GWP and PENRT.

For the parameter group ASL it is again the parameter that defines the average service life of buildings and for the parameter group ESD it is 93% the parameter that defines the percentage of brine-to-water heat pumps with geothermal probes.

On the right side of Figure 4 it can also be seen that the total effect $S^T$ is responsible for the largest parameter interaction, which is also the case for $S_1$. This reflects the same result as for the parameters and indicators before and shows a consistent result.

**Discussion**

From the results of the uncertainty analysis with respect to the method for performing LCAs based on large residential building stocks and the input parameters required for this, parameters can be identified across all three indicators considered whose fluctuations cause a large effect on the variance of the final result. It is striking that the same parameters prove to be the most important for all indicators considered – with the exception of parameter group PEF, which evidently has no effect on GWP. This was to be expected, as preliminary studies have shown that there is a linear correlation between PENRT/PERT and GWP. If the proportion of PENRT increases, the emissions (GWP) also increase. However, if the share of PERT increases, the GWP emissions decrease. If, for example, the linear correlation between the sum of PENRT and PERT for building operation is calculated with the GWP, then values for the correlation coefficient of $R = 0.99$ and the coefficient of determination $R^2 = 0.98$ are inherited. This indicates a strong correlation. A similarly strong value results between the embedded primary energy and the embedded emissions (e.g. $R = 0.99$ and $R^2 = 0.99$). Basically, this is due to the fact that the majority of the life-cycle based emissions can be attributed to fossil and renewable energy consumption.
The parameter that defines the average lifespan of the residential buildings under consideration has the greatest influence across all indicators (also for both operational and embedded parts) due to its fluctuation. In the case of the operational part of the indicators, a change in the lifetime of a building in annual steps leads to a defined number of years of reduced or increased energy demand and emissions. In the case of the embedded part, this parameter has an impact on the number of replacements of TBS components. The replacement of TBS components not only involves the disposal of the TBS components which reached their end-of-life, but also the production of the replacement components. Depending on the definition of the average life of the components, in combination with the average life of the buildings, this can have a large effect on the variance of the values.

With regard to the embedded part of all indicators, it can be said that the parameter defining a factor for the additional consideration of further TBS components (ACF) leads to the greatest variance of the results due to its fluctuation.

For the other parameter groups, a distinction must be made between the operational and embedded share and the energetic indicators (PENRT/PERT) as well as the emission-related indicator (GWP). For the operational part of the GWP, these are especially the parameters that define the percentage of renewable and non-renewable electricity in the parameter group SRP, which lead to a comparatively high variance in the result due to their fluctuation. In addition, the selection of the heat generator has a high influence on the result. In the case of the embedded share, besides the parameter groups ACF and ASL, it is the parameter that defines the percentage of floor space heated by underfloor heating in the parameter group HTS. In the case of the indicators PENRT and PERT, the primary energy factor of electricity in the parameter group PEF causes a high variance in the final result due to its fluctuation, followed by the percentage definition of the heat generators. Here in particular oil and gas boilers and heat pumps for PENRT and the biomass boilers for PERT must be mentioned. In the case of the embedded share, it is also the percentage shares of the heat generator (parameter group ESD) which, in addition to the parameter groups ACF and ASL, cause the greatest variance in the end result.

Conclusion

The presented results suggest the following data-related and methodological improvements in order to reduce uncertainties in large building stock LCA results:

1. To obtain more accurate estimates of the service life of a building, building-specific information on the renovation status and the structural condition of a building should be available. From this information, renovation versus replacement of a building can be evaluated.

2. In addition, building-specific information on the type and age of the heat generator and heat distribution would improve the accuracy of LCA calculations decisively. This information is independent of building age, as TBS components can be replaced and renewed without an entire building renovation. Thus, it should be available separately form year of construction and general renovation status.

3. In principle, it is important to know all components of the TBS components used (e.g., ventilation and air conditioning systems) and to include them in the scope of the LCA. Additional installations not only result in higher energy demand and emissions during the use phase of buildings, but also require embedded energy and cause embedded emissions. Currently, these are only included by a factor with a large fluctuation due to the related lack of information.

4. With regard to electricity in particular, there should be a clear definition of the sources from which it is obtained. Since this decision can be made on a building- or apartment-specific basis (e.g., for electric flow heaters) by the respective occupants, this information should also be available in this resolution. As the results show, the primary energy factor for the indicators PENRT and PERT as well as the non-renewable and renewable share of electricity, especially for the indicator GWP, can have a large effect on the variance of the result. Therefore, building- and apartment-specific information on electricity consumption should be available, in compliance with data protection.

If this information is made available for LCAs based on large building stocks, more accurate statements could be made in total about the life cycle-based energy and emissions performance of buildings. For the method and the tool urb+ used in this study, the provision of the building-specific information via a semantic 3D city model in CityGML-format would be the most feasible solution. The information would then be available in a central data format, could be used automatically for building-specific calculations and analyses, and the results could be written back into the model to be available for further research, e.g., the calculation of compensation measures based on the calculated emissions. In order to achieve this, an effort on the part of the municipalities and municipal public utilities is necessary to compile and collect this information. The challenge is not so much to record the data, which in most cases is already available, but rather to collect it in a uniform format, clean it up and make it available in an anonymized form to respect privacy concerns. If overarching strategies for sustainable development of the building sector are to be developed and implemented, then it is essential to include LCAs in the framework of the consideration and to create a data basis for a reliable implementation of these.

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References


