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Assessing the gap between a normative and a reality-based model of building LCA

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Abstract: Recognized as a powerful methodology for the evaluation of environmental burdens, life cycle assessment (LCA) must be performed with close-to-reality inputs to be robust and accurate. However, the necessary real-world data is hardly available at the design stage, resulting in current LCA practice being mainly based on standards and norms as hypothesis of building contexts, therefore inducing uncertainties in results. The current paper presents a methodology to collect a subset of such input data in a function of the context more accurately than the standards. It then studies the impact of such uncertainties in the LCA results. Through an academic building case study that measured data concerning the building occupancy (A), i.e. the hourly occupancy rate and density, the hourly appliance consumption rate (B), and the hourly conversion factors of environmental impact of the electricity mix (C), the LCA results for the GHG emissions and primary energy consumption are compared between normative- and measurements-based input parameters. The measured occupancy rate (A) is shown to impact the LCA results the most, especially the embedded impacts, by implying a new occupancy density: the building population increase of +32% leads to a significant increase of the embedded impacts related to furniture. The variability in appliance usage (B) is marginal between measures and standards and therefore does not lead to a significant change in LCA results. The use of hourly conversion factors (C) indicates an underestimation of the GHG emissions and, at the same time, an overestimation of the primary energy when assessed with mean annual values. The combined effect of simultaneously using the three reality-based input parameters (A, B, C) mostly affects the non-renewable part of the cumulative energy demand indicator (-9% reduction of the operational part), followed by the cumulative energy demand (-7%) and GHG emissions indicators (-3%). The research findings affect not only LCA research but also practitioners such as architects or building contractors who need to respect ambitious environmental targets.

Keywords: building; LCA; environmental performance; sensitivity analysis; close-to-reality assessment

Highlights:
* Novel approach using sensed data replacing normative coefficients in building LCA.
* Applicable to different dimensions affecting operational and embedded impacts.
* Applied to occupancy profiles and density, appliance profiles, electricity GWP.
* Demonstrates significant impact of occupancy density on building LCA.
* Reality-based appliance or occupancy profiles have less significance on building LCA.

Nomenclature

Abbreviations:

BED	Building energy demand
BES	Building energy system
CF	Conversion factor
DHW	Domestic hot water
EE_{Bldg}	Building embodied impact
EI	Environmental impact
G	Grid
HTS	Hourly time step
LCA	Life cycle assessment
NZEB	Net zero energy building
OI	Operative impact

Physical values:

CED	Cumulative energy demand	(kWh_{eq}/year*m^2)
CED_{nr}	Non-renewable part of the CED	(kWh_{eq}/year*m^2)
E	Energy	(MJ)
f_{ap}	Hourly appliance use rate	(-)
f_{occ}	Hourly occupancy rate	(-)
GHG	Greenhouse gases	(kg $CO_{2\ eq}$ /year*m^2)
GWP	Global warming potential	(kg $CO_{2\ eq}$ /kWh)
P_0	Nominal occupancy density	(m^2/p)
P_0	Nominal occupancy density	(m^2/p)
P_a	Nominal appliance power density	(m^2/p)

1. Introduction

During the design phase of buildings, common use includes the utilization of national standards to assess the life cycle performance of future constructions. Even if these standards provide a somehow realistic description and input data for life cycle assessment (LCA) purposes, they do not strictly correspond to what would happen in reality for a given specific building. Also, all significant contributors to environmental impacts should be included within the boundary of assessment. Therefore, a gap in the life cycle performance exists between those assessed during the design phase and the real operation of the building.

Nowadays, building planners can potentially collect and use more and more real-world data. The nature of such collected data ranges from user habits – such as the occupancy rate in the built environment (Verma et al., 2017) or the intensity of the use of appliances (Vuarnoz et al., 2019) – to energy carrier descriptions, with primary energy factor and emission factor better defined locally or temporally (Vuarnoz and Jusselme, 2016). The present paper investigates the impact on the building's LCA of using these input parameters instead of those provided by the technical standards. More generally, it deals with the uncertainties of input parameters on building LCA results.

Uncertainties are generally of crucial importance in LCA, and neglecting them or merely mentioning them is not sufficient (Norris, 2002). Early LCA studies in the literature treated the sources of uncertainties by classifying them in different groups (Huijbregts, 1998; Björklund, 2002). Hence, researchers focused their efforts on the development of methods for the evaluation of uncertainties in LCA results. Heijungs and Huijbregts (2004) reviewed the sources of uncertainties in LCA and methods used in other sciences for their assessments. In conclusion, they proposed distribution laws for the inputs and most suitable methods appropriate in the field of LCA. Despite their objective of being as general as possible with application in LCA of products and processes, these references were found to have limited applicability to the field of building design.

Various authors (Kohler, 2012; Leung et al., 2015) have recently highlighted LCA in buildings and its level of reliability. Some authors focused their research on identifying the biggest source of inputs' uncertainties on results (Ruiz et al., 2012; Hoxha et al., 2017; Häfliger et al., 2017).

In the building context, environmental impacts are typically divided into embodied impacts (related to the construction or the infrastructure) and operational impacts (related to the use of the building). Hoxha (2015) proposed an analytical method based on Taylor series expansion and the ANOVA method to address the evaluation of the embodied impacts' uncertainties. The impact of the lifetime of the materials has been investigated thoroughly by Blengini and Di Carlo, (2010) and Aktas and Bilec (2012). Both studies found that the variability due to these sources of uncertainties was in the range of 20% around the mean value. In order to improve the uncertainties linked to building lifespan, Hoxha et al. (2016) recommended the evaluation of the environmental impacts of a building for a range of values of the lifespan and not for a specific one.

Concerning the assessment of the operational impacts, conversion factors (CFs) are commonly used to convert final energy consumption into environmental indicators (EU, 2010). If average CFs are appropriate when describing thermal carrier and renewable supply, the approach does not reliably apply to the majority of electricity mixes (Schafer et al., 2018; Messagie et al., 2014; Kopsakangas-Savolainen et al., 2017). Also, the impact on the LCA results of buildings using mean annual CFs instead of hourly CFs has been evaluated by Vuarnoz and Jusselme (2018), Spork et al. (2014) and Roux (2016) and shown to be significant. Lu et al. (2013) proposed a method for the evaluation of uncertainties in energy consumption. Among the input parameters considered in sensitivity analysis, Ruiz et al. (2012) found climate as a parameter influencing the energy consumption of a building the most. Thermal transmittance of envelope and appliance load uncertainties are also found of crucial importance. Escamilla et al. (2017) proposed the use of geographic information systems to reduce the sources of uncertainties linked with geographical sources. Bonte et al. (2014) studied the influence of the behaviour of the building occupants in energy consumption and recommended that all evaluations must consider accurate profiles of the occupants for minimizing uncertainties of the results. Zhao et al. (2014) proposed a more detailed user behaviour profile for offices. In the definitive, the difficulty in accurately predicting how the building will effectively be used generates a gap between the assessments performed during the design phase compared to the real energy consumption of a building in operation. This has been identified in the building energy literature as the "performance gap", with numerous related publications (De Wilde, 2014; Cozza et al., 2019).

Despite the limited extent of the above survey of the state of the art, the question of the consequences of replacing key input parameters on the LCA results, typically replacing standard values with recorded data, has not yet been thoroughly studied. In the present study, real-world recorded data has been selected because of its current technological availability and potential to be accessible in practice. This approach aims to reveal the amplitude of input inaccuracies when using standard values as well as the magnitude of their impact on the LCA results. Through the help of a case study, a baseline evaluation is firstly performed with Swiss standards. The results thus obtained are then compared with those resulting from using the given reality-based input parameters. Through systematic, iterative changes and a combination of all key input parameters, their impact on the LCA results is analysed. Although the study restricts itself to a specific case study, as well as to a limited set of reality-based input parameters, the described methodology remains applicable to other contexts, both in terms of the case study building and variety of input parameters, towards the aim of solely including input data stemming from contextual field recordings.

2. Method

The goal of this work is to establish and interpret the magnitude of change in the building LCA results when replacing given inputs' parameters taken up from standards through real-world data collected in the context of the project. First, a case study consisting of a building project is addressed. An initial LCA assessment is performed on the basis of an architectural feasibility study. National standards belonging to the country in which the building is considered are used to detail the building context. This baseline represents the common current practice of building planners at the design phase.

In a second step, we identify which input parameters can be replaced by a more realistic one. Input parameters used for the LCA of the buildings come from either the architectural draft or from the standards (see Figure 1). For those belonging to the standards, those that are susceptible to being contextually refined by real-world data are identified by the technological availability to collect them (indicated in red in Figure 1). The data is then collected at the closest proximity to the context of the construction project, with the term "closer proximity" being understood in temporal, spatial and/or social terms, e.g., as close as possible to the intended building in its location, point in time and in the population concerned. The LCA is then performed in turn, each time replacing the considered standard value with the quantity collected in real-world conditions. A final LCA is performed with all the considered quantities changed – from standards to collected data – and combined.

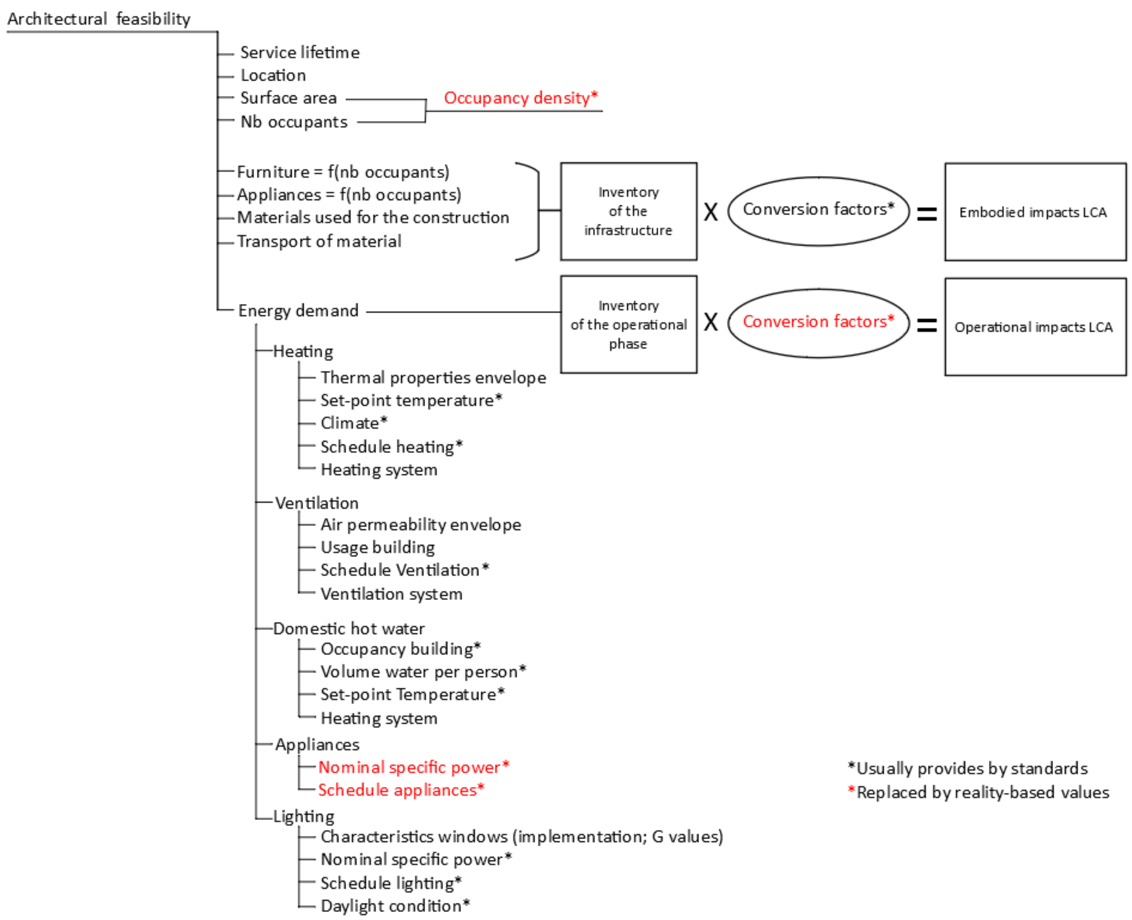


Figure 1: Synthesized overview of the required input parameters when performing building LCA.

Once the results are gathered, the interpretation of the changes in the obtained LCA results is performed. The impact of each replaced input data can then be evaluated with the realistic amplitude of change between standard values and real-world data. Based on the classification of the different magnitudes of changes, recommendations should reveal which input parameters have real importance on the building LCA results, within the framework of this case study.

The environmental impacts of a building and its systems are assessed according to the CEN standards (EN-15804, 2011; EN-15978, 2011) and those of appliances and furniture according to the ISO standards (ISO-14040-44, 2006). Within the system boundary, the impacts of all lifecycle stages of a building are considered to include the product stage, construction stage, use and exploitation, and end of life. In addition, the environmental impacts of furniture and appliances are also included. The functional unit considered is a square-meter energy floor area per year (m^2 ERA/yr), and the reference study period of the building is considered 60 years (SIA-2040, 2011). The life cycle indicators investigated are those suggested by the 2000-watt society vision (Jochem et al., 2004) and, more specifically, the Swiss standard SIA-2040 (2015), which relate to primary energy use (CED) and its non-renewable part (CEDnr) (Bösch et al., 2007; Frischknecht et al., 2007), both in kWh_{eq}/year-m^2 and GHG emissions in kg CO_2-eq /year-m^2 (IPCC, 2007). These indicators, which have also been used in various previous LCA research (Passer et al., 2012; Ferreira et al, 2018; Mateus et al., 2019; Thibodeau et al., 2019), are particularly needed in the construction sector for certification procedures (e.g., EU, 2016; SIA, 2017) and for sustainability assessments for quality labels, such as LEED (US Green Building Council, 2018), HQE (Alliance HQE-GBC, 2018), or BREEAM (Building Research Establishment, 2018).

The Swiss KBOB database (2014) is used for the evaluation of the environmental impacts of the building. Evaluated in accordance with the CEN standard (EN-15804, 2011), this database contains information about the environmental impacts of building materials and components. Representative of the Swiss context, it covers information for the production and end-of-life stages. Identified as negligible (Lasvaux, 2010), the impacts of the construction phase are considered by increasing the impacts of the production phase by 5%. For the use phase of the building, the replacement of the materials and components is considered based on their reference service life (Hoxha and Jusselme, 2017). The impacts of furniture and appliances are evaluated based on the information already published in the literature (Hoxha and Jusselme, 2017; Hoxha et al., 2020).

3. The case study

An appropriate case study consists of a building project in which the different quantities used as input parameters for LCA are known more specifically than the proposed values given by the standards in force in the concerned location. This is the case of the future smart living lab building, an inter-institutional research and development centre for sustainable building currently at the design stage. Its completion is planned for 2022 in Fribourg, Switzerland. The building will host researchers and their experimental setup, as well as the monitoring of operational performance in real-use conditions (Jusselme and Vuarnoz, 2016). Before the completion of the building, the smart living lab staff is working in a temporary office named Blue Hall, which is at a direct proximity to the construction site. Therefore, the case study fulfils the “close proximity” criteria of the methodology by involving (1) a population of occupants at least similar to the future occupants, if not to a certain proportion identical, (2) a spatial context in direct spatial proximity to the planned building, and (3) a distance in time of three to four years which would be difficult to diminish given typical construction time frames.

An architectural feasibility study of a smart living lab (Jusselme et al., 2016) is used to evaluate the environmental impacts for a reference service life of 60 years, as indicated in the Swiss norm (SIA-2032, 2010). The proposal architecture has a cuboid shape made of seven floors with a footprint of 22 x 29 m, without underground parking. This project, with an energy reference area of 4355 m², consists of the superposition of a generic floor that is composed of a combination of spaces with different destinations of use (offices, meeting rooms, toilets, and circulation) and a cafeteria, restaurant and technical rooms on the ground floor. The major axis of the building is shifted by 15° (anticlockwise) with the north coordinate. A square meter of energy reference area per year [m² ERA/year] is considered as a functional unit.

Windows are sized to correspond to 35% and 40% of the façade, respectively, for the ground floor and for the rest of the building. In line with the products currently available from the market (Jelle et al., 2012), triple-glazed windows (U value: 0.78 W/m^{2}K; thermal transmittance: 0.66) mounted with PVC frames are considered in the case study. External walls and the roof have a U value of 0.156 and 0.153 [W/m^{2}K], respectively, and comply with the SIA standard (SIA 380/1, 2016).

A ground-source heat pump with a coefficient of performance of 4.5 (Sarbu and Sebarchievici, 2014) is considered for the space heating and domestic hot water (DHW) demand. Heat pumps are currently the most popular systems installed in new energy-efficient buildings in Switzerland (Jusselme et al., 2015). Mechanical ventilation with heat recovery is planned to guarantee air quality to the users. The efficiency and final energy of the lighting system are assumed to correspond to the Swiss standard SIA 2024 (2015).

3.1 Normative model

All detailed assumptions and hypotheses of the normative model are presented in Hoxha et al. (2016). Also considered in the boundary of assessment are the appliances and furniture, of which the environmental impacts are evaluated according to norm IS0-14040-44 (2006).

The occupancy density provided by the Swiss standard SIA2024 (2015) proposes a value of 14 m^2/person, which leads to a baseline population of 195 people working in the building. No particular challenge in the design of the workspace is addressed by this usual occupancy density; therefore, no floor plan layout has been worked out. The same standard provides the hourly schedule of the use of appliances, the occupancy rate and all the other quantities mentioned in Figure 1.

Except for the solar thermal system, the sole source of external energy is electricity; therefore, the characterization factors of the Swiss mix used in this study are those from the KBOB database (KBOB, eco-bau et IPB, 2014). In these assessments, a workplace is planned for each of the 195 co-workers. Tables 1 and 2 present the inventory of the materials of the case study.

Table 1: Quantity of reference of the case study.

Inventory	Quantity	Unit
Excavation	311	m^3
Ground floor	622	m²
Structural materials	302	m^3
Stairs	205	m²
Internal floor	3540	m²
Roof	622	m²
External walls	431	m²
Windows	668	m²
Elevator walls	516	m²
Internal partitions	3844	m²
Doors	232	m²
Ventilation system	4355	m²
Heating system	4355	m²
Electrical equipment	4355	m²
Sanitary equipment	4355	m²

Table 2: Constitution of the main building components taken as a case study.

Elements	Materials	Quantity [kg/m^2]
Separator walls	Plasterboard (5 cm)	42.5
	Wood lath (6/6 cm)	5.1
	Glass wool (5 cm)	0.9
	Plasterboard (5 cm)	42.5
Internal walls	Gypsum fiber boards (1.25cm)	15
	Wood lath (16/6 cm)	7.8
	Glass wool (12cm)	7.2
	Gypsum fiber boards (2.5cm)	30
	Glass wool (4cm)	2.4
	Gypsum fiber boards (2.5cm)	30
	Wood lath (16/6 cm)	7.8
	Glass wool (12cm)	7.2
	Gypsum fiber board (1.25cm)	15
External walls	Wood covering (1.5 cm)	7
	Polyethylene sheet (0.02 cm)	0.2
	Chipboard (2.7 cm)	16.7
	Cellulose panel (λ=0.062 W/m K)	40.5
	Wood lath (12/35 cm)	29.57
	Chipboard (2.7 cm)	7.3
	Wood lath (4/6 cm)	1.7
	Wood covering (2.4 cm)	11.3
Roof	Gravel (8 cm)	160
	Bituminous sheeting (0.8 cm)	4.6
	Cellulose panel (λ=0.062 W/m K)	41.4
	Bituminous sheeting (0.3 cm)	2.3
	Wood covering (2.4 cm)	12.7
	Wood lath (12/18 cm)	15.2
Internal slabs	Wooden beams (18x60cm each cm)	72.85
	Precast concrete slab (10 cm)	277
	Linoleum (0.025 cm)	2.9
Slab	Cement screed (8 cm)	148
	ABS	1
	Polyethylene sheet (0.02 cm)	0.2
	Polyurethane (λ=0.032 W/m K)	3.6
	Bituminous sheeting (0.4 cm)	4.6
	Concrete (25 cm)	700
	Steel	20
	Poor concrete (8 cm)	175.2

Table 3 summarizes the quantity of furniture and appliances for each kind of office considered inside the building. Details of the environmental impacts of furniture and appliances can be found in Hoxha et al. (2017).

Table 3: Furniture and appliances of the offices and meeting rooms considered in the case study.

Item	Office 1 person	Office 2 people	Office 3 people	Office 5 people	Meeting 6 people	Meeting 9 people
Work table	1	2	3	5	3	5
Meeting table	1	0	0	0	0	0
Work chair	1	2	3	5	0	0
Meeting chair	4	0	4	4	6	9
Metal tambour	2	2	5	5	1	1
Monitor	1	2	3	5	0	0
Laptop	1	2	3	5	0	0
Work station	1	2	3	5	0	0
Keyboard	1	2	3	5	0	0
Mouse	1	2	3	5	0	0
Whiteboard	1	2	3	3	4	4
Clothes hanger	1	1	1	1	1	1
Coffee machine	0	0	0	0	1	1
Boiler	1	1	1	1	1	1
Desk lamp	1	2	2	5	1	1

The future final energy consumption of the case study is assessed with the EnergyPlus (2018) simulation engine. From the aggregated annual amount of energy demand, the values are then converted into primary energy and its non-renewable part and the corresponding GHG emissions through the use of mean annual conversion factors given by the Swiss database KBOB (KBOB, eco-bau et IPB, 2014).

3.2 Reality-based model

The case study building has been selected for its specific ability to provide information on several input parameters used to perform its LCA. These input parameters can thus be refined in the function of the context. In the Blue Hall, a population that is representative of population of the future research centre is already present and active in the proximity of the future building site. This offers the possibility to gain knowledge about the building usage habits, with the hypothesis that these habits will only undergo relatively small changes in the new building.

The occupancy density of the current temporary office is envisioned to be the same for the new building. Also, the current coworkers' work schedule is assimilated to be the same as in the new building. Consequently, measurements of hourly occupancy rate and appliance usage have been performed at the Blue Hall. In Figure 1, the different input parameters concerned with a change from standards to reality-based values are indicated with a red star. In the following sub-sections, we detail the way these close-to real-world input parameters have been collected.

3.2.1 Measurement of the occupancy density

The occupancy density in the future construction is assimilated to that of the temporary offices of the smart living lab located in the Blue Hall. The evaluation has been carried out on the basis of the existing layout of three existing offices. Eighteen desks are at disposal, for a total area of 149.3 m^2, leading to a space use of 8.3 m^2/desk. Extrapolating this value for the six identical floors of offices planned in the considered case study, the complete building would accommodate 258 people. A layout of a generic floor plan considering this occupancy density is shown in Figure 2. Compared to the initial case generated with the occupancy density proposed by the SIA-2024 (2015), the extra embodied impacts corresponding to the office furniture for the 63 additional co-workers are then accounted for in the new refined assessment.

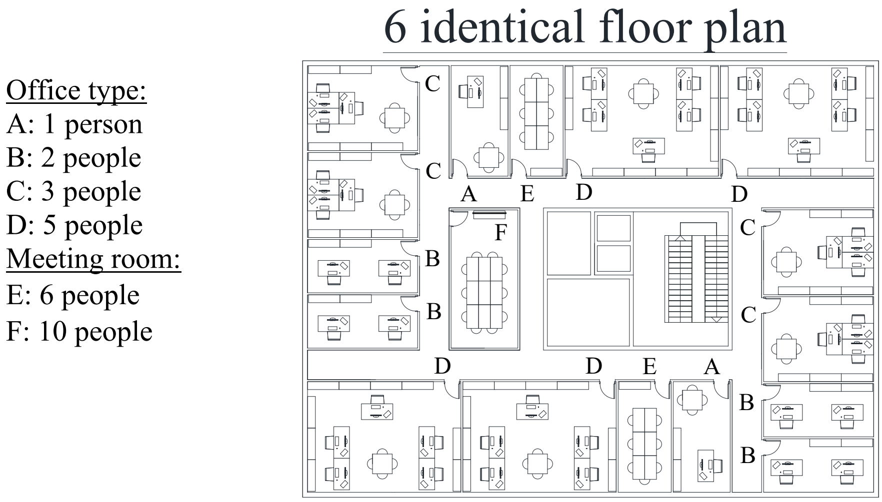


Figure 2: Floor map layout of the case study when considering the new occupancy density (footprint building: 22 x 29 m).

3.2.2 Measurement of the occupancy rate in rooms

In order to measure the occupancy rate in real conditions, a cost-effective method scalable both in terms of study duration and number of participants is used (Verma et al., 2017). Quantitatively accurate data is recorded through Bluetooth low-energy signal strength analysis. Each monitored room is equipped with a data logger (Raspberry Pi 2 Model B) programmed to receive and record Bluetooth packets. Each co-worker allocated to the monitored offices wears a bracelet containing a Bluetooth beacon (EMBC01, manufactured by EM Microelectronics, Switzerland), configured to transmit a signal every second (see Figure 3). By comparing received signal strengths, the system is able to detect the presence of the worker in one office room or the other. The aggregated data thus consists of the number of people physically present in a room at a certain point in time. Two office rooms have been monitored for 12 days at the Blue Hall, providing two different occupancy profiles. These profiles have been distributed randomly in the case study when refining the LCA. Figure 4 represents the two occupancy rates of the building users, assessed respectively by the Swiss standard and direct measurements with a merging process of the two measured datasets. For one day and per investigated room (five-people office), direct measurements result in an occupancy of 20.3 (h*pers) against 23.1 (h*pers) for the SIA-2024 evaluation.

Figure 3: Bluetooth bracelet and data logger (Verma et al., 2017).

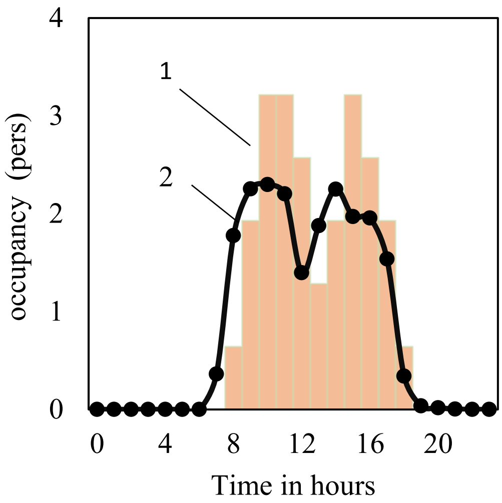


Figure 4: Occupancy rate for a five-people office room, from: (1) Swiss standard values (SIA, 2015); (2) direct measurement (Verma et al., 2017).

3.2.3 Measurement of the intensity of use

The time-dependent specific consumption per work space unit during real working conditions is directly recorded by Z-wave smart-plug devices (ZW075-C10, Aeon Labs LLC) (see Figure 5), and the signals are collected by a Raspberry PI 3 model B V1.2 during a period of three weeks for 12 co-workers located in the Blue Hall (January, 2017). We assume that a three-week period is enough to obtain a good overview of the monitored data; however, seasonal variations might limit the generalization of the results. Also, as it was a challenge to keep participants on board for three weeks, increasing the monitoring period was not an option. The raw data series are segmented into daily traces, which are aggregated into daily profiles by K-means clustering using the silhouette metric to identify the optimal number of clusters (Rousseew, 1997). Four distinctive clusters – describing four daily power consumption patterns of office co-workers – have been identified. To use these clusters for the case study considered, the obtained patterns of appliance usage are allocated proportionally to the planned full amount of office members. Finally, the location of work is randomized into different rooms, and the pattern representing the population per room is aggregated. The aggregate results of the four clusters are presented in Figure 6 and compared to values given from Swiss standard SIA-2024 (2015).

Figure 5. Z-wave measurement device.

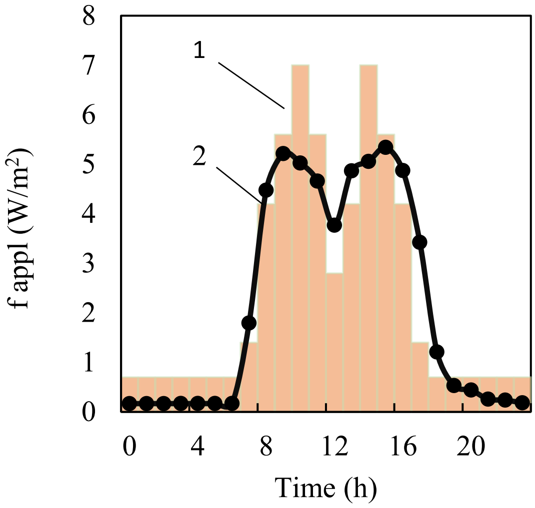


Figure 6. Appliance energy use profile according to (1) the Swiss standard (SIA 2015); (2) the aggregated and clustered measures at the temporary offices of the smart living lab.

As seen in Figure 4, the standby mode of appliances during the night is over-estimated in the Swiss standard SIA-2024 (2015). The effective nominal energy density (p_a) measured in the temporary SLL office is, respectively, 5.34 [W/m^2] against 7.00 [W/m^2] for the Swiss standard value (SIA-2024, 2015). Over one day, the standard-based assessment leads to 58.1 [Wh/pers] against 52.5 [Wh/pers].

3.2.4 Life cycle conversion factors of the grid mix

Based on the attributional approach and a cradle-to-grave life cycle boundary system, hourly electricity conversion factors more accurately describe the grid mix than do annual factors. Since the electricity consumption of a building varies with time, the environmental impacts related to the operational phase of a building assessed by combining the hourly variation of electricity consumption with the hourly electricity life cycle conversion factors are more accurate than the usual evaluation with mean annual values (Kopsakangas-Savolainen et al., 2017; Vuarnoz and Jusselme, 2018).

As the case study is located in Switzerland, we propose refining the LCA of the operational phase of the building by replacing the mean annual conversion factors of the Swiss electricity mix (KBOB database; KBOB, eco-bau et IPB, 2014) with the hourly values proposed by Vuarnoz and Jusselme (2018) for the year 2015-2016.

3.3 Overview of the investigated alternatives of assessments

The methodology to assess the impact of the reality-based approach proceeds as follows: (1) a baseline is fixed and consists of taking input parameters from national standards (Case 1 in Table 4); (2) consecutive changes in the choice of concerned input parameters generate three other scenarios of assessment (Cases 2-4 in Table 4); (3) the last scenario consists of taking measurement values for both the occupancy and the appliance use and hourly data for the conversion factors of the grid mix (Case 3 in Table 4). The aim of the intermediate scenarios is to analyse and evaluate the sensibility of each input parameter.

Table 4: Overview of the scenarios investigated in the study.

Case	Occupancy		Appliances		Grid	
	SIA	Measurements	SIA	Measurements	Yearly	Hourly
1.	x		x		x	
2.		x	x		x	
3.	x			x	x	
4.	x		x			x
5.		x		x		x

4. Results

4.1 Impact on the provisional building energy consumption

The annual building energy demand assessments obtained for each change of input parameters (Table 4) are presented in Figure 7. As the building energy demand is expressed in final energy, the change in the conversion factor of electricity (4) does not affect the results, which are equivalent to the baseline results (1).

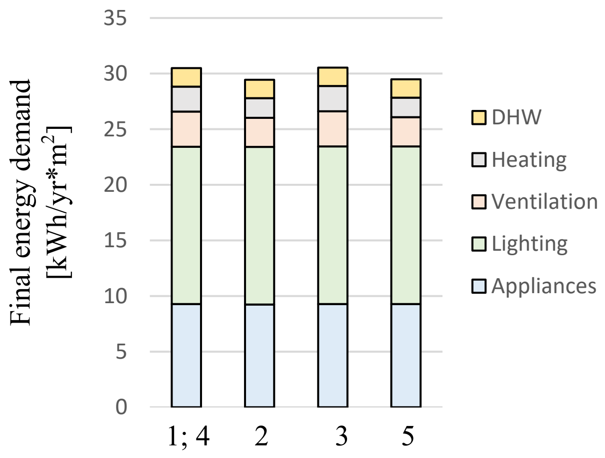


Figure 7: Building final energy demand resulting from the different input parameters detailed in Tab 4

Figure 7 shows that appliances and lighting are the most demanding end-use sectors, which is common for many recent and efficient constructions in temperate climates (Jusselme et al., 2015). The refinement of the occupancy rate shows a greater influence than the change of appliance usage. The combination of all changes (scenario 5) shows a 3% decay in the annual final energy demand compared to the baseline (scenario 1). When it comes to the daily patterns of energy consumption (see Figure 8), substantial differences are noticeable in the appliance usage, where the SIA norm clearly decreases their consumption for the lunch break, which is not the case in the data measured.

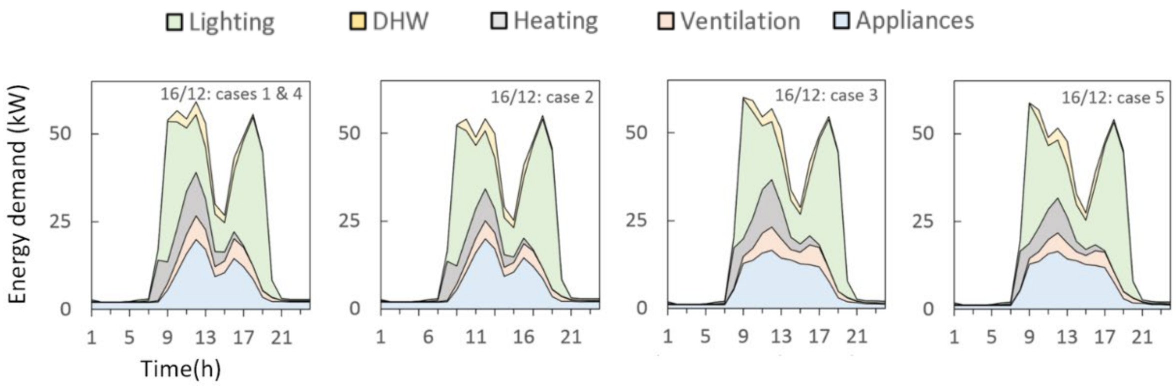
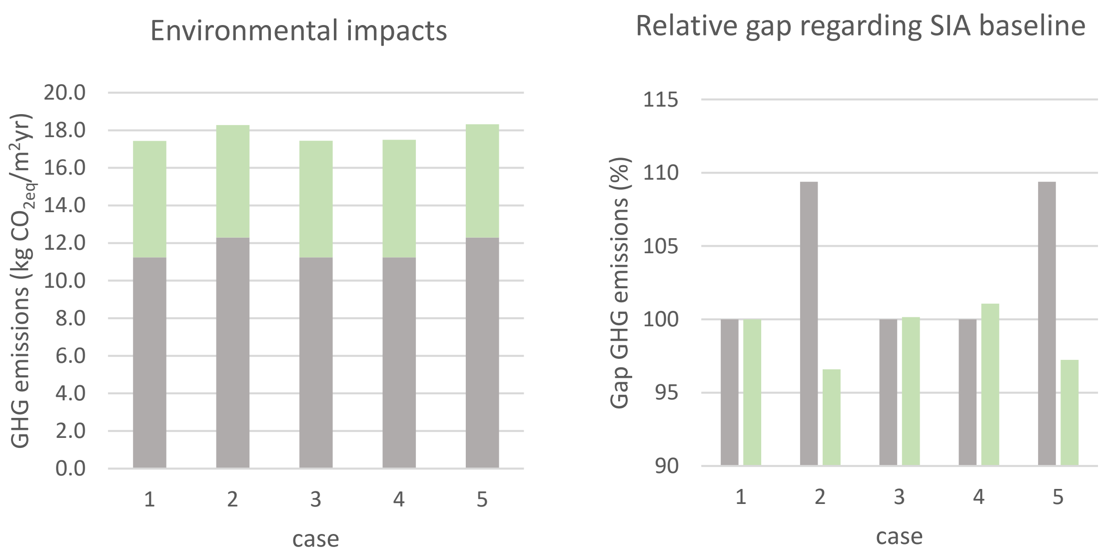


Figure 8: Daily simulated energy demand for a given day (18/12) evaluated with different input parameters according to Table 4. End-use sectors are coloured with respect to the legend of Figure 7.

4.2 Impact on the primary energy and GHG emissions

The primary energy and its non-renewable part (respectively, CED and CEDnr), as well as the GHG emissions obtained for the different alternatives of assessment (Table 4), are presented in Figure 9 (left), while Figure 9 (right) represents the relative gap obtained for each indicator for both the embodied impacts and the operational impacts. The primary energy and its non-renewable part (respectively, CED and CEDnr), as well as the GHG emissions obtained for the different alternatives of assessment (Table 4), are presented in Figure 9 (left), while Figure 9 (right) represents the relative gap obtained for each indicator for both the embodied impacts and the operational impacts.



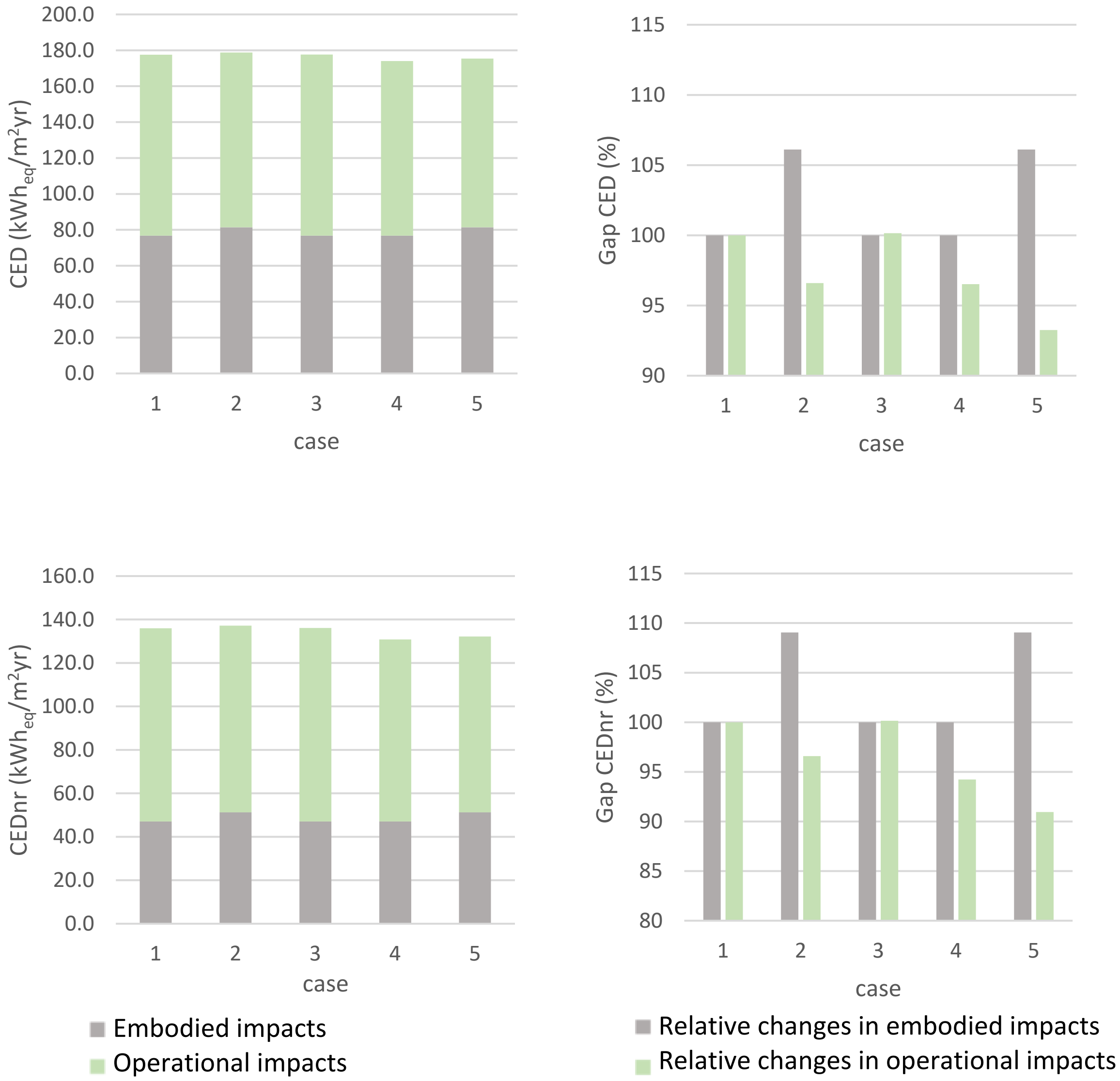


Figure 9: GHG, CED and CED$_{nr}$ assessments according to different input parameters detailed in Table 4 (right), gap in (%) of the change in the obtained results regarding the nature of the considered impact (left).

5. Discussion

At the scale of the complete life cycle analysis, the major impact induced by changing the SIA standard hypothesis to real measured data is observed for the GHG emissions, with an increase of 5.2% of the total emissions between scenarios 1 and 5. This difference results from the recorded increase in the number of building occupants and their related furniture. This contributes to a 9% increase of the embodied impacts, while these embodied impacts represent by themselves two-thirds of the total GHG emissions. This impact is far from being negligible, as it is known that the GHG emissions mitigation is the main challenge for the 2050 climate targets compared to CED and CEDnr (SIA, 2017). This difference in occupancy ratio has lower consequences on the CED and CEDnr performance because, for these indicators, the embodied impact represents only one-third of the total.

This finding confirms the relevance of extending the performance assessment at the life cycle scale and extending the scope of assessment to the furniture. Indeed, a conventional operational performance assessment would have missed this relevant point due to the discrepancies between the data of the grid mix, i.e. the mean annual characterization factors of the KBOB database (KBOB, eco-bau and IPB, 2014) and those published by Vuarnoz and Jusselme (2018) at the hourly time step. For the primary energy consumption, the highest differences do not appear with the cumulative scenario (scenario 5), but with the hourly grid (scenario 4): up to -3.9% for CEDnr and -2% for CED. This highlights the fact that the cumulative scenarios erase part of the differences, and uncertainties are not always cumulative.

The introduction emphasized that the sources of uncertainties were in the range of 20% around the mean value. Accordingly, all result variations unveiled in the presented study can be considered as substantial, as they affect up to 5% of the total impact. In order to make this variation more meaningful to an architect or a building engineer and better illustrate these uncertainties, comparing the GHG emission differences with other ranges of magnitude is suggested. In the considered case study, the building energy reference area is 4355 m², and the difference between scenarios 1 and 5 is 0.9 kg $CO_{2\text{-eq}}/m^2yr$, resulting in a difference in assessment of 235,170 kg $CO_{2\text{-eq}}$ for the whole building surface and its 60-year lifespan. Thus, in the considered case, changing standard values by close-to-reality data corresponds to three full years of the building GHG emissions, or to a gasoline car driven for 730,000 km, according to the KBOB database (KBOB, eco-bau et IPB, 2014).

6. Conclusion

In this article, we aimed at highlighting the sensitivity of the environmental building performance (namely the GHG emissions, CED and CEDnr) to the building context, generally described by standards as inputs of simulation tools. To that end, a comparison with close-to-reality inputs has been performed through a case study, where building occupancy, hourly appliances' consumption rate, and hourly conversion factors of environmental impacts of the electricity mix were available. Changing one hypothesis at a time and cumulating all of them allowed the investigation of their relative impacts on the LCA results by illustrating similarities and differences within the results.

Although the results are bound to the considered case study and therefore lack the potential for generalization, they demonstrate that the observed occupancy density difference of the standards has a major impact in terms of the GHG emissions prediction, specifically for the embodied impacts of the furniture that are associated with every building occupant. Regarding appliance usage, minor variations were observed at the yearly scale, while substantial differences were noted at the hourly time step, specifically during the lunchtime, where, contrary to the standard, no power decrease was observed. At the life cycle scale, the assessment of the cumulative changes brings a difference of 5% in the results. This result is significant, considering that only three hypotheses have been compared to close-to-real data among the dozen hypotheses used in building performance simulation (see Figure 1).

This paper also presented a methodology to gather and include real-life data whose availability is likely to increase in the future thanks to the Internet of Things and new monitoring techniques. This approach bears the potential to improve LCA accuracy and should be of great interest for architects and engineers who need to demonstrate the environmental performance of their projects from the design to the operational phase.

The order of magnitude of the gap between norms and reality highlighted by this study calls researchers and engineers to use as much data as possible data from real measurements within the scope of their analysis. This study shows the possibility to improve the reliability of assessment by using a real-based model with dynamic LCA data and calls for future research by using distribution laws for representing the uncertainties of inputs.

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