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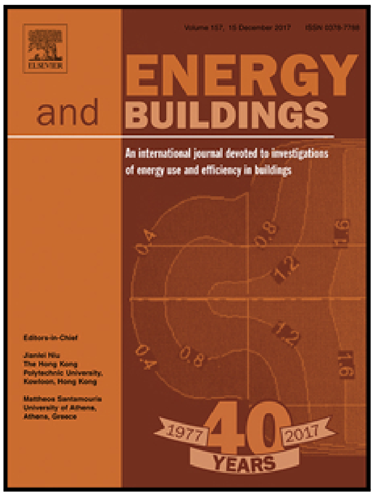

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Highlights

- Uncertain parameters have a high influence on the lifecycle-based energy efficiency.
- Uncertainty analysis must be performed to identify the impact of the uncertainties.
- Results allow the designer to prioritize decisions to decrease uncertainty.
- Enable lifecycle-based energy efficiency already at beginning of construction projects.

Uncertainty Analysis of Life Cycle Energy Assessment in Early Stages of Design

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Abstract

During building design and especially in early stages, important decisions influencing the lifecycle-based energy demand of buildings are made. Life Cycle Energy Assessment (LCEA) is used to evaluate this energy demand already in early stages of design. However, at that point, the building design and the related information can quickly change and are subject to potentially large uncertainty. This uncertainty in building information influences the LCEA and therefore decisions taken by the designer. Due to the uncertainty, it is difficult to distinguish between the performance of different design variants to decide for the best option. This study presents a method to perform LCEA and to assess and consequently strategically reduce the influence of uncertainties in buildings' information on the LCEA in early design stages. Uncertainty analysis is used to assess the influence of uncertainty on LCEA and to prioritize decisions to reduce uncertainty. The method is embedded in a multi-Level of Development (LOD) modelling approach covering the development of the building during the early stages of design. The method is applied to seven different building shapes as a proof of concept. It is concluded that the method renders valid results to assess the project-specific uncertainty in LCEA results.

Keywords

Life Cycle Energy Assessment (LCEA); Life Cycle Assessment (LCA); Early Design Stages; Uncertainty Analysis; Sustainable Building Development.

1 Introduction

When designing buildings in industrialised countries, certain energy efficiency standards are obligatory. In Europe, for example, the Energy Performance of Buildings Directive (European Commission, 2018) and the Energy Efficiency Directive (European Parliament and Council of 25th October 2012, 2012) provide regulations regarding energy efficiency for buildings. With the Energy Saving Ordinance (Energy Saving Ordinance - Energieeinsparverordnung (EnEV), 2013), Germany defines a minimum energy efficiency standard for residential and non-residential buildings, which has to be fulfilled by newly constructed as well as refurbished buildings. However, the Energy Saving Ordinance, as well as other standards only refer to the operational stage of buildings but do not consider the energy demand for construction, maintenance and end-of-life treatment (Eckrich et al., 2016).

In order to design and operate buildings in an energy-efficient and sustainable manner, their energy requirements must be assessed and optimised over their entire lifecycle (Ramesh, Prakash, & Shukla, 2010). To achieve this, it is not only necessary to analyse the energy demand during their operational stage but also during their construction and end-of-life stage (Basbagill, Flager, Lepech, & Fischer, 2013). Life Cycle Energy Assessment (LCEA), based on Life Cycle Assessment (LCA) methods, is used in this study to analyse the lifecycle-based primary energy demand and to assist the designer during the early design stages (Chau, Leung, & Ng, 2015; Ramesh et al., 2010).

With more strict energy standards, which aim to decrease the energy demand during the operational stage of buildings, more building material, in most cases insulation material, is needed to fulfil this task (Weiler, Harter, & Eicker, 2017). With more material and insulation input and the resulting lower energy demand during the operation of the building, the energy-related share for construction, maintenance and end-of-life of the building is getting larger (Weiler et al., 2017). It is therefore mandatory to not only analyse the operational stage of buildings, but the whole lifecycle.

When designing new buildings, there is a high potential in decreasing the total lifecycle-based primary energy demand (Gehin, Zwolinski, & Brissaud, 2007; Röck, Hollberg, Habert, & Passer, 2018). In order to do this cost-efficiently and without much effort, energy efficiency measures must already be taken into account in early stages of design (de Wilde, Augenbroe, & Van der Voorden, 2002; De Wilde & Van Der Voorden, 2004; Kovacic & Zoller, 2015).

Currently, energy calculation is often pushed to the end of the design process to generate compliance reports (Schlueter & Geyer, 2018). It needs to be integrated already in early design stages and within the design process at each detailing step, which affects the energy calculations, to enable the design of energy-efficient buildings. Therefore, designers require methods to obtain information about the total lifecycle-based primary energy demand of the building already in the early stages of design. Uninformed decisions about the design of buildings are made at those stages which might compromise the performance of the final design (Attia, Gratia, De Herde, & Hensen, 2012; Ritter, Geyer, & Bormann, 2015).

Moreover, the quality of information available needs to be ascertained, as the information needed for analysing the total lifecycle-based primary energy demand in early stages of design is incomplete and fraught with uncertainties (Hopfe, Augenbroe, & Hensen, 2013). The uncertainty of information and their impact on the calculation in the early stages of design must be assessed for providing meaningful and reliable results (Tian, Heo, et al., 2018).

To address the situation that essential decisions on lifecycle-based primary energy demand made in early stages of design are afflicted with uncertainty, the objective of the presented research is to develop a method to enable LCEA in early stages of building design. This method considers the trade-off between the embedded energy (EE), also known as embodied energy, and the operational energy (OE), as well as the analysis and assessment of the uncertain input information, according to the current stage of design. The method's feedback enables the designer[1] to develop lifecycle-based energy-efficient building designs and to interpret results correctly while knowing the impact of uncertain information on the LCEA. Additionally, by analysing the effect of input uncertainty on the building performance, the designer can improve the quality of the results by strategically prioritizing decisions to decrease uncertainty. This prioritization allows for steering the design quickly to a well-performing solution and drastically reduce potential later re-planning efforts by the right decisions in the early stages of design.

The use of Building Information Modeling (BIM) offers opportunities to share design information quickly and efficiently between the designer and consultants of different disciplines involved in the design process (Borrmann, König, Koch, & Beetz, 2015). However, to date, BIM models lack information on design intentions, variants and uncertainties. In the scope of the context of this research, the research group 'MultiSIM (FOR 2363)' funded by the German Research Foundation (DFG), Abualdenien and Borrmann (2019) developed a method to describe the level of maturity of entire digital building models in early design stages (Abualdenien & Borrmann, 2019). The models typically contain elements at different levels of development (LOD). The term LOD describes the level of geometric and semantic maturity of individual building components, but not the overall building maturity (BIMForum, 2019). For the LCEA and the related uncertainty analysis approach, the input parameters for the calculations, including related uncertainties, are extracted from a digital model following this approach. Methods, which embed machine learning in a component-based way, directly link to the multi-LOD approach and provide instant results for operational energy demand without time-consuming modelling and simulation to allow the uncertainty analysis quickly for each design case (Geyer & Singaravel, 2018; Geyer, Singh, & Singaravel, 2018; Singaravel, Geyer, & Suykens, 2018). In the *Concept and Methodology* section, the implementation of a component-based embedded energy calculation is described that is embedded in the multi-LOD approach. On this basis, the multi-LOD modelling and the uncertainty analysis for the LCEA are applicable in real-time in a design process.

The *Introduction* and *Literature Review* part of this scientific paper will be followed by the explanation of the study's *Concept and Methodology*, which describes the overall approach of the methodology and the taken assumptions. Moreover, the test cases, parameters and the calculation models are described. The concept and methodology are applied to a specific case study, including seven different building shapes that are potential solutions in the case study, for illustration and validation. For the final implementation of the LCEA and uncertainty analysis, the already mentioned parameters and further project-specific parameters are defined, which is described in more detail in the chapter *Setting up Calculation Models*. After

[1] In the following, the term designer is used as an umbrella term for architects in a designing role as well as engineers contributing to the design.

that, the calculated *LCEA and Uncertainty Analysis Results* will be interpreted and discussed. It can be seen that with conducting strategically prioritized decisions, the LCEA and uncertainty results are getting much more precise and therefore, much more interpretable for the designer. The study will end with a *Discussion* and *Conclusion* section.

2 Literature Review

As mentioned by Dixit (2017), existing studies, concerning to the design of energy-efficient building, primarily focus either on optimizing the embedded or operational energy while ignoring the trade-off that exists between the two (Dixit, 2017). This can also be stated when comparing state-of-the-art tools, which are concerning embedded energy or operational energy calculation and are currently used in research and economy/practice. Either they are only considering the operational stage and/or uncertainty in information (Hopfe & Hensen, 2011; Hopfe, 2009), or the whole lifecycle-based energy demand, including embedded energy, or only the embedded energy, but no assessment of uncertainty in input information, such as CAALA (Hollberg, Lichtenheld, Klüber, & Ruth, 2018), OneClick LCA (Bionova Ltd, 2019) or Tally (KTInnovations, 2019). Studies on uncertainty in LCA cover data uncertainties (Cavalliere, Habert, Dell'Osso, & Hollberg, 2019; Tecchio, Gregory, Ghattas, & Kirchain, 2019) or uncertainties due to methodological choices (system boundaries, reference service life, etc.) (Huijbregts, Gilijamse, Ragas, & Reijnders, 2003; Larsson Ivanov, Honfi, Santandrea, & Stripple, 2019), but no design uncertainty.

Currently, there is to our knowledge no study assessing both, the buildings' total lifecycle-based primary energy demand and the related uncertainty in the early stages of design.

2.1 Design Stages and its Basis

The definition of Level of Development (LOD) or stages of design, defined by professional bodies in the domain, primarily relate to increasing the level of information that can be derived from the building components step-by-step. Table 1 documents the design stages defined by three professional bodies – Royal Institution of British Architects (RIBA) (British Standard Institution, 2013), American Institute of Architects (AIA) (NIBS buildingSMART Alliance, 2015) and Building and Construction Authority Singapore (BCA) (Building and Construction Authority, 2013). These definitions do not include enough information for Stage 1 to be considered for LCEA. RIBA plan of work defines eight stages for building procurement activity, first with the strategic definition and preparation, next three with the design stage, and the remaining four with the construction and post-construction stage. AIA and BCA define five stages in a BIM based project delivery. The first three relate to the design stage and the remaining two with the construction and post-construction stage. Sawhney, Singh, & Ahuja (2017), suggests similar practices are being follwed in other regions for BIM-based project delivery (Sawhney, Singh, & Ahuja, 2017).

Table 1 Design stages and deliverables as defined by professional bodies

RIBA	AIA	BCA	Design Deliverables (as per BCA)

Stage 2- Conceptual Design	Step 2: Schematic Design	Conceptual Design	Building massing studies or other forms of data representation with indicative dimensions, area, volume, location and orientation
Stage 3- Developed Design	Step 3: Design Development	Preliminary Design	Generalized building component or system with approximate dimensions, shape, location, orientation, and quantity. May include non-geometric properties.
Stage 4- Technical Design	Step 4: Preparation of Construction Documents	Detailed Design	A more detailed version of a generalized building component or system with accurate dimensions, shape, location, orientation, and quantity. Non-geometric properties should be provided.

However, these definitions are missing the energy calculation perspective. This means that no parameters or parameter sets are included that can define the input parameters for an LCEA in different design stages. As already mentioned in the *Introduction* (see Section 1) Abualdenien and Borrmann (2019) defined a standard, which on one hand defines the building's design stages in BIM-models and on the other hand allows and enables the integration of LCEA-parameters, as well as other project relevant parameters, e.g. for structural planning in early design stages (Abualdenien & Borrmann, 2019). This standard is called the Building Development Level (BDL), whereby 5 BDLs are defined. BDL 1 to 4 is defined to consider the early design stages of buildings, further defining the above-mentioned design stages 1 to 4. Since BDL 1 only contains information about the building's footprint but no volumetric information, only BDL 2, 3 and 4 are used in this study for the calculations, analysis and assessments. BDL 5 defines a building that is already too detailed to be counted in the early stages of design and is therefore not considered. The concept of BDL provides for project-specific flexibility as the elements contained in the BIM model, and their respective LODs can differ between projects. Schneider-Marin and Abualdenien (2019) proposed a framework to facilitate an interdisciplinary design process using BIM (Schneider-Marin & Abualdenien, 2019).

2.2 Uncertainty / Sensitivity Analysis of Building Energy Models

The uncertainty or sensitivity analysis becomes an essential part of building performance simulation given that the design parameters are inherently uncertain at an early stage of design (Tian, Heo, et al., 2018). In the past, researchers have used various sensitivity analysis methods to simplify a model by parameter screening (De Wit, 1997), identify robustness of model (Heo, Choudhary, & Augenbroe, 2012; Manfren, Aste, & Moshksar, 2013), quality assurance (C. Hopfe, Hensen, Plokker, & Wijsman, 2007; Struck, Hensen, & Plokker, 2010) and provide decision-support (Christina J. Hopfe & Hensen, 2011; Struck, 2012; Struck, Jan Hensen, & Kotek, 2009). Furthermore, the uncertainty in the external factors also results in uncertain prediction such as microclimate (Sun et al., 2014), macroclimate (Tian, de Wilde, Li, Song, & Yin, 2018) and economic parameters (Rysanek & Choudhary, 2013). Heeren et al. (2015) has studied several internal and external factors which influences the environmental impact of buildings and ranked climate change, electricity mix, ventilation rate, heating system and construction material as highly influential factors (Heeren et al., 2015). However, modelling the uncertainty in the design parameters through the design process is not addressed which is based on the concept that with the design progress the uncertainty in the design parameters reduces and enables thus more accurate performance predictions (C. Hopfe et al., 2007; Christina J. Hopfe & Hensen, 2011; Rezaee, Brown, Augenbroe, & Kim, 2015; Singh & Geyer, 2019).

3 Concept and Methodology

This section describes the overall concept and methodological approach for analysing the information required at all considered BDLs. Section 3.1 describes the overall approach and the taken assumptions for the LCEA. Section 3.2 describes the test case building. Section 3.3 develops various building shapes as alternatives to the test case building to represent early BDLs. It is followed by a description of the calculation method for uncertainty analysis under Section 3.4. Section 3.5 describes the overall calculation method for LCEA, as well as the calculation of the embedded and operational energy and Section 3.6 presents the project specific definition of the design parameters, relevant for LCEA.

3.1 Approach and Assumptions

The total primary energy demand calculation is based on the approach of Life Cycle Energy Assessment (LCEA)[2], which is also used in several other published studies (Ramesh et al., 2010). LCEA is again based on Life Cycle Assessment (LCA) methods according to DIN EN ISO 14040 (DIN German Institut for Standardization e.V., 2009), DIN EN ISO 14044 (DIN German Institut for Standardization e.V, 2018) and DIN EN 15978 (DIN German Institut for Standardization e.V., 2012), which focuses on the assessment of the environmental performance of buildings. LCEA assesses all product-related energy inputs for manufacturing, producing components, materials, services for manufacturing processes and its use (Cabeza, Rincón, Vilariño, Pérez, & Castell, 2014). The energy inputs related to the multitude of products used in a building is considered for building LCEA as well as the energy input for building operation.

[2] In the following, the term Life Cycle Energy Assessment (LCEA) is used as an umbrella term for the calculation of the total lifecycle-based primary energy demand, including the operational and embedded energy.

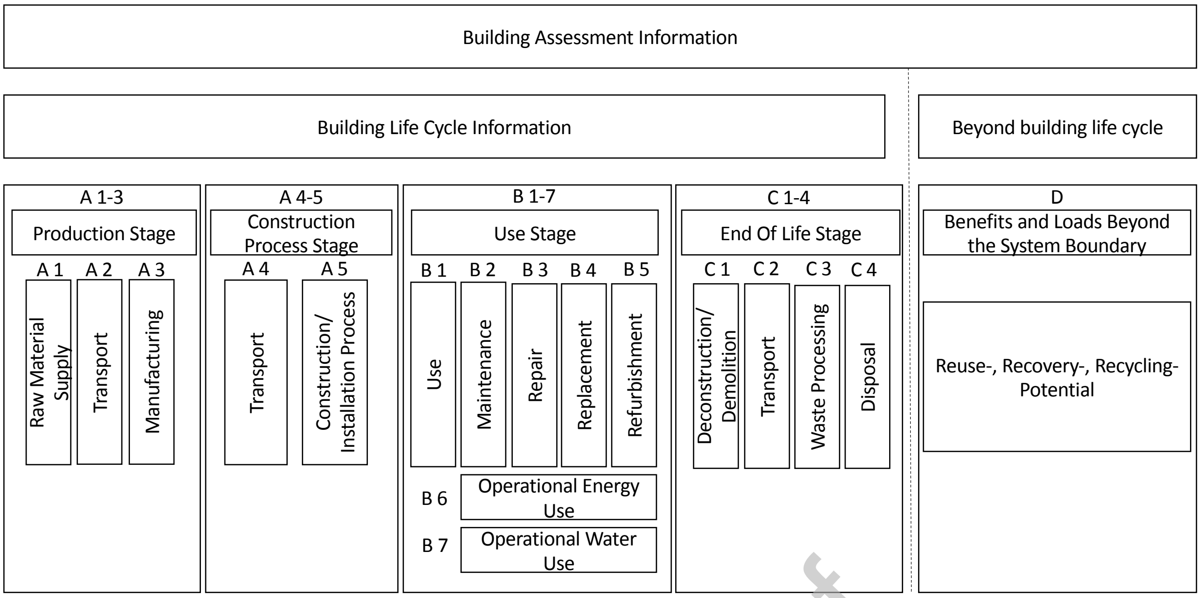

Figure 1 Representation of modular information for the various building lifecycle stages according to DIN EN 15978:2012-10; lifecycle stages marked in grey are considered in the study, if available.

In our study, the results of the LCEA refer to the primary energy demand in MJ. The calculation is split into two calculation models, one model for the operational energy calculation (OEC), considering the lifecycle stage B6, and another model for the embedded energy calculation (EEC), considering the lifecycle stages A1-3, B4 and C3 and/or C4 (see Figure 1).

OEC is performed by setting up a parametric simulation model with the dynamic energy simulation tool EnergyPlus (US Department of Energy, 2018). OEC includes the energy required to maintain the thermal comfort, provide lighting and operate the equipment.

For performing the EEC, the Oekobaudat LCA-database, version 2017-I, is used (Federal Ministry for the Environment Nature Conservation and Nuclear Safety, 2019).

It should be noted, that only the lifecycle stages the Oekobaudat provides data for can be considered. This can vary between different building materials. The Oekobaudat guidelines stipulate that only LCA data for stages A1-3 of a material or product must be available in order to be included in the database as a data record. For the waste treatment and disposal stages, process datasets are used to fill the gap if the information is not contained directly in the material dataset, e.g. “construction waste disposal” was used for stage C4 of the insulation. Therefore, for all materials considered we used life cycle stages A1-A3 and C3 and/or C4. Stage B4 *Replacement* includes stages C3 and/or C4 of the material which is getting disposed and stages A1-A3 for the new material. When interpreting the results, this has to be kept in mind (Harter, Schneider-Marin, & Lang, 2018). Additionally, it has to be noted, that, amongst others, missing LCA data for different life cycle stages in material specific datasets, varying transport distances of the same material, generic material datasets, non-availability of LCA datasets for exactly the same materials which are used in the building, can lead to uncertainties in the LCEA calculation. Due to the fact that each of the mentioned topics represent individual research areas in itself, they will not be further investigated within the framework of this study.

The considered Reference Service Life (RSL) of buildings is 50 years. According to Cabeza et al. (2014), this RSL is used in the majority of studies concerning LCEA/LCA for buildings (Cabeza et al., 2014). Both models use the same input information for the calculation, sampling the same range, providing the results for primary energy and referring to the same defined early stages of design. The calculated results of both models are merged and assessed to consider the trade-off between the embedded energy and operational energy. The uncertainty assessment is performed using variance-based sensitivity analysis method described by Saltelli et al. (2008; 2010) (Saltelli et a., 2010; Saltelli et al., 2008).

3.2 Test Case

We are using an office building as a test case, which was built at the end of 2016 (Ferdinand Tausendpfund GmbH & Co. KG, 2019). It is representative of a typical medium-sized office building. The location of the building is Regensburg near Munich, Germany. The climate of Munich is classified as Cfb (Warm temperate – full humid – warm summer) in Koppen-Geiger climate classification, which represents most part of western Europe (Beck et al., 2018). The building has a total area of 1,200 m^2, equally distributed on three floors with a rectangular floor plan.

3.3 Uncertainty Shapes Used in the Study

The building shape is one of the uncertainties at an early stage of design. In this research, seven alternative building shapes, as shown in Figure 2, are developed, based on the rectangular floor plan of the test case, to represent this uncertainty. These shapes are most commonly used for medium-size office buildings (Asadi, Amiri, & Mottahedi, 2014; Neufert & Neufert, 2010) and thus represent general design options at this BDL. All the shapes have an equal probability of occurrence; thus, it follows a uniform distribution. In our case, the geometry of the building is assumed to remain the same throughout the BDLs, but their corresponding information will become more precise along the process (see Subsection 4.4). *Shape1* represents a rectangular building, matching the test case, whereas building shapes *Shape2* to *Shape6* represent a small range of possible building designs. *Shape7* is similar to *Shape1* but includes a basement. The geometrical parameters *Width*, *Length*, ratio of *LengthA* to *Length (rLenA)* and the ratio of *WidthA* to *Width (rWidA)* describe the footprint of the building in each shape. They appear in building shapes *Shape 2* to *Shape 6* (see Figure 2). In *Shape2* to *Shape6*, the area is always equal to (*Length* × *Width) - ((1-rLenA)* × *Length)* × *((1-rWidA)* × *Width)* and increasing the value of *rLenA*, *rWidA* increases the floor area. These parameters are selected in a way to keep the floor area of all the shapes equal. By controlling the exterior dimensions such that the average floor area remains constant between all shapes, *Shape3* and *6* have the same range of exterior wall area, which is larger than the exterior wall area of *Shape1* and *7* but again different to *Shape2*. For *Shape4* and *5*, the range of exterior wall area is also the same, and the largest of all shapes.

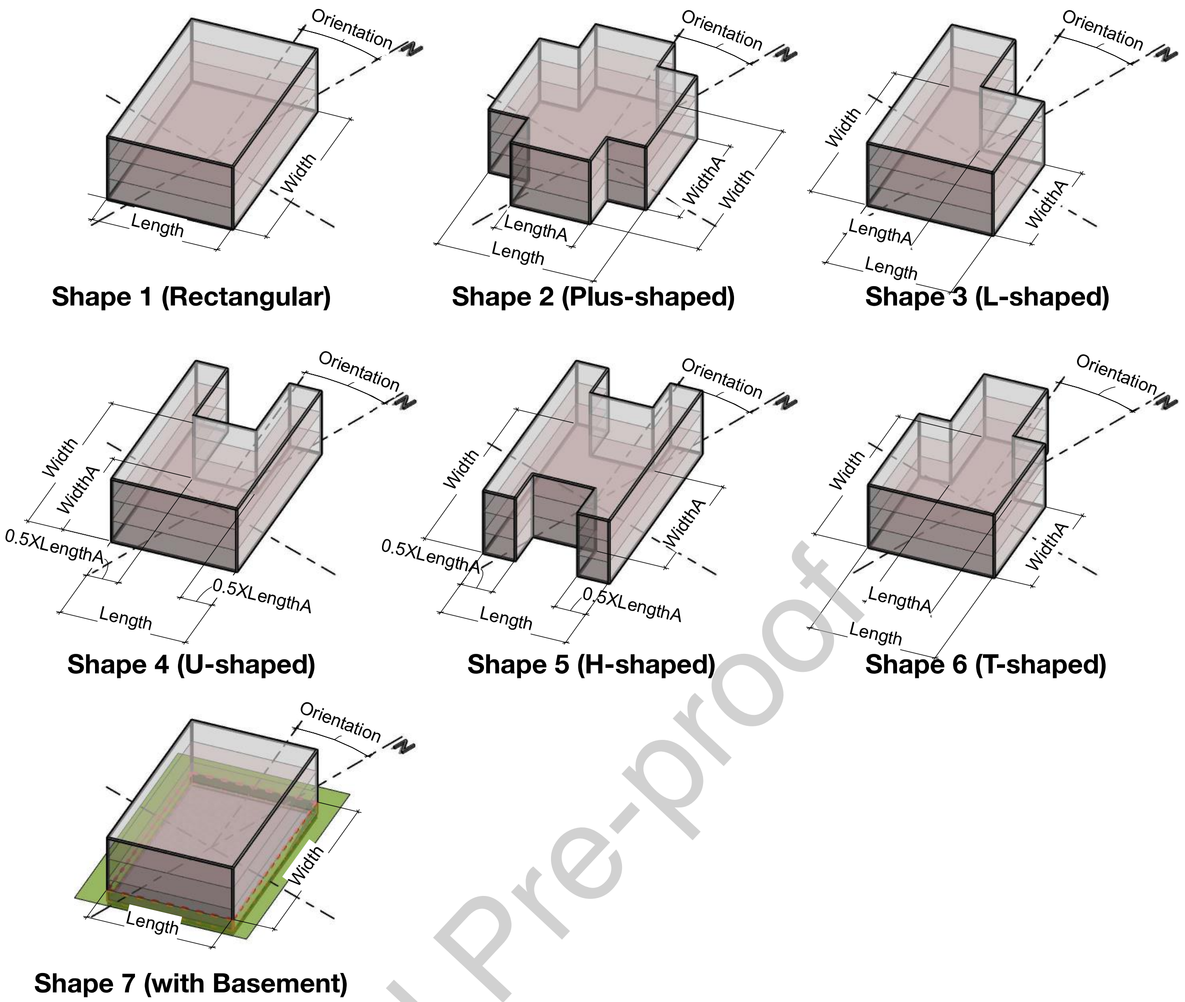

Figure 2 Seven Building Shapes for LCEA in Early Design Stages

3.4 Uncertainty Analysis using a variance-based method

The uncertainty analysis using variance-based method is based on the decomposition of model output variance (Menberg, Heo, & Choudhary, 2016; Saltelli, Tarantola, Campolongo, & Ratto, 2004). It is used to calculate two sensitivity indicators – first-order effect and total effect. The first-order effect is a measure of uncertainty which can be removed if the parameter is certain, thus indicative of the importance of a parameter (Saltelli & Tarantola, 2002). The total effect indicates the effect of a parameter, including higher-order effects and parameter interaction (Saltelli et al., 2010). The uncertainty attributed to a group of parameters is calculated by summing up the value of their first-order effect. Since the sum of first-order effects of all the parameters is close to 1, the uncertainty caused by the higher-order and interaction effects is ignored. The accuracy of the estimated uncertainty contribution depends on the number of samples, which is 500 in this case. The number 500 is selected based on two previous studies (Menberg et al., 2016; Singh; & Geyer, n.d.). This corresponds to $n \times (p + 2)$ simulations based on sampling scheme described by Saltelli et al. (2008), where n is the number of samples and p is the number of parameters (Saltelli et al., 2008). This sampling scheme is based on Latin hypercube sampling (LHS) method with some additions as explained by Saltelli et al. (2008) (Saltelli et al., 2008). There is no prescribed limit for the number of samples; however, the accuracy of the method is tested using Mean Absolute Error (MAE). The MAE, in any case, does not exceed 0.02. It should be noted that running simulation is the most time-consuming time-step in the whole process. It takes approximately 600 minutes to calculate the energy demand for all the samples.

3.5 Life Cycle Energy Assessment

OEC is performed using a state-of-the-art dynamic energy simulation tool for a period of one year. Since the results of OEC and EEC are referring to primary energy in MJ and the same RSL of the building, the values are summed up and presented as a single primary energy value. The minimum, maximum and mean value are provided as results concerning all sampling sets and building shapes. These results are analysed, using variance-based analysis methods described in Subsection 3.4. The merged analysis can be conducted for the sum of primary energy as one single parameter. With providing the information to the designer, the designer can consequently strategically reduce the influence of uncertainties in buildings' information on the LCEA in early design stages, in order to increase the results' precision. The overall concept is graphically described in Figure 3. Additionally, Table 2 shows the elements and systems which are included, according to each considered lifecycle stage, in the LCEA calculation. The 'x' for the constructional elements (exterior and interior walls, windows, baseplate, roof and floor slabs) in lifecycle stage B6 refer to their u-value, which influences not only the EEC but also the OEC.

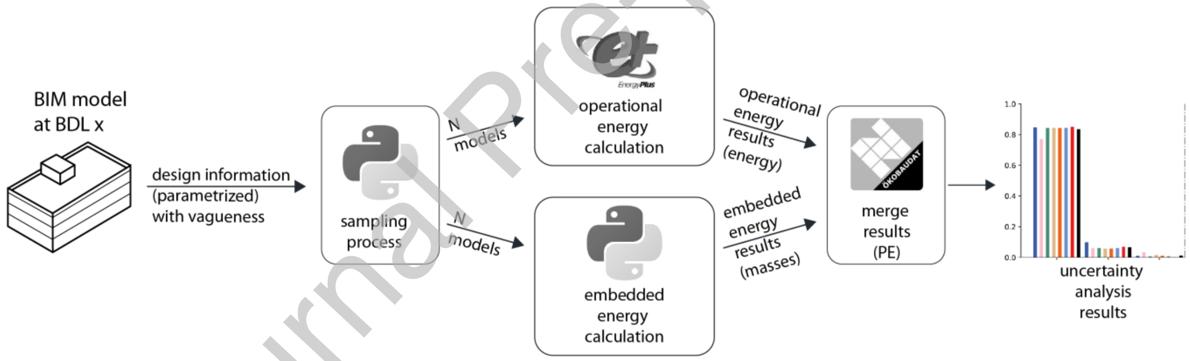

Figure 3 Uncertainty analysis of LCEA calculation

Table 2 Elements and systems included in the LCEA calculation; Lifecycle stages according to DIN EN 15978 (see Fig. 1)

Life cycle stage	Exterior walls, windows	Baseplate	Floor slabs	Roof	Interior walls	Heating demand	Cooling demand	Lighting demand
A1-A3	x	x	x	x	x			
B4	x			x	x			

B6	x	x	x	x	x	x	x	x
C3-C4	x	x	x	x	x			

3.5.1 Operational Energy Calculation (OEC)

The OEC is performed by setting up parametric simulation models in EnergyPlus (US Department of Energy, 2018). We have developed a program to generate an EnergyPlus input file for a combination of parameters. After running the EnergyPlus simulation, the results are read to map the operational energy requirement for each combination of parameters. The simulation model considers the effect of available daylight while calculating the energy requirement for lighting. For the LCEA-parameters, please refer to Table 5. The simulation model calculates the annual energy demand, which is multiplied with the RSL of the building to get the operational energy requirement for the whole lifecycle of the building. The results are converted using datasets from Oekobaudat to arrive at primary energy values. The heating is provided by a gas boiler and electricity mix is used for lighting and cooling.

3.5.2 Embedded Energy Calculation (EEC)

The EEC model considers the primary energy demand needed for the production (A1-A3), exchange (B4) and end-of-life stages (C3/C4) of the building's construction elements. For the use stage, only the exchange of material, according to its durability, is considered, i.e. its end-of-life stage and the production stage for the new material.

The calculation model for the EEC was developed on the basis of the standards and norms described in Subsection 3.1 (Harter et al., 2018) and implemented by using python and SQL programming language. The model uses the samples generated by variance-based sampling (see Subsection 3.4), as input information for the component based-calculation (see Table 4). The building model is therefore split into building components (external walls, roof, baseplate, etc.) for calculation. Afterwards, all results are summed up to generate a single EE value. The geometric information of each building component, the information about the wall thickness, length and height, referring to the construction material, is used to calculate the material volumes of the components the building is constructed of. By multiplying the material volume with the material-specific density, the material masses are calculated in the next step. The windows are an exception as they are related to the unit square meter. The different window-to-wall ratios of all exterior walls are considered to calculate the total window area of the building.

The volume of insulation material is calculated according to the construction material, using the information about the wall thickness and the u-values. The u-values thereby refer to country-specific energy standards, e.g. defined by the German Energy Saving Ordinance (Energy Saving Ordinance - Energieeinsparverordnung (EnEV), 2013) or by the 'Kreditanstalt für Wiederaufbau (KfW)' (Kreditanstalt für Wiederaufbau (KfW), 2019), which has to be defined by the designer. In our study, the u-values were used in accordance with the German Energy Saving Ordinance.

The calculated masses, volumes and areas are then multiplied with the material-specific primary energy values, which are referring to the respective functional unit and are stored in the SQL-database. In Equation 3, the calculation of the EE for each building material/component is exemplarily shown. The LCA-values (e.g. PE for producing 1 kg of construction steel (Production Stage A1-A3)) stored in the SQL-database are sourced from the Oekobaudat database (Federal Ministry for the Environment Nature Conservation and Nuclear Safety, 2019) and multiplied with the specific building material/component mass.

$$\boldsymbol{EE = m \times \sum_{i=A1}^{C4} PE_i} \quad (1)$$

where EE = Embedded Energy [MJ]; m = material mass [kg]; $\sum_{i=A1}^{C4} PE_i$ = sum of primary energy (PE) demand for all considered lifecycle stages A1 to C4 [MJ].

This calculation is conducted for each sampling in each BDL and for every building shape and therefore embedded in the multi-LOD approach (see Figure 4 for graphical representation of EEC). This approach enables the EEC in real-time in a design process.

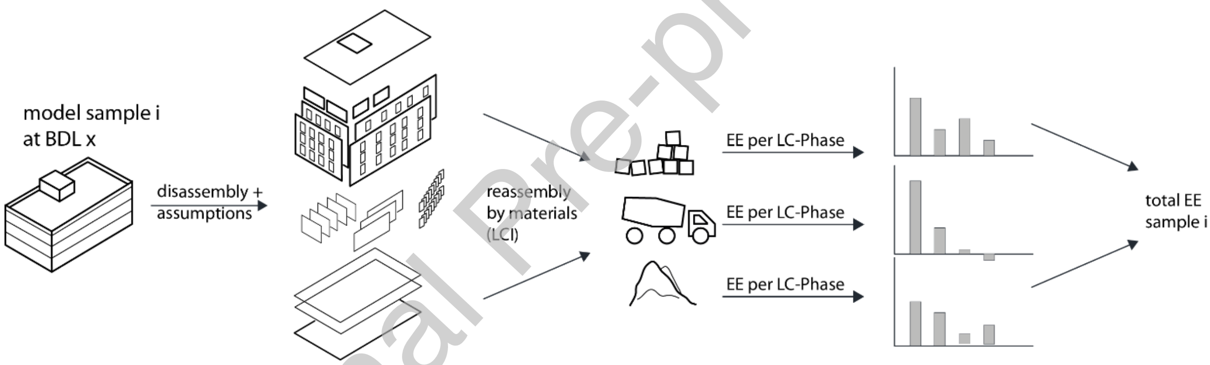

Figure 4 Lifecycle-based EE calculation

3.6 Definition of LCEA Parameters

Since the existing LOD-definitions do not include the energy calculation or LCEA perspective, specific parameters have to be defined to allow LCEA in early design stages and integrated into the BDL standard by Abualdenien and Borrmann (Abualdenien & Borrmann, 2019) (see Subsection 2.1). The project-specific definition of LCEA parameters can be seen in Subsection 0. It has to be noted that two numeric parameters have to be defined for each of the parameters. The initial value (input value) for the calculation represents the mean value of a defined minimum and maximum, and the uncertainty value describes a range of uncertainty with a uniform distribution, within which these parameters are indicated.

The project specific LCEA parameters (see Subsection 0) are used and relevant for the LCEA calculation considered in BDL 2, 3 and 4 in the scope of this study. The methodology allows the analysis and assessment of each parameter specifically, but for simplification reasons, the parameters are grouped to be further used in the study to present the calculation and uncertainty analysis results.

We grouped the parameters based on their nature (see Subsection 4.3). In this case, the *Geometrical Parameters* define the total floor area and volume of the building, which is of extreme importance from the perspective of space requirement. The *Internal Spaces and Technical Specifications* are relevant to fulfil functional requirements. The group *Window Construction* includes all parameters concerning the transparent parts of the exterior walls. The groups are also related to the design process, as the parameters contained in one group tend to be determined at the same time.

4 Setting up Calculation Models

When setting up the calculation models, it has to be kept in mind, that all used definitions of parameters are chosen explicitly for calculating the LCEA and conducting uncertainty analysis for the seven building shapes, considered as test cases, in the scope of this study. These definitions can vary from study to study and are not suitable for reproduction since construction projects and buildings always have individual factors, e.g. location, climate, etc., that have to be explicitly considered and which influence the mentioned parameters. The study instead presents and validates the study's methodical approach that is applicable to other construction projects by adjusting the mentioned parameters.

4.1 **OEC Model**

For setting up the OEC model, additional parameters have to be defined. The remaining details of these parameters are listed in the following Table 3:

Table 3 Parameters for developing the operational energy model

Parameter	Detail
Location and Climate	Munich, Germany, Köppen-Geiger climate classification - Cfb (warm temperate – fully humid – warm summer) (Beck et al., 2018).
Thermal Comfort	Heating Setpoint 20 °C; Cooling Setpoint 24 °C; Heating Setback point as 10°C; Cooling Setback point 28°C.
Lighting Level	500 lux
Occupant Load	1 person/ 10 m2
Zoning	One zone per floor (internal walls included to provide thermal inertia)

4.2 **EEC Model**

The additional specific parameters needed for the EEC model consist of material-specific information, including exact material definition and the RSL (see Table 4). The information about the RSL is given in years and sourced from the definition of RSLs of components for LCA according to the Sustainable Building Assessment System (BNB) (BBSR - Bundesministerium des Innern für Bau und Heimat, 2017). These definitions are used for all calculations in every BDL. They can be adjusted for other projects, based on the available data, material-specific LCA-datasets in the Oekobaudat database and definition of RSL of components for LCA in accordance with the Sustainable Building Assessment System (BNB). In the case of this study and for simplifying the proofing of the results, only the defined materials of Table 4 are considered for the calculations and assessments.

Table 4 Material Definition as Input for EEC model

Material Related Input Information for EEC Model	*Definition Oekobaudat dataset*	*RSL (years)*
Insulation Material External Walls	Mineral wool (façade insulation)	40
Insulation Material External Walls Basement	XPS altern	40
Construction Material	Concrete of compressive strength class C 20/25	50
Window	Insulated glazing, triple pane; Aluminum frame profile, powder-coated; Window fitting for tilt and turn window	40
Steel	Reinforcement Steel wire	50
Construction Material Internal Walls	Gypsum plasterboard (fire protection)	20

Table 4 also shows the Oekobaudat datasets which are assigned to the different materials for the EEC. The LCA-datasets for the windows were previously calculated by using the tool eLCA of the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (Federal Institute for Research on Building - Urban Affairs and Spatial Development, 2019), which is also using Oekobaudat datasets for calculation. The datasets, which are used for the window calculation, are also listed in Table 4.

4.3 Project Specific Definition of LCEA Parameters

For the simulation of the OEC and EEC in the mentioned BDLs, the input values have to be defined for the different introduced shapes. As already mentioned, the LCEA-parameters are linked with varying uncertainty in different BDLs. The uncertainty changes along the BDLs (see Subsection 4.4), influenced by the increasing accuracy of the information, which is provided by the designer via the building's BIM-model. In this way, the designer influences and controls the LCEA performance of the building through their design decisions. The uncertainty of LCEA-parameters, therefore, changes in the course of the BDLs and is based, for example, for BDL3 on the uncertainty analysis results from BDL2. The uncertainties for all BDLs are shown in Table 5 of Subsection 4.4. The parameters *Internal Walls, Reinforcement, Basement* and their units are shortly described for better understanding. The parameter *Internal Walls* defines the percentage of internal walls volume compared to the interior volume of the building without exterior walls and floor plates. The parameter *Reinforcement* defines the mass of steel in kilogram, related to one cubic meter of reinforced concrete. The parameter *Basement Depth* describes the depth of the basement into the ground in meters. The parameter group *Building Operation* and *System Efficiency* are an exception for the LCEA, because they cannot be influenced by the designer in early stages of design but are relevant for the calculation of the OEC. Because of this, the parameters are assigned an input and uncertainty value, which does not change over the course of the early stages of design. But it is important to include these parameters in the study to see the interaction effect between these parameters and other design parameters.

Table 5 shows all mean values for the LCEA-parameters to calculate the LCEA for the introduced building shapes. The parameters are representative for this size of office buildings and rely on actual and empirical values for this size of an office building, which is taken for demonstration purposes. The input values are sourced from the building's BIM-Model.

Table 3 Specific Definition of Values of LCEA-Parameters used for all considered BDLs and for all Shapes

Group	*LCEA-Parameters*	*Shape 1 & Shape7*	*Shape 2-6*
Geometrical Parameters	Length [m]	15.0	17.3
	Width [m]	27.0	31.2
	Height [m]	9.0	9.0
	rLenA	-	0.5
	rWidA	-	0.5
	Basement Depth [m] (only Shape7)	2.0	-
	Orientation [°]	20.0	20.0
Internal Spaces and Technical Specifications	Infiltration [-]	0.6	
	Construction Thickness External Walls [m]	0.2	
	Internal Walls [%]	13	
	U-Value Wall [W/m²K]	0.28	
	U-Value Ground Floor [W/m²K]	0.35	
	U-Value Roof [W/m²K]	0.2	
	Reinforcement [kg/m3]	140.0	
Window Construction	U-Value Window [W/m²K]	1.3	
	G-Value Window [%]	0.6	
	Window to Wall ratio North [%]	30	
	Window to Wall ratio West [%]	30	
	Window to Wall ratio South [%]	30	

	Window to Wall ratio East [%]	30
Building Operation	Operating Hours [h]	9.0
	Lighting and Equipment Heat Gain [W/m²]	20.0
System Efficiency	Boiler Efficiency [-]	0.85
	Chiller COP [-]	4.0

4.4 **Definition of Uncertainty at each BDL**

In Table 6, the uncertainty of LCEA-Parameters for all BDLs is presented. These values are used as initial values, which indicate the range for generating the sampling sets. For the purpose of this study, the initial ranges for BDL2 were chosen to provide a starting point from a rough design. The reduction of the uncertainty range of higher BDLs then follows the results of the uncertainty analysis of the previous BDL, such that the parameter group with the highest uncertainty contribution is set to be more certain. The uncertainty of the grouped parameter *Window* remains the same along all BDLs, for example. This appears because the uncertainty contribution of the grouped parameter *Window* is never the highest throughout the course of BDLs and therefore remains unchanged (see following Figure 5 and Figure 6). The grouped parameter *Technical* will for example remain the same until BDL3, until the influence of the uncertainty of ±25% of the Technical parameter is highest and will therefore be provided by the designer with an increased accuracy in BDL4, ergo an uncertainty of ±5% (see following Figure 5 and Figure 6).

The application of the ranges means, that, e.g. the LCEA-Parameter *Length*, with a defined input value for *Shape1* of 15.0 m, is sampled for BDL2 in the range of ±10%, hence from 13.5 m to 16.5 m. This will then affect, amongst others, the calculation of the floor area, the material mass of the floor slabs, base plate, external walls. The underlying distribution for sampling the parameters and creating the sampling sets is a uniform distribution. The sampling sets serve as input for the OEC and EEC. The uncertainties should be adjusted to individual project requirements by the designer. For example, there could be cases where geometrical parameters are subject to legal or construction restrictions such that there would be no uncertainty in some dimensions.

Table 4 Specific Definition of Uncertainty of LCEA-Parameters at each BDL

Grouped Parameters	*Uncertainty BDL2*	*Uncertainty BDL3*	Uncertainty BDL4
Geometrical	±10%	±2%	±1%
Technical	±25%	±25%	±2%
Window	±25%	±25%	±25%
Building Operation	±5%	±5%	±5%

System Efficiency	±5%	±5%	±5%

5 LCEA and Uncertainty Analysis Results

The results are presented in the following sorted by BDLs. The LCEA results and the uncertainty analysis results are, therefore conceptualised in an easy to understand way. Therefore, a graphical representation of the results is chosen. The designer, with the help of an energy specialist, gets a quick overview of the results. A designer familiar with early design stage uncertainties can interpret their value in order to place them in the context of the project and make decisions for the further course of the project.

The LCEA-results or total lifecycle primary energy demand results are graphically represented (see Figure 5 and Figure 6) as total primary energy value in MJ for all seven shapes in the course of BDLs. Since these results are based on defined sampling sets, the mean values, the interquartile ranges and the maximum and minimum values are represented for the results.

The uncertainty analyses are based on the LCEA-results. The influence of each parameter group's uncertainty on the end result is analysed and shown. The uncertainty results are presented for the total primary energy demand in comparison in the course of BDLs. These results are based on the merged results of the OEC and EEC. The results for the grouped parameters *Building Operation* and *System Efficiency* are shown in lighter colors (see Figure 5) because they cannot be influenced by the designer but are crucial for the OEC, as already described in Subsection 4.3. Based on the results of each BDL, decisions are made, and the uncertainty for the grouped parameter with the highest impact is reduced to validate the correct functionality of the model with the results of the uncertainty analysis of the following BDL.

For a better comparison of the results, the LCEA and uncertainty analysis results for BDL2 to 4 and for all building shapes are presented in Figure 5 and Figure 6.

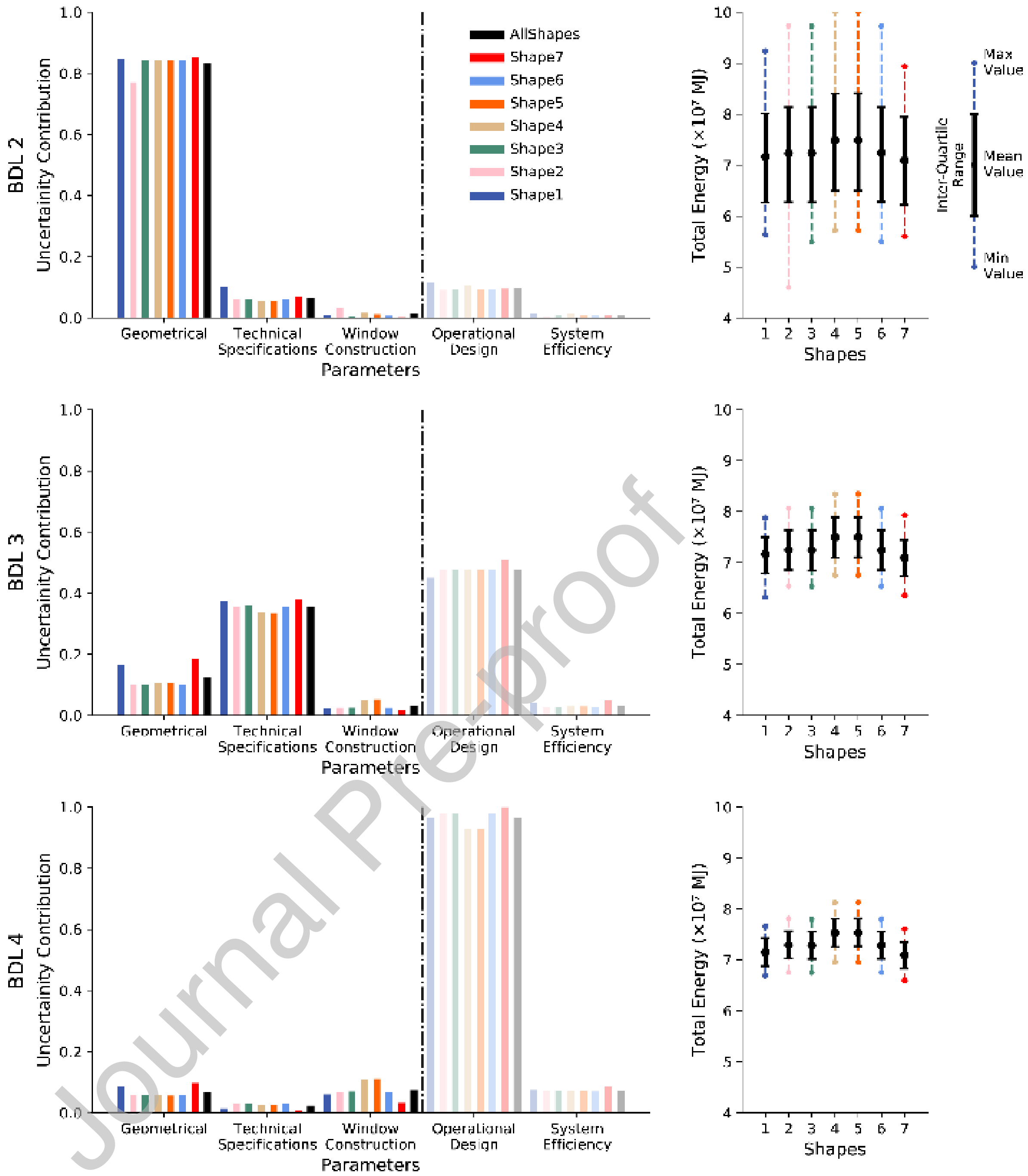

Figure 5 LCEA and uncertainty analysis results for BDL 2 to 4 and for all building shapes

5.1 Results for BDL2

As can be seen in Figure 5, *Shape4* and *Shape5* account both for the highest mean value in total primary energy, as well as the highest maximum and minimum values. *Shape2, 3* and *6* show the medium range for mean value and maximum value. *Shape1* and *Shape7*, the most compact of the shapes, display the lowest mean and maximum values. *Shape2*, *3* and *6* have the lowest minimum values and therefore seem to display the highest potential for minimizing the total energy demand.

The uncertainty analysis results show that, with the defined uncertainty (see Table 6), the *Geometrical Parameters* have the highest impact on uncertainty with a share of about 0.8 in terms of the first-order effect. The second-highest impact is observable for the parameter group *Technical Specifications*, followed by the group *Window Constructions*. If the grouped parameter of *Building Operation* was included in the scope of the analysis, it would have the second-highest influence on the results, even with the relatively low defined parameter range of ± 5 %. However, it was not included as it is not influenced by the designer in early design stages but left to decisions in later stages.

The designer can easily calculate and conclude that with the defined input values for the LCEA-parameters and the defined uncertainty for each LCEA-parameter in BDL2, the overall LCEA results (see *Total Energy* values in right graph Figure 5, for BDL2) can only be provided with a range of results of ±61% around the average mean value, when comparing all shapes. With regard to the lifecycle-based energy efficiency or to lowering the total lifecycle primary energy demand, the designer looking at the lowest minimum can conclude, that *Shape2* provides the most potential for minimizing the total primary energy demand. However, *Shape1* and *7* provide a smaller risk of high energy demand considering the given uncertainty correctly as they display the lower mean values.

Furthermore, in summary, the results in BDL2 can only be given with a very high degree of inaccuracy due to the high uncertainty of information. This considerably restricts the possibility of target-oriented interpretation and communication of the results. However, since the parameter group with the highest uncertainty contribution is known, the designer can manage to minimize the uncertainty for exactly this grouped parameter and to provide more precise information for BDL3 via the BIM model. This more precise information strategically lowers uncertainty, which is shown by the LCEA calculation for BDL 3 (see Table 6).

5.2 **Results for BDL3**

For BDL 3, the uncertainty of the grouped parameter *Geometrical* is reduced from ±10% to ±2%, taking into account the results of BLD 2 showing this parameter to have the highest contribution to the uncertainty of the results. All other values for the input parameters are kept with the same uncertainty as at BDL2 (see Table 6).

We are comparing the results for the total primary energy of BDL2 with those for BDL3 in Figure 5. It can be seen that *Shape4* and *5* still represent the highest mean, minimum and maximum values, followed by *Shape2*, *3* and *6*. *Shape1* and *7* now have not only the lowest maximum and mean values, but also the lowest minimum values. All shapes still show the same, but a significantly smaller, inter-quartile range.

When assessing the results for the uncertainty analysis of BDL3 it can be seen, that, now that the uncertainty for the grouped parameter *Geometrical* has decreased by 8%, the grouped parameter *Technical Specification* has the highest uncertainty contribution overall shapes.

This was to be expected since the *Technical Specification* accounted for the second-highest contribution in BDL2. This can be rated as the first proof of the study's methodology.

It is interesting to see that the grouped parameter *Geometrical* still has the second-highest share in uncertainty contribution. The uncertainty contribution of *Building Operation* is gradually increasing from BDL2 to BDL3, even though its uncertainty is remaining at ± 5% in both BDLs.

For the designer, this means that by reducing the uncertainty of the grouped parameter *Geometrical*, it is possible to make a much more precise statement about the total lifecycle primary energy demand. This is because the fluctuation range of the results has been highly reduced from ±61% at BDL2 to ±32% at BDL3 when comparing all shapes. With lowering the uncertainty for the mentioned grouped parameter, now *Shape1* and *7* can be seen as the shapes which allow the realisation of better lifecycle-based energy efficiency or to lower the total lifecycle primary energy demand, compared to all other shapes.

Overall, the total primary energy results become much more representable, interpretable and communicable to the designer. To now generate even more precise results for BDL4, the designer should now focus on lowering the uncertainty for the grouped parameters *Geometrical* and *Technical Specifications*. Since the *Geometrical* parameter still has, with ±2% uncertainty, an impact which is not to be neglected, it has to be considered again.

5.3 **Results for BDL4**

With the new, more accurate design information at BDL4 (see Table 6), the uncertainty in the design parameters has now decreased for the grouped parameter *Geometrical* from ± 2% to ±1% and for the *Technical Specifications* from ± 25% to ± 2%.

The interpretation of the results at BDL4 in Figure 5 remains the same. The only change is now a significantly lower interquartile range. Also, the range of the highest maximum and lowest minimum value decreased again, when comparing all building shapes. This was to be expected and represents validation of BDL3.

It can be seen that after reducing the uncertainty for *Geometrical* and *Technical Specifications*, the *Geometrical* parameters have the highest uncertainty contribution, except for *Shape4* and *5*, for which the window construction has the highest contribution. The latter is due to the fact that *Shape4* and *5* have the highest average exterior wall area, i.e. the contribution of the windows is higher than for all other shapes. The significance of the *Geometrical* parameters is interesting since the uncertainty decreased to ± 1% and the uncertainty for the *Window Construction* parameter is still at ± 25%, which illustrates how crucial the parameter *Geometrical* is for the LCEA in our case study. This represents essential information for designers in the early planning stages. Again, contribution by the parameter *Building Operation* increases further.

The designer now has total primary energy values with a highly reduced fluctuation range of the results of ±61% in BDL2 and ±32% in BDL3 to ±21% in BDL4, when comparing all shapes. From this, it can be deduced for the designer that already the initial reduction of the uncertainty of the parameter *Geometrical* caused a minimization of the fluctuation range in the total primary energy results of 29% from BDL2 to BDL3. The reduction of the uncertainty for again the *Geometrical* parameter and the *Technical Specifications* caused a reduction of 11% from BDL3 to BDL4. This again emphasizes the enormous importance of using uncertainty analysis in early design stages, without which the project-specific effect of the *Geometrical* parameter could not have taken place so efficiently, early and quickly.

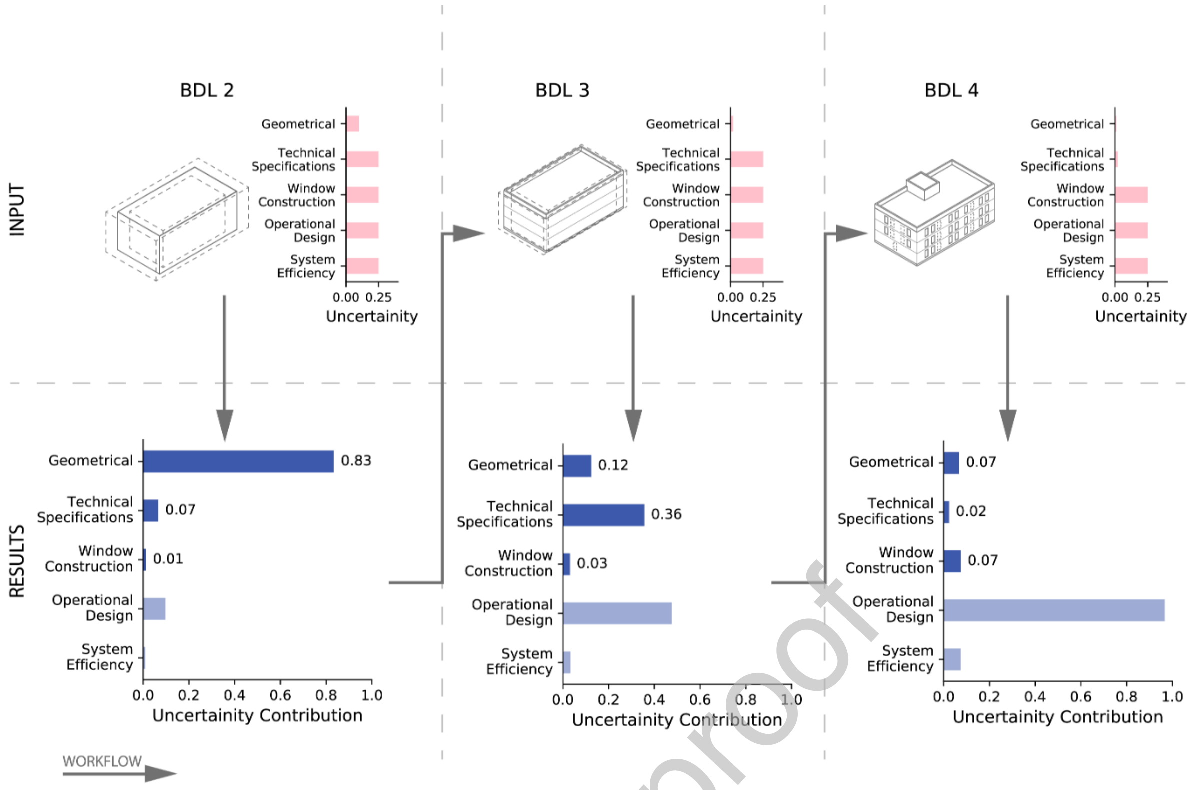

Figure 6 Uncertainty in Parameters and resulting Uncertainty Contribution according to BDL (average all shapes)

6 Discussions

A method for conducting LCEA and uncertainty analysis already in the early stages of building design has been introduced in this paper. Thereby, a possibility to strategically reduce the influence of uncertainties in LCEA-parameters has been described, to show an efficient way to reduce their impact on the LCEA results and thereby to make the results more accurate, precise and better to interpret for the designer.

The minimisation of uncertainties across the BDLs also produces the expected result and additionally shows the expected trends, which means that with decreasing the uncertainty of the grouped parameter with the highest influence, the grouped parameter with the second-highest influence appears as the parameter with the highest influence in the next BDL. Additionally, the inter-quartile range and scattering range of min and max values decrease with lowering the uncertainty along the BDLs. The methodology and calculation results therefore render plausible and expected results and trends. In addition, the graphical representation of the results enables the designer to quickly understand, interpret and communicate the results, concerning the impact of uncertain parameters on the LCEA results as well as the overall LCEA results, in the course of BDLs. This enables the designer to better discuss and justify decisions which have to be or are already made.

Although the selected case is representative, we recommend that the definition of parameters and uncertainties is adapted to the specific project in order to obtain the desired results. However, performing the simulation using EnergyPlus is time-consuming, thus, adapting it to the new case may not be time efficient. Machine learning-based model can be used to make the whole process quick. The methods mentioned in the introduction for quick calculation of operational energy demand as well as the methods presented in this paper's method section to calculate the embedded energy demand based on LCA methods allow for applying the uncertainty analysis for each individual design case. If project-specific uncertainties are determined and used for the respective input parameters, the calculation will give a clear indication which input parameter groups should be decided on and further specified to reduce uncertainties in the energy calculations.

Nonetheless, we expect conclusions on uncertainties and parameters and their groups to be comparable for buildings and climate conditions that are similar to the given case. In the results for the case, the differences between shapes that can be detected are due to the parameters with the highest uncertainty contribution for each BDL, respectively.

It can be noticed that the energy demand across different building shapes varies a lot, thus, shape also contributes to the uncertainty in energy prediction at early stage of design. For BDL2, the geometry of the different shapes causes a higher range for *Shape2* to *6*, as the range of floor areas is larger. The higher mean values for the total primary energy demand for these shapes can be deduced from the fact that these shapes are less compact, i.e. they have a larger exterior all area for the same volume, with *Shape4* and *5* being the least compact. In BDL 3, the geometrical parameters, as described above, still play a role, but technical specifications are more significant than others. Since these parameters concern the exterior building parts to a large extent, compactness of the shapes as described for BDL2 is still an important factor. For BDL4, the higher interquartile range can be derived from the largest exterior wall area, for which the window to wall ratio plays a significant role. Furthermore, the results indicate that operational parameters, such as lighting systems and use of the building, should be considered in early design stages. At BLD 3 these parameters have the highest influence. Designers should consider realistic scenarios to reduce uncertainty.

The results do not significantly differ between shapes due to uncertainty, as the values are overlapping. This means that for relatively simple geometries which are comparable because they render the same floor area, no general recommendation for a building form can be given. In the case of our study, this may mean that the choice between the individual building shapes does not have much influence, but for other projects, building shapes and LCEA parameter definitions may be quite different. To apply the method to other case studies, the new case study has to be checked first, on being able to provide the needed information for the calculation models and second, the LCEA-parameters have to adapted adequately in the calculation models, as already mentioned above. Future research should analyse this further to determine an 'optimized combination' of parameters where trade-off effects apply, e.g. amount of insulation vs heating demand; window-to-wall ratio vs cooling and/or daylight; etc. In Figure 5, at BDL2, a good performance is visible for Shape 2. This parameter combination is lost in the process as currently no optimization assistance for the decisions is implemented.

The results in this paper are presented as a single performance criterion for cumulated lifecycle-based operational and embedded energy, using the total primary energy demand as an indicator. In light of the pressing environmental problems related to climate change, global warming potential needs to be investigated in addition. This, however, requires the inclusion of variations in energy supply systems, as they strongly influence the amount of greenhouse gas emissions.

7 Conclusions

From the study's results, it can be concluded, that it is very important to provide modelling approaches and calculation methods to conduct LCEA already in early design stages, to provide designers results for the lifecycle-based energy demand of buildings, which can be improved in further steps. However, the presented results show that there is a significant influence of uncertain parameters on the LCEA in early stages of design. It is therefore essential to also provide methods and calculation approaches to the designer, to perform uncertainty analysis, to assess the impact of the uncertainties on the LCEA results, as well as to identify the uncertain parameters with the highest impact on the calculation

This information is highly valuable for the designer not only to prioritize decisions to decrease uncertainty and its impact on the LCEA results, but also to communicate and discuss results and decisions with the client or future building owner. It additionally enables the designers to analyse individual building cases in the course of BDLs and to provide the information in the transition along the BDLs that best reduces uncertainty. The LCEA results of each BDL can influence design decisions. However, the influence on the design decision depends very much on how the designer decides on measures based on the LCEA results of each BDL. In addition to questions regarding the optimisation of the lifecycle-based energy demand of buildings and the reduction of uncertainties in its calculation in early design stages, there are questions regarding, for example, life cycle costs or the statics of the building. These questions and topics can be weighted differently by the designer and result in conflicting goals that have to be investigated and weighed up. Within the framework of this study, no general statements can be made about the influence of the LCEA results in early planning stages on concrete design decisions, since they are highly depending on each specific building, which is being assessed. However, the LCEA results can help the designer to find the right parameters for improving the LCEA results in early design stages and to allow the topic of the lifecycle-based energy demand of buildings to flow transparently and soundly into the planning already in early design stages.

The method renders plausible results, as the reduction in uncertainty and the increasing accuracy of LCEA-parameters reduces uncertainty in the overall results without changing average results. For future assistance in the design process, the representation of additional information will be required as to which parameter combinations provide the lowest total primary energy values.

For further research, it is therefore important, to refine the existing method and models to enable possibilities for design assistance. For this purpose, various combinations of building-specific energy supply models and construction and insulation materials have to be investigated and analysed along their whole lifecycle. Additionally, the presented and mentioned methodological approaches need to be implemented in a user-friendly and easy to use tool for designers, which can be embedded in BIM-Software. Due to the easier usability the tool is used more and therefore more results and analyses can be carried out. From this, guidelines for designers can be derived which presents on which parameters to focus first to reduce the uncertainty in LCEA in early stages of design. In addition, an important future step in the development of an assistance approach to support the designer in the design process is the development of lifecycle-based energy-efficient buildings. The method presented in this study thus contributes significantly to establishing and implementing energy efficiency in the building sector and also points out concrete applications.

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