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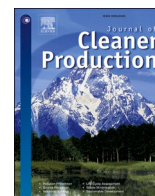
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Assessing and comparing the environmental impact of smart residential buildings: A life cycle approach with uncertainty analysis

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ABSTRACT

While there is an increasing integration of connected devices in buildings to reduce energy consumption, little evidence exists regarding the effective environmental impact of the smart devices installed. One goal of this study is to comparatively assess the impact of integrating connected devices on the environmental performances of existing buildings. Additionally, it aims to discuss the added value regarding environmental performance between a strategy of integrating connected devices and a refurbishment strategy. A non-refurbished connected building will thus be compared with a non-connected refurbished building. The approach's novelty lies in carrying out an uncertainty analysis, which addresses uncertainties in the environmental modelling of sensors, heating gains, and other influential building parameters, such as occupancy scenarios and building lifespan. The Life Cycle Assessment model is built on the results of a dynamic building energy simulation and integrates environmental data on connected devices fromecoinvent. Environmental indicators are calculated using ImpactWorld+. The methodology is applied to a multi-storey residential tower in France, characterised by a low insulation level. The alternatives compared include the original building without sensors, two connected alternatives (monitoring and management) that lead to a reduction of heating loads by 10 and 30% respectively, and a refurbished alternative. Results confidently show that using connected devices is always better than keeping the original building state. Yet, refurbishing the building is the preferable option across almost all indicators. Finally, the results point out that energy gains allowed by connected devices should be better quantified in further work through measurement campaigns.

1. Introduction

1.1. Context of smart building LCA

The building sector is responsible for more than 35% of global energy consumption (International Energy Agency, 2019). The contribution of the operational phase has been significantly reduced in recent buildings such as low-, near- or zero-energy buildings (Chastas et al., 2016; Röck et al., 2020). However, the European building stock is quite old, with more than 60% having been built before the 1960s, and more than 80% having been built before the 1990s (BPIE, 2011). In addition, the renovation rate is very slow as efficient renovations, which are able to reduce the energy consumption by more than 60%, concern only 0.2% of the European building stock yearly (European Parliament and European

Council, 2020). Therefore, achieving energy conservation during the use phase is still a key factor to tackle energy and environmental issues, especially in buildings to be renovated. Over the last decades, the Building Internet of Things has sped up the development of user-centric building energy management systems (Moudgil et al., 2023; Pasini et al., 2016). These systems rely on a network of sensors and actuators that are supported by algorithms for dynamic energy management. Generally, data collected from sensors can help to (i) study how a building operates (occupancy, residents activities, energy consumption, etc.) and understand user comfort preferences (Amayri et al., 2020), (ii) reconstruct representative time series of the operation of building types to improve the reliability of building energy performance prediction (Amayri et al., 2020; Schalbart et al., 2021), (iii) understand the consequences of the residents actions on their energy consumption to make them change their personal habits (Bavaresco et al., 2019), (iv) monitor and manage

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Acronyms

BEMS	Building Energy Management System
CED	Cumulative Energy Demand
DBES	Dynamic Building Energy Simulation
DRD	Distribution of the Relative Difference
EPD	Environmental Product Declaration
GHG	Greenhouse Gas
GWP	Global Warming Potential
HSM	Heijungs Significance Metric
ICT	Information and Communication Technology
LCA	Life Cycle Assessment
PBT	Pay-Back Time
PED	Primary Energy Demand

technical equipment in real time to provide cost reductions and efficiency gains while enhancing user comfort (Reynolds et al., 2018; Robillart et al., 2018, 2019). For all these reasons and given the ease of application and the reasonable cost of sensors, the digital transition of the building sector is a way to improve building energy efficiency.

As a matter of fact, the trend is towards an increase in the number of smart devices implemented in buildings. However, we lack perspective when it comes to assessing the long-term impacts of these technologies, considering their high replacement rate, their operational electricity consumption, or the energy consumption of data storage. To meet the European energy policy goals, i.e., the achievement of carbon neutrality by 2050 (Regulation, 2021), we must address the issue of the environmental performances of smart buildings during their whole lifecycle. The main risk is a shift in the environmental load, i.e., that the environmental burden due to the production and operation of smart devices outweighs the efficiency gains provided by smart energy management systems.

To mitigate this risk, Life Cycle Assessment (LCA) is the reference framework for assessing the environmental impacts of a system during its lifecycle (ISO 14040, 2006; ISO 14044, 2006). LCA consists of different phases where the goal and scope of the study are first defined, before inventorying the substances emitted to or extracted from the environment. Then, substances are aggregated in the impact assessment phase into many environmental indicators that express the potential of the studied system to cause environmental problems and damages. Results are interpreted at each step of the LCA, which is an iterative process. LCA is commonly used as a comprehensive decision support tool, helping decision makers select the most sustainable alternatives. Dedicated methodologies have been developed since the 1990s to improve the environmental quality of buildings (Peuportier et al., 1997; Polster et al., 1996). The environmental assessment of buildings accounts for the impacts of construction and finishing materials, renovation processes, energy systems, auxiliary equipment, energy consumption and disposal processes. However, few studies have investigated the impact of implementing smart building systems from a life cycle perspective. In this work, a methodology is proposed to perform a comparative life cycle assessment of smart buildings including uncertainties.

1.2. Review of smart buildings LCA

1.2.1. Framework for smart buildings LCA

Regarding the issue of the environmental performances of intelligent building energy management systems (BEMS) compared to non-connected ones, a set of eleven studies listed in Table 1 has been found. The articles were first found based on research on Web of Science and Scopus with the keywords “LCA OR life cycle assessment”, “building OR home”, “connected OR smart OR energy management system OR sensor”, leading to 579 results. After removing articles not in English and

duplicates, the 445 remaining articles were screened by reading titles, abstracts and full texts, as shown in Fig. 1. Only studies focusing on buildings and comparing smart and non-smart alternatives were selected, thus papers on the environmental performances of smart cities (Mujan and Aleksic, 2015; Ringenson and Höjer, 2016; Ipsen et al., 2019), underground stations (Gangoellis et al., 2015, 2016), or home smart objects (Castorani et al., 2018; Pierucci et al., 2018) were discarded. The identified framework for comparing connected and non-connected buildings is structured based on the LCA phases below.

1.2.1.1. Goal and scope of the studies. The selected articles aim to assess the environmental balance between the effects caused by the increasing resource consumption through producing, operating and disposing of a BEMS on the one side, and the direct saving effects that are due to optimise energy management on the other side. Some studies also investigate the influence of higher-order effects (Pohl et al., 2019), such as the rebound effect (Pohl et al., 2021; Scheepens and Vogtländer, 2018; Walzberg et al., 2017, 2020) (when an improvement in efficiency leads to an increase in demand as the savings are reinvested to purchase other products and services), or the influence of user behaviour (Pohl et al., 2022). In the 11 articles, the studied BEMSs aim to optimise either lighting consumption (Kumar and Mani, 2017), global electricity consumption (Louis et al., 2015; Louis and Pongrácz, 2017; Scheepens and Vogtländer, 2018; van Dam et al., 2013a; Walzberg et al., 2017, 2020), or heating consumption (Louis et al., 2015; Beucker et al., 2016; Louis and Pongrácz, 2017; Scheepens and Vogtländer, 2018; Pohl et al., 2021, 2022; Pannier et al., 2022).

Two energy efficiency strategies emerge from the literature: energy monitoring and energy management. In the first case, the building is monitored with ambient sensors and smart meters to provide real-time information on the energy consumption of the building (van Dam et al., 2013a; Louis et al., 2015; Louis and Pongrácz, 2017; Scheepens and Vogtländer, 2018; Pannier et al., 2022). A user interface can advise the occupants on how to achieve energy savings. In the second case, actuators can additionally act on building systems to optimise energy consumption by automatically switching off some devices, based on data collected by sensors. It generally requires smart plugs, the number of which tremendously varies depending on the study (van Dam et al., 2013a; Louis et al., 2015; Beucker et al., 2016; Louis and Pongrácz, 2017; Walzberg et al., 2017, 2020; Pannier et al., 2022; Pohl et al., 2021, 2022).

In order to assess and compare the environmental impacts of various BEMS, the choice of a relevant functional unit is required. It will help to define and quantify the inputs and the outputs of the system under study. In the reviewed articles, the functional unit was defined as “the operation of a BEMS and the achievement of energy savings during its lifespan”. The lifespan of a BEMS is usually considered to be 5 years (van Dam et al., 2013b; Louis et al., 2015; Louis and Pongrácz, 2017; Pohl et al., 2021, 2022). One paper (Pannier et al., 2022) expands the scope of the study to the building level to account for the replacement of Information and Communication Technology (ICT) devices during the building operating lifetime. The environmental balance of the smart building is then performed by comparing its environmental performances during the building’s entire lifetime to that of an identical building with no sensors nor actuators, which serves as a baseline.

1.2.1.2. Life cycle inventory. With regard to the environmental modelling of smart devices, the products are generally assessed from cradle to grave. One of the most recent articles (Pohl et al., 2021) excludes the transportation and End of Life lifecycle stages from the scope of the study as previous works have shown that the production and use phases are the most decisive when assessing the environmental effects of ICT devices (Castorani et al., 2018; Louis and Pongrácz, 2017; Teehan and Kandlikar, 2012). The paper otherwise extends the scope to other

Table 1
Scope and outcomes of the articles related to the environmental performances assessment of smart buildings.

Article	Building typology	Consumption item assessed	Variables	Characteristics of ICT devices			Modelling framework			Results		
				Type	Lifespan	Direct energy savings	LCA software	Environmental database	Environmental indicators	Most impactful lifecycle stages	Pay-back time	Connected alternative better?
van Dam et al., 2013; van Dam et al., 2013a)	Individual house in Nederland	Electricity	Energy savings User involvement	Smart meters Smart plugs	5 years	Between 2 and 10 %	ND	Ecoinvent v2.2	CED Ecocost	Operation (67–78% of the CED) Production (22–33% of the CED)	0–1.5 years	YES
(2015); Louis et al. (2015)	Individual house in Finland	Heating Electricity	Energy savings	Ambient sensors Smart meters Actuators Smart plugs	5 years	ND	SimaPRO	Ecoinvent v3.1	ReCiPe 2008 indicators	Operation (84% of the GHG emissions) Production (15% of the GHG emissions)	ND	YES, for energy monitoring NO, for energy management
(2016); Beucker et al. (2016)	Multifamily housing in multiple locations	Heating	Electricity production mixes Time horizons	Ambient sensors Smart meters Actuators	Neglected	20%	ND	Ecoinvent v2.2	ReCiPe 2008 indicators	ND	ND	YES, especially in regions with GHG-intensive electricity generation
Kumar et Mani, 2017; Kumar and Mani (2017)	Office in India	Lighting	Type of lighting devices Origin of the products	Motion sensors	10 years	Depending on the lighting device	GaBi 6	Ecoinvent v3.1 GaBi 2015	CML 2001 indicators	Production Transport	0.5–11 years	YES, for fluorescent and incandescent light bulbs NO, for LED devices
Louis et Pongrácz, 2017; Louis and Pongrácz (2017)	Individual house in Finland	Heating Electricity	Energy savings Number of inhabitants Variability of the electricity mix	Ambient sensors Smart meters Actuators Smart plugs	5 years	Assessed by DBES	SimaPRO	Ecoinvent v3.1	ReCiPe 2008 indicators	Operation (23–97% depending on indicators) Production (2%–96 %) Disposal (<1–47%)	ND	YES, for energy monitoring (except for a one-person household) NO, for energy management
(2017); Walzberg et al. (2017)	Set of individual houses in Canada	Electricity	User behaviour Load shifting strategy	Smart meters Actuators Smart plugs	Neglected	Assessed by agent-modelling	ND	Ecoinvent v3.1 Open IO-Canada	Impact 2002+ indicators	ND	ND	YES
Scheepens et Vogtlander, 2010; Scheepens and Vogtländer (2018)	Individual house in Nederland	Heating Electricity	Energy savings Level of insulation of the building	Smart meters Actuators	15 years	Assessed by DBES	SimaPRO	Ecoinvent Idemat LCI	Ecocost value ratio	ND	3–12 years	YES, especially in poorly insulated buildings
(2020); Walzberg et al. (2020)	Set of individual houses in Canada	Electricity	Variability of the electricity mix Variability of the electricity tariffs User behaviour	Smart meters Actuators Smart plugs	Neglected	Assessed by agent-modelling	ND	Ecoinvent EXIOBASE 3	GHG emissionns (Impact, 2002+)	ND	ND	YES, in most of the cases NO, in some cases when load shifting is performed

(continued on next page)

Table 1 (continued)

Article	Building typology	Consumption item assessed	Variables	Characteristics of ICT devices			Modelling framework			Results		
				Type	Lifespan	Direct energy savings	LCA software	Environmental database	Environmental indicators	Most impactful lifecycle stages	Pay-back time	Connected alternative better?
(2021); Pohl et al. (2021)	375 individual house with smart heating in Germany	Heating	Load shifting strategy Dwellings monitored have different rooms number, temperature levels, heating systems, occupants, ...	Ambient sensors Actuators Smart plugs Control unit	5 years	Between 2 and 20 %	GaBi	GaBi SP39 ecoinvent v3.5	Climate change (ReCiPe, 2016) Primary energy demand (PED) Abiotic depletion (CML, 2001–Jan. 2016) Ecotoxicity (USEtox 2.1)	Production (20 to >99%) Operation (<1–80%)	0.5–3.1 years (for PED and GWP)	based on economic metrics YES, when energy savings are beyond 6 % (GWP, PED) NO, when 2 and 4% of energy savings are achieved
(2022); Pannier et al. (2022)	Multifamily housing in France	Heating Electricity	Energy savings Energy performance Variability of occupancy	Ambient sensors Smart meters Actuators Smart plugs	10 years	20 % (uncertain factor)	Brightway2	Ecoinvent v3.4	Climate change (Impact World+) CED Ecosystem quality (Impact World+) Human health (Impact World+)	ND	ND	YES, especially in a poorly insulated building NO, in some cases for energy management in well-insulated buildings
(2022); Pohl et al. (2022)	375 smart home systems in Germany	Heating	Dwellings monitored have different rooms number, temperature levels, heating systems, occupants, ...	Ambient sensors Actuators Smart plugs Control unit	5 years	4 % of household's annual heating demand	GaBi	Gabi SP39	Climate change (ReCiPe, 2016) Metal depletion (ReCiPe, 2016)	ND	ND	NO, in average: no significant benefits, nor additional burden for GWP NO, additional burden for metal depletion

ND = not documented.

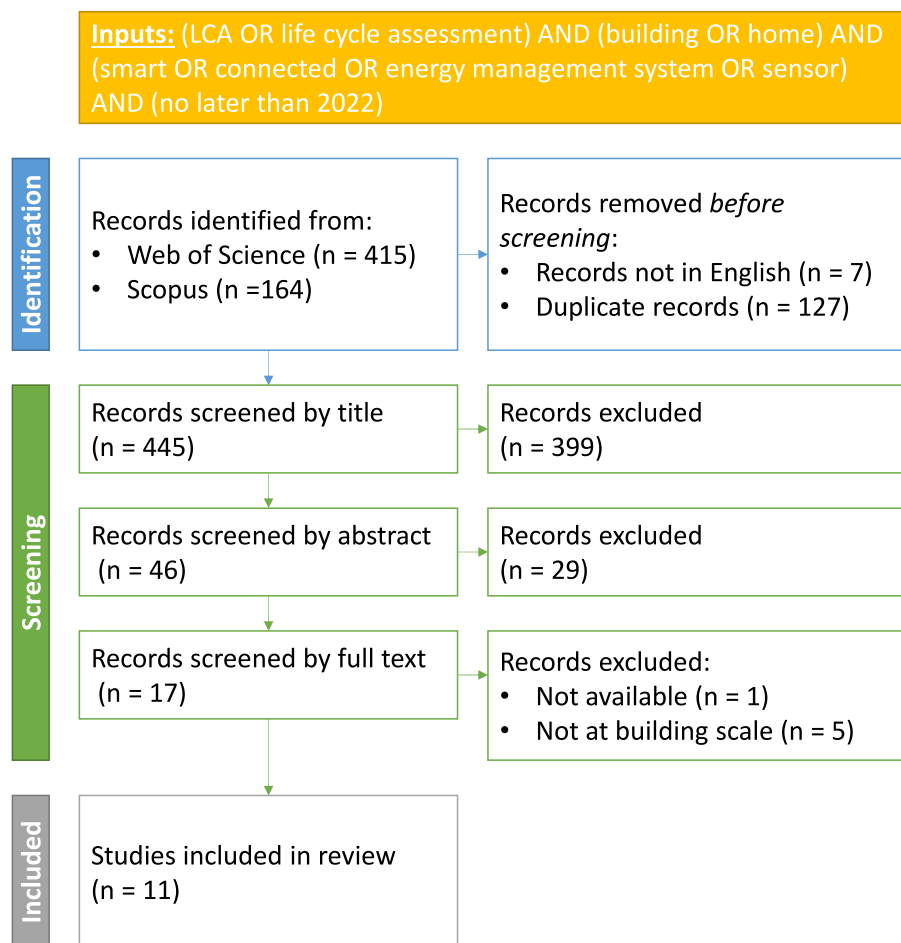


Fig. 1. Articles screening process.

unexplored background processes, such as the energy consumption due to data transmission, based on literature (Schien and Preist, 2014). In other cases, researchers usually explain that sensors are dismantled, and the sub-components are weighed and measured (Louis et al., 2015; Louis and Pongrácz, 2017; van Dam et al., 2013a). Then, the most relevant environmental data based on the physical and technical characteristics of the sub-components are selected. The environmental data collection is seldom detailed as some data may be confidential. Only one article gives a complete overview of the assumptions made to model BEMS (Louis et al., 2015).

To assess the energy consumption of a connected building, the authors use the energy consumption of an identical non-connected building as a baseline, based on expert knowledge, literature, dynamic building energy simulation (DBES) or agent-based modelling. The consumption is computed for a typical year and multiplied by the system operating lifetime. Most of the studies assume a fixed electrical mix, which data originating from the ecoinvent¹ database. Some papers account for long-term (prospective scenarios) (Beucker et al., 2016) and short-term (hourly, daily or seasonal) (Louis and Pongrácz, 2017; Walzberg et al., 2017, 2020) temporal variation and uncertainty of electricity production in the LCA of buildings.

Papers emphasize how difficult it is to precisely estimate the direct energy savings achieved by BEMS. Depending on the source (expert-knowledge, literature, or specific simulations), they range between 2% and 20% (see energy savings column of Table 1). Uncertainties in energy savings scenarios are thus usually considered: this involves studying

different savings values rather than applying uncertainty analysis (van Dam et al., 2013a; Louis et al., 2015; Louis and Pongrácz, 2017; Scheepens and Vogtländer, 2018; Pohl et al., 2021, 2022; Pannier et al., 2022). One study (van Dam et al., 2013a) investigates an evolutive scenario, based on previous ones (van Dam et al., 2010), that depicts the decreasing energy efficiency of the energy management system as the involvement of users drops over time.

1.2.1.3. Life cycle impact assessment. Most articles focus on the cumulative energy demand (CED) or global warming potential (GWP). Besides, some articles refer to an indicator named eco-cost (Scheepens and Vogtländer, 2018; van Dam et al., 2013a), expressed as the amount of money that should be invested to reduce the environmental pollution and materials depletion to a level aligned with the carrying capacity of the earth (Vogtlander, 2010, Čuček et al., 2015; Pohl et al., 2022). Nonetheless, the use of a single environmental score is criticised as the data aggregation process is complex and somewhat subjective, also making uncertainty studies impossible to perform (Kravanja and Čuček, 2013). The most recent articles encompass a growing body of environmental indicators, including mid-point indicators that reflect environmental problems (such as climate change or acidification) (Beucker et al., 2016; Louis and Pongrácz, 2017) and end-point indicators that reflect damages caused to several areas of protection (such as human health, biodiversity and resources) (Pannier et al., 2022).

1.2.1.4. Results interpretation. Finally, to assess whether the efficiency gains enabled by BEMS outweighs the environmental burden due to their production and operation, a frequently used indicator is the pay-back time (PBT) (Kumar and Mani, 2017; Pohl et al., 2021; Scheepens

¹ <https://ecoinvent.org/>.

and Vogtländer, 2018; van Dam et al., 2013a). It corresponds to the time when the net saving effects become positive. If PBT exceeds the BEMS lifespan, then it means that implementing BEMS leads to an environmental burden shift.

1.2.2. Results of smart buildings LCA

Table 1 provides insights into the main outcomes of the studied papers. Most articles agree that the use phase is the most contributing lifecycle stage (Gangolells et al., 2015, 2016; Louis et al., 2015; Louis and Pongrácz, 2017; van Dam et al., 2013a). This is particularly true for BEMS that integrate smart plugs, as their operational electricity consumption is significant. In multi-criteria assessments, it turns out that smart systems contribute primarily to human and marine toxicity, water eutrophication, global warming, and abiotic depletion (Louis et al., 2015; Louis and Pongrácz, 2017; Pohl et al., 2021).

The question of whether the environmental balance favours a connected solution over a non-connected one is not unanimous. The results depend on the variables assessed. Some papers approve the implementation of BEMS, arguing that the PBT is considerably shorter than the operating lifetime of the system (Gangolells et al., 2015, 2016; van Dam et al., 2013a). However, a multi-criteria assessment highlights that even though the environmental balance is positive with respect to some criteria, no net savings can be achieved for abiotic depletion and ecotoxicity, regardless of the energy savings scenario (Pohl et al., 2021). Some studies show that BEMS perform better in poorly insulated buildings (Pannier et al., 2022; Scheepens and Vogtländer, 2018). However, this is not always the case when the building has a good energy performance (Kumar and Mani, 2017; Pannier et al., 2022), as the amount of energy saved thanks to BEMS is lower. Finally, the studies that investigate higher-order effects (such as rebound or long-term effects) (Scheepens and Vogtländer, 2018; Walzberg et al., 2017, 2020) emphasize that smart buildings are less prone to rebound effects when the BEMS is environmentally effective but delayed in becoming economically profitable. Indeed, it mitigates the risk that users reallocate the money saved to potentially polluting products and services.

1.2.3. Research gaps

Although the issue of uncertainties in the results is addressed in the discussion section of some articles (Louis and Pongrácz, 2017; van Dam et al., 2013a), only two papers perform respectively a prospective (Beucker et al., 2016) and a stochastic LCA (Pannier et al., 2022). Among the sources of uncertainties that have not been explored, one deserves particular attention: environmental modelling of smart devices. Indeed, the assumptions made are usually simplified because inventory data for ICT devices are scarce (Louis et al., 2015; Louis and Pongrácz, 2017; Pohl et al., 2021; van Dam et al., 2013a). Another long-term uncertainty is related to the period for which BEMS are actually used. The risk is that the involvement of users weakens over time (van Dam et al., 2010), or that ICT devices become obsolete.

Regarding data processing, PBT has been the original metric used to assess the environmental balance of connected buildings (van Dam et al., 2013a). At that time, the papers were solely focusing on one to two impact categories. When multiple impact categories are assessed, PBT differs depending on the environmental indicator (Pohl et al., 2021). Thus, it is not the most relevant index that allows for a trade-off. Further articles employ statistical metrics that provide supplementary information about how much a connected alternative performs better, in terms of probability, compared to a baseline for each impact category assessed (Louis and Pongrácz, 2017; Pannier et al., 2022). Moreover, recent research has investigated the statistical metrics that are the most appropriate to address uncertainties in comparative building life cycle assessment (Pannier et al., 2022). This offers new perspectives to tackle uncertainties in comparative LCA and provide reliable and robust results.

To sum up, the current research gaps are related to the inclusion of a wide range of uncertain factors, to the metric to assess the alternatives'

performances, and to the set of environmental indicators considered.

1.3. Aim of the study

The present paper aims at assessing and comparing the environmental performances of building alternatives, including connected and refurbished alternatives, to account for the sustainability potential of smart buildings. The main novelty is to carry out a comparative assessment that includes uncertainties. Uncertain inputs are mainly related to the environmental modelling of sensors, heating gains, and to other buildings' influential parameters such as occupancy scenarios and building lifespan. The stochastic LCA is expected to be dynamic (based on DBES) and comprehensive (based on the recent life cycle impact assessment methods (Bulle et al., 2019)).

The paper is organized as follows. Section 2 gives an overview of the methodology used to assess and compare the environmental performances of building alternatives. Section 3 synthesises the framework and the tools provided to perform stochastic dynamic LCA. Section 4 introduces the case study and clarifies the inputs and the associated uncertainties used to perform the comparative life cycle assessment. Section 5 presents the results of the study. Finally, in Section 6 the most important findings are discussed.

2. Methodology for stochastic comparative LCA of connected buildings

The following methodology was applied to compare the different versions of a building using stochastic dynamic LCA:

1. Definition of the alternatives to compare;
2. For each alternative, data collection to build the LCA model and uncertainties characterisation;
3. Finally, uncertainty analysis and comparison of stochastic results.

The three stages are discussed in the following subsections.

2.1. Definition of the alternatives to compare

The main goal is to compare the environmental performance of a non-connected building with that of a connected building; therefore, at least two alternatives are defined. The first one is the baseline: a non-connected building, without sensors or connected actuators. The second alternative is a connected building and contains sensors and/or actuators. Several strategies are possible for the connected alternative. Based on previous literature, "energy monitoring" (sensors and advice to users), and "energy management" (sensors, advice, and actuators to control energy systems) strategies are included.² Other alternatives can be investigated and compared, such as the different energy performance of the building envelope or various energy systems with more or less adjustable production.

2.2. Data collection and uncertainty characterization

To perform the stochastic dynamic LCA of the building alternatives, different inputs are required, such as (i) data on the building envelope and energy systems; and (ii) data on connected devices. Information on uncertainties also needs to be gathered; it consists in selecting uncertain factors and identifying their probability distribution. These aspects are detailed below.

The data on the building are necessary for both the energy and environmental calculations. A lot of information is required, including

² The general methodology is described in this section. Detailed information on alternatives and smart devices considered in this study are presented in section 4. Case study.

building geometry, thermal properties of components, material quantities, use scenarios, and energy systems. The mentioned parameter values are rarely known precisely, and must thus be considered uncertain. Regarding the energy and environmental calculation, it is recommended to perform DBES prior to the LCA. This is because the energy consumption varies over time just as the environmental impacts of the energy production: e.g. GHG emissions of electric production are higher during cold days when electric heating induces a peak demand. Performing DBES thus allows for a more precise assessment of the temporal evolution of building consumption (Roux et al., 2016), and LCA simulations have a dynamic and thus more realistic inventory. After determining energy consumption, energy gains are estimated. The reduction of heating, cooling or electricity consumption is defined based on data from the literature for the energy monitoring and energy management strategies.

Besides information on the building envelope and systems, the connected sensors and actuators installed in the building to decrease its energy consumption are listed. Environmental data on connected devices are scarce in environmental databases. Data for some devices are available as Environmental Product Declarations (EPDs), e.g., in the French environmental database for buildings INIES (INIES, 2015), but integrating uncertainties into their environmental modelling is not possible. This is because the environmental data are pre-calculated for the entire lifecycle; thereby preventing modification of inputs such as the battery lifetime, or the energy consumption of the product in use. Two options are proposed to obtain a more flexible environmental dataset for connected devices:

- If the connected objects are known and available, they are dismantled and separated into their sub-components. Then the sub-components are weighed and measured. This option was applied in (Louis et al., 2015).
- If the connected objects are not known or unavailable, similar devices, available as EPDs, are selected. Then EPDs are read and analysed to extract data on their sub-components and subprocesses. This option was applied in (Pannier et al., 2022).

In both options, environmental data are allocated to the scale of each device's sub-components. Uncertainties can be considered at this sub-component scale, allowing the stochastic life cycle impact assessment to be computed with any environmental indicators. Besides the impacts related to the connected devices, the impacts of sending and storing data on an external server are also included, following data from the literature.

The uncertainties and variabilities related to the environmental modelling are collected alongside the gathering of information on the building alternative and its connected devices. This can be done based on data from the literature. For instance, probability distributions already defined in previous work (e.g. in (Marsh et al., 2022; Pannier, 2017)) can be used, or a literature review on the value of uncertain factors can be performed as in (Hoxha et al., 2014) in order to create probability distributions reflecting the observed heterogeneity of values of the uncertain factor. Another option is to define the probability distribution of factors based on expert knowledge. Using probability distributions, uncertainty analysis can be performed to study how the uncertainty in input data affects both the environmental impacts of the alternative and the alternatives' ranking.

2.3. Uncertainty analysis and comparison of stochastic LCA results

The last stage consists in comparing the LCA results to identify the alternative with the least environmental impact. The approach to comparing the alternative should be suitable for stochastic LCA, as uncertainties in the connected devices and the building are included in the study.

The following approach is proposed to manage uncertainties in

comparative LCA. Uncertainty analysis are performed in order to understand the level of uncertainty in the results caused by uncertainties in the input. In a comparison context, a good practice is to use dependent sampling (Heijungs, 2021; Henriksson et al., 2015; Pannier et al., 2023) (also called paired simulation or blocked simulations (von Brömssen and Röö, 2020)) for the uncertainty analysis, i.e., using the same sampling for all alternatives compared. Then, different metrics can be used to analyze the comparative stochastic LCA results (Mendoza Beltran et al., 2018; Heijungs, 2021; Pannier et al., 2023), all relying on pairwise comparisons between alternatives. Some metrics indicate *how often* one alternative performs better than the second in the pair, and other metrics indicate *how much* one alternative performs better (Heijungs, 2021). Both pieces of information are important: if the *how often* information indicates that an alternative is almost always the best, but the *how much* information shows only small impacts differences, then the two alternatives will lead to similar environmental consequences. Two indicators can be used in order to assess the two pieces of information at the same time:

- the Distribution of the Relative Difference (DRD), proposed in (Pannier et al., 2023);
- the Heijungs Significance Metric (HSM), proposed in (Heijungs, 2021).

In the DRD, the impact differences between alternatives $a_{i,1}$ and $a_{i,2}$ are computed for one simulation i and normalised by the maximal impact value, as in Eq. (1). The process is repeated for all N simulations, so that a distribution of impact relative difference is obtained. It can be displayed as boxplot. A boxplot with mostly positive (or negative) values indicates that one alternative is clearly preferred. A flattened boxplot centred on the 0-axis indicates that both alternatives lead to similar environmental impacts.

$$\text{Relative Difference} = \frac{a_{i,1} - a_{i,2}}{\max(a_{i,1}, a_{i,2})} \quad \text{Eq. 1}$$

The HSM gives the probability that an alternative performs at least λ % better than the second alternative. In Eq. (2), K_{4,a_1} tells how often the ratio between $a_{i,1}$ and $a_{i,2}$ exceed a fixed threshold of $1 + \frac{\lambda}{100}$. The Heaviside step function (Eq. (3)) is applied to count the occurrences, and the sum is divided by N to get a probability. A large value of K_{4,a_1} indicated that a_1 often performs significantly better than a_2 .

$$K_{4,a_1} = \frac{1}{N} \sum_{i=1}^N \Theta \left(\frac{a_{1,i}}{a_{2,i}} - \left(1 + \frac{\lambda}{100} \right) \right) \quad \text{Eq. 2}$$

With

$$\Theta(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases} \quad \text{Eq. 3}$$

Both indicators DRD and HSM are computed in this study.

3. Stochastic LCA framework

The stochastic framework, applied for each of the building alternative, is shown in Fig. 2 and in Fig. 3. The role of each part is explained in the following paragraphs.

The first step involves modelling the building in the *Pleiades*³ software and defining the probability distributions of the uncertain factors.

DBESs are conducted before the LCA simulations for a more accurate assessment of the temporal evolution of energy loads. These simulations are run using the *COMFIE* model (Peuportier and Blanc-Sommereux, 1990) within the *Pleiades* software, (step 2 of Fig. 2). The reliability of *COMFIE* has been validated by comparison with other models (Brasselet

³ <https://www.izuba.fr/logiciels/outils-logiciels/>.

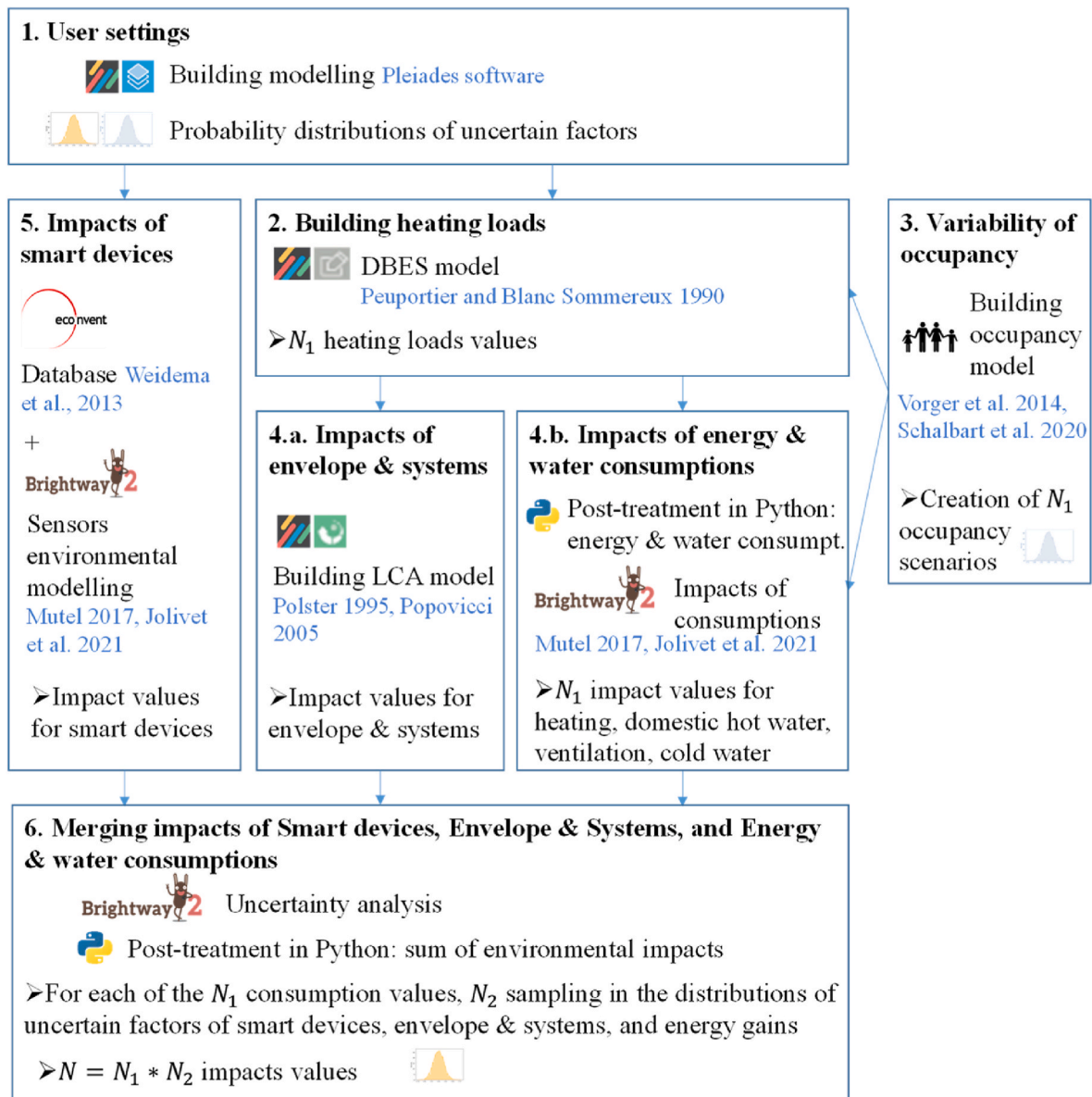


Fig. 2. Stochastic LCA framework applied for each building alternative.

et al., 1993; Brun et al., 2013; Judkoff and Neymark, 1995; Peuportier, 2005) and with data measured in several buildings (Munaretto et al., 2017; Peuportier, 1993).

Occupancy significantly affects the building energy performance (Tian, 2013; Salehi et al., 2015). Therefore, Vorger's stochastic occupancy model (Schalbart et al., 2021; Vorger et al., 2014), integrated into *Pleiades*, is used (step 3 in Fig. 2) to generate realistic occupancy scenarios and appliance consumption data. Based on data from a French time use survey, time-inhomogeneous Markov chains are used to simulate the presence and activities of occupants at 10-min intervals. The related appliances' energy consumption is determined from measurement campaigns data. For each DBES simulation in the uncertainty analysis, a different occupancy scenario is generated. Consequently, a set of N_1 heating load values is available at the end of step 2 in Fig. 2.

The *EQUER* simulation engine (Peuportier et al., 2013; Polster et al.,

1996; Popovici, 2005) from *Pleiades* is used to perform the LCA simulations. A consequential-oriented approach is followed in this decision support tool. This approach consists in applying the 50/50 substitution method⁴ to recycled materials, to consider avoided impacts for electricity exported to the grid, and to separately account for the impacts of construction and end-of-life of biogenic material (-1/+1 approach) (Hoxha et al., 2020; Polster et al., 1996; Schrijvers et al., 2016). The reliability of the tool was assessed by comparing it with other building LCA models (Lebert and ARMINES - CES BYCN CSTB Fédération maisons de qualité IZUBA Energies, 2014; Peuportier et al., 2004; Salmon et al., 2011). This tool was used in step 4. a. of Fig. 2 to calculate the impacts related to the building envelop and its systems. Impacts related to the use phase are post-treated in *Python* and in the framework *Brightway2* (Mutel, 2017) in step 4. b. of Fig. 2, using the N_1 heating loads values of the DBES software as well as from the other energy and water

⁴ In the 50/50 substitution method, benefits and burdens of recycled materials are shared equally between the building supplying the material to be recycled and the building using the recycled material.

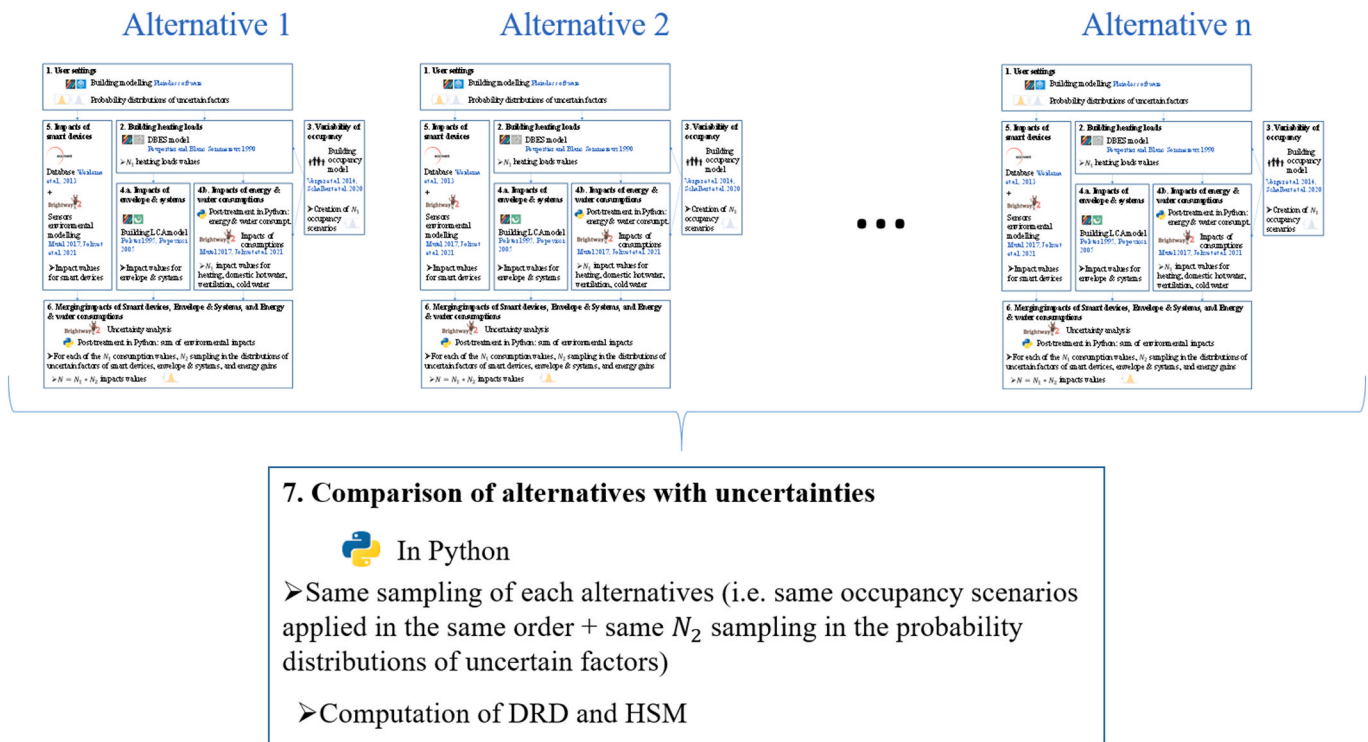


Fig. 3. Comparison of alternatives in the stochastic LCA framework.

consumptions obtained by the occupancy model in step 3.

Connected devices are modelled with the *Python* framework *Brightway2* (Mutel, 2017) in step 5 of Fig. 2. First, to this end, sub-components and sub-processes needed during the lifecycle of connected devices are linked with environmental data from ecoinvent v3.4 (Weidema et al., 2013). Subsequently, data are assembled by indicating the quantity of sub-product or sub-process required to obtain one connected device. Specifically, quantities are stored as parameters using functions of the *lca_algebraic* library (Jolivet et al., 2021). This approach creates parametric inventories for the connected devices, allowing for easy changes to quantities and performing uncertainty analysis. Finally, LCA calculations are performed, and environmental indicators are calculated using ImpactWorld+,⁵⁶ (Bulle et al., 2019), as they are based on consensual methods in LCA. The list of indicators assessed is depicted in Table 2.

Uncertainty analysis is performed in step 6 of Fig. 2 as follows For each of the N_1 possible occupancies, N_2 values are sampled from the distributions of uncertain factors. Overall, the number of simulations reaches $N = N_1 * N_2$ for all alternatives.

The same predefined sampling is applied to each alternative, allowing dependent sampling: for any simulation i in $[1, N]$, the same occupancy and the same values of uncertain factors are applied to all alternatives. Pairwise comparisons of alternatives and the calculation of indicators, DRD and HSM, are performed using *Python*, as described in step 7 shown in Fig. 3.

4. Case study

The residential building studied is a 17-storey tower (see Fig. 4), consisting mainly of apartments with four main rooms, with a total living area of 2700 m². It is representative of the social housing stock

built in France in the 1970s, consisting mainly of both low-rise large apartment blocks and high-rise towers. The tower is located in the south-west of France, which has an oceanic climate with mild winters and hot summers. The climatic file of Agen from the French thermal regulation (République française, 2010, 2012) has been applied in the simulation to be representative of this climate. As it was built in 1976, it has a relatively low level of insulation. The concrete wall and the slab are not insulated: their thermal resistance is $R = 0.11 \text{ m}^2 \cdot \text{K/W}$. Only the roof is lightly insulated with 10 cm of polyurethane, leading to a thermal resistance of $R = 3.45 \text{ m}^2 \cdot \text{K/W}$. The flats have two main orientations with windows only on the north and south facades. The performance of double glazing is of $U = 2.42 \text{ W/m}^2 \cdot \text{K}$. A humidity-sensitive single-flow mechanical ventilation system provides air renewal in the dwellings. The energy used for heating and domestic hot water in the entire building is provided by two gas boilers. Occupancy parameters such as heating setpoint or presence are not derived from real data but randomly sampled at each simulation using Vorger’s model (Schalbart et al., 2021; Vorger et al., 2014).

This building is already equipped with temperature and humidity sensors in each dwelling and on the roof, as well as automation gateways to collect data from sensors and to act on the building’s heating system. The aim is to assess each apartment’s exact heating consumption based on the building’s global heating consumption and to help occupants decrease their heating consumption. Based on the existing monitoring in this non-refurbished building, different connected building alternatives have been developed.

4.1. Building alternatives and simulations inputs

Four alternatives are studied and summarised in Table 3.

The first alternative corresponds to the “original building” without sensors. Based on data provided by the building’s energy manager, a DBES was carried out with a 30-min simulation time step. Complementary simulation hypotheses can be found in (Lagarde, 2022). The mean heating loads of this low-insulated building reached almost 180 kWh/(m² · yr).

⁵ <https://www.impactworldplus.org/>.

⁶ Results are provided at the midpoint level in the article and at the endpoint level in the supplementary material of this article.

Table 2
Description of the ImpactWorld + indicators at midpoint level.

Midpoint level impact category	Acronym	Unit	References (Bulle et al., 2019)
Climate change, short term	Clim. Change, st	kg CO ₂ eq	(De Schryver et al., 2009; Joos et al., 2013; Levasseur et al., 2016; Myhre and Drew, 2013)
Climate change, long term	Clim. Change, lt	kg CO ₂ eq	(De Schryver et al., 2009; Joos et al., 2013; Levasseur et al., 2016; Myhre and Drew, 2013)
Fossil energy use Mineral resources use	Energy Ressources	MJ _{deprived} kg _{deprived}	Fatemi Emamghais (2013) De Bruille (2014)
Photochemical oxidant formation	P. Oxidant	kg NMVOC eq	(Commission of the European Union. Joint Research Centre. Institute for Environment and Sustainability, 2011)
Ozone layer depletion	Ozone D.	kg CFC-11 eq	(Margni et al., 2008; Struijs et al., 2009)
Freshwater ecotoxicity	Ecotox.	CTUe	(Huijbregts et al., 2005; Hauschild et al., 2008; Rosenbaum et al., 2008, 2015; Kounina et al., 2014; Hellweg et al., 2009; Wenger et al., 2012; Fantke et al., 2011, 2012; Fantke and Jolliet, 2016)
Human toxicity cancer	Hum. Tox. Cancer	CTUh	Fantke et al. (2012), 2011; Fantke and Jolliet (2016); Hauschild et al. (2008); Hellweg et al. (2009); Huijbregts et al. (2005); Kounina et al. (2014); Rosenbaum et al. (2015), 2008; Wenger et al. (2012); Huijbregts et al. (2005)
Human toxicity non cancer	Hum. Tox. N. Cancer	CTUh	Fantke et al. (2012), 2011; Hauschild et al. (2008); Hellweg et al. (2009); Huijbregts et al. (2005); Kounina et al. (2014); Rosenbaum et al. (2015), 2008; Wenger et al. (2012); Huijbregts et al. (2005)
Water scarcity	Water	m ³ _{world} eq	Boulay et al. (2018)
Freshwater acidification	F. Acid.	kg SO ₂ eq	(Roy et al., 2012b, 2014b)
Terrestrial acidification	T. Acid.	kg SO ₂ eq	(Roy et al., 2012a, 2014a)
Freshwater eutrophication	F. Eutrop.	kg PO ₄ P-lim eq	(Helmes et al., 2012; Tirado-Seco, 2005)
Marine eutrophication	M. Eutrop.	kg N N-lim eq	Roy et al. (2012b)
Land transformation, biodiversity	Land Tr.	m ² _{arable land} eq	(Curran et al., 2011; de Baan et al., 2013)
Land occupation, biodiversity	Land Occ.	m ² _{arable land} eq-Y ^F	de Baan et al. (2013)
Particulate matter formation	Particulate M.	kg PM2.5 eq	(Fantke et al., 2015; Gronlund et al., 2015; Humbert et al., 2011)
Ionising radiations	Ioni. Rad.	Bq C-14 eq	(Frischknecht et al., 2000; Garnier-Laplace et al., 2009; Margni et al., 2008)

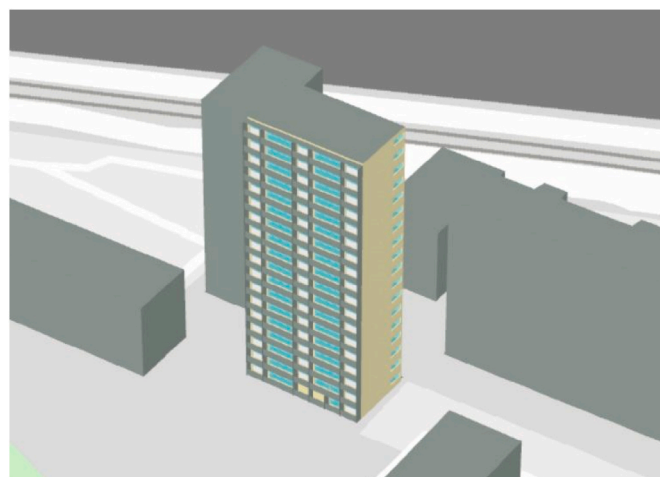


Fig. 4. Residential tower under study.

Table 3
Building alternatives studied.

Icons	Alternative names	Gains	Sensors
	Original building	No energy gains	No sensors
	Building monitoring	Gains: around 10%	Automation gateway + 1 outdoor sensor + 2 indoor sensors per apartment + a user interface
	Building management	Gains: around 30%	Same as Building monitoring + an additional automation gateway
	Refurbished building	Gains assessed using DBES	No sensors

on existing literature (ADEME et al., 2019), it has been estimated that such feedback helps users to reduce the heating load by 10% (this is an uncertain factor, see the probability distribution in Table 4). The energy consumed to send and store the collected data on an external server was included in the scope and estimated based on (Sénat et al., 2020); however, the impacts of using existing servers or installing new servers have not been included in the scope and should be considered in future studies.

The third alternative, called “building management” is equivalent to building monitoring. It includes additional connected devices, allowing the boiler to be controlled according to weather and building usage conditions. In addition to the classical boiler regulation based on the external temperature, a complementary regulation is based on the mean apartment temperature, and the hot water network flowrates were adapted based on the indoor temperatures of the apartments. It is assumed that this optimal control strategy decreases the loads by 20% (this is an uncertain factor, see the probability distribution in Table 4). Overall, user feedbacks and optimal control strategies reduce the heating loads by 30%.

The fourth alternative corresponds to the same building after a refurbishment. The walls, windows and ventilation system were upgraded to meet the requirements of the French thermal regulations for existing buildings (République française, 2017, 2007). The new building characteristics can be found in (Lagarde, 2022). The heating loads of the renovated building reached almost 46 kWh/(m². yr). No sensors are installed in the “refurbished building”, as a previous study (Pannier et al., 2022) showed that the environmental benefit of smart buildings

In the second alternative, called “building monitoring”, the original building is considered. However, in this alternative, data from indoor and outdoor temperature and humidity sensors are additionally collected using a gateway. Users receive feedback on their heating set-points and consumption via an interface. The connected devices correspond to those already installed in the tower. As the devices were known and available, they were dismantled to measure and weigh their sub-components. Then, environmental data were assigned to them. Based

Table 4
Uncertain factors.

Type	Factor	Default	Min.	Max.	Standard Deviation	Unit	
1	Building and usage	Boiler efficiency	90	80	95	2.5	%
2		Gains through feedback	10	5	25	2.5	%
3		Gains through boiler optimal control strategy	20	10	30	4	%
4	Occupancy	Randomly generated scenarios with the model of Vorger (Schalbart et al., 2021; Vorger et al., 2014)					
5	Outdoor temperature and humidity sensor	Building lifetime	80	50	200	20	yr.
6		Mass of plastic	0.15	0.135	0.165	0.0075	kg
7		Mass of aluminum	0.00216	0.0018	0.00252	0.00075	kg
8		Area of printed circuit board	0.0042	0.0032	0.0052	0.00005	m ²
9		Mass of radio transmitter	0.001	0.0009	0.0011	0.00005	kg
10		Mass of diode	0.001	0.00095	0.00105	0.000025	kg
11		Length of cable	0.05	0.045	0.055	0.0025	m
12		Mass of packaging	0.096	0.0086	0.106	0.005	kg
13		Mass of battery	0.117	0.1158	0.1181	0.000585	kg
14		Transportation distance (factory to building)	185	166.5	203.5	9.25	km
15	Indoor temperature and humidity sensor	Battery lifetime	10	6	14	2	yr.
16		Sensor lifetime	15	10	20	2.5	yr.
17		Mass of plastic	0.036	0.031	0.041	0.0025	kg
18		Mass of aluminum	0.0054	0.00459	0.00621	0.000405	kg
19		Area of printed circuit board	0.0036	0.003	0.0042	0.0003	kg
20		Mass of radio transmitter	0.001	0.0009	0.0011	0.00005	kg
21		Mass of packaging	0.017	0.015	0.019	0.001	kg
22	Automation gateway	Mass of battery	0.025	0.02475	0.02525	0.000125	kg
23		Transportation distance (factory to building)	2620	2358	2882	131	km
24		Battery lifetime	10	8	12	1	yr.
25		Sensor lifetime	15	10	20	2.5	yr.
26		Mass of plastic	0.2705	0.2	0.33	0.03525	kg
27		Area of printed circuit board	0.015	0.01	0.02	0.0025	M ²
28		Mass of radio transmitter	0.001	0.0009	0.0011	0.00005	kg
29	Sensors End of Life	Mass of diode	0.001	0.00095	0.00105	0.000025	kg
30		Mass of packaging	0.15	0.135	0.165	0.0075	kg
31		Electricity consumption	43.8	39.42	48.18	2.19	kWh/yr.
32		Transportation distance (factory to building)	540	486	594	27	km
33		Gateway lifetime	10	8	12	1	yr.
34	Sensors End of Life	Transportation distance (building to waste treatment center)	1000	800	1200	100	km
35		Recycling rate	0.5	0.1	0.9	0.25	%

decreases as energy performance improves.

The functional unit for the LCA simulations is defined as follows: a residential tower of 2700 m² spread over 17 floors studied over its entire lifecycle, including the construction, use, renovation and end of life phases. It is assumed to be built for 80 years (the building lifetime being an uncertain factor with values ranging from 40 to 200 years). Regarding the use phase, heating, water and electricity consumptions for domestic appliances are included. The occupancy scenarios are randomly sampled from Vorger's model (Schalbart et al., 2021; Vorger et al., 2014) for each apartment in the tower and for each simulation; but the same set of scenarios is applied to all the alternatives compared. Energy consumption is obtained through DBES simulations. Energy consumption is assumed to be the same for each year of the building's lifetime. The building's covering, energy systems and joineries are refurbished every 10, 20 and 30 years respectively. In the end of life phase, building materials are assumed to be landfilled,⁷ while the end-of-life of smart devices has been more carefully modelled considering processes for waste electric and electronic equipment and recycling rates.

4.2. Uncertainties

The 35 uncertain factors considered in this study are listed in Table 4. They mainly relate to the environmental modelling of sensors (factors

#6 to #35). Other factors, directly linked to the use of connected devices, were also included, such as boiler efficiency (#1) and heating gains by feedback (#2) and by an optimal boiler control strategy (#3), as shown in Table 4. In addition, occupancy scenarios (#4) and the building lifetime (#5), which have been shown to be particularly influential in previous studies (Pannier et al., 2023), were taken into account. Normal distributions are assumed for all uncertain factors, except for occupancy, which is discussed below. Truncation is considered to avoid negative values being sampled. The default value in Table 4 corresponds to the mean of the truncated normal distribution. The parameters of the probability distribution were defined based on data from the literature, such as from the French environmental database for buildings INIES (INIES, 2015), from previous studies (Pannier et al., 2023), and from assumptions based on expert knowledge. The normal distributions are randomly sampled using Latin Hypercube Sampling. Unlike other uncertain factors, occupancy (#4) is treated as a categorical factor. For each simulation, an occupancy scenario (previously created with Vorger's realistic occupancy generator (Schalbart et al., 2021; Vorger et al., 2014) is sampled. More precisely, based on the stochastic modelling of a French time use survey and measurements campaigns data (see § 3), presence, temperature setpoints, appliances and water consumptions are generated randomly on a yearly basis with a 10-min interval.

No uncertainty is assigned to background data. Only values related to the products and processes of the building or its connected objects may vary.

⁷ This point was not explored in depth in the article, but would be worthwhile in future studies, for instance following the end-of-life information defined in (Mastrucci et al., 2017) or in (Pannier et al., 2023).

5. Results

Before comparing the four alternatives by analysing the stochastic uncertainty analysis results with the DRD and HSM, the deterministic results are given in the next sub-section. For both the deterministic and the stochastic results, the environmental indicators listed in Table 2 are assessed. The aims are to identify (i) whether the non-refurbished connected alternatives perform better than the original one, and (ii) whether refurbishing is a better option than adding smart devices.

5.1. Deterministic results

The deterministic results are shown in Fig. 5. In these results, the values of the uncertain factors correspond to the mean value of the probability distribution. In addition, a mean occupancy scenario is considered; it corresponds to the mean of the uncertainty scenarios generated with Vorger's occupancy generator. In Fig. 5, each group of 4 bars corresponds to an environmental indicator and each bar stands for one alternative. The colours in the bars represent the lifecycle stages. The results are presented relatively to the original building alternative, which counts as 100 %.

Different conclusions can be drawn from this graph. First, the impacts related to the deployment of connected strategies (for the monitoring and management cases) are negligible. The black color representing the impacts of connected devices is visible only for some indicators, such as short-term climate change, ozone depletion, freshwater ecotoxicity, human toxicity (cancer and non-cancer), water scarcity, freshwater acidification, and freshwater eutrophication. Its contribution does not exceed 0.3% of the lifecycle impacts (the highest share being for the human toxicity non-cancer indicator and the management alternative). In addition, the pink colour representing the energy to send and store data is not visible and it contributes no more than 3×10^{-6} % of the lifecycle impacts (the highest share being for the ionising radiation indicator and the management alternative).

Second, regarding the impacts related to the other lifecycle stages, heating (in red) and, more generally, the building's use phase (heating, domestic hot water, ventilation, electricity, water, in shades of orange) contribute to most of the impacts over the entire lifecycle. It ranges between 27 and 99 % (the highest share being for the ionising radiations occurring during the original building lifecycle). This is in line with the results found in other LCA articles on buildings (Cabeza et al., 2014). There are, however, exceptions for some indicators (mineral resource use and land occupation), for which the impacts associated with

materials and components (construction, renovation and end of life phases) are predominant. Furthermore, for some indicators (freshwater ecotoxicity and human toxicity cancer), the impacts related to materials and components become predominant in the refurbished alternatives, whereas the use phase is the most contributing for the other alternatives.

Third, the ranking of alternatives is the same for almost all indicators. The original building alternative generates the most impacts. Then come the two connected alternatives, with the monitoring alternative producing greater impacts than the management alternative, as less energy can be saved. Finally, the renovation alternative has the lowest impact, due to the significant decrease in energy consumption during the use phase obtained with this alternative. The gain between the refurbishment and original alternatives is very significant for the climate change indicators. This ranking is valid for all indicators except freshwater ecotoxicity, human toxicity cancer, and the land occupation, due to the increase of the impacts related to the materials and components in the refurbished alternative, as insulation and cladding are added to the walls. A contribution analysis has been performed to understand which additional materials lead to this significant increase. The results (presented in more detail in §2 of the supplementary materials) have shown that these changes for the refurbished alternative are related to the use of: (i) aluminum to hold the cladding in place (affecting freshwater ecotoxicity and human toxicity cancer); (ii) glass wool (affecting freshwater ecotoxicity, human toxicity cancer and land occupation); and (iii) wooden uprights maintaining the insulation layers (affecting human toxicity cancer and land occupation).

The same conclusions can be drawn at the endpoint level, as shown in the supplementary materials of this article.

5.2. Stochastic results

The following results compare the environmental performances of the four alternatives under uncertainties. For each alternative, a Latin Hypercube Sampling ($N_2 = 2000$) has been carried out on each of the $N_1 = 882$ randomly generated occupancy scenarios, bringing the total number of outputs to $N = 1,764,000$. The computational cost reached 11 h for an unconnected alternative (8 h for the DBES, and 3 h for the uncertainties analysis), and one additional hour for a connected alternative as different energy gains through connected devices are studied. Based on the uncertainty analysis results, two metrics are assessed (as explained in section 2.3): the distributions of relative difference (DRD) and the Heijungs Significance Metric (HSM).

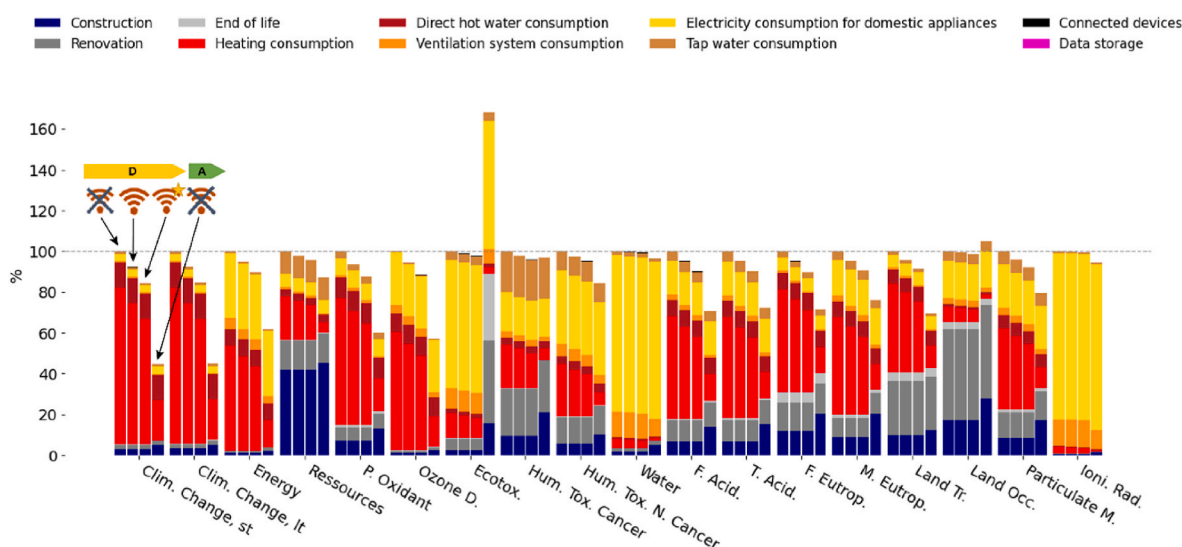


Fig. 5. Deterministic results for midpoint indicators.

5.2.1. Distributions of the relative differences

The first metric studied is the DRDs, which are displayed as boxplots in Fig. 6. The relative difference between one alternative and the original building (i.e., the non-connected version of the building) is computed based on a pairwise comparison. Each group of three boxplots corresponds to an environmental indicator, and each boxplot stands for one pairwise alternative comparison. The boxplot indicates the range around the mean value that encompasses up to 90% of the outputs, whereas the whiskers highlight the lowest and highest values of the distribution. Values mostly above the 0-axis indicate that for a given indicator, the connected or the renovated alternative performs better than the baseline. On the contrary, a flattened boxplot centred on the 0-axis shows that neither of the compared alternatives has a significant potential for reducing environmental impacts. Finally, for boxplots below the 0-axis, the original building performs better.

Compared to the deterministic results, the following points are observed:

- The alternative ranking remains unchanged. Renovating the building reduces its environmental impact more than adding connected objects. This can be observed as the average of the boxplot comparing the original and refurbished alternatives is higher than the average of the other boxplots. Then, the management strategy performs better than the monitoring one. In addition, as observed in the deterministic results, the ranking changes for three indicators. For freshwater ecotoxicity and land occupation, it is preferable to keep the original building or to install connected devices in it, rather than refurbishing it. For human toxicity cancer, the conclusions may change depending on the values taken by the uncertain factors: as the boxplot for this indicator crosses the 0-axis, we learn that the refurbished alternative is preferable in most cases, but for some combinations of values of the uncertain factors, the refurbishment generates more impacts.
- For some indicators such as climate change, the ranking between the four alternatives remains stable despite the uncertainties, as the

three boxplots do not overlap. However, for other indicators, overlaps between the yellow and the orange boxplots indicates that for some uncertain factor values, the management strategy may be better than refurbishment. In order to clarify this point, the DRD between the management and the refurbished alternatives has been drawn in Fig. 7. We can observe that for almost every environmental indicator calculated, refurbishing the building is a better option. For marine eutrophication and particulate matter formation, some combinations of values can lead the refurbished alternative to produce greater impacts than the management alternative. However, these combinations of values have a low probability of occurring. As shown in Fig. 7, the refurbished alternative is detrimental to the environment compared to the management alternative for the following indicators: freshwater ecotoxicity, land occupation, and to a lesser extent, human toxicity cancer.

- For any combination of values, the monitoring and the management alternatives perform better than the original building.
- For water scarcity the ionising radiation, and to a lesser extent for land occupation, the boxplots are flat and close to the 0-axis, meaning that, despite the uncertainties, choosing one alternative or the other will only slightly change the conclusions from an environmental point of view. There is therefore no need to focus on these indicators when making decisions.
- The uncertainties are higher for the refurbished case compared to the other cases (orange boxplots being larger than the red and yellow boxplots). This can be explained by the fact that occupancy has more effect in buildings consuming less energy (de Meester et al., 2013; Ioannou and Itard, 2015).

Additional information has been obtained considering the uncertainties. Using connected devices is always preferable than keeping the original building state. However, refurbishing the building is the preferable option for almost all indicators. It is more efficient than implementing a management strategy in nearly all cases. This

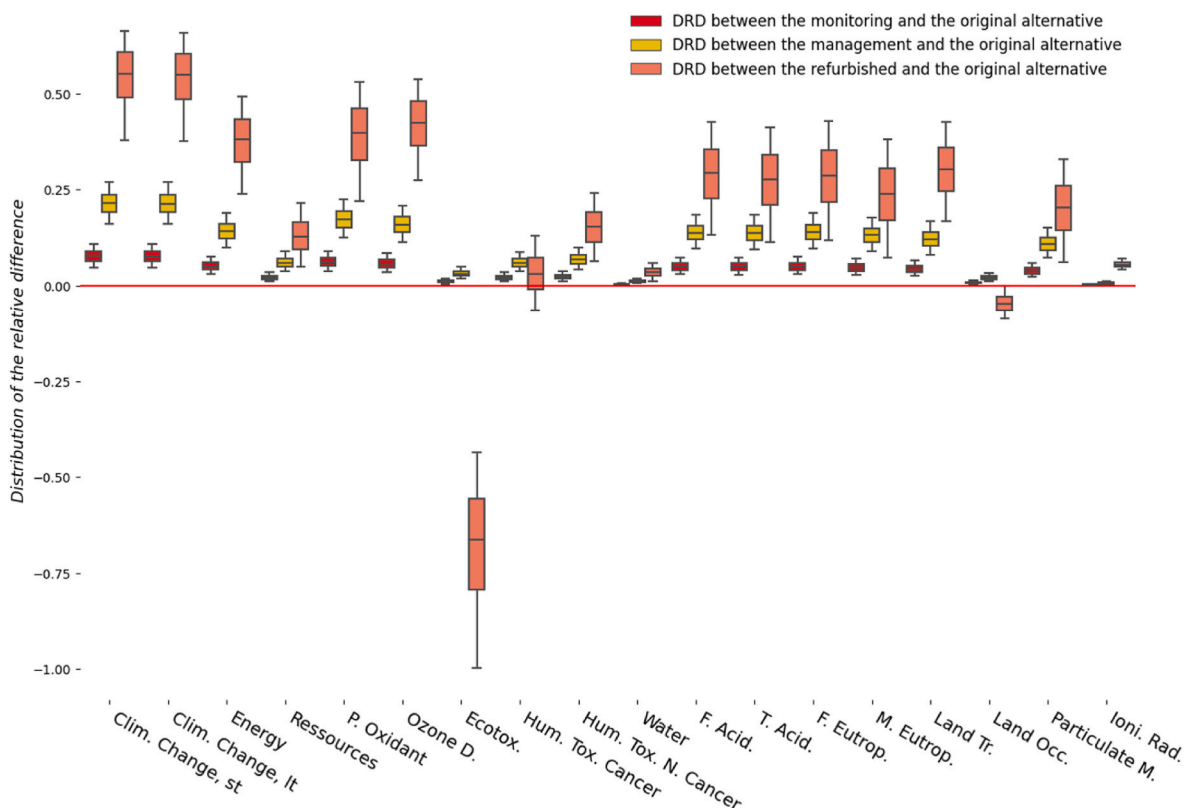


Fig. 6. DRD between the original and the other alternatives for the midpoint indicators.

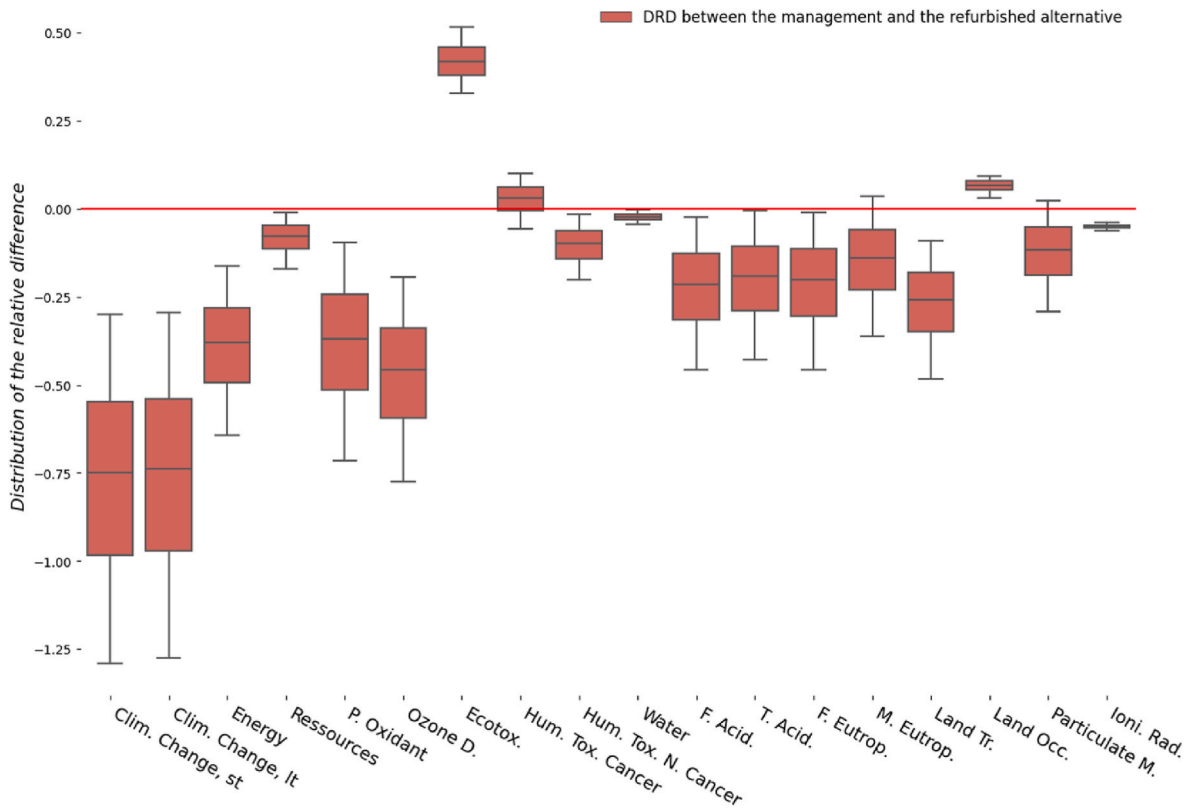


Fig. 7. DRD between the management and the refurbished alternatives for midpoint indicators.

conclusion can be altered for only three indicators. First, regarding land occupation, since the boxplot is quite flat and close to the 0-axis, choosing the original or the refurbished alternative results in similar environmental effects, allowing this indicator to be disregarded. Second,

for human toxicity cancer, avoiding refurbishment is advisable for some values of the uncertain factors, but in over 87% of cases, refurbishment is the better option. Third, freshwater ecotoxicity is the only indicator for which the refurbishment strategy should not be executed. If

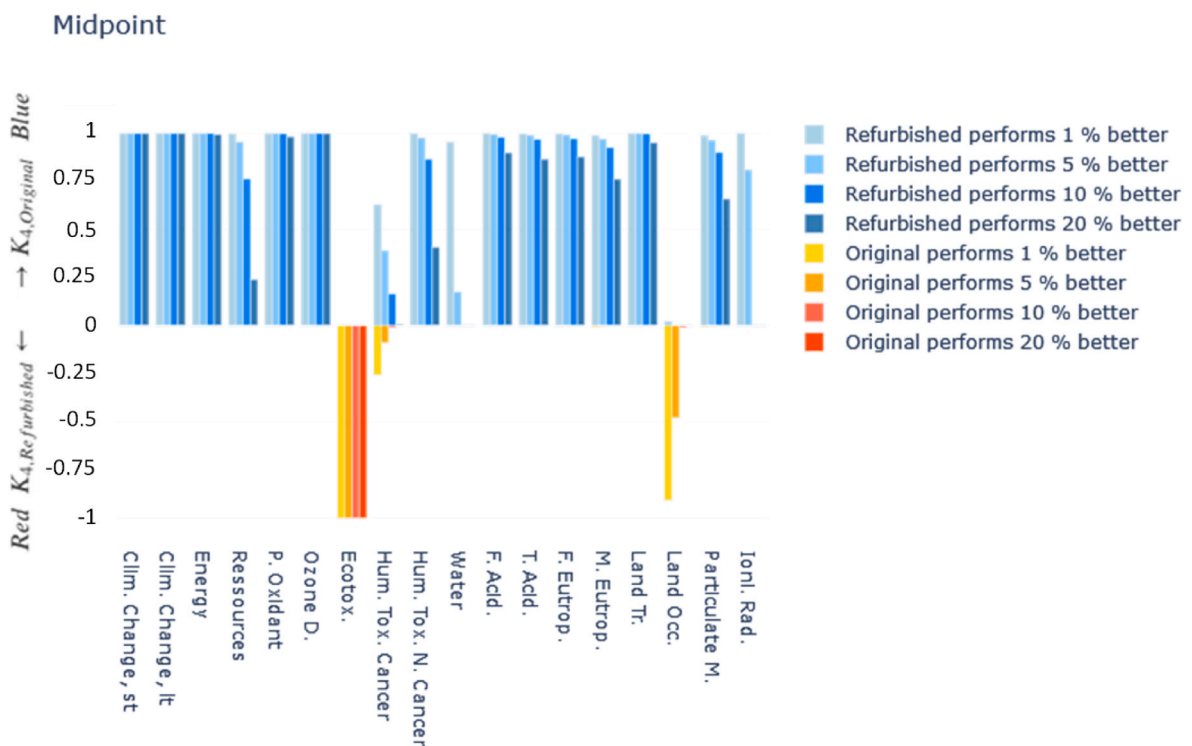


Fig. 8. HSM for the midpoint indicators. Comparison between the refurbished and the original alternatives.

freshwater ecotoxicity is an important environmental consideration within the project context, then the management strategy should be preferred over refurbishment.

5.2.2. Heijungs significance metric

Another method to interpret the stochastic results is to compute the HSM. The HSM results are shown in Fig. 8 for the pairwise comparison between the original and the refurbished versions. In this graph, each set of 4 bars corresponds to one environmental indicator. A bar above the 0-axis (colored in blue) indicates that the refurbished alternative performs better, while a bar below the 0-axis (colored in orange) signifies that the original alternative performs better. Each bar within the set of 4 bars stands for a different threshold: the first bar gives the probability that an alternative performs at least 1 % better than the other; and the last bar gives the probability that an alternative performs at least 20 % better than the other. For instance, regarding mineral resource use, the last blue bar indicates that in 24 % of cases, the refurbished alternative performs at least 20 % better than the original alternative.

For many indicators, there is a high probability that the refurbished alternative performs significantly better (in terms of climate change short-term and long-term, fossil energy use, photochemical oxidant formation, ozone layer depletion, freshwater acidification, terrestrial acidification, freshwater eutrophication, marine eutrophication, land transformation, and particulate matter formation). The probability that the refurbishment performs at least 20% better than the original building exceeds 60% for 11 indicators out of the 18 midpoints studied. In addition, for freshwater ecotoxicity, there is a high probability that the original alternative performs significantly better. For other indicators (mineral resource use, human toxicity non-cancer, water scarcity and ionising radiation), the refurbished alternative always performs better than the original one, but the probability is lower, meaning that the impact difference between the two alternative is quite small. Lastly, for human toxicity cancer (and to a lesser extent for land occupation), ranking changes are possible, as both blue and orange bars are visible.

In Fig. 9, the HSM results are presented for the pairwise comparison between the management and the refurbished versions. Ranking

changes are more frequent (e.g. for the indicators mineral resource use, freshwater acidification, terrestrial acidification, freshwater eutrophication, marine eutrophication, and particulate matter formation): small orange bars are visible. For three indicators (freshwater ecotoxicity, human toxicity cancer and land occupation), the management alternative is preferred to the refurbishment.

The same conclusions are observed for the DRD and the HSM metrics. Both metrics allow us to identify with a high level of confidence, an alternative that performs significantly better for most of the environmental indicators. In addition, both metrics allow us to identify indicators that can be discarded as the alternatives lead to similar environmental consequences. The interpretation may slightly differ depending on the chosen metrics due to the thresholds chosen (i.e. from which probability value can an alternative be considered as significantly better).

6. Discussions and perspectives

The results of this study indicate that, despite the fact that smart buildings require more devices, they help decrease the environmental impacts of unrefurbished buildings. However, refurbishing a building is generally a better option than installing smart devices.

The results obtained depend on the assumptions made. For the management and the monitoring cases, some assumptions are debatable:

- the energy gains have been assessed based on existing literature, but these gains are difficult to evaluate, and they may vary over time as (i) the energy reduction potentially changes at each time step, and (ii) energy consumption can increase again after some time due to the disengagement of occupants, changes in habits, or rebound effects.
- the type of devices installed to obtain the gains could slightly differ due to devices availability or new technological developments.
- the environmental modelling of smart devices, is probably not perfect as devices have been dismantled, measured and weighed. Using

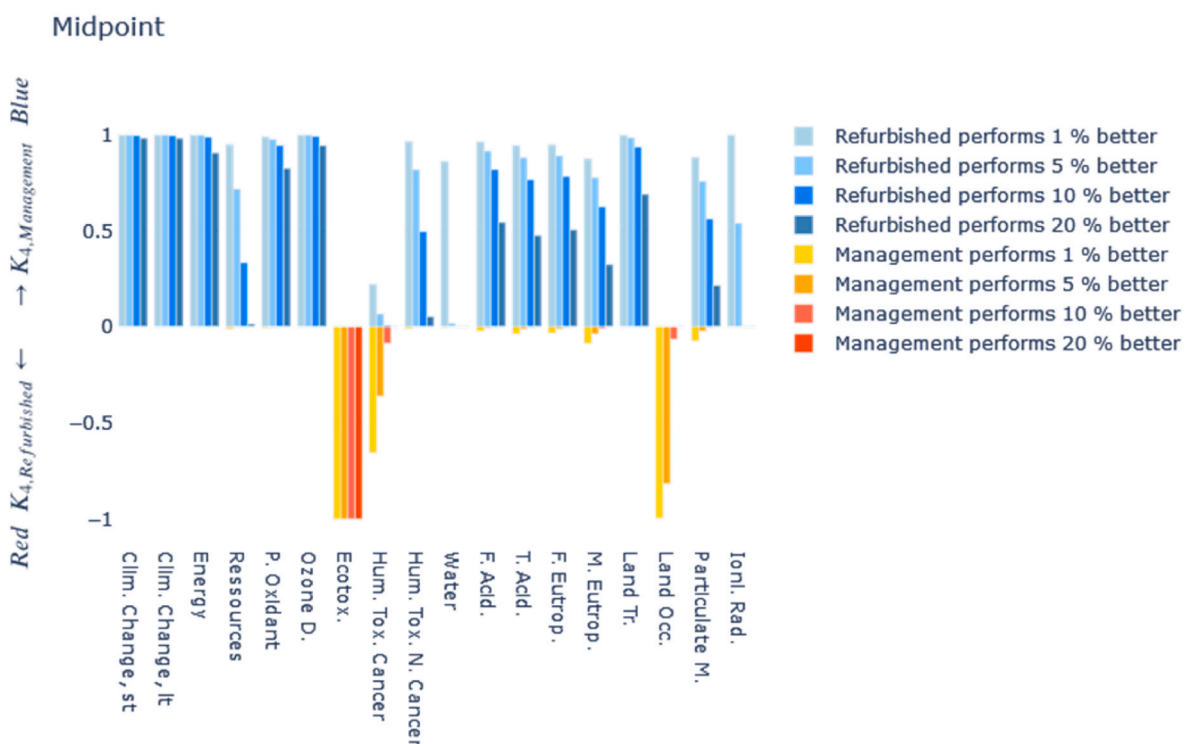


Fig. 9. HSM for the midpoint indicators. Comparison between the refurbished and the management alternatives.

data from suppliers like EPD could lead to more reliable results, but the use of data would be less flexible and prevent uncertainty analysis from being performed.

Regarding the last two points, the assumptions made about the devices seem to have a small effect on the results: even when uncertainties are considered, the effect of smart devices is almost negligible. However, assumptions about the energy gains due to the inclusion of connected devices have more significant effects on the results, as can be seen from the dispersion of uncertainties between the original and connected alternatives. Additional measurement campaigns could be conducted on real instrumented buildings to understand the range of potential gains enabled by connected devices in real-life conditions, as well as the evolution of these gains over time. If the energy gains become too small, there is no longer any environmental benefit in adding connected devices.

For the refurbished building, even though the energy gains were assessed using DBES, they are subject to uncertainties: first weather and occupancy conditions may change over both short- and long-time horizons, and second, real renovations may differ from the planned renovations. For instance, habits may change after the refurbishment even if the same occupants live in the building (Peuportier, 2014). Adding connected sensors to a newly refurbished building could be an interesting option to identify to what extent the renovation works are beneficial. For three indicators, the refurbished alternative has more impacts than the original one. This effect could be limited or cancelled out by using other materials for the renovation: aluminium with a higher recycled content, use of bio-sourced materials, etc.

More than 8 h were required to run the DBES using stochastic occupancy model. Uncertainty analysis took 3 h for an unconnected alternative, and more than 4 h for a connected alternative. We deliberately carried out a large number of simulations to ensure convergence and to obtain an accurate dispersion of results. However, this results in heavy computational costs. Practitioners aiming to quantify the effects of uncertain factors on the LCA results may not be able to manage such a time consuming process. Nonetheless, appropriate outcomes can be obtained by running fewer simulations, as observed during a convergence analysis.

In this study, four alternatives were compared, leading to six pairwise comparisons.⁸ The conclusions remain easily interpretable as the ranking is quite stable in this study. Yet, increasing the number of alternatives compared would make the results interpretation and visualisation much more complex. Statistical tests could be applied in such cases to groups of alternatives having similar environmental impacts (Henriksson et al., 2015).

Different thresholds need to be set for the interpretation of uncertain results. For the DRD metric, the impact difference up to which an alternative performs significantly better than the other must be set. For the HSM, two thresholds should be fixed: one on the probability that an alternative performs better than the other, and another one on the impact difference significance between alternatives. As these two metrics have rarely been applied, additional research is required to improve and automate the definition of these thresholds.

7. Conclusion

As buildings increasingly incorporate connected devices to reduce energy consumption, it is crucial to evaluate the environmental benefits of this technology. This study aimed to assess and compare the environmental performances of connected and conventional buildings, and to determine whether it is better to install connected devices or to renovate the building. A key aspect of this research was performing

⁸ For instance, one pairwise comparison consists in comparing the original with the monitoring alternative.

uncertainty analysis on the results.

The study focused on a 17-storey tower, comparing four alternatives from an environmental point of view, using LCA: the original unrefurbished building, two connected alternatives that achieve two different levels of energy savings, and the refurbished building. Uncertain factors were selected based on environmental modelling of sensors, heating gains, and other influential parameters such as occupancy and building lifespan.

The findings indicate that connected alternatives offer environmental benefits despite uncertainties. The contribution of connected devices to the building's overall lifecycle impacts is almost negligible. However, energy refurbishment significantly reduces environmental impacts more effectively than the installation of connected devices. The uncertainty analysis showed that the refurbished alternative performs significantly better than the others for almost all indicators: for 11 out of 18 midpoints studied, the probability that refurbishment performs at least 20% better than the original building exceeds 60%. For two indicators (freshwater ecotoxicity and to a lesser extent, land occupation), it is preferable to install connected devices in the original building. For human toxicity cancer, the choice of the least impacting alternative may change due to uncertainties. Additionally, for water scarcity and ionising radiation, the impact differences between alternatives are small, indicating that choosing one alternative over another leads to similar environmental consequences.

The same conclusions were supported by both the Distribution of the Relative Difference and Heijungs Significance Metric, which compare LCA alternatives including uncertainties and help determine how much and how often one alternative performs better.

The results align with previous research: while smart buildings generally offer environmental benefits, their advantage diminishes in energy-efficient buildings, making renovation a more effective strategy. The conclusions could be affected by external factors such as rebound effects or changes in occupant habits, which might reduce energy gains. This was addressed by considering variability in occupancy and energy gains. Therefore, similar results are expected in other non-refurbished housing. Nonetheless, further research and measurement campaigns are necessary to better quantify the energy gains enabled by connected devices or renovations over longer periods.

CRedit authorship contribution statement

Clémence Lagarde: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation. **Maxime Robillart:** Writing – review & editing, Validation, Resources. **David Bigaud:** Writing – review & editing, Validation, Funding acquisition. **Marie-Lise Pannier:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jclepro.2024.143004>.

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