# A pilot using a Building Digital Twin for LCA-based human health monitoring


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## Abstract

The construction industry is experiencing a technological transition towards Digital Twins from a static digital information environment to a more dynamic one, enriched with real-time sensing and Artificial Intelligence support. This paper describes a method for leveraging a building digital twin for monitoring the indoor environmental quality and its long-term effects on human health. Whilst most Green Building Standards include life cycle assessment studies before beginning the construction, the long-term effects of exposure to indoor contaminants and other sources are not systematically considered. To tackle the complexity of this issue, the deployment of a digital twin of the occupied environment is required to provide a constant feed of data from various types of sensors. The pilot study described in this article aims to assess the requirements associated with a Digital Twins system for carrying out life cycle assessment calculations sourced from dynamic data feeds.



**Keywords:** Digital Twin; LCA; human health; sensinsg; BIM; linked data


## 1 Introduction

The building and construction sector has greatly benefitted from Building Information Modelling (BIM) in the last decades, allowing not only more effective planning and collaboration, but also convenient ways to exchange building data to perform analyses and simulations across different use-cases. BIM-sourced data remains a fundamental necessity for designers, constructors and facility managers, taking advantage of the rich semantics within BIM models. This is true for many application domains, not least for the Life Cycle Assessment (LCA), an internationally recognized and standardized methodology across all industries, which has become almost common practice to carry out in coupled BIM-LCA models (Tsikos and Negendahl 2017, Crippa et al. 2020). Within these models, building semantics and valid background and foreground life cycle inventory (LCI) data about each building component is required. BIM can only partly satisfy these information requirements, assuming that the data is valid and accurate (Tsikos and Negendahl 2017, Crippa et al. 2018). The remaining inputs are highly dependent on domain expertise and adequate methodologies to create an accurate LCA model and thereby provide meaningful outputs. Within the field of design and construction, the vast majority of these models account mostly for the impact on the environment, but do not consider the long-term effects of buildings on their occupants (Al horr et al. 2016), which we aim to study and explore within this article.

The impacts on human health can be quantified by monitoring the indoor air quality of inhabited spaces. This is achieved with the use of specialized sensors able to detect the concentrations of the air pollutants emitted inside the building (by materials in the building components, equipment and furniture, but also occupancy). The limitations of BIM when it comes to real-time data and its connectivity issues make it less suitable to use (Boje et al. 2020b). The real-time behavior of building components, as well as the user-related factors for the physical building under investigation can only be put into context with the use of a Digital Twin (DT). We therefore present a pilot case study on a real building along with its DT, its connection to the BIM, the use of sensors and the link between this data and the LCA-based calculation of the impacts of indoor air pollutants on human health.

Moreover, the second section of the paper expands also on the role of semantics in linking and sharing information. The overall methodology of the study is laid out in section 3. Section 4 presents the methodology testing on a real-life building. After this, the technical implementation requirements of the building digital twin are outlined and discussed. Finally, the implications and limitations of the study are outlined.

## 2 Background

### 2.1 Life Cycle Assessment

LCA is standardized by ISO 14040:2006 and ISO 14044:2006 norms, which define guidance on: (a) the setting of goal and scope for an LCA, (b) the analysis stage, (c) the calculated impact assessments stage, (d) the interpretation of the results, (e) the reporting of results, (f) the known limitations, as well as (g) the relationships between LCA phases. However, the standards do not provide exact guidance on operational methodologies (as these depend on each process or product), nor on the computational structure of LCA – which can be formalized using a matrix representation (Heijungs and Sun 2002). The construction industry is known to be one of the most wasteful industries in terms of materials, and one of the main contributors to pollution and carbon emissions worldwide. The aim of conducting LCA, and in particular the life cycle impact assessment (LCIA) phase of LCA of a building, is to predict the potential impacts on the environment and on human health and thus apply more responsible construction methods, as well as use more efficient and environmentally friendly materials.

LCA is a data intensive process, and in order to reconstruct the full inventory of a product (i.e. the flows of materials and energy that are involved in its entire lifecycle), and especially of a complex product like a building, it is often necessary to rely on approximations based on educated guesses and incomplete available information. This is equally true for LCA studies of construction products that have already been produced, as well as for products that are at their design stage. Moreover, the more the boundaries of the studied system (i.e. of the lifecycle of the studied product) are extended, the higher is the amount of data and information that is necessary to collect. The same occurs whenever something along the inventory of processes changes, such as a change in materials, labor or other logistical assumptions initially made.

The use of LCA databases such as ecoinvent[1] helps acquiring specific inventory data on certain materials, pre-fabricated or manufactured components, across their entire lifecycles. However, their use is highly contextual, depending on the country of use, the region, the availability of nearby resources, the regulations force and the economic factors for each process. LCA databases

[1] https://www.ecoinvent.org/

have seen increased use across many industries, and LCA studies are being facilitated into the construction industry via the use of BIM. The coupling of LCA databases and BIM is of immense support in estimating the impact on the environment in the early design phase of a building. However, the consideration of the long-term effects of buildings on the health of their occupants still remains underexplored with respect to the other impacts addressed in LCA, even when the LCA study is supported by the use of BIM, apart from the identification of potential toxic materials in the early design phase. Estimating the life cycle costs for the client (i.e. the subject who buys or rents the apartment or the house), the cost and impact on the natural environment does not tell anything about how the building, its materials and usage will impact its occupants (Al horr et al. 2016). This is due to a lack of information on the behavior of the building: its actual use by the occupants, the efficiency of its technical systems, its materials' and furniture's emissions, the exchanges with the outdoor environment (i.e. temperature, air composition, etc.) and the complexity of the mechanisms that affect the indoor air quality effects on humans occupying it regularly. Although BIM can be used to represent and simulate certain use cases of the built environment, such applications remain highly out of scope.

## 2.2 Digital Twin

### 2.2.1 Definition

The concept of "digital twin" is neither new, nor revolutionary, but it is currently experiencing a resurgence and a period of "hype" within many industries, due to a need for digitalization and the benefits this would bring. Many recent studies have compiled various lists on its definitions, trying to pinpoint where it all started (Negri et al. 2017, Tao et al. 2019, Fuller et al. 2020, Moyne et al. 2020). Within the white paper by Grieves (Grieves 2014), an initial attempt to define the digital twin paradigm is made, by distinguishing between 3 key components: (1) the Physical, (2) the Virtual and (3) the Data Connection. Extending this, Tao (Tao and Zhang 2017) proposed a five-dimensional model for the digital twin paradigm: the Physical (1), the Virtual - also referred to as Models (2), the Data (3), the Connections (4) and Services (5). Based on this fundamental structure, one can begin to perceive a digital twin as a complex cyber-physical system, which aims to take full advantage of the real-time connection between a so-called "digital object" and its corresponding "physical twin" and keep then within a state of synchronization.

### 2.2.2 Applications

A digital twin can have many practical applications in real life, the most prevalent being energy monitoring and dynamic allocation for buildings, districts and grids, flood monitoring, structural monitoring for buildings, bridges and nuclear facilities, etc. These applications represent focused uses of a digital twin via specific domain models (energy, structural analysis, flood models, etc.) which are offered as services on top of the platform. The latter can represent and manage a digital twin in conjunction with its physical twin, often connected via sensor networks and Internet-of-Things (IoT).

### 2.2.3 Inputs to indoor human health assessment within LCA

We have previously explained that LCA can be used to estimate the long-term effects on human health, but in order to assess the indoor health effects (on the building occupants) highly contextualized real-time data about the inhabited environment would be necessary. The use of a digital twin is thus required to provide a live feed of sensor data related to occupancy, air-quality, lighting, temperature and the presence of potentially toxic materials within the proximity of the daily occupants. Using real-time data from sensors to feed LCA calculations implies 2 things:

1) Constant re-evaluation with time;
2) Improvement in accuracy as the volume of data gathered by the digital twins increases.

The constant re-evaluation of LCA based on different, temporally varying, input scenarios leads to the concept of a "temporally differentiated" or "dynamic" LCA (DLCA) process. This approach was envisaged as a means to automate LCA from BIM sourced data in the past (Russell-Smith and Lepech 2011), however requiring a high level of automation. The "dynamic" nature of the assessment is associated to the impact of changing the input data for LCA or LCIA. On another level, the term "dynamic" is more generally attributed to the concept of considering different

inputs to LCI and LCIA with their variations over time. (Beloin-Saint-Pierre et al. 2020) elicit a glossary of 18 different terms which characterize key temporal considerations, among which DLCA assumes a level of dynamicity within the system and a temporal differentiation of flows.
The evaluation of indoor human health impacts using the approach illustrated in this paper can be categorized in the realm of DLCA approaches. The DT should be able to generate results in terms of human health impacts expressed in DALYs (Disability Adjusted Life Years), using as inputs either the results from a theoretical model of indoor emissions (Wu and Apul 2015), or the pollutant's concentrations recorded by the sensors (Collinge et al. 2013), in conjunction with an existing LCI and external databases. The following formula from (Collinge et al. 2013) can be used to calculate the impact from indoor pollutants:

$$h_{(t_1-t_2,x)} = C_{(t_1-t_2,x)} \cdot f_{indoor} \cdot BR \cdot N \cdot CF_{(x,i)} \quad (1)$$

Where:

- $h_{(t_1-t_2,x)}$: End-point damage score for chemical x for time interval ($t_1$-$t_2$) [DALY]
- $C_{(t_1-t_2,x)}$: Concentration of chemical x for time interval ($t_1$-$t_2$) [mcg/m$^3$]
- $f_{indoor}$: Fraction of time occupants stay indoor [-]
- $BR$: Breathing rate [m3 person$^{-1}$ hr$^{-1}$]
- $N$: Number of occupants [person]
- $CF_x$: Characterization factor for chemical x for effect i (cancer or non-cancer)[DALY/mcg$_{intake}$]

## 2.3 Semantic Models and Linked Data

The prime challenge in applying a DT in a specific application domain is the correctness of the data, its semantics and its integration with domain-specific models (Boje et al. 2020b). This poses an integration problem at a system design level, and an interoperability one on the data level. The use of semantic models, such as BIM, is mandatory in order to express and source building-related data. The use of IoT and sensor networks is also mandatory for our use case, in order to feed the correct data at the right time. The context of BIM and sensor-fed data needs to be constructed in order to provide valid input for domain-specific DLCA models to ensure correct calculations and estimations.

Within the process of contextualizing DLCA for human health impacts assessment, there are requirements to produce a semantic model along the digital twin pipeline, and the requirement to link and validate the data as it moves and transforms across. To tackle these challenges, the use of semantic web technologies such as the Resource Description Framework[2] (RDF) and the Web Ontology Language[3] (OWL) ontologies is recommended. Ontologies are best suited to represent complex socio-technical systems, and can represent virtually any "thing", from abstract classes to real-world individuals with the use of the Tbox and Abox statements. The description logics at their core also allow to formalize rules and validate the integrity of our models and data (Pauwels et al. 2017). The use of semantic web technologies to represent and integrate web-based systems and architectures for digital twins have already been investigated (Chevallier et al. 2020) (Boje et al. 2021) and show promise in their convenience when extending domains and linking data over the web.

# 3 Methodology

The presented pilot is encapsulated and dependent from the overarching research methodology of the SemanticLCA project. Figure 1 outlines the following steps:

1. Literature review - a review of literature on LCA, DLCA and existing LCA databases – these have been conducted outside of the scope of this article, some of which have been referenced in the previous section.
2. Requirements analysis – based on previous literature, several requirements are identified for monitoring human health within inhabited spaces using LCA calculations most notably: sensors,

[2] https://www.w3.org/TR/rdf-schema/
[3] https://www.w3.org/TR/2004/REC-owl-features-20040210/

a BIM, a digital twin and a validated LCA model;
3. Pilot setup – the selected real-life building is described. The layout is analyzed in terms of its sensor network deployment as well as optimal sensor placement, according to the requirements established above.
4. DT deployment – the existing sensor infrastructure is contextualized under a digital twin using existing technologies and semantic models.
5. Dataset integration – the integration of sensors, BIM, sensor data and LCA models based on semantics.
6. Testing and validation – initial data collection is tested along the established digital twin pipelines and prepared for gradual validation in different contexts.

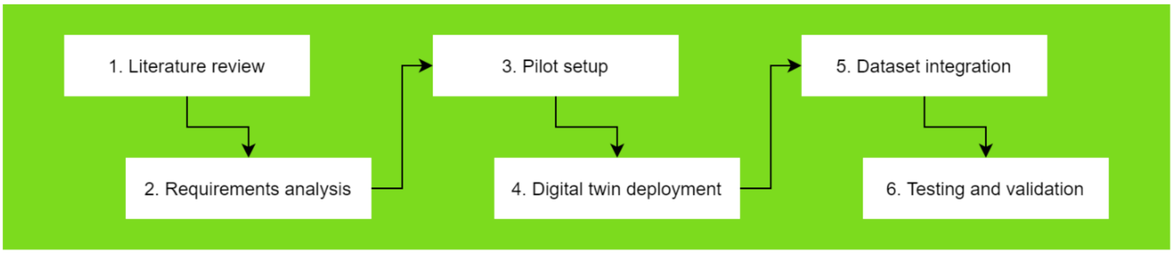


**Figure 1.** Building digital twin for LCA-based human health monitoring methodology

## 4 Pilot requirements and setup

Based on the literature review presented above and the nature of the pilot building under investigation, the following key requirements were identified:

1) the sourcing of spatial data, geometry, components descriptions and materials of the building from an up-to-date BIM;
2) the real-time sensing data capture for several values (described in Table 1);
3) the coupling of 1) and 2) using a Digital Twin for feeding dynamic LCA models.

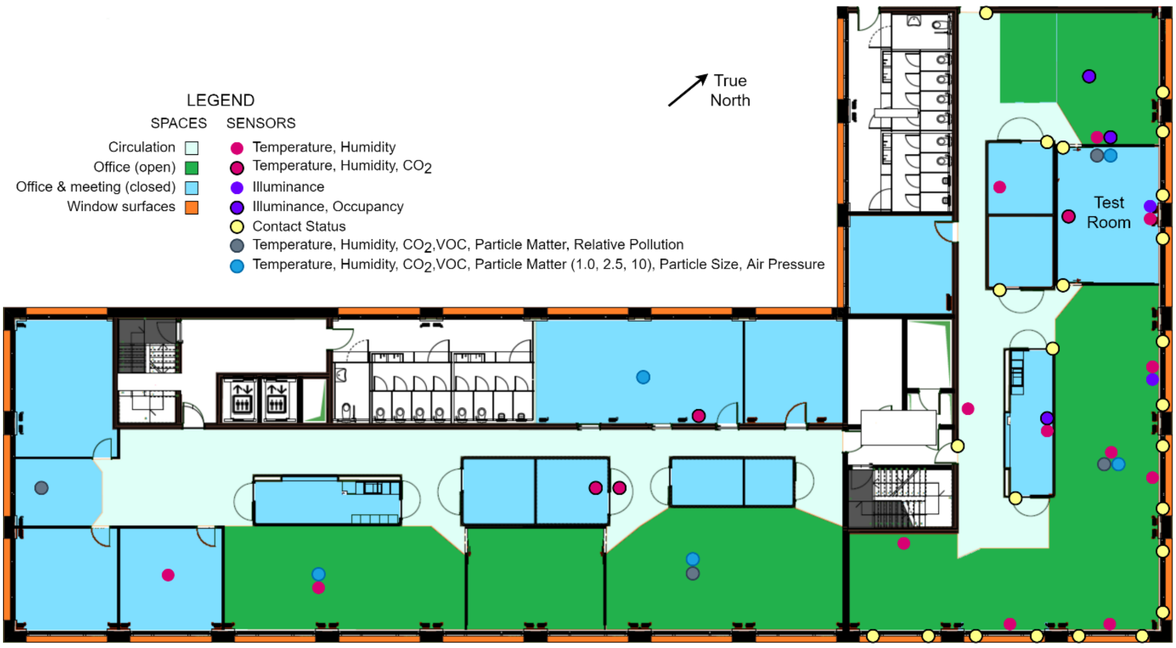


**Figure 2.** Floor plan of pilot building with deployed sensors and spatial layout

### 4.1 Building description

The pilot building investigated during this research project is located in a formerly heavy industrialized district in Luxembourg, which has been re-purposed over the last 20 years into a commercial and residential district. Within close proximity of the building, some industrial activity is still taking place on a daily basis, being the cause for various sources of pollution.

The pilot building itself is a recent construction and was designated as a 5-storey office building. The design was set around a low-tech passive-house building with very limited mechanical ventilation and with large window surfaces on the façade for maximizing solar energy gains, adapted with remote controlled solar blinds. A part of the second floor of the building was fully adapted with extra sensing devices to monitor the air-quality, presence and the status of certain doors and windows as part of the on-going SemanticLCA research project. Under normal working conditions the office spaces shown in Figure 2 are fully utilized by the employees. The figure depicts two types of office spaces: closed and open. The closed spaces can consist of normal offices or meeting rooms, which make it of particular interest to monitor the changes in air-quality relative to occupancy rates. In Figure 2 one can notice that the floor plan consists of two separate departments, with the one on the right-hand side being equipped with significantly more sensors. The similarity of space usage and the proximity of the two departments will enable a comparison and discussion around the level of sensing equipment required in the long-term monitoring of the building.

## 4.2 Sensing and actuation equipment

The positions of the deployed sensors is shown in Figure 2, with their descriptions listed in Table 1. The majority of the sensors are custom made for monitoring certain key parameters, usually temperature, humidity, carbon dioxide concentrations. On the right wing of the floor, all windows and doors are equipped with contact sensors to detect if these are open or closed at any given time. These are complemented by several sensors from the retail sector for covering additional parameters at key locations.

**Table 1.** List of deployed sensor types on the network as shown in Figure 2

| Symbol | Measurement parameters | Type | No |
|---|---|---|---|
| | Temperature (C°), Relative Humidity (%), Absolute Humidity ($g/m^3$), Dewpoint (C°) | custom-made | 14 |
| | Temperature (C°), Relative Humidity (%), Absolute Humidity ($g/m^3$), Dewpoint (C°), Carbon Dioxide Concentration (ppm) | custom-made | 4 |
| | Illuminance or luminous flux per area (lx) | custom-made | 2 |
| | Illuminance or luminous flux per area (lx), Occupancy (presence detection) | custom-made | 3 |
| | Contact Status (closed or open) | custom-made | 24 |
| | Temperature (C°), Relative Humidity (%), Carbon Dioxide Concentration (ppm), Volatile Organic Compounds (ppb), Particle Matter (µg/m3), Relative Pollution (%) | Foobot | 4 |
| | Temperature (C°), Relative Humidity (%),Carbon Dioxide Concentration (ppm), Volatile Organic Compounds (ppb), Particle Matter 1.0, 2.5 and 10 (µg/m3) , Typical Particle Size (µm), Air Pressure (hPa) | Sensilla Technologies | 5 |

The placement of the sensors was distributed to optimize the area coverage, and detect differences between certain locations, which can infer additional information about events within the office environment. Recommendations from previously established research on the subject (Eliades et al. 2013)(Lee et al. 2019), as well as manufacturer documentation, were considered. Sensors should usually be placed within open space, at heights varying from 1.3 to 1.7 meters, not too close nor too far from the floor or the ceiling, and several placement patterns have been investigated (Yoganathan et al. 2018). However, this is often hard to achieve due to existing furniture and circulation areas which must be kept clear. As such, the current placement was instead focused on capturing average values of temperature and humidity (and in certain cases also carbon dioxide) within certain spaces and on certain openings (near certain windows and doors) in order to be able to determine air exchanges. Additionally, sensors from different manufacturers were placed at the same location in order to compare readings of similar types, or detect anomalies or faults. Illuminance sensors were placed on some windows on the right side of the layout (Figure 2) and some spaces have both illuminance and presence detectors for establishing occupancy statuses. Due to privacy reasons, this could not be done across a larger surface of the floor plan.

Mechanical actuators are present for the remotely controlled blinds system which spans across the whole building façade. These can also be manually controlled by occupants, who can quickly change the light intensity within a space or the air flow in the case that a window is open. Several other sensor bridges and actuators are present permitting some changes of the system, but these are not show on Figure 2.

### 4.3 Technology infrastructure for a digital twin

We can consider the described floor as the physical twin of our office environment, which is monitored using the sensor network described above. The fusion of several technologies can enable the creation of a digital twin at level 1 (Boje et al. 2020b). For this pilot case study we have considered the inclusion of traditional sensing devices, a BIM model, an ontology layer and several dedicated simulation models for a DLCA for human-health. The sensing data is captured and stored in a dedicated time series database, the BIM is sourced in an Industry Foundation Classes[4] (IFC) format, and its IfcOwl equivalent, whilst the context of the pilot is captured via an ontology layer which combines several graphs. The management of the pilot is done via an adapted interface of the 4D Collab prototype, previously presented (Boje et al. 2021), and its own 4D Collab ontology (Boje et al. 2020a), with the addition of a Sensor class. The alignment to IFC allows the inclusion of the building context, basic elements, their geometry and declared materials within the BIM. These are all regarded as sources of information to feed into an LCA model for measuring the long-term impacts on the human health of the occupants. The implementation of the model to compute the human health effects over time is a process currently under development, based on previous research as explained in section 2.2, which is implemented using the Brightway2[5] suite of libraries. These are then able to generate results in terms of human health impacts expressed in DALYs. The challenge lies in full automation of the process via appropriate information pipelines in the short-term, but most importantly in being able to provide valuable insights back to the digital twin and in the analysis of potential actions in the long-term.

### 4.4 Results on human health impacts

Based on the data gathered on the pilot, the values for total Volatile Organic Compounds (TVOC) and Particle Matter (PM) - 2.5 (mcg/m$^3$) were manually extracted in order to evaluate the impact on human health measured in DALYs, from the formula introduced in section 2.2. The room chosen for this example is marked in Figure 2, and several assumptions were made, such as: 4 occupants (N); an indoor occupancy rate of 0.33 ($f_{indoor}$) – accounting for typical 8h working time inside the offices (Wu and Apul 2015); a typical breathing rate (BR) of 0.54 as recommended by (Collinge et al. 2013); and a typical distribution of VOC (Collinge et al. 2013). Based on these assumptions and actual measured values, the results are shown in Table 2. The current daily exposure levels are an input into the DLCA calculation itself, which should account for the whole building, across its entire lifecycle, allowing us to estimate the long-term effects.

**Table 2.** Results of calculated impacts on human health in DALYs based on data from Figure 3

| Indicator | | Week impact [DALY] | Daily impact [DALY] |
|---|---|---|---|
| **PM2.5** | Non-cancer | 3.87e-3 | 7.54e-5 |
| **TVOC** | Cancer | 1.22e-3 | 2.00e-5 |
| | Non-cancer | 5.75e-5 | 9.38e-7 |

[4] https://standards.buildingsmart.org/IFC/RELEASE/IFC4/ADD2_TC1/HTML/
[5] https://brightway.dev/

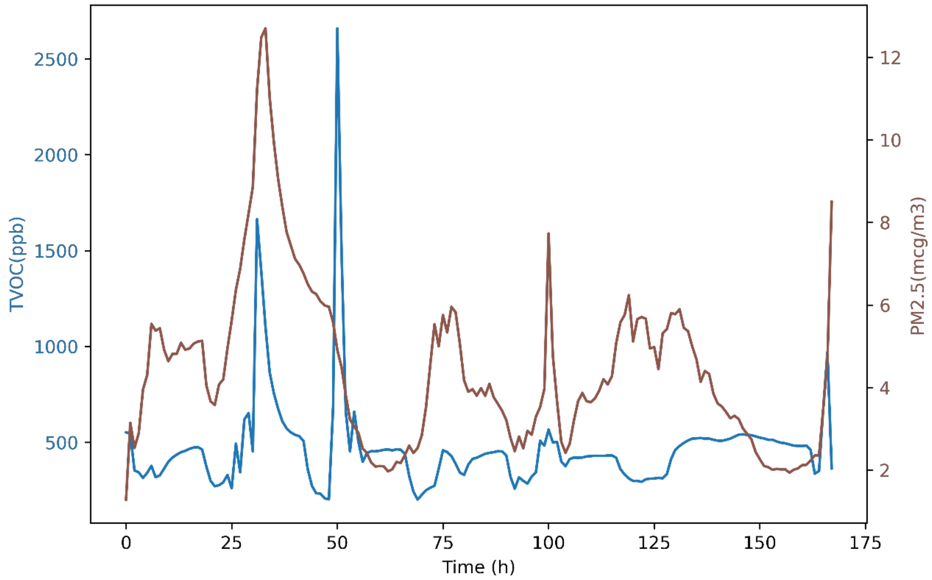


**Figure 3.** Sample sensor measurements for TVOC and PM 2.5 for a 1-week interval

## 5 Critical analysis

### 5.1 Sensor data

The deployed sensor network provides a constant flow of sensing data of various parameters. However, each sensor type, its observations and limitations need to be well understood by the system. The data accumulated within a time series dataset offers a high exploitation potential to perform aggregations using various mathematical expressions in preparation of higher-level algorithms and the LCA simulations. However, this requires a good understanding of the incoming data and a good understanding of how it should be cleansed and pre-processed in order to be usable at higher levels. Additionally, due to the hybrid sensors in place, the reading times (timestamps) of observations are not the same and therefore the digital twin has a different synchronicity rate with each sensing device. The preparation of such data often requires a specific time parameter, which can affect the accuracy of the data.

In section 4.2 we described the need for several sensors to deduce an airflow exchange within a space. The detection of such events using captured data needs to be cross-referenced with the status of certain openings (doors and windows) in order to confirm that such an event was indeed possible. This requires additional context and knowledge of the placement and relationships between sensors which is hard to co-relate using raw data. Still, an access to the ventilation systems data readings, or the Building Management System logs, would in most cases serve this purpose.

### 5.2 From BIM to Digital Twin

In section 2 we argued that a BIM model is insufficient to provide all the required information about the building within the current case study. The use of building geometry using IFC is very limiting due to its implicit representation (needs to be generated following the IFC specification). The use of component materials is often vague, and the quality depends on the explicit statements within the BIM model which are often missing. Imbedded semantics within the BIM model can provide additional context in terms of the intended use of the building (such as the types of spaces for example), but in the end it is down to actual sensed data via the DT that will allow a more realistic prediction.

Section 4.4. shows an example of determining the impacts on human health using sensor data, as well as other assumptions (number of people, use of spaces, breathing rate). However, this cannot account for the dynamic environment in reality. Ideally, presence detection should be correlated with existing sensor data automatically and contextualised by the DT. Current lack of models to deploy such a use are scarce and remain challenges to be addressed in the future.

### 5.3 The role of semantics in facilitating a meaningful context

The challenge in developing DT lies in managing and connecting the dots of all the components discussed above. We can see that the BIM domain dominates the building representation. The central ontology at this stage is the IFC schema. Several more light-weight and specialised ontologies which aim at representing BIM assets at the micro scale have been identified and analysed, covering definitions for geometries, meta-data and how they can be linked (BOT[6], FOG[7], OMG[8], etc.), which need to be aligned and tested for an LCA use-case. From the sensing perspective, the SOSA and SSN[9] ontologies seem to be the go-to models for representing sensors and their observations at higher levels. However, an open LCA ontology suited for our use case is yet to be developed. The input from ontologies such as the ones previously mentioned would need to be directed to provide meaningful context to a dynamic-LCA ontology for human health, which would then enable to feed the LCA calculations and subsequently the interpretation of these results. The role of semantics for such a sensitive, complex scenario, is evident and would contribute immensely towards the automation of our buildings.

## 6 Conclusion, limitations and future work

The estimation of the impact of buildings' indoor environment quality on human health in the long term in LCA is significantly underexplored with respect to other environmental impacts categories. The requirements to enact the pilot were described from an overview of the literature and the constraints of the pilot site. The placement of sensing equipment, its link to the BIM and digital twin were also described conceptually and a critical analysis of the status-quo was given in section 5. Preliminary manual processing of the data showed how human health impacts can be calculated and what the challenges are related to interpreting sensor data and contextualizing it. Future work will focus on developing and integrating a novel LCA ontology, as well as integrate and evolve the pilot using additional sensors and actuators to better understand and control the office environment.

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