Creating Virtual Indoor Monitoring Sensors to Enhance LCA Inventory for Monitoring Energy and Well-being in Buildings During Use Phase

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Summary

The buildings' operational phase is considered the longest phase where buildings contribute the most to their overall environmental impact. In this context, Life Cycle Assessment (LCA) helps to quantify both the background and foreground of the environmental impact of the buildings' components and performances. Different LCA dimensions were introduced to tackle this issue, aiming to quantify the environmental impact of the buildings' components and performances. In this setting, the LCA impact significantly depends on the life cycle inventory components. However critical issues evolve around these components identified to affect the overall LCA impact. One major component is the indoor sensors used to provide input data to the inventory with the scope of energy optimisation while maintaining optimum indoor conditions. The relevant research has shown considerable progress along this path, yet with notable shortcomings. These include a lack of understanding of the significance of the trade-off between the characteristics of the integrated technologies and their optimisation efficiency. This gap was further highlighted, particularly in the adoption of indoor sensors considering their environmental impact weightings against their optimisation outputs.

The primary aim of this research is to create and integrate virtual indoor monitoring sensors into LCA inventory to optimize energy consumption and well-being performance during buildings' use phase. Accordingly, this Thesis presents a holistic approach to virtualise indoor monitoring sensors while providing credible measurements for energy optimisation purposes. Informed by current research, the methodology was demonstrated in a step-by-step approach to answer the research questions. Mainly, different simulation engines were used for different purposes. For instance, the Computational Fluid Dynamic (CFD) simulation and thermal imaging were used to optimise the physical sensors' positions to guarantee high-accuracy measurements at a later stage of the virtualisation. The methodology also traced and analysed multiple dynamic and static indoor boundary conditions of influence on the sensors measurements. This approach has significantly helped in understanding the sensing measurements behavior

under different conditions, which provided more certainty around the virtual measurements. The virtual sensors resulted in a decrease of CO2 emissions by 11.698.76 ton of CO2 per each physical sensing unit. Accordingly, the developed solution contributed to phasing out the physical sensors and therefore, their associated embodied carbon. Thus, this finding is considered significant in eliminating the associated carbon from a pivotal LCA inventory component. Furthermore, the resulting high-accuracy measurements of the developed virtual sensors also factored in maintaining the occupants' well-being conditions and the associated energy consumption.

The founded equations in virtualising indoor sensors resulted from the extensive CFD, and EnergyPlus simulations and data analysis. These simulations were used to define variables governing the indoor sensors' measurements were practical representations of different indoor and outdoor influencing factors that control indoor measurement behaviours. The achieved virtual sensors' high-accuracy measurements were validated by using physical sensors in the case study zone. Furthermore, the comparison to the widely used Machine Learning (ML) models indicated higher accuracy of this Thesis' framework.

In summary, the key findings of this Thesis open a new path to virtual indoor sensors research. The identification of the indoor environment parameters of interest to energy and well-being performances narrows the scope of the assessment to a building's case-specific. As a result, this finding has effectively helped in reducing the number of needed sensors. Furthermore, the findings emphasised the need to optimise sensors' locations for higher accuracy measurements. The software simulations used to identify optimum sensors' locations have also contributed to finding a relationship between different location measurements, which was used to reduce the number of sensors. Additionally, the total virtualisation equation found to virtualise indoor temperature represents another significant contribution to the indoor virtual sensors' research field. Overall, the successfully achieved new level of highly accurate virtual sensors' measurements of temperature, pressure, CO2 levels, and humidity can be counted as a significant step in narrowing the physical components of the LCA inventory.

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Nomenclature

Acronym	Meaning
UNEP	United Nations Environment Programme
GHG	Green House Gas
COVID-19	Coronavirus Disease 2019
LCA	Life Cycle Assessment
DLCA	Dynamic Life Cycle Assessment
CO2	Carbon Dioxide
DLCI	Dynamic Life Cycle Inventory
AI	Artificial Intelligence
ML	Machine Learning
BIM	Building Information Modelling
SRI	Smart Readiness Indicator
ISO	International Standardization Organization
WHO	World Health Organisation
BSI	British Standards Institution
HSE	Health Safety and Environment
CIBSE	Chartered Institution of Building Services Engineers
COSHH	Control of Substances Hazardous to Health Regulations
EPA	Environmental Protection Agency
PMV	Predicted Mean Vote
PDD	Predicted Percentage of Dissatisfied
AMV	Actual Mean Vote
VOCs	Volatile Organic Compounds
HVAC	Heating, Ventilation, and Air Conditioning
ANN	Artificial Neural Networks
MLR	Multiple Regression Model

GA	Genetic Algorithm
AHU	Air Handling Unit
IAQ	Indoor Air Quality
ARAMAX	AutoRegressive Moving Average with eXogenous inputs
RC	Reinforcement Learning with Classification
PM	Particulate Matter
MLP	Multi-layered Perceptron
LR	Linear Regression
SVM	Support Vector Machine
GBM	Gradient Boosting Machine
RF	Random Forest
IEQ	Indoor Environmental Quality
EPBD	Energy Performance of Buildings Directive
HDD	Heating Degree Days
DDF	Degree Day Factor
IFC	Industry Foundation Classes
PEF	Product Environmental Footprint
NiMH	Nickel Metal Hydride
OSBSS	Open Source Building Science Sensors
BACS	Building Automation System
IoT	Internet of Things
CFD	Computational Fluid Dynamics
BaU	Business as Usual
LoRaWAN	Long Range Wide Area Network
RTC	Real-Time Clocks

Chapter 1 | Introduction

1.1 Background

Recognizing the growing significance of climate change as a global concern, the United Nations Environment Programme (UNEP) has emphasised the imperative for all nations to pursue efforts to drastically reduce Green House Gas (GHG) emissions (UNEP, 2021). The pre-COP26 measures agreed upon during the 2015 Paris Agreement on climate change (IPCC, 2018), would have only reduced predicted 2030 emissions by 7.5%. To meet the global targets, reductions of 30% are needed to stay on the least-cost pathway for 2°C and 55% for 1.5°C (UNEP, 2021; Cohen et al., 2022). Given this global context, there is a pressing need for every sector in the industries to commit to these emission reduction targets, particularly, the building and construction sector (circa 40%energy consumption and carbon emissions) (IEA, 2018).

The construction industry, in particular, stands at a crossroads of challenges and opportunities. The surge in urbanisation, paired with rising energy consumption and associated Greenhouse Gas Emissions (GHG), poses threats to our natural environment, endangering biodiversity life on our planet (Leung, 2015; Clémençon, 2016; Waisman et al., 2019). Yet, It has the potential to reduce energy demand, improve process efficiency, and cut down carbon emissions (Rezgui and Miles, 2010; Alreshidi et al., 2018; Li et al., 2019). This scenario paints a grim picture, indicating the necessity of implementing effective reduction strategies to help decrease carbon footprint throughout each life cycle phase in this sector (Röck et al., 2020).

Of these cycles, the operational phase of buildings is the most intense phase concerning carbon emissions, presenting challenging issues to energy consumption rate and associated occupants' well-being levels. In fact, with 90% of human time typically spent indoors (Tran et al., 2020), several indoor environments' conditions, such as thermal comfort, directly impact our mental and physical well-being (IPCC, 2013; Bueno et al., 2016). The COVID-19 pandemic has further highlighted the criticality of indoor environments, as buildings can act as transmission hubs for pathogens, highlighting the need for effective indoor environment monitoring and control (Negishi et al., 2018; Morawska and Cao, 2020). Consequentially, recent research highlighted that 70% of the total energy consumption in the construction industry is devoted to maintaining optimal indoor environments (Ganesh et al., 2021). In this context, monitoring and controlling the indoor environment is becoming essential for balancing our living conditions, while reducing our associated carbon footprint (Negishi et al., 2018; Mujan et al., 2019; Morawska and Cao, 2020; Desogus et al., 2021; García-Sanz-Calcedo et al., 2021).

While carbon emission refers to the greenhouse gases released into the atmosphere, typically measured as a flow over time, embodied carbon refers to the carbon footprint associated with the entire lifecycle of a product or a process (Huang and Ling, 2021). The impact of carbon emissions from energy performance and product manufacturing is significant and complex (Zhang et al., 2020). In this context, the evolution of energy-efficient smart buildings emphasises the application of indoor environment monitoring sensors for demand-responsive energy management (Pang et al., 2020; Li et al., 2021; Maturo et al., 2022). Indeed, these components can improve energy efficiency and reduce the environmental impact of a building, however, from a Life Cycle Assessment (LCA) perspective, a trade-off between their carbon saving and embodied carbon must be further investigated (Mohebbi et al., 2022). This issue triggers an argument about whether a virtual machine can replace a physical machine to save more embodied carbon across buildings' use phase cycle. Certainly, since embodied carbon and environmental impact are fundamental to the LCA principles, virtual components in indoor monitoring and control systems can be a significant breakthrough in the area of LCA impact. In fact, virtual machines provide the benefits of (a) decreased embodied carbon (Huang et al., 2021), (b) encryption and secure control (Martin et al., 2021), (c) Backup functions for existing physical sensors (Cotrufo et al., 2019; Hong et al., 2021), and (d) ability to learn from historical data, improve accuracy and predict future (Kallio et al., 2021; Martin et al., 2021).

1.2 LCA in Operational Phase

This section clarifies the LCA stance taken in this thesis with a focus on indoor environments to reduce energy demand and enhance occupants' well-being while mitigating environmental impacts. As such, the following sub-sections clarify the research's LCA interpretation as well as introducing the concept of LCA

1.2.1 LCA for Indoor Sensors' Application

LCA is a tool designed to assess the environmental impact of a product or a process across its entire life cycle (Cabeza et al., 2014). An LCA model typically details the progression of the life cycle from the extraction of raw materials to their final disposal. According to ISO 14040, this entails (a) the scope of the assessment, (b) the life cycle inventory analysis, (d) the life cycle impact assessment, and (e) life cycle interpretation (ISO, 2006). On a different scale, Dynamic Life Cycle Assessment (DLCA) is defined as an LCA that incorporates elements of temporally induced changes that affect results and interpretation of the modelled system (Sohn et al., 2020; Cornago et al., 2022). With this perspective, two classifications of embodied carbon emerge from the sensors used for indoor environment monitoring sensors, namely (a) direct carbon accumulation linked to the existing sensors, and (b) indirect accumulation of additional smart systems components. The direct accumulation can be sourced to (a) embodied carbon from an excessive number of sensors and associated batteries' usage (Hayat et al., 2019), and (b) carbon emission as a result of poor measurement accuracy (Ruano et al., 2018; Mena et al., 2022). The indirect accumulation points to (a) operating characteristics, including the level of representation in addressing different energy demand scenarios (Zhu et al., 2022), and (b) additional sensing systems requirements (Fokaides et al., 2020; Li et al., 2021).

1.2.2 Potential of Virtual Indoor Monitoring Sensors in LCA

In pursuit of reducing the embodied carbon associated with indoor monitoring sensors, this thesis focuses on the transition from physical to virtual sensors. Typically, a physical sensor is a device that captures specific physical conditions and translates them into signals that can be analysed by instruments or human observers (Brunello et al., 2021). According to the same authors, virtual sensors are designed to process various data and produce values approximating those directly reported by physical sensors. As introduced in the previous part, the physical sensing device accumulates embodied carbon from its physical presence and performance process, while a virtual sensor only accumulates embodied carbon from its performance process. This means that, while the quantifiable environmental impact of LCA is present considering the physical entity of the sensing device, the DLCA is also present taking into account the dynamism within the process performance of those devices. Yet, it is arguable that the virtual nature of sensors can still imply an environmental impact as the literature showed a subjective understanding of this topic. For instance, (Mytton, 2020) Argued the difficulty in evaluating the environmental impact of cloud computing due to limited access to essential data for a comprehensive environmental impact assessment. However, a study indicated that the ecological environmental performance of cloud digital systems is at an acceptable level, suggesting that advancements in cloud technologies align with environmental sustainability (Cao and Bian, 2021). Another study demonstrated that eco-aware approaches in cloud applications can significantly reduce the CO2 footprint, emphasising the potential of cloud technologies to mitigate environmental impact (Wajid et al., 2015). Furthermore, (Dodge et al., 2022) Argued that the geographic region of the data centre plays a significant role in the carbon intensity of a given cloud instance. Given this context, the literature showed more consensus on the possibility of carbon footprint reduction, given echo-aware approaches, that outperform the carbon footprint from physical sensors.

1.2.3 Sensors as an LCA Inventory Component

In DLCA involving sensors' application, the relationship between the assessment goal and consequential modelling necessitates that sensors are merely Dynamic Life Cycle Inventory (DLCI) enabling tools (Cornago et al., 2022). According to (Collinge et al., 2013), the inventory analysis for the DLCA focuses on different dimensions including, (a) dynamic modelling of unit processes, (b) temporal variations in industrial systems, and (c) temporal variations in emission resources. The latter is strongly connected to the physical sensors considering them as a source of emission from both their manufacturing and process performance. Following this background, the next subsection introduces the challenges and limitations associated with indoor sensors' applications.

1.3 Research Motivation

Current research in the use of sensors for reducing energy demand and enhancing occupants' well-being involves several limitations and gaps, including:

- An unclear understanding of the optimal number of sensors required (Dong et al., 2019; Zhu et al., 2022).
- Lack of clarity and justification on optimal sensor placement for improved accuracy (Pei et al., 2019; Abdelrahman et al., 2022).
- Insufficient guidelines on minimising the embodied carbon linked to indoor environment monitoring and control systems (Mohebbi et al., 2022).

Furthermore, recent research has explored various applications of indoor environment sensors. Some studies have integrated Artificial Intelligence (AI) and Machine Learning (ML) techniques to enhance adaptive systems, such as air conditioning (Valladares et al., 2019; Zhu et al., 2022). These AI and ML-driven applications have demonstrated improvements in environmental parameters and energy consumption compared to traditional methods. Other investigations have focused on optimising sensor placements to reduce biases in temperature measurements, especially in buildings with specific ventilation characteristics (Arnesano et al., 2016). Additionally, there have been efforts to develop open-source platforms for measuring diverse indoor parameters, however limitation of the complexity due to potential sources of error and debugging is acknowledged. Some research has also delved into predicting specific indoor conditions, like humidity, using advanced ML models. However, several limitations have been reported, including the need for multiple scenario testing.

1.4 Research Objectives

Overheating and over-cooling of indoor environments result in excessive consumption of fossil fuel-sourced energy with sizeable associated GHG emissions, affecting our environment. Fundamentally, high-accuracy monitoring and control of indoor environments are becoming crucial to address energy performance and occupants' well-being. However, it comes with its carbon cost. Furthermore, the indoor monitoring system is not affordable to the vast majority of existing public buildings sector. Therefore, a persistent need to decrease embodied carbon from smart monitoring systems is evident. This decrease is crucial to Buildings' LCA, reducing considerable environmental impact from our buildings' use phase.

This research aims to reduce the number of physical sensors by relying on virtual sensors in non-domestic buildings. The rationale behind the focus on non-domestic buildings is their endemic high energy consumption patterns. The aim is to ensure accurate indoor measurements needed for an adaptive indoor environment, and subsequently, energy and well-being optimisation. To achieve this aim, the following research questions are posited:

1. RQ1: Which criteria should be considered to select and prioritise the indoor environment parameters necessary to conduct dynamic life cycle assessment, taking into account a wide range of configurations, including occupancy schedules and geographical location?

2. RQ2: What is the minimum number of physical sensors and their optimal positioning to provide accurate dynamic accounts of indoor environments?

3. RQ3: Can virtual sensors replace physical sensors while ensuring data accuracy and reducing direct and indirect environmental impacts?

1.5 Research Contribution

This thesis offers two primary contributions. The first contribution is to phase out the embodied carbon of physical indoor sensors. This goal will consider relevant strategies for transitioning to virtual sensors. The second contribution is to Optimise energy performance during the buildings' operational phase by facilitating high-level accuracy of indoor parameters measurements. Both goals seeks to eliminate the embodied carbon associated with a pivotal LCA inventory component for energy optimisation. The anticipated results are therefore considered significant to the LCA impact within the scope of energy optimisation during the buildings' use phase.

Additional contributions include a holistic definition of the indoor environment parameters of the interest in energy and well-being optimisation. By defining those parameters, a case-based approach can then inform the minimum selection of the sensors based on the defined scope. It also pursues accurate sensing data for the needed actuation through optimal sensors' positioning.

1.6 Thesis overview

The thesis is formulated into seven chapters to answer the presented research questions. This introduction chapter provides the relevant background of this research field. Accordingly, a contextualisation for the thesis approach is therefore established. The second chapter presents a comprehensive literature review. It starts by reviewing the current state of the art in the research field with the legislative dimension. This strategy aimed at setting the scope of the intellectual commitment by considering existing regulations. It further investigates current practices in indoor parameters' definitions and also analyses the current applications in predicting indoor sensors' measurements. This is followed by an LCA inventroy analysis reflection in the context of conducted approaches.

Following the literature review chapter, the third chapter outlines the methodology approach based on the formulated knowledge. In answering the research questions, it presents a structured cross-validation approach for high-granularity results. As such, it introduces multiple prerequisites to reach the final goal of sensors' virtualisation.

The fourth chapter then presents the results and validation. Accordingly, it compares the virtual sensors' results to existing physical sensors' measurements. It further analyses and reflects the concluded results in the context of the commonly used ML modelling.

Following the results and validation chapter, the fifth chapter provides a discussion of the findings. It starts by reflecting on the implications of the findings through their interpretation within the current literature. It then discusses the results concerning each research question.

The sixth chapter then presents the generalisability of the proposed framework. Accordingly, it details the main use case for holistic understanding. It further describes the proposed algorithms for the virtual sensing system. The goal is to provide a universal application of this thesis's findings for the wider benefits.

Finally, the conclusion chapter summarises the overall findings. It starts by reflecting on the impact of this thesis's findings on the current research field. Subsequently, it presents the research contribution to the field of indoor virtual sensors. It also reflects on current limitations associated with the findings.

Chapter 2 | Literature Review

This chapter presents a holistic review of current indoor environment monitoring research, setting the stage for virtualising indoor monitoring sensors. Hence, it aims to identify gaps in current indoor environment monitoring, including the adoption of indoor sensors. The approach is to answer the proposed research questions, by highlighting the underlying factors that hinder the trade-off associated with carbon accumulation resulting from adopted monitoring solutions. However, given the broad scope of energy performance and well-being optimisation in indoor settings, this chapter will also explore additional research areas pertinent to this study's context. The exploration of advanced modelling methods is intended to aid in defining the environmental impact of indoor environment conditions and subsequently, sensors. These include Building Information Modelling (BIM), energy simulation, and Smart Readiness Indicator (SRI) assessment. Along this direction, it begins by examining the state-of-the-art methods of indoor monitoring and the implications of sensors' deployment on energy efficiency and occupants' well-being. Drawing upon evidence, the focus will also be on the current challenges directly related to the indoor monitoring sensors application as part of the LCA inventory for energy optimisation.

As stated in the research objective part, the selection of non-domestic buildings as a case study is justified due to their significant energy consumption, carbon emission, and complex occupancy schedules. Buildings, such as schools, hospitals, and government offices, typically have higher energy usage and associated carbon footprints compared to residential buildings. Studies show that public buildings account for a substantial portion of total energy consumption in the building sector, essentially, with the HVAC systems being the major contributors. Therefore, focusing on non-domestic buildings, this research can address the highest contributors to CO2 emission and accumulation across buildings' categories.

Given this context, the adopted scope of the LCA in this research is to optimise the LCA impact resulting from energy consumption during the buildings' use phase. It further considers optimum indoor environments as a product of energy performance. Accordingly, This exploration aims to set the stage for an informed methodology to answer the presented research questions in the previous chapter.

2.1 Literature Review Methodology

A comprehensive systematic review was conducted to pinpoint up-to-date research studies by utlising research keywords, reflecting the presented research questions. It also includes relevant work in indoor monitoring and control, and LCA inventory as illustrated in (Figure 2.1). Accordingly, the adopted approach for this review consists of four primary phases:

- **Planning Phase:** In this stage, the scope of the research questions was formed. It involves applications of indoor monitoring sensors to non-domestic buildings during their operational use phase. It further seeks to incorporate the defined scope of the LCA to investigate relevant dimensions of indoor sensors.

- **Search Phase:** A comprehensive set of different research sourced from Science-Direct, Springer, and SCOPUS by utilising specific keywords, in relation to the research questions. The aim is to offer a broad and also in-depth view of indoor monitoring sensors' application dimensions. Accordingly, the used keywords were: ("Indoor monitoring sensors" OR "Virtual sensors" OR "Embodied carbon" OR "BIM" OR "Machine learning prediction") AND ("LCA inventory"). As can be also seen in Figure 2.1, the inclusion of the literature starting from the year 2007 is aimed at covering the period following the publication of the International Standardization Organization (ISO) 14040, which defines the principles and framework for the LCA. This can help in tracking the development timeline of addressing the trade-off between carbon emission and embodied carbon in indoor environment monitoring and control which can also be seen in Figure 2.2. Before further filtering, this keyword set yielded 7,067 documents, of diverse formats including, book chapters and journal articles.

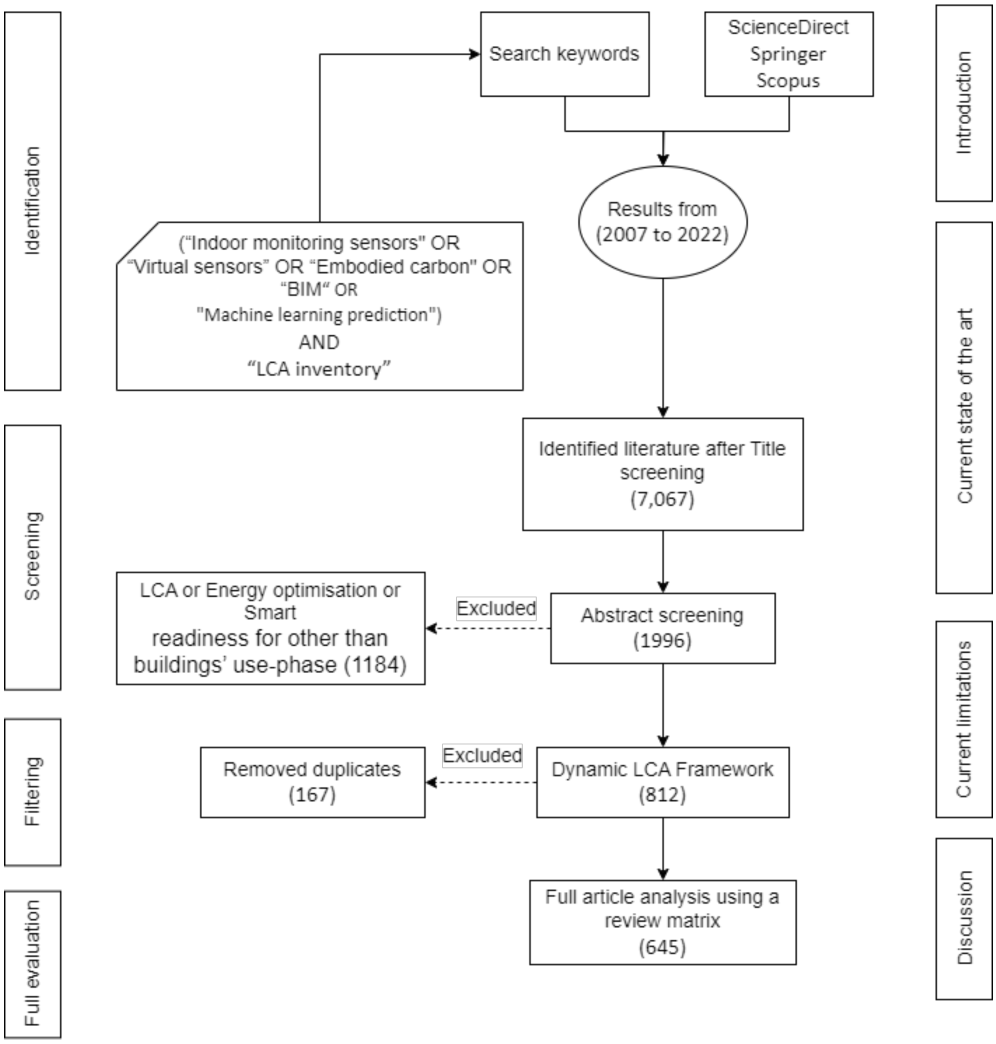

Figure 2.1: Literature Review Methodology

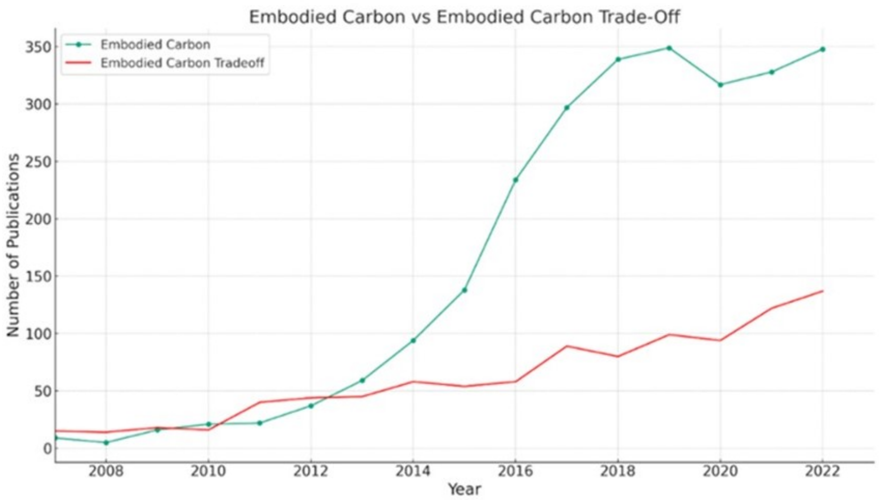

Figure 2.2: Embodied Carbon Trade-off Between Smart Systems and Their Performance Optimisation

- **Filtering phase:** The title screening helped identify full-text publishing and eliminate off-topic subjects such as irrelevant sensors, LCA applications other than in buildings, or different building LCA phases. This step was followed by abstract screening to identify the application of indoor environment monitoring tools during the buildings' use phase with the components of monitoring and automation, virtual sensors, and carbon reduction. Accordingly, 167 publications were excluded, and 645 publications were concluded for the full evaluation in the following phase.

- **Evaluation phase:** In this phase, a qualitative evaluation of the remaining publications was carried out to assess their quality and impact regarding clarity and consistency. As mentioned earlier, given the broadness of this research field, some papers were included in this stage to provide more insight into possible methodology approaches. Accordingly, the identified gaps can then inform this research approach and also reflect on the future path for further improvements.

2.2 State-of-the-Art Research Landscape in Indoor Environments Monitoring

The research is gradually, yet slowly advancing on the operational trade-offs concerning embodied carbon in energy efficiency tools, including indoor sensors, as illustrated in Figure 2.3. Compared to physical sensors, it is observable that there is a considerable gap in utilising virtual indoor sensors. As reviewed, this slow progress is further complicated by the evidence of common inconsistencies in the assessment of embodied carbon across various LCA dimensions of the building components (Chen et al., 2022; Xu et al., 2021). The indications showed that these discrepancies stem from unavoidable assumptions associated with business-as-usual (BaU) applications for the sensors. As a result, less detailed approaches were given to the upstream and downstream LCA of these adopted components. Given these inconsistencies, there is a compelling argument for reducing the physical components in smart systems as a more effective strategy for embodied carbon reduction. This not only simplifies the assessment process but also offers a more straightforward path to improved LCA impact.

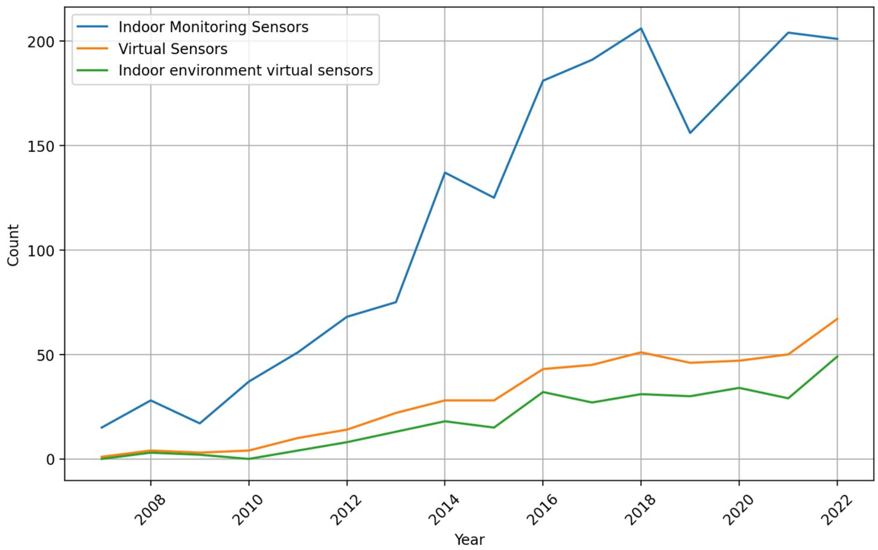

Figure 2.3: Research Progress in Indoor Monitoring Sensors Following The Publication of ISO 14040.

As highlighted, this issue indicated a shortcoming in the overall embodied carbon resulting from indoor environment monitoring. Building on this understanding, the following subsection will explore criteria governing the identification of indoor environment parameters in the context of optimum indoor environment conditions. Given the existing guidelines concerning optimum indoor environments, the exploration will first consider these standards for collective analysis. While the goal is to seek answers to the first research question, it also contextualises best practices concerning sensors' measurement accuracy that need to satisfy these standards requirements. This strategy will further help in investigating hypothetical modelling approaches to virtual indoor monitoring sensors across the research's landscape.

2.3 Indoor Environment Parameters' definition

This section investigates the current research, in an attempt to answer the first research question *"Which criteria should be considered to select and prioritise the indoor environment parameters necessary to conduct dynamic life cycle assessment, taking into account a wide range of configurations, including occupancy schedules and geographical location?"*. Along this direction, the section aims to formulate a comprehensive understanding of relevant legislation and current practices in scoping the criteria for defining indoor environment parameters. The goal is to establish the relevant knowledge of the adopted tools and corresponding limitations. It also reflects on the LCA dimension associated with indoor monitoring conditions. Accordingly, it seeks to analyse complex issues such as occupancy dynamics and identify possible viable solutions for reducing the carbon footprint of the indoor monitoring process.

2.3.1 Criteria Determining Indoor Environments Parameters

The UK building regulations documents such as Part L2B, and Part F Volume 2, recommend the safety, health, and welfare of the occupants in indoor environments while promoting energy efficiency, in non-domestic buildings (UK Government, 2013, 2010). Within these regulations, different indoor environment set-points were aligned with the World Health Organisation (WHO) guidelines. Accordingly, they define the indoor environment as *"All the physical, chemical, and biological factors external to a person, and all the related behaviours"*. The WHO reported that indoor air pollution is responsible for a staggering 2.8 million deaths annually. Furthermore, the organisation reported that *"Approximately one-quarter of the global disease burden is due to modifiable environmental factors"* (Brusseau et al., 2016), which indicates the critical role that indoor environment quality has in both public health and global well-being. These recommendations are consequential to further regulatory bodies' guidelines, such as the British Standards Institution (BSI), Health Safety and Environment (HSE), and the Chartered Institution of Building Services Engineers (CIBSE). For instance, the Control of Substances Hazardous to Health Regulations (COSHH), details workplace exposure limits for hazardous substances including dust, gas, and fumes (Moon et al., 2021). The Environmental Protection Agency (EPA) 2013 report also indicated that exposure concentrations vary depending on several factors including individuals' behaviour and activities, pollutant sources, and geographical location (NRC, 2013). It is, therefore, the idea behind this maximum exposure time implies a limited tolerance per category occupants and building type. Concisely, the Literature showed different criteria for identifying and prioritising indoor environment parameters. This approach is found dependent on several factors such as occupancy profile, space type, and even geographical locations (Erlandson et al., 2019; Wei et al., 2023). In more detail, parameters such as thermal, visual, and Indoor Air Quality (IAQ) are often considered the most important due to their high link to occupancy well-being and energy consumption. Moreover, demographic factors such as gender and age also play a significant role in indoor environments' thermal sensations (Andargie and Azar, 2019; Yang and Moon, 2019). Consequentially, the literature pointed out the necessity of calibrating thermal comfort taking into account different occupant classes and activities (Rohde et al., 2020). Accordingly, the research pointed to (a) physiological-based comfort (Djongyang and Tchinda, 2010), and (b) design-oriented, including productivity and enhanced well-being (Ganesh et al., 2021).

To further understand the implications of occupancy-focused indoor environment conditions, and their implications on energy optimisation, further thermal comfort definitions were examined. Accordingly, the BS EN ISO 7730 defines thermal comfort as a condition of mind that expresses satisfaction with the thermal environment (International Organization for Standardization, 2005). The standard further determines the thermal comfort using Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD). In this setting, it is important to acknowledge that the PMV and PPD may not be always representative, compared to other regulations set points. However, in consistency with the PMV approach, the research has also attempted to further define thermal comfort as a consensual well-being (Rohde et al., 2020). The research has also presented a comparison between the PMV and Actual Mean Vote (AMV) as a result of demographic variation and their implications on indoor energy performance (Del Ferraro et al., 2015; Enescu, 2017).

With these different perceptions of indoor environments, understanding the vital role of multidimensional patterns is crucial to optimum indoor conditions. Along this direction, the literature analysis indicated different indoor parameters with their corresponding influences on the indoor conditions, as illustrated in Table 2.1.

Table 2.1: Reviewed Dimensions of Indoor Environment Parameters in Non-domestic Buildings.

References	Parameters	Dimensions
(Al Horr et al., 2017) (Gwak et al., 2019)	Physical parameters	Temperature, Humidity, and Airflow
(Allen et al., 2016) (Potrč Obrecht et al., 2019)	Chemical Parameters	CO2 levels, VOCs, and particulate matter
(D'alessandro et al., 2020) (Awada et al., 2021)	Biological Parameters	Bacteria and viruses
(Chen et al., 2020a)	Behavioural Parameters	Occupancy profiles user preferences and set points
(Salimi and Hammad, 2019) (Dong et al., 2019)	Technological Parameters	Sensors' accuracy, data frequency, and automation
(Zuhaib et al., 2018)	Environmental Parameters	Seasonal variations and time of the day

Building on the understanding of these criteria, recognising the dynamic interrelation among different indoor environment parameters is substantial to maintaining optimum indoor conditions. Accordingly, optimum indoor environment conditions can result in increased energy consumption, and therefore, environmental impact. As a result, the complex interactions among these factors highlight the challenges in establishing and upholding the optimum conditions. However, reflecting on the reviewed regulations and literature definitions, the evidence seems to suggest that a case-based indoor parameters' definition, is substantive to defining optimal indoor conditions, of less environmental impact. From an LCA perspective, the building type and occupancy activity, provide further detailing to the LCA inventory input data, that is specific to each building's case. As reviewed, these can include different dynamic entities that factor into energy control approaches and their environmental impact. accordingly, the following subsection explores this dynamism from the context of the LCA inventory scope formation.

2.3.2 Integrating LCA Inventory for Energy Optimisation

This subsection investigates underlying factors in the characterisation of the indoor environment parameters as an input to the LCA inventory. The goal is to explore possible tools that can be used in shaping the system boundaries of the inventory input data. These boundaries can then be used to inform the level of detail needed to optimise the trade-off between optimisation tools and their environmental impact.

The research has introduced the Attributional LCA (ALCA) as being focused on the direct environmental impact of a system boundary whereas the Consequential LCA (CLCA) addresses the indirect effects of the system boundaries (Hansen et al., 2023). Considering the broader dimensions introduced in the previous section, both LCA sub-concepts of ALCA, and CLCA, can shape the LCA inventory for indoor parameters' monitoring. In addition to the direct effects, accompanying indirect effects in the LCA inventory analysis are important determinants to define the modelling choices in quantifying the influence of the optimisation on the environmental impact. According to the scope of this study, a case-specific approach to internal and external dynamic factors can better define indoor parameters (Chiesa et al., 2019). In more detail, internal factors can be named as occupancy profile, and HVAC scheduling, while outdoor factors can mainly be represented in weather conditions.

However, the presence of the physical components within the LCA boundaries can imply environmental impact. As such, the following investigate the feasibility of those components. The goal is to form an understanding of the trade-off between the viability of those components against their environmental impact.

- **Hardware-based Energy Optimisation**

The research approach on hardware-based energy optimisation was mainly focused on HVAC control, using indoor monitoring sensors as an IoT source that require sub-systems characteristics. (Al-Obaidi et al., 2022) suggested that IoT models come into three main models, including (a) IoT to device, (b) IoT to a cloud system, and (C) IoT to a base station. With different physical architecture and corresponding energy consumption, this particular classification can imply different LCA consequential impacts. (Kim et al., 2022) suggested multiple hardware approaches, highlighting physical indoor sensors as a data mining source for different software modelling approaches. Indeed, those approaches can vary in their overall environmental impact, compared to their system architecture as highlighted earlier by (Al-Obaidi et al., 2022). However, it is still arguable that data mining and computational approaches come with their environmental impact. Along this direction, the research has shown different approaches to optimise energy consumption in data centres where servers accommodate software data. (Zhou et al., 2015) highlighted the carbon emission in data centres from a geo-location perspective and proposed a carbon-aware control framework through a triple elements trade-off that consists of electricity cost, Service Level Agreement (SLA), and emission reduction budget. The proposal was to make decisions on geographical load balancing, capacity sizing, and server speed scaling. (Sharma and Saini, 2016) had a similar approach to the cloud centre at a micro-level methodology by switching off the idle notes and using live migration of virtual machines. However, this methodology may restrict continuous access to live sensing data.

Based upon that, an initial understanding can be formulated that multiple approaches to reduce the environmental impact of computational systems are well-founded in the literature. This observation can later be used in weighing different modelling choices against their environmental impacts. For more understanding of current software-based approaches, the following subsection presents important publications pertinent to this perspective.

- **Software-based Energy Optimisation**

The research has also shown interest in developing software energy optimisation strategies. (Ye et al., 2021) highlighted that despite the effort, current applications are only capable of providing static models, that lack the occupancy profile dynamism. The study used sensors' data and developed an enhanced deep learning model of Sequence-to-Sequence Long Short-Term Memory (Seq2Seq LSTM). The results showed higher accuracy compared to different models by capturing the temporal and spatial patterns of time series data. Concisely, (Ye et al., 2021) developed adaptive ML-based building models and Model Predictive Control (MPC) systems. The study achieved high accuracy, yet acknowledged a limitation of further dynamic consideration, within a large building context. A review by (Michailidis et al., 2023) analysed the research from 2015 to 2023, and identified the most highly cited model-free HVAC control applications. The review highlighted the use of Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), and Artificial neural networks (ANNs) in different HVAC types. The review indicated the significance of learning from surroundings and highlighted the Markov Decision Processes (MDPs) mathematical framework to decrease uncertainties. The presented equations aimed to describe the interaction of the agent with the surrounding environment to enhance RL. Accordingly, the review concluded that DRL has significant potential since it learns from dynamic surroundings, including occupancy dynamics and external weather conditions.

In summary, both optimisation approaches acknowledged the significance of the dynamic factors to achieve better results. They further highlighted the role of indoor sensors in capturing different spatial and temporal factors, including time series. These facts can further help in modelling the indoor environment parameters' weightings on energy consumption under different conditions. However, it was observed that less information was given concerning the environmental impact of those systems. As highlighted, the definition of the environmental impact of those systems are substantial determinant of the LCA inventory towards higher LCA impact. In light of this analysis, the following subsection narrows the scope by further analysing the current sensors' applications. The goal is to investigate factors that may affect the accountancy of current approaches in relation to their overall optimisation efficiency.

2.3.3 Modelling Approaches to Sensor Deployment in Buildings for Energy Efficiency

This section investigates the underlying factors influencing indoor environment monitoring as critical to both energy optimisation and human well-being. The exploration will also touch on the trade-off between carbon emission and embodied carbon of the monitoring sensors. Along this path, a review of associated modelling tools that help evaluate these factors will be included. The goal is to offer a detailed exploration background of the current research to assist the methodology in answering the first research question outlined in the previous chapter.

As established in the previous chapter, several studies have pointed to the role of various factors of air quality, dampness, infestations, and lighting, as well as housing tenure and design, on our mental and physical health (Monier et al., 2011; Bueno et al., 2016) It was also noted that maintaining the health and well-being of occupants needs to be balanced with the associated carbon emissions and embodied carbon. As presented, different legislation published by both national and international bodies were found to govern this balance. In this context, the deployment of sensors in buildings, particularly for energy performance optimisation, has been a topic of significant interest in recent years. In pursuit of seeking to know how current methods approach this purpose, diverse modelling approaches were identified. However, the choice of approach depends on the specific objectives of the deployment, the characteristics of the building, and the desired outcomes in terms of energy efficiency and occupant well-being. As such, the following subsections will review the current modelling approaches for indoor monitoring sensors' deployment.

2.3.3.1 Sensor-Based Inverse Modeling for Indoor Energy Optimisation

One of the prominent modelling approaches is the inverse modelling technique which uses statistical learning and time series analysis to improve knowledge from data (Simon et al., 2019; Gunay et al., 2021). The review showed that this approach can accurately assess buildings' thermal properties with a small number of cost-effective sensors. Arguably, this approach consents to the Seq2Seq LSTM from the previous section, indicating the significance of adopting the time dimension in predictive modelling. Along this direction, (Ramallo-González et al., 2018) Applied inverse modelling to 6 monitored real and 1000 simulated buildings of 16 representative variables used to characterise the building's geometry, fabric and occupants' dynamics. The results showed that Inverse modelling can accurately assess buildings' thermal properties with a small number of low-cost sensors. (Hong and Lee, 2019) Argued that physics-based building energy models such as EnergyPlus rely on some unknown input parameters such as internal thermal mass and air infiltration leading to uncertainty in simulation results. The study proposed physics-based models with sensor data used to calculate the zone air infiltration rate and internal thermal mass for optimised energy simulation. Although this approach was constrained by the free-floating HVAC mode, further development could lead to a more refined assessment of proposed retrofits, potentially enhancing the LCA impact. It is also important to acknowledge their idea behind overcoming the simulation shortcomings by using the sensors to capture the influences of the uncertainty factors found in the simulation.

Additional inverse modelling approaches with different objectives, such as cost-effectiveness and aesthetic considerations, were also highlighted. For instance, a study proposed a research question *"What types of sensors are useful for building energy management and where do we deploy them in a building?"* (Agarwal et al., 2016). The study argued the similarities in energy consumption profiles across different zones of a building and proposed inference logic to decrease the number of physical sensors arguing their cost and aesthetic impact. The study found a high energy consumption baseline for the case study building and indicated a 48% energy consumption reduction by relying on the proposed minimum indoor monitoring sensors. Furthermore, a study applied ANN, Genetic Algorithms (GA), and Multiple Regression Models (MLR) to model the supply air temperature of the Air Handling Units (AHU) in three different case study buildings in Canada (Torabi et al., 2021). The authors suggested that the generated inverse models can function as virtual temperature sensors that help in performance control, however acknowledged that physical sensors are essential in fault detection in AHU performance. Furthermore, the study highlighted further limitations on generating predictive models that assist in characterising the performance of the AHUs. Further inverse modelling approaches relied on different strategies utilising ML modelling and indoor sensors as can be seen in Table 2.2.

Table 2.2: Summary of Inverse Modelling Approaches and Findings

Reference	Methodology	Inverse Modelling Approach	Findings
(Hong and Lee, 2019)	Integrating physics-based models with sensors data	Enhanced accuracy of simulation results	Informed decision-making on energy retrofits and efficiency improvements
(Ramallo-González et al., 2018)	Reliability of inverse modelling in characterising thermal properties	Assessment of buildings' thermal properties	Accurate evaluation of retrofit impacts
(Han and Zhang, 2020)	Energy-saving building system integration with a smart and low-cost sensing/control network	Integration of smart sensing/control network	Satisfactory thermal comfort and indoor air quality with energy savings
(Lee and Hong, 2019)	Validation of an inverse model of zone air heat balance	Validated inverse model in EnergyPlus	Enhanced energy modelling of existing buildings
(Asadi et al., 2019)	Calibrating energy model using automated optimisation-based algorithm	Optimisation-based framework utilising a Harmony Search algorithm	Reliable calibration of building energy models
(Boodi et al., 2022)	Comparative analysis of thermal-network models including white, black, and grey-box	Comparison of various inverse modellings for building thermal networks	Lack of standardisation in model configuration.
(Gunay et al., 2020)	G A to estimate model parameters based on sensor data	Inverse grey box modelling for diagnosing sensors and actuator anomalies.	Identification of HVAC faults using sensor data, based on the model parameters' interpretation
(Rusek et al., 2022)	Controlled variables, using crowd-sensing to model user activity in different conditions.	Understanding energy consumption concerning occupancy.	Correlation between occupancy and energy consumption.

The table indicated different goals by integrating sensors and various ML modellings, which will be covered in the following subsection. Nevertheless, it is observable that the integration of sensors comes as a method to capture different dynamic conditions, particularly occupancy, to later correlate with energy consumption. However, while inverse modelling has been acclaimed for its potential in energy performance optimisation, recent research highlighted some of its limitations. (Purnomo et al., 2020) emphasised the criticality of addressing dynamic factors and suggested that the choice of methods can significantly influence the accuracy and efficiency of the model. As also indicated by (Rezaee et al., 2019), inverse modelling can provide feasible solutions, but there is an inherent challenge in identifying the most optimal and practical solutions for real and dynamic world applications. In contrast, ML modelling has shown interesting capabilities to learn the behaviour of these dynamics. The reviewed methodologies indicated that ML models can learn from sensors' data to predict indoor energy consumption. From this perspective, the following subsection will review the adoption of indoor monitoring sensors in ML models for energy performance optimisation. The goal is to formulate a further context of the indoor sensors within the LCA inventory.

2.3.3.2 Machine Learning Modelling to Predict Indoor Sensing Measurements

Despite the complexity involved, ML models are largely adopted by the research to predict indoor sensors' measurements. They mainly come as supervised and unsupervised learning models (Elmezughi et al., 2022). The supervised models are used where the model learns a function between the input and output data. On the other hand, unsupervised models are used to extract hidden rules from unlabeled data. However, the non-linear behaviour in the dynamics behind energy consumption in buildings necessitates precise modelling approaches to decrease potential bias in their results (Zhang et al., 2021). In this context, the literature defined ML as *"a computer program is said to learn from experience E concerning some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience"* (Zhou, 2021). Based on this definition, ML has been increasingly explored to predict indoor sensors' measurements, using their historical data to predict sensing measurements for energy control optimisation. However, few approaches argued that this methodology can improve by using a sufficient amount of historical sensing data, which is time-consuming. In overcoming this issue, (Ghahramani et al., 2017) proposed an adaptive hybrid metaheuristic approach to optimal HVAC control settings without any historical data. The study relied on one dynamic factor of the outdoor temperature and produced promising results however acknowledged the role of dynamic occupancy profile on energy consumption fluctuations. In contrast, (Abade et al., 2018) Aimed to improve occupants' experience in the context of smart environments with ML support. The solution monitored environmental factors such as temperature, light intensity, noise, and CO2 to estimate the presence of occupants and subsequently used ML to infer the number of individuals in the room. While the study offered promising results, the experiment was limited to a specific room characterised by limited occupancy changes. This highlights the recommendations from the previous study which emphasised the importance of comprehensive occupancy profile data. Indeed, limited indoor environment boundary conditions can lead to poor LCA inventory formation, however, it is observable that the occupancy profile can be estimated by inferring different parameters. for further analysis of the influence of limited boundary conditions, it is important to investigate different ML modelling settings, namely Black Box, White Box, and Grey Box models.

- Black Box Models: The Black Box models are data-driven, establishing mathematical relationships between variables based on system performance data (Li and Wen, 2014). They are more dependent on ML algorithms and do not require prior knowledge of system physics. Their efficacy is closely tied to the availability and quality of data. Given sufficient data, the interoperability of Black Box models indicates their potential integration with existing building management systems to enable energy optimisation goals (Zhang et al., 2021). However, while they can be highly accurate, they lack the inclusion of the occupancy dynamic profile as reviewed by (Gassar and Cha, 2020). As a result, both Whit Box and Black Box use mathematical domains such as MATLAB and EnergyPlus to predict energy savings, particularly on retrofit. This fact was previously highlighted within the software-based energy optimisation subsection, highlighting more focus on static modelling for the overall energy performance.

- White Box Models: These models are grounded in the physical properties of building materials, and utilise thermal dynamic equations to capture the inherent physics of the system (Rätz et al., 2019). Therefore, they are based on explicit knowledge of the system's underlying physics. However, their practicality is sometimes limited due to the need for detailed building information, which can be challenging considering the indoor dynamic conditions. One example is the EnergyPlus modelling which requires extensive detailing for the building physical models and different indoor boundary conditions to achieve high-accuracy results (Gassar and Cha, 2020). However, based on the reviewed methods from the previous Table 2.2, EnergyPlus still needed to be validated by different inverse modelling for higher accuracy. Nevertheless, there's still a notable preference for White Box models over Black Box models in certain applications, due to their closer alignment with physics-based models particularly of time dependency factors (Fung et al., 2021).

- **Grey Box Models:** These models come in a combination of features from both white and Black Box models (Li and Wen, 2014; Rätz et al., 2019). They are usually adopted when there are limited measured data, offering a balanced approach that integrates both physical and data-driven approaches from both models. As a result, they combine the transparency of White Box models with the flexibility of black-box models, making them particularly suitable for complex modelling tasks. This strategy is similar to the reviewed inverse modelling. In essence, it can refer to integrating historical sensing data with the EnergyPlus simulation model for higher accuracy optimisation results. Given this context, this strategy requires the continuous presence of physical sensors to periodically run the optimisation.

Despite the advancements in these modelling approaches, the gap remains concerning real-world applicability. This includes their scalability and performance under diverse building types and climates. For instance, several outdoor dynamic factors define the environmental context of a building. In detail, Urban Canyons are narrow passages of trapped air formed by tall buildings in urban areas, and therefore, may unpredictably decrease IAQ levels in the event of natural ventilation (Buccolieri et al., 2022). Also, the Urban Heat Island effect is a phenomenon where temperature increases in a specific urban area due to human activities or architectural characteristics (López-Guerrero et al., 2022). Both phenomena are, therefore, polar to the other as high temperatures may require natural ventilation that decreases the IAQ levels. This fact emphasises the need for a high-accuracy modelling approach that is inclusive of both external and internal factors affecting indoor environments. In this context, (Zekar and El Khatib, 2018) Evaluated the trade-off between accuracy loss and increased computational efficiency by comparing various modelling types. The study developed and assessed an ANN Black Box model, A Grey Box model of AutoRegressive Moving Average with eXogenous inputs (ARMAX), and a White Box model Reinforcement Learning with Classification (RC), against a physically detailed model of EnergyPlus. The outputs demonstrated that simplified building representations in urban environments result in a limited loss of accuracy compared to a detailed model. The study recognised certain assumptions as limitations, however, it emphasised the significance of Urban Canyon analysis and the Urban Heat Island Effect in understanding the impact of various building layouts and conditions. Aiming to address these uncertainties, Grey Box models have been highlighted by (Harb et al., 2016) for their potential to forecast the thermal response of buildings for energy demand management, with a focus on different building types. Furthermore, a hybrid approach of both Grey Box and Black Box models was proposed for predicting indoor air temperatures in typical two-story houses (Cui et al., 2019). The study observed reliability in predicting average temperatures on both floors. However, in the absence of indoor sensors, relying on Black Box modelling only can overlook those dynamic factors usually picked by the indoor sensors. Furthermore, the use of sensors in the White Box and Grey Box models did not factor in the trade-off between their embodied carbon and the overall optimisation impact.

In contrast, A study adopted Multi-layered Perception (MLP) to predict a building's energy consumption (Chammas et al., 2019). The study used 10 wireless indoor sensors and weather data to gain insight into the energy performance of the case study building. To compare the outputs to different types of models, the study also developed additional classification algorithms models. These include Linear Regression (LR), Support Vector Machine (SVM), Gradient Boosting Machine (GBM) and Random Forest (RF). The study demonstrated better outcomes and acknowledged negligible differences across all adopted models. The study also highlighted the importance of adopting weather data to improve overall accuracy. This highlight implies the continuous use of sensors, which necessitates a considerable amount of their embodied carbon across the buildings' operational phase.

Given the reviewed modelling strategies, the choice of a specific model is mainly dependent on the characteristics of the data (Chen et al., 2020b). Further considerations include sensors' accuracy and embodied carbon which was overlooked by the reviewed research. Therefore, since the sensors are considered a main source of capturing the dynamism in the indoor environment, their application requires a religiously defined scope. This scope can then consist of (a) level of representation and measurement accuracy, and (b) associated embodied carbon to establish optimisation trade-off. For more detail, the following section explores sensors' applications. The goal is to establish further understanding centring around their application boundaries and identify gaps that can inform high-level representation of the indoor environment conditions.

2.4 Selecting Indoor Environment Factors for Robust Energy Optimisation

After thoroughly examining different modelling approaches to energy performance prediction, it was identified that sensors' measurements' accuracy and associated embodied carbon were overlooked. Accordingly, it is essential to explore the possible indoor factors under which the sensors operate. By gaining more certainty, this exploration is therefore significant to the quality of the LCA inventory input data resolution. As such, it also attempts to answer the first research question, concerning the configuration's range.

Despite the identified shortcomings, different research showed more focus on the sensors' application. (Yoganathan et al., 2018) proposed a data-driven approach using partition-based clustering algorithms, an information loss approach, and the Pareto principle. The study deployed a large number of sensors in an open office space and used the Pareto principle to identify each cluster. Accordingly, it considered 20% of the deployed sensors as more representative of the indoor conditions. The incorporation of methods like the Pareto principle in sensors' positioning strategies highlights the importance of capturing the most influential factors in indoor environments. Furthermore, the study also recognised the significance of addressing boundary conditions, such as ambient temperature, humidity, building location, and orientation. This case-based approach can provide guidance when applying the methodology to different buildings. Accordingly, indoor parameters of interest to sensors can vary with their regulatory set-points respectively. In this context, (Khovalyg et al., 2020b) reviewed and compared the requirements for indoor thermal environment and ventilation for acceptable air quality across different international standards. The review identified the role of different factors in shaping the standards. These include climate, building typology and demographic factors. This finding further sets the boundary of indoor environment conditions under legislative criteria.

As understood, the definition of the indoor parameters of interest to sensing has different dimensions depending on the building case. As a result, this definition comes as a crucial step in approaching sensors' identification. For more context, the following subsection addresses the indoor environment parameters' definitions.

2.4.1 Indoor Environment parameters definition

As highlighted in the previous subsection, the LCA for energy performance during the operational phase is significantly influenced by the input data, facilitated by the sensors as part of the inventory. Accordingly, the accurate measurements of the indoor environment parameters provide effective input data. This certainty further ensures that the LCA outputs reflect the actual environmental impact of the buildings' performances (Morales-Velazquez et al., 2017). Hence, accurate definition of the indoor parameters is vital prior to sensors' identification. On that account, the literature showed different criteria to identify the influence of indoor environment parameters on energy consumption and occupants' well-being. As mentioned in the previous section, the SRI assessment can be used to highlight features of the highest influence on environmental impact and occupants' well-being (Ożadowicz, 2022). While the assessment comes as an evaluative method, combining it with computational energy simulation engines can provide more certainty about the indoor parameters.

Another approach highlighted the potential of using the buildings' energy consumption data to identify the parameters of interest for sensing and control. A study by (Khovalyg and Ravussin, 2022) demonstrated that electricity consumption in buildings can be reliably predicted using data from a subset of buildings. This approach is particularly beneficial as it can provide insights into the energy use characteristics and demand load features of buildings (Guan et al., 2016). Furthermore, integrating user information with the physical characteristics of buildings can derive influential elements that impact energy consumption. Such data-driven methods can be instrumental in estimating energy consumption attributes (Tian et al., 2021). Moreover, the consideration of specific energy consumption patterns of buildings has been emphasised, suggesting that each building should be investigated as a unique unit (Safa et al., 2017). It is therefore becoming evident that a custom-based approach to identify indoor parameters of interest is crucial to achieve the anticipated LCA goals. While the case-based approach can result in different criteria in defining indoor parameters, the occupancy interaction indicated universal dynamic criteria that influence indoor conditions.

In addition to the identified criteria, another dimension in choosing the reliable types of sensors. For instance, the sensor's attributes, such as high sensitivity, low power consumption, and multiple operation modes, are essential features for both effective monitoring and reduced environmental impact (Shahzad and O'Nils, 2018). Furthermore, the environmental footprint of the sensor, particularly when considering the materials used in its manufacturing, is another significant consideration. For the full picture of the sensors' environmental impact, further review will be analysed in a dedicated section.

In summary, the comprehensive approach to assessing a building's smart readiness can identify possible gaps in it is current indoor environment parameters performance (Li et al., 2019). Accordingly, this strategy supports the selection of indoor monitoring sensors as both effective and aligned with the overall LCA inventory goals. However, to achieve certainty of the intended monitoring parameters, the following subsections will review the characterisation of indoor environment parameters. The goal is to provide a detailed exploration of how these parameters are identified, measured, and prioritised according to a building's context.

2.4.2 Indoor Environment Parameters Characterisation

The dynamism in indoor environment parameters is a complex interplay of various dimensions that significantly influence both human well-being and the building's energy performance (Mishra et al., 2016; Ma et al., 2021). In this setting, Ill-informed HVAC systems, especially with poor knowledge of changing occupancy scenarios or a building's change of use, have a significant energy load due to unnecessary heating or cooling (Leung, 2015; Maddalena et al., 2020). Furthermore, with the cold and moisture affecting human health and causing sick building syndrome, the increasing heating costs have pushed for less natural ventilation in return for decreased heating load but poor IAQ (Stabile et al., 2017). In this case, a responsive action from the mechanical ventilation to improve the IAQ can cause pressure differentials between buildings' zones, which may lead to infiltration and air pollutants from the deterioration of the building's material (Shi et al., 2020). Moreover, the simultaneous increase in heating and airflow rate from mechanical ventilation to improve the IAQ can also increase the carbon footprint compared to its expected levels. As highlighted in Section 1, enclosed microclimates with a high airflow rate can also create infectious environments, i.e., COVID-19 virus resettling behaviour due to different air shear forces (Morawska and Cao, 2020; Noorimotlagh et al., 2021). Furthermore, relying on natural ventilation to improve the IAQ can also increase the heating load in winter, and decrease the buildings' efficiency as a barrier to the infiltration of outdoor pollutants as a result of excessive natural ventilation (Stabile et al., 2017).

With this established pattern of different indoor environment parameters interactions, Monitoring is becoming essential to maintain the desired equilibrium in indoor environment conditions. However, as highlighted, occupants' thermal sensations differ based on their demographic characterisation. Therefore, aligning indoor parameters' setpoints with this demographic classification, while considering buildings' typology is crucial to energy performance optimisation (Rupp et al., 2019; Zhang and de Dear, 2019). As such, The research showed different characterisations for the dynamic inputs of time variances to address a wide range of thermal comfort scenarios in non-domestic and mixed-use buildings (Fouquet et al., 2015; Vilches et al., 2017; Feng et al., 2022).

Despite the literature showing a case-based approach in LCA, informed by the weightings of pre-defined domains, concepts related to future prediction and time-dependency inventory analysis for carbon reduction dominated this research landscape with the main drive for impact (Ross and Cheah, 2017; Lueddeckens et al., 2020). The variation in these approaches comes from the fact that, according to ISO 14040, the goals of the LCA impact assessment are strongly linked to their input data. For instance, the accuracy of the output results in reducing energy consumption is highly dependent on the level of resolution in the indoor sensor measurement inputs, as part of the DLCI (Feng et al., 2022). However, compelling evidence from the literature has also highlighted that the calculated impacts from the LCA are prone to deviation from their actual impact due to the lack of foresight in characterising the LCA input data (Chau et al., 2015; Vuarnoz et al., 2020). As defined in Section 1, the level of indoor parameters' representation using sensors needs a more detailed assessment to achieve the anticipated environmental impact. However, on one hand, a lower level of accuracy in measuring indoor environment parameters can decrease the level of data resolution within the LCA inventory and therefore affect the expected impact (Kumar et al., 2016; Pantazaras et al., 2018). On the other hand, high accuracy in sensing data obtained from multiple sensors can reduce carbon by effective energy performance optimisation, but increase embodied carbon from the excessive number of sensors (Pantazaras et al., 2018). Thus it is important to characterise indoor environment parameters of the highest influence on occupants' well-being and energy consumption, as a first step in defining the minimum number of sensors to reduce their environmental impact. Along this path, the following subsection will review the research on case-specific parameters' definitions. The goal is to formulate a critical understanding of indoor parameters' definition strategies.

2.4.3 Defining Key Parameters in Indoor Monitoring

As the characterisation of indoor environment parameters is an evolving field of research, a growing focus on the need for custom assessments of specific buildings' contexts is evident. Early on, the literature adopted questionnaire-based methods to assess bench-marking for indoor environmental quality (Dykes and Baird, 2013). The research has also presented a comparison between the PMV and AMV as a result of demographic variation and their implications on indoor energy performance (Del Ferraro et al., 2015; Enescu, 2017). The findings were that those methods are subjective and may not necessarily adhere to best practices. However, there's a growing realization that many national and international standards do not adequately address regional differences and diversity factors in indoor environments. This necessitates the integration of various indoor environmental factors into a combined indicator (Khovalyg et al., 2020a). In this direction, a study by (Li et al., 2021) assigned different weighting to each parameter, to create a model that more accurately reflects the preferences and priorities of the majority of occupants. Hence, this can be typically used to prioritise or give importance to specific parameters or factors over others considering the occupants' well-being and the associated energy consumption.

Recently, (Ganesh et al., 2021) conducted a literature review covering the last 5 decades to investigate factors affecting indoor environment quality. The review highlighted that the studies lacked the depth of assessing pivotal factors, including thermal and visual comforts. The study emphasised the need for more custom methods in approaching indoor environment quality conditions. However, the significance of shaping indoor environmental conditions has also attracted considerable attention in recent research. (Gupta and Kapsali, 2016) found that indoor environments' conditions and air quality are significantly influenced by the interaction between the performance of building fabric and systems, with the occupants' dynamic profile. This has led to more exploration of holistic approaches that integrate building design, systems, and occupants' behaviour. Along this line, (Wei et al., 2022) reviewed various green building certification schemes and identified different parameters used to assess Indoor Environments Quality (IEQ) in offices and hotels. Their findings highlighted the predominant focus on thermal, acoustic, visual, and IAQ, with the IAQ parameter contributing the most to the overall optimum conditions. (Wang and Zheng, 2020) also emphasised the growing attention towards green buildings, particularly in the areas of design, energy simulation, and post-occupancy evaluation, highlighting the need for integrated analysis of energy consumption, indoor environmental quality, and occupant satisfaction during the operational stage. However (Janjua et al., 2019) pointed out that the environmental performance of buildings is significantly affected by the service life of a building and the replacement intervals of its components. This calls for a more in-depth understanding and consideration of the entire life cycle of building components and systems when assessing their impact on indoor environmental conditions.

For more picture of the the indoor environment dynamics, the following subsection focuses on both external and internal dynamic factors shaping the indoor environment parameters. As such, the exploration will be focused on two main elements, including the internal occupancy dynamics and the external weather-changing influence. The goal is to explore possible dynamic relationships between dynamic factors and indoor environment parameters' behaviour.

2.4.4 Indoor Environment Parameters' Dynamics

Based on the reviewed literature, each building has a distinguished energy and well-being performance. Thus, understanding the complex relationship between the HVAC system performance, the building's layout, structure and occupancy dynamics plays a pivotal role in determining indoor environment conditions. Along this path, a study by (Mavrogianni et al., 2014) highlighted the impact of occupancy patterns and it is influence on buildings' operations, suggesting that this factor can significantly influence indoor overheating levels. This suggests that relating different occupancy profiles to heating performance can help in adjusting the heating setpoint. Based on this understanding, the heating capacity is to relate proportionally to heat gain from occupants as they present. Similarly, (Zhang and Ardakanian, 2019) emphasised that understanding and incorporating occupancy patterns can lead to substantial reductions in energy consumption while maintaining indoor thermal comfort. However, additional factors of structure specifications strongly combined with the indoor heating capacity, can significantly influence the indoor temperature. For instance (Zahiri and Elsharkawy, 2018) found that many buildings face challenging indoor environments' conditions. The study attributed these challenges to thermally inefficient building envelopes, and also to the habits of occupants in managing buildings, resulting in increased heating consumption. (van den Brom et al., 2019) further indicated that the influence of occupants on heating consumption varies depending on the building characteristics. This can include buildings' operational schedules or the type of service that the building provides to the occupants. This finding can also correlate to the regulatory setpoints considering the occupants' activity and the buildings' types.

Another study presented a methodology for predicting indoor air temperatures based on weather information and basic building characteristics (Aguilera et al., 2019). The methodology achieved a 92% accuracy rate (F1-score) and an error margin of ±1°C when tested in pre-known conditions. However, the model's accuracy significantly declined to 30% when applied to entirely new settings within the same climatic conditions, and it further deteriorated when tested in different climatic zones. It was observed that the number of occupants significantly influenced the accuracy of the indoor air temperature predictions, whereas building-related parameters such as construction year and floor area had a minor impact on the model's performance. This finding further highlights the occupancy profile as the dominant dynamic factor. Another study predicted indoor temperature based on Newton's cooling law specifies that the rate of heat loss of an object is proportional to the temperature differential between the object and its surroundings (Hietaharju et al., 2018). The study used different building types where sensors were deployed. While the study concluded high accuracy in predicting the indoor temperature, multiple factors could point to further investigation. These include a restricted data set of 100 hours, the inclusion of automatic heating controls, and the lack of separation between energy used for heating and hot water. Additionally, the sensor placement and the use of tabular values for key parameters introduced potential errors. These factors collectively raise questions about the level of dynamism in the model's approach.

From a different perspective, in cold climates, indoor temperature has been observed to have a stronger association with outdoor temperature (Saeki et al., 2014; Zhai and Helman, 2019). Hence, the role of heating is to increase the building's indoor base temperature, to reach a pre-defined setpoint of a thermal comfort sensation. In this context, to quantify the energy needed for heating, the concept of Heating Degree Days (HDD) is commonly employed (Lindelöf, 2017; Kohansal et al., 2022). HDDs are calculated based on the difference between the indoor base temperature and the average outdoor temperature. When the outdoor temperature falls below the heating setpoint, it indicates a need for heating. Therefore, the HDD calculated from an estimated base temperature is almost perfectly proportional to the heating demand, until the temperature settles at the pre-defined setpoint (Kohansal et al., 2022). Conversely, since the outdoor temperature fluctuates across the day, the HDD value also changes accordingly, therefore, multiple HDD readings are important to trace dynamic indoor heating demand.

Although the HDD can provide an understanding of the outdoor temperature that influences indoor temperature, internal information on buildings' thermal characteristics is as important to determine the heating load needed to reach associated setpoints. The Degree Day Factor (DDF) represents the difference between the outdoor temperature and the indoor base temperature, which is typically the temperature at which a building neither gains nor loses heat (Ashrae, 2009). Thus, DDF essentially translates the HDD into actual heating demand, by considering how the building responds to external temperature changes (Sha et al., 2019).

HDD can be expressed as:

$$\text{HDD} = \sum_{i=1}^{n} \max(0, T_{\text{base}} - T_{\text{outdoor}})$$

Where T_{base} is the indoor base temperature, and T_{outdoor} is the average outdoor temperature.

Also, DDF can be expressed as:

$$\text{DDF} = \frac{\text{Heating Load}}{\text{HDD}}$$

Where the heating load is specific to the building's thermal characteristics, obtained through energy simulations or empirical data (CIBSE, 2006).

This suggests that reaching an indoor setpoint temperature can be determined by multiplying the HDD by the DDF to calculate the energy needed for heating and adding that to the indoor base temperature, where:

$$T_{\text{indoor}} = T_{\text{base}} + (\text{HDD} \times \text{DDF}) \tag{2.1}$$

As mentioned, the derivation of this equation is based on the principle that heating demand in a building is directly proportional to the difference between indoor and outdoor temperatures. HDD measures the cumulative need for heating over time based on external conditions, while DDF scales this need according to the specific building's characteristics, such as insulation and ventilation characteristics. However, additional dynamic factors including the occupancy presence also contribute to the overall indoor temperature through heat gain. Accordingly, this equation is a simplified model that assumes the heating system is the only factor affecting indoor temperature which is inaccurate (Lundgren Kownacki et al., 2019; Laskari et al., 2022). In addition, the (HDD x DDF) metric is in °C-days and does not directly report Celsius units similar to other variables within the equation. While this equation does not account for the heat losses and gains resulting from occupancy dynamics and ventilation change, it is still arguable that those changes can be captured by temperature sensors.

In a mathematical context, the relationship between an unknown variable and other given values in an equation is often complex and highly dependent on the specific context. For instance, regression models can be used to predict one parameter based on the known value of another, providing a structured way to deal with unknowns (Agarwal and Saxena, 2011). In more complex scenarios involving boundary conditions, unknown values can be defined in terms of initial and boundary data, provided that certain global relations are satisfied by specific functions (Tian, 2016). Furthermore, the equation and its variables can be subject to empirical calibration based on the observation of actual sensing measurements for both indoor and outdoor temperature measurements to validate its output accuracy.

Since the DDF is specific to each building's case, it reflects multiple boundary conditions of a building. It is therefore essential to conduct buildings' energy simulations to get a more precise value for the DDF. Overall, the reviewed strategies and the presented equation provide a useful road map for establishing a mathematical relationship that addresses the dynamic factors, particularly temperature. This becomes more useful as it was reviewed that the temperature parameter is strongly connected to heating and IAQ. Along this direction, the following section will review additional simulation tools commonly used in the literature.

2.5 The Role of BIM in Indoor Environment Monitoring and Control

Building upon the previous introduction of the SRI in defining indoor environment parameters, this section aims to explore further aspects associated with BIM in defining indoor parameters. The goal is to build a comprehensive understanding of its potential in the current applications and constraints associated with the subject. Given this context, the research showed diverse interests in employing BIM to simulate indoor parameters as well as retrieving live sensing data. As such, the following subsections review the adoption of energy simulation and digital twin buildings.

2.5.1 BIM Energy Simulation for Indoor Environment Characterisation

The integration of BIM energy simulation during the design stage helps to reduce the gap between the design and actual energy performance, as well as improve existing buildings' energy performance (Shan et al., 2020). Accordingly, the dynamic data sourcing provided by BIM energy simulation is significant in characterising indoor environment parameters, which also allows accurate sensors' identifications (Chang et al., 2018). In this direction, the use of EnergyPlus software can provide the actual energy load for the indoor environment parameters under different occupancy profiles and weather conditions (Brandi et al., 2020). However, given the sensitive nature of characterising indoor parameters in highly dynamic conditions, it is important to highlight that the EnergyPlus simulation may not be sufficient as a stand-alone tool (Kim et al., 2019). Along this path, the SRI assessment helps to quantify case-specific weightings that enhance the energy simulation input data for optimised results (Fokaides et al., 2020). In more detail, while the SRI assessment investigates the buildings' smart readiness, identifying key performance indicators for the buildings directly contributes to the parameters' definitions and weightings. As such, diverse weighting for indoor parameters is a substantive performance indicator that defines the simulation model boundary conditions, Figure 2.4.

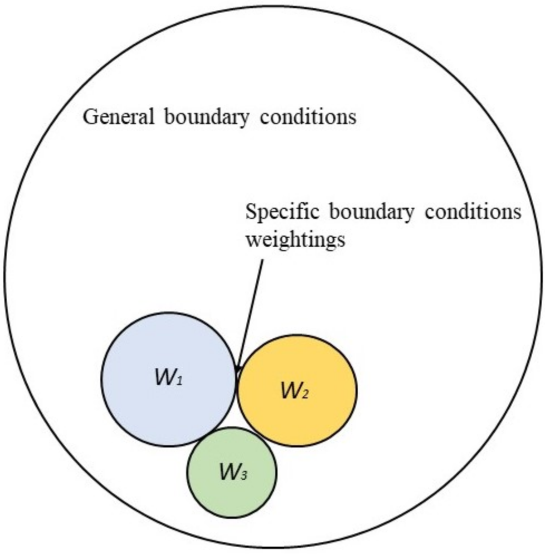

Figure 2.4: Illustration of Case-specific Boundary Conditions Using the SRI Assessment

The application of EnergyPlus software is commonly used for its ability to calculate different indoor environment parameters' loads, which is essential for managing indoor heating and cooling demands effectively. However, the literature also points out the limitations of relying solely on EnergyPlus, given it is permeable to errors resulting from poor input definitions. To address this, the following subsection will explore the evolution of BIM in the context of digital twins. The aim is to investigate the current approaches in utilising live-streaming data models that continuously update and evolve in response to real-world dynamic changes.

2.5.2 Giving context to sensed Data through BIM

As presented in section 1, the studies discussed BIM as a part of calculative methodologies that combine different simulating tools for data sourcing. This has motivated the research to explore web-based BIM methodologies to collect, process, and automate buildings' information for different use cases (Sobhkhiz et al., 2021). One common use case is combining BIM models, indoor sensing devices, and ML applications to characterise, predict and control energy performance in indoor environments (Collinge et al., 2011; Hollberg et al., 2016; Soust-Verdaguer et al., 2017; Meex et al., 2018; Ghoroghi et al., 2022). In more detail, the contribution of the BIM models in this problem-solving has different dimensions, of which the energy analysis is crucial in defining the buildings' energy performance. The research has also acknowledged various limitations in using this combination. For instance, Table 2.3 describes various uses of this combination during the buildings' design and use phases, and summarises the limitations. While there was a lack of actuation in some cases, the whole combination of BIM, sensors, and actuation, acknowledged the influence of the occupancy parameter on indoor energy consumption. Furthermore, the research also pointed to the significance of sensors' accuracy which can be attributed to different factors, including the lack of optimum positioning.

Further studies suggested BIM Digital Twin models as sustainability performance indicators, including the dimension of estimating embodied carbon within the buildings (Nizam et al., 2018). Also, (Boje et al., 2020) described BIM Digital Twins as "information-intensive" models that are crucial to supporting the optimisation of LCA impacts. Along this direction, a study showed an interest in building materials embodied carbon using a digital representation of BIM-based -LCA (Basbagill et al., 2013). They developed a decision support method that assists designers in predicting which decisions most critically determine a building's embodied impact. However, (Crippa et al., 2020) Pointed out that numerous LCA tools rely on databases of industry-average values, which may not account for the actual embodied energy across suppliers' materials. This finding further supports the argument of phasing out physical components to decrease the overall embodied carbon with integrated systems. Along this direction, a study proposed an MLP model to predict indoor parameters without the need for indoor sensors (Martínez-Comesaña et al., 2021). The results showed relative errors of 6% for temperature, 5% for relative humidity, and 12% for CO2 levels. The study acknowledged a limitation of the amount of data that did not cover different seasons. It also emphasised the importance of defining the number of sensors and their optimum positioning.

Other studies emphasised the need to integrate sensors for optimum results. (Lu et al., 2020) proposed a system architecture to develop a digital twin containing different characteristics including the Industry Foundation Classes (IFC) model and real-time sensing data. The study suggested that AI-supported decision-making would highly improve energy management, space utilisation, and failure prediction. In a similar direction, different studies proposed dynamic PMV optimisation using sensors. However, a study highlighted different limitations of these approaches, including the overlooking of thermal exchange across buildings' zones (Zahid et al., 2021). The study proposed a combined parametric BIM and real-time sensors to generate real-time 3D visualisation of indoor thermal conditions. To address the highlighted issue, the study used thermal interpolation to account for indoor partitions' thermal resistance. It is important to highlight that the study did not approach possible accumulated carbon from either the computational system or the physical sensors.

Table 2.3: The Use of BIM in Optimising Energy Performance and Comfort

Authors	**Parameters and Methods**	**Used Technology**	**Phase**	**Limitations**
(Shahinmoghadam et al., 2021)	Thermal comfort based on PMV-PDD	BIM, Sensors	Use phase	- Inconsistencies in outputs due to assumptions - Low sensing accuracy
(Chang et al., 2018)	Thermal and visual comforts based on (1) Comfort (2) Energy saving (3) Well-being standards	BIM, Sensors	Use phase	Low sensing accuracy
(Valinejadshoubi et al., 2021)	Thermal comfort monitoring, Sensors based alert system	BIM, Sensors	Use phase	Limitations on space tested and number of sensors
(Utkucu and Sözer, 2020)	Energy performance evaluation for thermal comfort	BIM	Design phase	Restricted boundary conditions
(Hollberg et al., 2020)	Embodied carbon assessment	BIM	All phases	Exclusion of the design process
(Valladares et al., 2019)	AI agent to control and balance thermal comfort within acceptable PMV values	Sensors, Actuation	Use phase	Controlling accessibility issue

With this established, the literature pointed out that indoor monitoring sensors have two sides of LCA impact during the building use phase. The first is by adapting energy performance according to the dynamic changing needs. The second is to provide measures for optimum indoor environment conditions. However, as a consequence, inaccurate sensors' measurements can mislead decisions on energy optimisation actions. Furthermore, the presence of physical indoor sensors over the entire buildings' operational phase can accumulate a significant carbon footprint as previously highlighted. Accordingly, the following section investigates current approaches to tackling these issues. The goal is to further support the argument of needing to transition to virtual indoor monitoring sensors.

2.6 Summary

The reviewed literature concerning indoor environment parameters definitions showed multiple approaches of different scopes and tools. These definitions were primarily sourced from existing regulations and code guidance. In answering the first research question, the criteria for selecting and prioritising the indoor environment parameters are mainly defined by a case-based approach of boundary conditions that aid an energy simulation process. Along this line, the consensus on gaining high-accuracy indoor parameters' definitions was centered around tracing the impact of dynamic factors on indoor parameters' behaviour. This focus was notable across the research centered around the utilisation of indoor sensors to capture the influence of weather and occupants' presence on parameters' behaviour such as heating and cooling energy consumption. accordingly, a high-level energy model, simulating different dynamic conditions can provide a breakdown of energy consumption among different indoor parameters. While this is vital for the LCA subject of this research, it also helps in defining and prioritising indoor parameters of the highest interest to sensing. This strategy can then come as a pre-step in defining the indoor monitoring sensors. It can further help in defining the minimum number of sensors to address the parameters of the highest interest. As indicated, the SRI assessment can define the applicability of smart devices' installation according to it is evaluation results (Ożadowicz, 2022). Thus, the SRI assessment can be counted as a prerequisite to the sensors' definition and installation that is highly linked to LCA inventory formation. In more detail, since there is a strong correlation between the indoor parameters, LCA inventory, and the LCA impact goals, an LCA goals-oriented can highly support the definition and the prioritisation of the indoor environments parameters.

After investigating the answer to the first research question, the following section will address both the second and third research questions. While those research questions are consequential to the first research question, the examination of the literature shows high relevance to the previous sections, and therefore, it is built upon the knowledge gained so far, in this chapter.

2.7 Reducing the Environmental Impact of Indoor Monitoring Sensors

Building upon the knowledge gained from the previous sections, this section aims to answer both the second and third research questions. This dual strategy is mainly because of that the second research question of defining the minimum number of needed sensors can be a first step towards virtualising sensors, which is the main focus of the third research question.

The incorporation of smart systems, particularly sensors, has been recognised as a crucial approach for achieving optimal indoor environment conditions. Yet, as highlighted in the previous sections, it's essential to investigate the trade-offs of their efficiency against the implications of their embodied carbon. In general, the identified research of embodied carbon in LCA for the buildings' use phase showed a focus ranging from the products manufacturing stage to the up-cycling buildings' products stage (Rasmussen et al., 2019). Despite the slow progression, the literature showed limited interest in embodied carbon as a product of systems integration, including sensors, or inefficient energy management during the operational phase as highlighted in Table 2.4. However, it is still arguable that recent research has begun to shed light on this matter. For instance, a study by (Zhu et al., 2022) emphasised the need to consider the embodied carbon of building components, including advanced technological systems, in the broader context of building sustainability. Consequently, while the integration of smart systems can lead to operational energy savings, the embodied carbon of these systems can offset some of these savings. (Pomponi and Moncaster, 2016) further emphasised the importance of a holistic approach to embodied carbon assessment in the built environment. They argued that while smart systems can offer energy optimisation benefits, it's crucial to account for their embodied carbon to ensure a positive environmental impact.

Table 2.4: Overview of Studies on Indoor Monitoring Sensors and Their Environmental Impact

Reference	**Approach/Study**	**Key Findings**	**Limitations/Considerations**
(Han and Zhang, 2020)	Integration of a smart sensing/control network with embedded PIR/CO2 sensors.	Energy savings while maintaining satisfactory thermal comfort and IAQ.	Limitation of semantic scalability.
(Afroz et al., 2020)	Integration of CO2 mass balance equation with CO2 sensor into the BMS.	Reducing energy consumption while promoting a healthier indoor environment.	Potential increase in embodied carbon due to integration of additional sensors.
(Rosselló-Batle et al., 2015)	Analysis of embodied energy from building components.	Significant embodied energy resulting from building components.	Emphasises the consideration of embodied carbon in building components.
(Guerra-Santin et al., 2014)Guerra-Santin et al., 2013	Monitoring activities in low energy buildings.	Importance of monitoring activities in low energy buildings.	Increase in embodied carbon due to systems' additions.
(Röck et al., 2020)	Analysis of embodied GHG emissions of buildings.	Emphasised reducing GHG emissions by optimising embodied impacts.	Highlights the challenge of embodied carbon in monitoring sensors.
(Oti and Abanda, 2019)	Integration of embodied energy/CO2 computation	Automating the computation of embodied energy/CO2 of buildings.	Emphasises the need for a unified methodology for embodied carbon assessment.
(Chen and Ng, 2016)	Operational phase and its effect on embodied energy.	Inclusion of recurrent embodied energy in building life.	complexity of considering the entire LCA of building components.
(Dixit et al., 2015)	Embodied energy of construction materials	Buildings contribute to 40% of global energy consumption.	Emphasises the need for a whole life cycle approach to reduce embodied carbon.
(De Wolf et al., 2017)	Measuring embodied carbon dioxide equivalent of buildings.	A need to improve data quality for embodied CO2e assessment.	Challenges and inconsistencies in measuring embodied carbon.

As presented in Table 2.4, different publications pointed to the need to assess embodied carbon from systems' integration, indicating existing inconsistencies in assessing their embodied carbon. As previously highlighted, this assessment can help to track the trade-off between smart systems functionality and their carbon footprint. The studies also highlighted the limitations of semantic scalability, calling for a consensus approach to decrease embodied carbon from smart systems' additions.

In addressing this issue, the European Commission launched a guideline for Product Environmental Footprint (PEF), where a specific environmental product footprint against 15 impact categories was required on products, including sensors and batteries (Verbeke et al., 2020). Along this direction, the literature focused on the environmental impact of sensors' batteries. (Boyden et al., 2016) discussed the increasing environmental impact of lithium-ion batteries, which are still widely used across several types of Indoor wireless sensors due to their long lifespan. (Hayat et al., 2019) compared several types of sensors' batteries and suggested the Nickel-Metal Hydride (NiMH) batteries as having the lowest environmental impact, however, it has less power density, higher cost, and a higher discharge rate, which shortens the life span and subsequently accumulates carbon. Another factor that can contribute to the accumulated carbon from sensors is the high sampling rate (Wang et al., 2020). On the one hand, this can provide higher resolution data readings that help in timely actions by automated HVAC systems. On the other hand, the continuing active status of the sensors consumes the batteries in shorter times. Table 2.4 shows different approaches to sampling frequency with some studies using ML as an alternative to live sensing data.

Table 2.5: Approaches to sampling rates of implications on battery consumption

Authors	Dynamic Parameters	Methodology	Time Horizon
(Abade et al., 2018)	Thermal comfort, occupancy	Sensors	1 Minute
(Collinge et al., 2011)	Thermal comfort	Sensors	1 Second, 5 Seconds
(Valinejadshoubi et al., 2021)	Thermal comfort, occupancy	Sensors	5 Minutes
(Rebai et al., 2015)	Sensors' data	Sensors	30 Minutes
(Valladares et al., 2019)	Thermal comfort	Sensors	algorithm, ML 10 years
(Wall et al., 2021)	Indoor air quality	Sensors	1 Minute
(Ali et al., 2016)	Thermal comfort, occupancy, light intensity, CO2	Data logger and OSBSS sensors' platform	1 Minute
(Xiong et al., 2019)	Visual comfort	Personalised visual satisfaction	Every step-change
(Pino-Mejías et al., 2017)	Heating and cooling	Linear regression and ANN models	-
(Nelson and Culp, 2022)	Thermal comfort	ML	-
(Pedersen et al., 2022)	Air quality, thermal comfort	BACS assessment and smartness evaluation	-
(Lu et al., 2019)	Thermal comfort	Sensors	5 Minutes

Building on the insights provided in Table 2.5, it's evident that while the integration of indoor sensors can be seen as an enhancement to energy optimisation, they introduce new dimensions of embodied carbon. One of these dimensions is the high sampling rate in wireless sensors which consumes more batteries. Also, as highlighted, an ill-informed HVAC system can accumulate embodied carbon due to low-accuracy sensors' measurements. Therefore, there are two ways in which embodied carbon accumulates from sensors' applications. The first is the accumulation from the physical characteristics of the sensors, and the second is the accumulation from the operational characteristics of the sensors. Along this line, the research showed different approaches to assessing embodied carbon from smart systems. (García-Sanz-Calcedo et al., 2021) calculated the embodied carbon and energy of HVAC systems installed in 6 healthcare centers for a lifetime period of 15 years using the equation:

$$E = \sum_{i=1}^{n} (C_i \cdot K_i) + C_f + C_t + C_c \tag{2.2}$$

Where *C* is the total amount of embodied carbon in the HVAC healthcare facility, expressed in kg, *ci* is the embodied carbon emissions of each material, *ki* is the amount of material used, *cf* the emissions incorporated into the building during the construction process, *ct* is the emissions from transport of materials and mobility of workers, and *cc* indicates the emissions incorporated from the building construction. The results showed that the calculated embodied carbon is equivalent to the CO2 emitted for 2.3 years of the entire building's operation phase.

While this methodology can be adopted for quantifying embodied carbon from physical sensors and batteries, another dimension of embodied carbon needs to be addressed. As highlighted, the accumulation of embodied carbon can also result from low-accuracy sensors' measurements. In this context, the research pointed to optimum sensors' positioning using different techniques. For more investigation on best practices, the following section reviews current approaches in optimum sensors' positioning.

2.8 Optimising Indoor Monitoring Sensors Positions

The optimised positioning of indoor sensors is crucial to obtaining high-accuracy measurements, particularly to enhance the LCA inventory for optimised energy performance. Accordingly, this section explores the optimal positioning of indoor sensors by investigating the capabilities of Computational Fluid Dynamics (CFD) simulation. By simulating airflow, temperature distribution, and other relevant environmental parameters, CFD models can provide a detailed understanding of the indoor micro-climate. However, given that indoor environments can include different services and appliances, the CFD simulation may not be sufficient to track the thermal influence of these elements. Therefore, further exploration of the usefulness of thermal imaging was conducted. The resulting thermal mapping for indoor environments can then help in understanding sensors' measurements' behaviour at different locations. Hence an established correlation between the measurements can then be used in the virtualisation process.

2.8.1 CFD for Optimised Indoor Monitoring Sensors' Positioning

Sensors' manufacturers often provide guidelines for optimal installation and positioning. However, given the unique design and characteristics of each building, additional factors should be considered. Recent literature pointed to two primary considerations including (a) the distribution of indoor temperature and air velocity (Luo et al., 2023) and (b) the presence of heat and high air velocity sources close to sensors (Pei et al., 2019). Driven by these factors, the research explored multiple approaches for sensors' positioning, including algorithm, error-based, and CFD modelling (Rebai et al., 2015; Arnesano et al., 2016; Papadopoulou et al., 2016; Uyeh et al., 2021). Among these approaches, the CFD showed reliable results on temperature, air velocity, and pressure mapping, with notable limitations when capturing localised anomalies. For instance, abnormal temperature fluctuations near heat sources such as lighting fixtures, or increased air velocity near ventilation in and outlets, can affect sensors' accuracy. (Zhang et al., 2013) suggested that the temperature distribution in a room can be seen as the temporal and spatial synthesis of the influence of all these heat sources, as expressed in the equation:

$$\frac{\partial \theta}{\partial t} + \frac{\partial \theta u_j}{\partial x_j} = \frac{\partial}{\partial x_j}\left(\frac{v_t}{Pr_t}\frac{\partial \theta}{\partial x_j}\right) + \frac{q}{Cp_p} \tag{2.3}$$

where θ represents air temperature, *uj* is the air velocity, *vt* is the turbulent viscosity, *q* is the heat source, *t* is the time, *xj* is the coordinate, *Prt* is the turbulent Prandtl number, *Cp* is the specific heat of air, and *p* is the air density. Accordingly, the paper discussed the interplay of convection, diffusion, and external heat sources to describe the temperature distribution in a room. Particularly, the expression of:

$$\frac{\partial}{\partial x_j}\left(\frac{v_t}{Pr_t}\frac{\partial\theta}{\partial x_j}\right) \tag{2.4}$$

Represent the movement of heat due to molecular motion, as heat diffuses from warmer areas to cooler areas. The paper also discussed the concept of the Contribution Ratio of Indoor Climate (CRI) on how far the heat generated by a source diffuses in space. The CRI for a heat factor at a location xi is defined by the equation:

$$u_{CRIm}(x_i) = \frac{u_{\theta m}(x_i) - \theta_n}{Q_m} \tag{2.5}$$

Where $u_{\mathrm{CRIm}}(x_i)$ °C is the temperature at position *xi* calculated by CFD when the heat source *Qm* and the heat sink are both set. In more detail, this equation aims to quantify the influence of a specific heat factor on the indoor temperature distribution at a given location *xi* when a heat sink uniform of high to low temperature applies. This difference provides insight into the temperature rise or fall caused by the heat source *Qm* at that specific location. By dividing this temperature difference by the total heat transfer *Qm*, the equation offers a normalized measure of the contribution of the heat factor to the temperature at different locations in the indoor environment where a gradient pattern can be established. Based on this approach, observation of multiple sensors' measurements from different locations can help in analysing possible relationships between those measurements. Subject to empirical validation, this developing theory can offer insight into reducing the number of sensors using the identified relationship, given one reference sensor.

However, (Mustakallio et al., 2017) Observed that the temperature gradient in occupied hours with ventilation is much higher compared to unoccupied spaces, with no ventilation. This observation suggests that dynamic occupancy and ventilation patterns play a crucial role in determining temperature gradients and air shear forces in indoor spaces due to constantly changing air velocity and heat gains. Along this path, (Borro et al., 2021) highlighted the potential of CFD-based simulations in predicting contagion risk in indoor environments, especially in the context of the Sars-CoV-2 pandemic. The study emphasised the significant role of HVAC systems in governing the movement of airborne contaminants within indoor environments, such as droplets containing the virus. Moreover, CFD simulations offer gradient mapping of temperature, pressure, and air velocity that can support the prediction capabilities of indoor sensors (Zhao et al., 2021). In particular, this approach provides foundational boundary conditions that govern factors directly affecting sensors' measurements. For instance, considering the current value of a physical sensor, boundary conditions, and a historical measurement of a secondary sensor, ML can be used to find relationships between those variables to predict a current value for the virtual sensor. Along this direction, (James et al., 2013) presented that:

$$Y = \int (X) + \varepsilon \tag{2.6}$$

Where $\int$ is a fixed unknown function of $X_1, \ldots, X_p$, and ε is a random error term that is independent of X and has a mean zero.

This outlined relationship can be promising in predicting secondary sensor measurements given the reference sensor's current values, simulated boundary conditions, occupancy profile, and historical data. It is, therefore, indoor sensors can capture the behavior of an interplay under different boundary conditions, and as a result, equation 2.6 can be more relevant.

While the factors influencing temperature gradients are dynamic, more static, normally localised, can influence temperature gradients and also alter sensor measurements' accuracy. In tracing those localised sources of possible influences, studies showed interest in thermal imaging sensors to detect and estimate occupants (Savazzi et al., 2019; Mikkilineni et al., 2019; Chidurala and Li, 2021). Building on this argument, thermal imaging can be utilised to identify thermal anomalies such as temperature and air velocity emitted from lighting fixtures and ventilation inlets and outlets. This aids in creating more clear guidance on optimising sensors' positioning for higher measurement accuracy. Furthermore, according to notable limitations within the literature, occupancy profiles can also be augmented in calculating the sensors' predictions for optimised accuracy.

2.8.2 Thermal Imaging for Enhanced Sensors' Positioning Optimisation

While the CFD provides accountancy for the indoor environment thermal conditions, localized heat emitted from lighting fixtures and increased hot air velocity closer to vents can also influence the accuracy of the sensors (Shinoda et al., 2021). As mentioned, the literature highlighted various benefits of thermal imaging to detect localised sources of heat emittance. Based on this, static thermal imaging can add a layer of granularity to the CFD simulation. In more detail, the CFD simulation provides a clear understanding of the distribution of indoor temperature and air velocity, while thermal imaging aids in identifying localised sources of heat and high air velocity. This multilayered modelling approach can, therefore, inform the selection and optimised positioning of the indoor monitoring sensors of high-accuracy measurements.

Given these simulations consider different boundary conditions, the impact of the occupancy parameter, especially the dynamics of human presence, can significantly affect sensor measurements within the indoor environment. There is a strong correlation between different indoor environment parameters and the occupancy parameter that can be reflected in indoor sensing measurements. In light of this, the following section will examine the correlation between dynamic occupancy patterns and key indoor environmental factors.

2.9 Impact of Occupancy on Indoor Environment Conditions

As mentioned in this review, the influence of occupancy on indoor environmental parameters such as temperature, CO2 levels, and humidity is a subject of ongoing research. Studies have found that occupancy significantly impacts indoor temperature, with a higher number of occupants leading to increased temperature levels (Yang et al., 2016; Zhang et al., 2022; Wang et al., 2020). However, the evidence suggests that there is still disagreement in the literature in relating occupancy presence to a particular indoor parameter. For instance, several studies suggested a strong correlation between occupancy number and CO2 concentration (Nitter et al., 2020). In contrast, other studies observed an overestimation of CO2 when the actual number of occupants is low (Yang et al., 2018). Given that occupancy patterns can influence additional indoor environment parameters such as temperature, and air quality, a collective approach using those parameters can further enhance the quantification of occupancy influence on these parameters. Along this path, different approaches to estimating the influence of occupancy include CO2-based statistical models, Camera-based face recognition, and ML algorithms (Yang et al., 2018; Anand et al., 2021). As established, the literature indicated that relying on a single parameter may not comprehensively understand occupancy's influence on indoor conditions. Therefore, a multi-faceted approach that considers various indoor environmental parameters could offer more insights into the role of occupancy. This, in turn, could improve the accuracy of predictive sensing measurements. Considering the outlined literature foundational to the modelling approach, validation comes as substantive evidence to the claims made in this study. Since the collected data is observatory data, empirical validation is adopted and a comparison of virtual sensing measurement to the actual live sensors' readings is intended for validation. Therefore, to further explore factors affecting these dynamic interrelations, particularly to characterise indoor environment parameters, the next section will review the role of BIM, particularly energy and CFD simulations in characterizing these dynamics. The aim is to establish a comprehensive view of optimizing building performance while considering environmental implications.

2.10 Limitations in Current Indoor Environment Characterisation Prior to Sensors Installations

Despite only a few publications having explicitly addressed the energy and well-being performance during the buildings' use phase from a LCA perspective, there has been increasing interest in different areas that can be accounted for supporting the subject. It was also notable that, although the literature presented different methodologies for the application of IoT and ML systems, shortcomings were noticeable in the correlation between what-if scenarios and embodied carbon and the impact results.

Moreover, the reviewed research addressing the optimisation of sensors' positioning has neglected key factors of other influences that can have an impact on the quantity and accuracy of the sensing data. However, the collaborated review highlighted the use of energy and CFD simulations for multi-scenario awareness and enhanced data resolution. The validation methodologies relied on the algorithm and trained ML with limited scenario focus and less employ-ability for the BIM models. Therefore, despite different approaches to validate the presented methodologies, there was a clear lack of any structured and integral LCA framework for buildings' energy performance. These facts highlighted a considerable gap in the current state of the art of the LCA of energy and well-being performance during the building's operational phase. Based on reviewed papers, the limitations in the LCA framework are as follows:

- Lack of any consideration of embodied carbon from systems interactions and performance.
- Lack of any consideration of multi-scenario analysis, including dynamic factors.
- Lack of consideration of pre-assessment analysis, that contribute to more accurate results.

As established from the literature, the smart readiness assessment will determine the available and upgradeable AI infrastructure to help in forming the entities that could be responsible for the corresponding activities within the LCA inventory. As reviewed, a building is to be assessed against three main domain weightings:

- Minimum energy performance with optimum adaptability to occupants' needs.
- Ability to provide adequate infrastructure to AI and automation systems with the minimum amount of embodied carbon.
- Existing communication network.

In line with the LCA goals, these domain weightings can be addressed by a set of domain services of (a) thermal comfort, visual comfort, and well-being parameters; (b) automated systems in place; and (c) decision-making support. However, the smart systems' integration for the above-mentioned domain services can be expensive, especially in large-scale buildings. Moreover, major integration for existing HVAC and lighting systems can also come with embodied carbon. Therefore, the interrelation between the LCA domain weightings and domains' services can also consider the energy and CFD simulations for a more precise definition of temporal scope and uncertainty expectations. These accurate definitions can then reduce both the carbon footprint and the costs of any system upgrade by prioritizing areas of high demand. With that capacity, historical energy consumption data for each zone, occupancy profile, and energy simulation can assist in identifying areas of high demand. Further investigations showed more consideration for multi-scenario analysis and energy simulation than embodied carbon and smart readiness assessment. This highlights a key reason behind the deviation of Business as Usual (BaU) LCA impact due to neglect of the embodied carbon. Table 3 highlights further limitations of the inclusiveness issue of interrelations between pre-assessment requirements among different approaches from the reviewed literature.

Table 2.6: Summary of Studies on SRI Assessment and Thermal Interactivity

Ref-ID	SRI	Embodied carbon	Thermal interactivity
(Arnesano et al., 2016)			x
(Nagy et al., 2014)			x
(Collinge et al., 2011)			
(Wall et al., 2021)			
(Ingrao et al., 2021)		x	
(Omar, 2018)	x		
(Sözer and Aldin, 2019)			
(Märzinger and Österreicher, 2019)	x	x	
(Magruk, 2015)	x		
(Mamani et al., 2022)			
(Yoganathan et al., 2018)			
(Eliades et al., 2013)			x
(Panteli et al., 2020)		x	x
(Asdrubali et al., 2020)		x	
(Valladares et al., 2019)			x
(Corry et al., 2015)			
(Aste et al., 2017)			
(Su et al., 2021)			
(Moayedi et al., 2019)			
(Ben-David and Waring, 2016)			
(Cuerdo-Vilches et al., 2021)		x	
(Fouquet et al., 2015)		x	
(Batov, 2015)	x		
(Junker et al., 2018)	x		

2.11 Current Limitations in LCA Inventory Analysis for Indoor Environment Monitoring

LCA particularly evolves the environmental pressures, the trade-offs, and the areas for achieving improvements considering the entire life cycle of built assets from design to recycling (Bueno et al., 2016; Bischof and Duffy, 2022). However, current approaches to LCA inventory formation do not consistently factor in life cycle variations in (a) tracing dynamically changing indoor environments, (b) Embodied carbon from poor energy systems performance, and (c) embodied carbon from integrated smart systems. In fact, key limitations and challenges faced by current LCA methods and tools have been reported in the literature, including boundary conditions of site-specific considerations (Bueno et al., 2016).

Several local impacts need to be considered when analysing LCA inventory, such as (a) microclimate, (b) model complexity (Anand and Amor, 2017) (buildings involve a wide range of materials/products, interacting as part of a complex assembly or system), (c) scenario uncertainty (Bueno et al., 2016; Anand and Amor, 2017) (the long-use phase of buildings, including the potential for future renovation, poses uncertainty problems in the practicality of employing indoor monitoring sensors across the entire operational phase. Also, traditional LCA inventory methodologies do not address indoor and outdoor environmental impacts on health and well-being, (e) recycled material data, including embodied carbon in physical sensors and associated battery consumption (Hayat et al., 2019). Therefore, carrying out LCA inventory assessment for indoor monitoring sensors application over the operational phase, as stated in the ISO 14040 standard, requires multidimensional methodologies and can be complex to carry out. In this case, contextualisation for the LCA to a specific phase can be driven by goals and scope definitions which factors in the inventory analysis. This contextualisation can then underpin different assessments and tools that are useful for the LCA. In more detail, a case-based approach is substantial to determine indoor parameters that need to be addressed by indoor monitoring sensors. Moreover, the literature showed notable limitations in optimising indoor sensors' positioning. Despite the utilisation of the CFD models, further investigation showed negligence to localised thermal influences that may affect the sensors' accuracy and subsequently LCA inventory input data.

In reducing the environmental impact of indoor sensors, the literature showed more focus on ML algorithms of complex structures that may not be affordable on a wider scale. It is therefore, there is a persistent need for clear guidance in understanding the environmental impact across the process of deploying indoor monitoring sensors.

2.12 Summary

This literature review chapter has provided a comprehensive survey of the existing research and developments in the field of indoor environment monitoring. A particular focus was adopted for the indoor environment parameters characterisation specific to a building case. This approach was considered foundational to building knowledge on how to answer the first research question *"Which criteria should be considered to select and prioritize the indoor environment parameters necessary to conduct dynamic life cycle assessment, taking into account a wide range of configurations, including occupancy schedules and geographical location?"*.

Furthermore, the investigated techniques concerning the optimal positioning of sensors explored different thermal mapping tools including the CFD simulation and thermal imaging. Given the identification of the most representative positions to provide reliable parameters' measurements, this approach was specifically tailored to answer the second research question *"What is the minimum number of physical sensors and their optimal positioning to provide accurate dynamic accounts of indoor environments?"*.

Assessing both broader and relevant science, key theoretical frameworks and empirical studies were also examined to establish the context within which this research is situated. In this direction, comparative analyses of various indoor environment conditions were explored using numerical modelling to find patterns and relationships for virtualising indoor sensors. This is considered particularly useful in answering the third research question *"Can virtual sensors replace physical sensors while ensuring data accuracy and reducing direct and indirect environmental impacts?"*.

In conclusion, the literature review has set a solid foundation for this research path, identifying the critical parameters that influence indoor environment characterisation and mapping prior to virtualising indoor sensors. Contributing to the main objectives of this thesis, , phasing out the associated carbon of indoor monitoring sensors as an LCA inventory is considered a significant step in achieving LCA goals. As such, the following chapters will build upon this foundation, presenting a path towards reliable indoor environment monitoring sensors.

Chapter 3 | Research Design and Methodology

3.1 Overview of research approach

This chapter outlines the research methodology employed for this study. It begins by exploring the philosophical foundations of scientific research, positioning the present study within the pertinent scientific context. Subsequently, the research approach is detailed, expanding on the research questions introduced in Chapter 1 and the methods used in answering them. This chapter aims to offer a comprehensive understanding of the thesis, seamlessly connecting the different chapters, research questions, and adopted approaches.

3.1.1 Theoretical Background

The theoretical foundation of any research is pivotal, as it offers an angle from which the study can be perceived and interpreted (Melnikovas, 2018). Thus, in navigating the complexities of the investigation, it's important to acknowledge the broader academic context and the scholarly works that could inform the adopted approach. According to (Cai et al., 2019), the choice of a suitable theoretical framework is critical to establishing the significance of a research question leading to a convincing argument. In contrast, (Lynch et al., 2020) emphasised that a well-defined set of research questions and theoretical framework determines the boundaries for selecting and developing effective methods. Furthermore, (Newman and Hitchcock, 2011) stress that the research questions dictate the selection of research methods. In this setting, this research design and methodology chapter serves as a bridge connecting this study to the wider academic context by detailing the philosophical underpinnings, and research questions to address them.

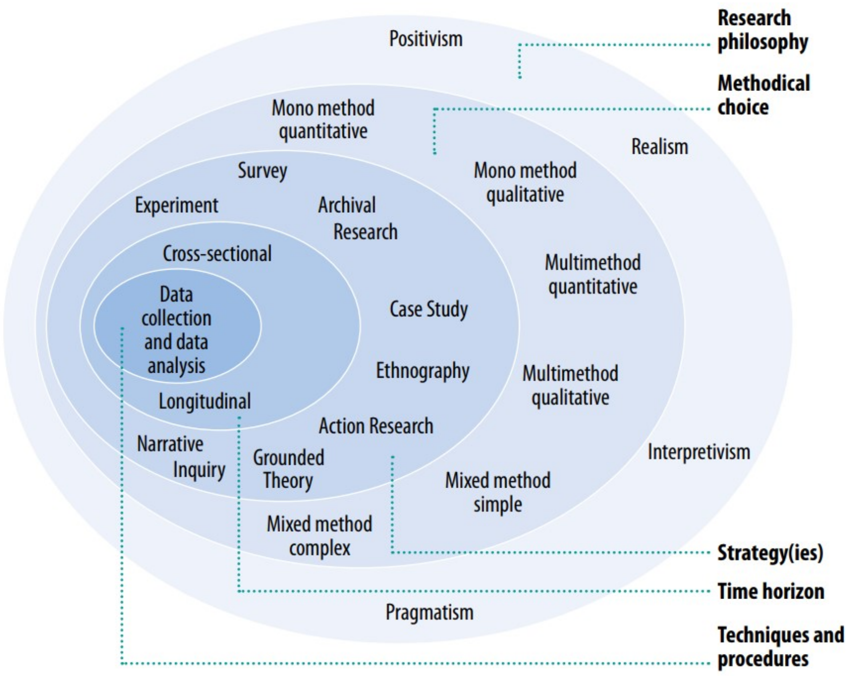

Figure 3.1: The Research Onion (Melnikovas, 2018).

The physical science research is fundamentally empirical, often characterized by its reliance on laboratory experiments where research involves manipulating one or more variables to observe the effect on other variables (Bolinger et al., 2022). This empirical nature is evident where case studies offer in-depth investigations of specific instances or entities, providing rich, contextual analyses grounded in real-life situations (Cavaye, 1996). However, chosen strategies are pivotal in ensuring that the research objectives align with the data collection and analysis methods. Given this context, a mixed-methods approach, combining both qualitative and quantitative methods, will be employed. This approach is supported by (Hitchcock and Newman, 2013), who advocate for an interactive quantitative-qualitative framework, highlighting their shared foundations and objectives. This comes as a response to (Reio Jr, 2016) call for a deeper exploration of theory-building in research methods, particularly addressing the concept of generalisation across both research types. This specific point can significantly amplify the applicability of proposed frameworks to extend their relevance and contribute to scientific progress.

3.1.2 Research Design

The layers of the research onion model provide a systematic approach to understanding and designing a research methodology. Starting from the core philosophical theories and extending outwards to possible strategies, this comprehensive research guide helps in following logical and informed choices that align with the research questions and objectives.

Given the empirical nature of the sensing measurement data, the philosophical theory of this thesis leans towards positivism. This approach is therefore, largely deductive, as it aims to test the efficacy of the statistical approach and machine learning algorithms in extracting and validating virtual measurements from real-world sensor data. As such, this research strategy involves an experimental case study of real-world settings, where data collection would be both quantitative considering the sensors' measurement data, and qualitative as per their influence on energy systems performance. As such, the overall research design stages are illustrated in Figure 3.2, and a breakdown for each stage follows.

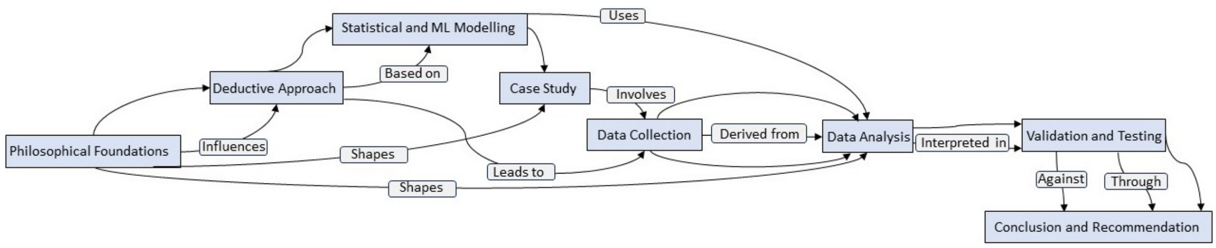

Figure 3.2: Summary of The Research Design

Stage 1: Philosophical Foundations

The significance of the philosophical stance of a research project is that it forms the bedrock upon which the entire research is built. (Denzin and Lincoln, 2011) suggested that each interpretive paradigm makes specific demands on the researcher, influencing the questions they pose and the interpretations they derive. In contrast, the research explored the employment of multiple theories within a single research study, suggesting that there isn't a one-size-fits-all approach to research (Shan, 2022). It is therefore, this philosophical foundation influences not only the choice of research methods but also the interpretation of the subsequent research stages including the results In the context of this research, particularly when addressing complex issues like building energy optimization and sensor deployment, the underlying philosophical beliefs play a substantial role in shaping the research design, methodology, and interpretation of results. These beliefs provide a lens through which the researcher views the world, influencing every aspect of the research process.

In particular, this stage explores the areas that can effectively reduce environmental impact from the indoor sensing application as an LCA inventory tool. Aiming for energy and well-being performance optimisation, the transition to virtual sensors theory accompanies a multifaceted approach of simulation engines, existing theories, and hybrid numerical and ML modelling.

Stage 2: Deductive Approach and Hypothesis Formulation

Given the positivist stance, this research adopts a deductive approach, starting with a general hypothesis and then seeking specific data to test this hypothesis. This fits with the aim is to testing a previously established theory in a different situation or comparing categories at different time periods (Elo and Kyngäs, 2008) This approach is particularly useful in the context of virtual sensors' measurements depending on different variables at different times. However, since this thesis aims to develop a new theory concerning virtual sensors, an inductive approach will also be involved. Given the qualitative data used such as SRI assessment and the quantitative numerical modelling, a combination of deductive and inductive approaches is aimed to facilitate the process of the research theory development (Young et al., 2020). Following this path, this stage involves the formulation of specific theories based on the existing literature and the identified gaps pertaining to LCA with the scope of reducing the environmental impact of indoor energy and well-being performances.

Stage 3: Selection of Modelling Techniques

With the aim to validate virtual measurements from real-world sensor data, this stage involves the selection and justification of specific modelling approaches including statistical modelling and machine learning algorithms. The criteria involved are formed based on their potential efficacy in handling the type and complexity of the data at hand. Along this path, The selection between a machine-learning algorithm and regression depends on the measurement quality, irrespective of the sample size as the evidence shows that sample size on prediction performance has been found to be robust and Scalable (Cui and Gong, 2018). Furthermore, results from different models show good agreement, reinforcing confidence in the fundamental physical and numerical implementation of the governing equations across disciplines (Kollet et al., 2017). In this context, the use of CFD simulation along with numerical modelling will be combined to formulate and validate virtual sensors' measurements.

Stage 4: Experimental Case Study Design

Case study research designs inherently possess varied scientific objectives and thus, differ in data collection and analysis methods. Continuing from the previous stage, a combination of different methods can better evaluate the theoretical contributions of this thesis in terms of understanding, building, developing, and testing (Ridder, 2017). As such, this stage involves designing the experimental case study, detailing the real-world settings to be studied, the data collection methods, and the criteria for selecting these settings. The aim is that the study remains grounded in practical, real-world scenarios for generalised application.

Stage 5: Data Collection

Data collection is a pivotal stage in research, serving as the foundation upon which subsequent analysis and interpretations are built. In the context of this study, data collection is twofold: quantitative and qualitative. Quantitative data is derived from the sensors' measurements, capturing empirical evidence of building energy performance. Qualitative data, on the other hand, evolves around the influence of these measurements on energy systems performance, capturing the underlying and contextual factors, that might not be immediately evident or quantifiable in the numerical data. This form of data collection is often emphasized in research for its ability to provide objective results (Bradley et al., 2007). In this context, the CFD simulation being a quantitative method of data collection, solves the governing equations of heat and air velocity transfer and other related phenomena. The results from CFD simulations are typically presented in numerical form, speculating the dynamism in air velocity profiles, temperature distributions, and pressure drops. Similarly, the energy simulation predicts the energy consumption of a building based on various parameters like building envelope properties, HVAC system performance, and occupancy patterns. However, the SRI assessment can be both quantitative and qualitative data collection methods. The quantitative aspect involves collecting data on the energy performance, efficiency, and usage patterns of smart devices and systems of a building. The qualitative aspect can involve assessing occupants' comfort, and their interactions with smart systems. It is, therefore, the qualitative data that can provide insights into the reasons behind certain quantitative findings offering a context that numerical data alone might not capture.

According to the literature, the selection of wireless indoor monitoring sensors was based on their flexible deployment, compatibility with web-based systems, and database-linking capabilities (Figure 3.3). However, the selection of the sensors was fundamentally based on the characterised indoor environment parameters at a pre-stage of SRI assessment and energy simulation. Additional criteria focused on accuracy, coverage and that the sensors provide accurate, reliable, and comprehensive data for various indoor monitoring applications.

Stage 6: Data Analysis and Interpretation

Given the nature of the collected data, a dual approach analysis that employs both ML algorithm and numerical modelling was adopted. For instance, ML algorithms have emerged as powerful tools for data analysis, especially given the complex and multifaceted nature of the data-driven energy simulation models (Fan et al., 2019). This method is particularly beneficial to this research in uncovering patterns, and relationships that might not be immediately apparent within the collected sensing data. However, while ML algorithms will be applied to uncover patterns and relationships in the data, CFD-based and historical sensors' measurements will be integrated into numerical modelling. A study by (**?**) used numerical modelling and suggested that there is a similar relationship for diffusion of different parameters through porous media. This approach underscores the importance of utilising numerical modelling to identify potential relationships and patterns among various parameter measurements. As such, it aids in comprehending the patterns and distributions that establish the characterisation of the data obtained from certain sensors' positions. The results derived from both these analytical methods will then be interpreted in light of the research hypotheses in transitioning to indoor virtual sensors with the implications for building energy and well-being performance optimisation.

Stage 7: Validation and Testing

Validating the reliability of research findings is a critical aspect of any scientific study. Given the nature of this research, the validation and testing stage was based on the nature of both qualitative and quantitative approaches. In this context, (Hayashi et al., 2019) argued that qualitative research "Should adopt a processual view approach of validity since it should not be the product of a single test or just one step in the research". The study further indicated that "Validity is better evidenced in quantitative studies than in qualitative research studies", highlighting fundamental, conceptual, and knowledge-based distinctions between quantitative and qualitative research or combined methods. As such, the paper suggests that validity should be continuously assessed throughout the research process rather than just at the end.

In this context, the continuous validation was planned through a processual process starting from supporting the energy simulation with the SRI assessment, to further validate sensors' optimum positioning using the CFD simulation and thermal imagining. Furthermore, this stage involves validating the results against established benchmarks and cross-validation techniques. However, at the final stage, virtual sensing measurements from predefined sensors' positions, are to be compared against real-time sensing measurements from the exact sensing locations. The results will then be analysed and compared with established dynamic boundary conditions for semantic scalability in other buildings.

Stage 8: Conclusion and Recommendations

Drawing from the analysis and validation, this stage involves concluding the research, highlighting the key findings, and their implications, and providing actionable recommendations for practitioners, policymakers, and future researchers. As such, the conclusion of this thesis serves as a synthesis of the entire investigation, based on the research questions and analysis conducted. Furthermore, recommendations, are derived from the conclusions and are aimed at suggesting future actions and directions.

3.2 Case Study Site

This section describes the case study zone, elaborating on the criteria and implications of choosing this category of indoor spaces. This multi-activity space is subject to different regulations concerning indoor environment parameters, hence, the sub-space segmentation strategy applies accordingly. This multi-activity space with constantly changing occupancy patterns with combined ventilation reflects the majority of existing public buildings' conditions. Accordingly, eliciting a generalised framework for developing high-accuracy virtual sensors' measurements in this environment is considered a significant contribution to this field of science.

Influenced by the reviewed literature, the information provided in the remainder of this chapter represents the first layout in answering the RQ1 *"Which criteria should be considered to select and prioritize the indoor environment parameters necessary to conduct dynamic life cycle assessment, taking into account a wide range of configurations, including occupancy schedules and geographical location?"*. Thus, contributing to the wider knowledge necessitates using universal specifications as aimed in this case study space selection.

The location selected for the study is a zone within the Cardiff School of Engineering, Queen's Building, in Wales UK, designed to accommodate up to 200 individuals. The space is multi-activity where students socialise and study, with a small microwave area designated for light catering needs. It has a mixed mechanical and natural ventilation system, with 15 manually open-able windows on the north side and one on the east side. The case study room is located on the first floor and is 350 m2 with 24 square meters of north-facing double-glazing windows and 4 square meters of east-facing same type of manually opened windows, Figure 3.3. With 70% adiabatic walls around the space, the room has masonry external walls connecting a concrete frame. The occupancy schedule is defined according to the educational institution's scheduling that influences the combined ventilation operating hours. Accordingly, the space is mechanically ventilated by a terminal unit regulating the volume of conditioned primary air provided by a central VRF Fan coil air handler that serves additional rooms.

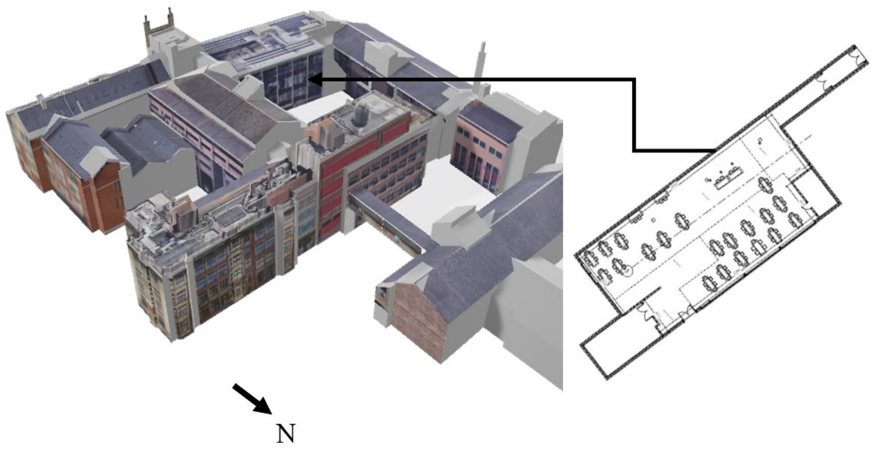

Figure 3.3: Case Study Zone

It is important to point out that this case-specific approach is essential due to the unique characteristics of the building, including its thermal properties, occupancy patterns, and energy usage profiles. Since each building has unique characteristics and complexities that require a customized approach, a generic strategy would not effectively address the specific challenges present. Therefore, a case-specific approach allows us to identify and account for possible variables that influence sensors' measurement behaviors. Along this direction, the integration of the SRI is considered foundational to identifying indoor environment parameters of interest to sensing. It also helps in identifying those parameters' weightings on energy performance and well-being conditions. Those two factors are substantive to determining the types of indoor sensors suitable for a specific building type. Furthermore, the SRI assessment results help in defining the existing boundary conditions for more granular Energy simulation results.

3.3 Description of Data Collection Instruments

This section outlines the data collection instruments used in this study. The adopted approach is underpinned by a strategic choice of network technology that is both reliable and scalable. Based on the definition of the parameters from the energy model results, the chosen wireless sensors were tailored to measure the parameters of the highest influence on energy and well-being performances. To enable this, a Low Power Wide Area Network (LP-WAN) was set-up to send the collected data to a central server for the subsequent analysis. However, since the level of accuracy in measuring indoor parameters is substantive to LCA inventory input data, additional simulation tools were employed to enable optimal positioning for the indoor sensors. On this account, these instruments serve as an empirical foundation for the subsequent modelling techniques, enabling the extraction of patterns and the formulation of the methodology, testing, and validation evidence (Büchter et al., 2020). Hence, the enhanced approach to collecting the data is also focusing on limiting constraints on the analysis and the research outputs. Furthermore, it is anticipated that the comprehensive data collection will also influence the recommendations and directions for future research. In this context, the following subsections will outline the data collection methods adopted in this research.

3.3.1 Identifying Indoor Monitoring Sensors

The literature established a case of the significance of indoor environment monitoring necessitating rigorous instrumental monitoring. It also highlighted the importance of a case-based approach depending on the indoor environment parameters of the highest interest. It is, therefore, running energy simulation for the case study zone is considered a strategic approach to understanding the specific conditions of the indoor parameters prior to identifying relevant sensors. These requirements necessitate a strategic approach to identifying indoor features of interest to the sensing system. Along this path, a dual approach combining SRI assessment and energy simulation was adopted. The SRI assesses 9 technical domains against 7 impact criteria as illustrated in Table 3.1.

Table 3.1: Overall SRI Scores for Different Domains

Domain	Overall SRI score (%) +SRI class						
	% Optimise energy efficiency and overall in-use performance		% Adapt its operation to the needs of the occupants				% Adapt to signals from the grid (energy flexibility)
Heating	%	%	%	%	%	%	%
Cooling	%	%	%	%	%	%	%
Domestic hot water	%	%	%	%	%	%	%
Ventilation	%	%	%	%	%	%	%
Lighting	%	%	%	%	%	%	%
Dynamic building envelope	%	%	%	%	%	%	%
Electricity	%	%				%	%
Electric vehicle charging		%		%		%	%
Monitoring and control	%	%	%	%	%	%	%

Consequently, the information used in formulating the boundary conditions was extracted from an SRI assessment to enhance the energy model inputs, as shown in

Figure 3.4. The resulting outputs of emission associated with thermal load and energy consumption are therefore crucial to understanding which parameters to be measured. This identification directly contributes to the definition of indoor monitoring sensors about space conditions and performance. Furthermore, since the SRI assessment inputs contain energy consumption data, including energy systems characteristics, the result of this assessment can cross-validate the energy model for more granularity. In particular, the assessment will investigate a possible correlation between the SRI score and the level of energy consumption among the indoor parameters.

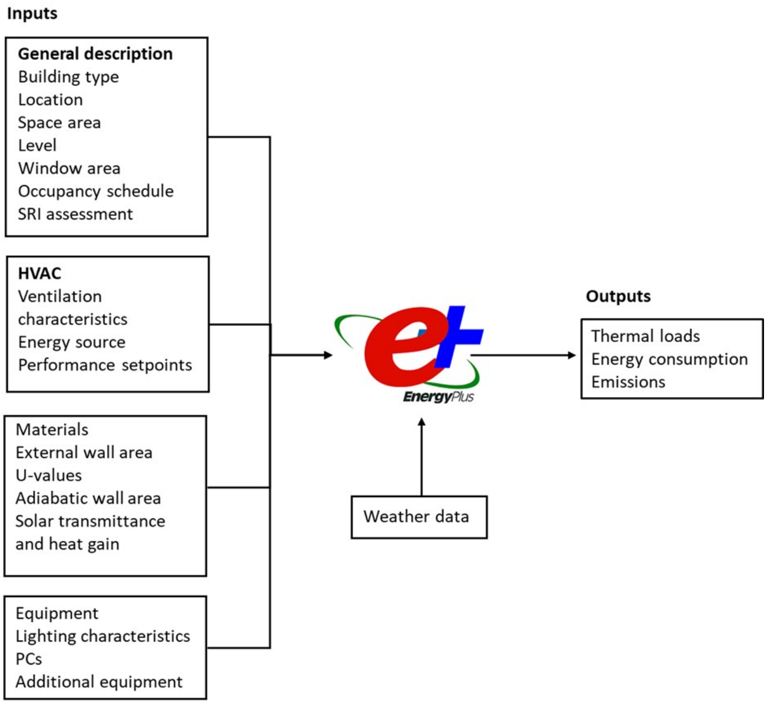

Figure 3.4: Inputs and Outputs of the Energy Model

Accordingly, the defined indoor sensors' criteria of flexible mobility, accuracy, and practical applicability contributed toselectingf the BME680, SCD41, and PMS5003 indoor sensors. The BME60 measures temperature, humidity, gas, and pressure, while the SCD41 measures the CO2 levels and the PMS5003 measures the particulate matter levels as illustrated in Table 3.2.

A combination of those 3 types of sensors forms a Low Power Remote Device (LoRD) unit, based on the sensors' performance specifications to operate for an extended period of time without permanent power infrastructure. Accordingly, each LoRD is operated by Saft LSH20 Lithium Battery 3.6V D Size Li-SOCl2 LSH-20, in line with

Table 3.2: Indoor Monitoring Sensors Used in The Case Study

Instrument	Measured Parameter	Sampling Rate	Accuracy	Supply Voltage
BME680	Temperature, Humidity, Gas, Pressure	5 Minutes	±1.0°C, ±3%, ±15%, ±0.25%	1.71 V to 3.6 V
SCD41	CO2	15 Minutes	±40 ppm	3.3 to 5V
PMS5003	Particulate level	30 Minutes	$50\%@0.3\mu$, $98\%@>=0.5\mu$	2.4 V to 5.5 V

all sensors' supply voltage specifications as illustrated in Figure 3.5.

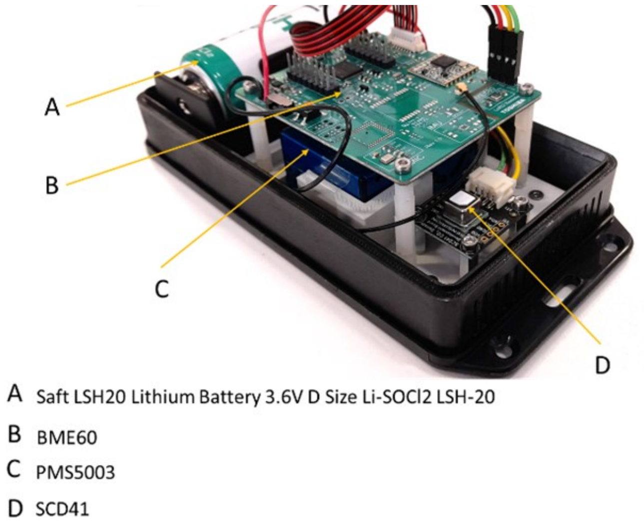

Figure 3.5: LoRD Unit

As the literature also highlighted the importance of the outdoor temperature in predicting the indoor temperature, a weather station (Davis Vantage Pro2) was deployed on the rooftop of the building. The objective is to collect external weather data including constant HDD values specific to the building location for higher accuracy calculations. Moreover, as indicated, facilitating hourly measurement for the HDD value is crucial in predicting indoor environment temperature.

Given that wireless sensors were considered in line with the identified criteria identified in the literature including flexible installation, additional benefits of this strategy were also considered. Primarily, while the theory of virtualising indoor sensors is influenced by accurate measures from optimal positioning, the potential lack of permanent power infrastructure specific to sensors' optimised locations can limit wired sensors' installation. Thus, wireless sensors' selection is particularly significant for the generalization of the virtualised sensing systems, resulting in a wider range of applicability.

3.3.2 Wireless Network System

The collection of indoor environment parameters measurements was set to use a Long Range Wide Area Network (LoRaWAN) technology to transmit acquired data to a central server for later analysis. Accordingly, the sensing units transmit data from the network to a gateway and subsequently to a traditional IP as shown in Figure 3.6.

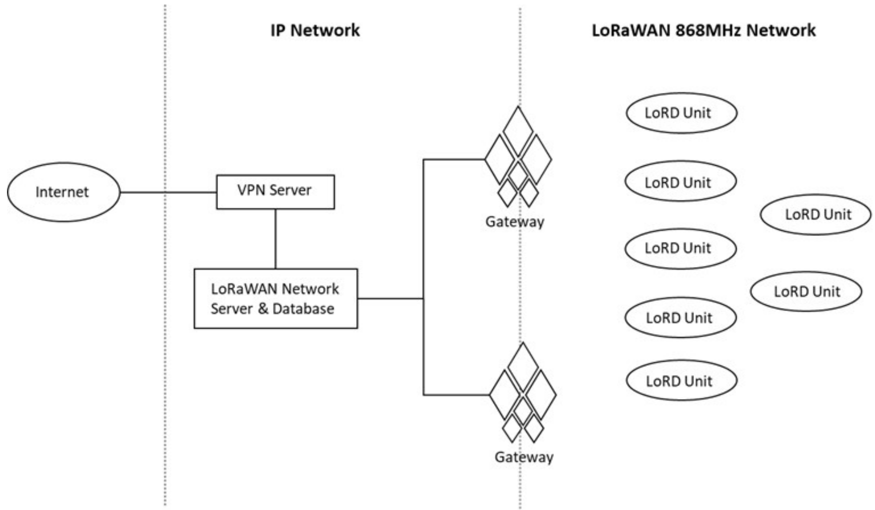

Figure 3.6: System Diagram of The LoRD Network

Given the dynamic nature of the case study space, the system adopted higher frequency readings across the sensing units. Accordingly, the BM60 was set to measure every 5 minutes, while the SCD41 was set to take measures every 15 minutes for the CO2. The PMS5003 was also set to take measures every 30 minutes. Based on the literature, these sampling rates were assumed adequate for optimum energy performance concerning occupancy-changing demands.

Building upon the established necessity to provide high-accuracy measurements by optimising sensors' locations, additional tools are employed. These tools enable the precise measurement of variables to support the comparison and extrapolation of findings across diverse study populations and contexts. The goal is to identify patterns, test hypotheses, and establish cause-and-effect relationships, to support the sensors' positioning. In this direction, the optimised positioning facilitated by the CFD simulation and thermal imaging is considered foundational to understanding and formulating those patterns. As such, the following sections outline the CFD simulation and thermal imaging used to establish these patterns.

3.3.3 CFD Simulation

A BIM model was created to include the case study zone to be simulated in the Autodesk CFD software as illustrated in Figure 3.7. The model also included the surrounding areas to detect possible air circulation and thermal interchange influences with a pressure differential of 5 Pa assumed between those spaces. Also, air density is assumed at 1.2047×10^{-5} g/mm^3, and the CO_2 density as 1.773×10^{-5} g/mm^3. The material setup specified glass wool for the building's envelope, representing wall insulation, and additional materials such as concrete, steel, and wood were used to model the remaining structure. Aiming for high accuracy, the convergence criteria were set to 1×10^{-5} after which, further iterations are considered unlikely to change the solution significantly. These boundary conditions were tested by simulating two scenarios of occupancy including 70 and 200 individuals in relation to the space capacity. The granularity of the results allows the identification of thermal hot spots and cold spots, as well as areas of high and low air velocity and pressure, which are critical for sensor placement. Moreover, the detailed setup helps in identifying resistant elements to both heat and air velocity, resulting in a better understanding of the room's thermal distribution.

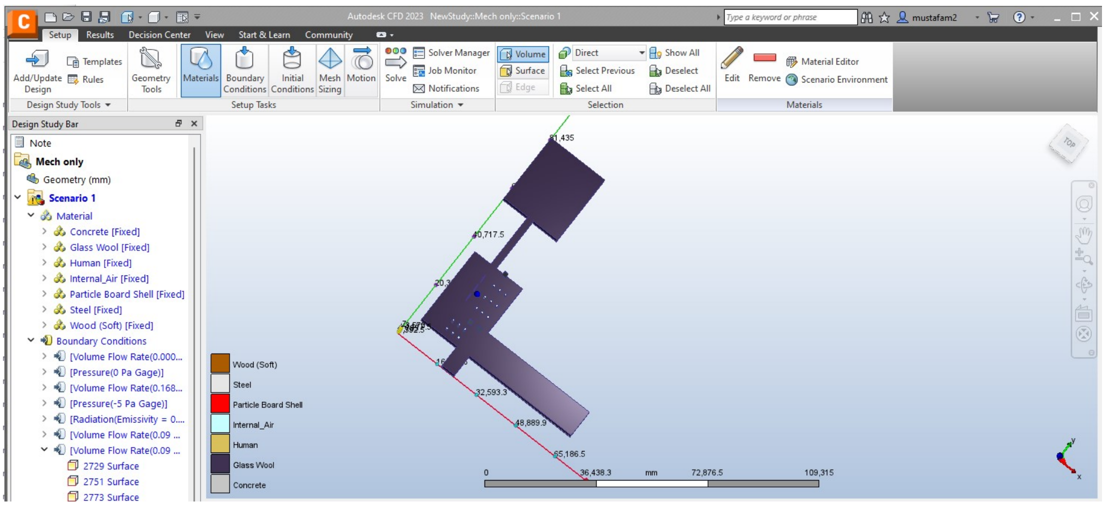

Figure 3.7: Case Study Zone in The Autodesk CFD Environment

While the goal is to identify positions within the space where temperature and air velocity have the least influence on sensors' measurements, an augmented approach of thermal imaging is also adopted. This approach directly helps in answering the second research question "What is the minimum number of physical sensors and their optimal positioning to provide accurate dynamic accounts of indoor environments?". By detecting localized heat emitted from lighting fixtures and increased hot air velocity closer to vents, more certainty about the definition of sensors' optimised location can be formulated. For this reason, a Thermal Camera is to be used to detect those anomalies for more enhanced resolution of thermal anomalies. As such, a FLIR ONE Pro thermal camera, of specifications in Table 3.3. was adopted.

Table 3.3: Thermal Camera Specifications

Specification	**Details**
Thermal Resolution	160 × 120
Battery Life	Approximately 1 hr
Object Temperature Range	-20°C — 120°C (-4°F — 248°F) and 0°C — 400°C (32°F — 752°F)
Accuracy	±3°C or ±5%, typical percent of the difference between ambient and scene temperature. Applicable 60 sec after start-up when the unit is within 15°C — 35°C and the scene is within 5°C — 120°C.
Operating Temperature	0°C — 35°C (32°F — 95°F), battery charging 0°C — 30°C (32°F — 86°F)
Spot Meter	Hottest, coldest and 3 spot measurements

As established, this dual CFD simulation and thermal imaging is aimed at guaranteeing maximum accuracy measurements provided by the indoor sensors. This approach comes consistent with high LCA inventory input data resolution. Based on this, the next section addresses indoor sensors' positioning strategy.

3.4 Indoor Monitoring Sensors' Positioning

As established, sensors placed near HVAC vents or windows may report temperatures that may not be representative of the room's actual temperature conditions. Similarly, variations in air velocity closer to vents could affect the sensors' ability to accurately measure parameters such as humidity or indoor air quality. As such, criteria for optimum sensors' positioning were defined as (a) temperature characteristics, including thermal distribution, and heat gains, (b) air velocity, including vector plots, velocity magnitudes, and draft regions (c) pressure distribution, including HVAC effects. Accordingly, multiple optimal positions were identified as illustrated in Figure 3.8. Also, additional ad-hoc positions were nominated for accuracy validation.

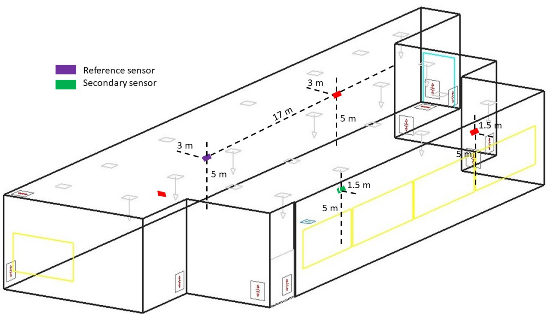

Figure 3.8: Sensor Positions Guided by The Autodesk CFD Simulation Coupled with Thermal Imaging, At Different Coordinates

In meeting these criteria, the combination of CFD simulation and thermal imaging is considered crucial to enhance the LCA inventory input sensing data as outlined in Figure 3.9.

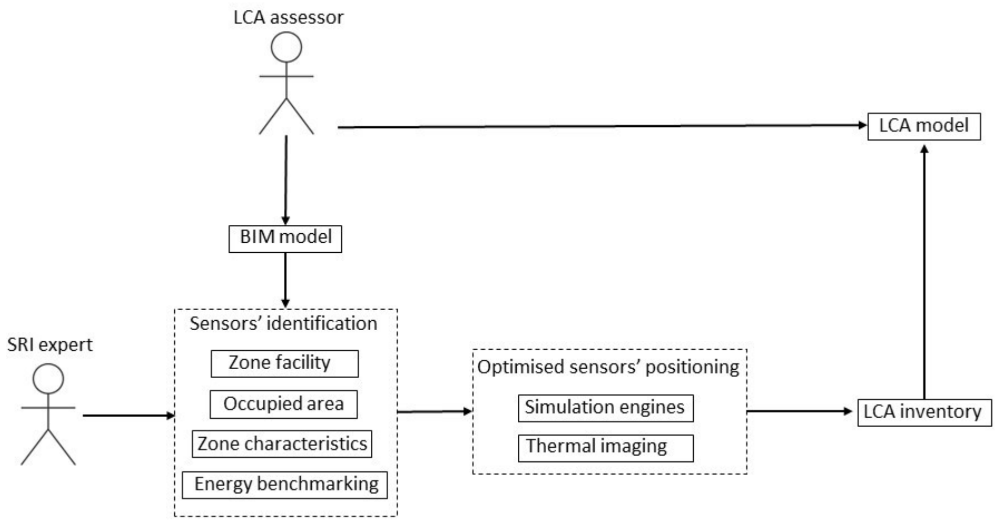

Figure 3.9: Sensors' Optimal Positioning Strategy to High Accuracy LCA Inventory Input Data

Following the sensors' deployment, the measurement data is to be transmitted to the server where acquirable from an Influx database interface as illustrated in Figure 3.10. Furthermore, the data gathering was tested to ensure that the buffering scheme and Real-Time Clocks (RTC) synchronization of the sensors are reasonable for long-term indoor environment monitoring. While this strategy helps in retrieving timely actions over a long time, it is knowledgeable that the selected sensors are battery-operated, and thus, RTC calibration will be needed constantly. This is considered a typical real-case scenario for indoor monitoring sensors monitoring, by which, adding more value to virtual sensors.

Figure 3.10: Influx Database Interface

It is important to acknowledge that, at this stage, the initial sensors' reading showed proportional behaviour given the optimised positioning. While this indicates the potential for reducing the number of sensors, dynamic boundary conditions are considered substantive governors for the dynamic behaviour of these measurements. Along this path, the next subsection presents the numerical modelling followed for this particular matter.

3.5 Minimising the Number of Indoor Monitoring Sensors

According to RQ2 " What is the minimum number of physical sensors and their optimal positioning to provide accurate dynamic accounts of indoor environments?", this section presents the numerical modelling to reduce the number of sensors. The approach utilizes equation 2.6 presented in the literature. Upon defining the main reference sensor, historical data of one year, are to be assessed to find a relationship between established CFD gradients using the equation:

$$Y = \int (X) + \varepsilon \tag{3.1}$$

Where Y is the virtual sensor measurement, $\int$ is a fixed unknown function of the reference sensor capturing building thermal performance under various occupancy profiles, X is the current value of the reference sensor, and ε is a random error term representing a historical relationship in measurements between the reference sensor point and the secondary sensor.

One year of data will be fed to an ML regression model to find the relationship between the given values of the reference sensor, historical data for the secondary sensor, and simulated boundary conditions, including the occupancy profile.

3.6 Virtualising Indoor Monitoring Sensors

As the literature established, the indoor temperature is measured by the HDD, DDF, building-specific base temperature, and heating capacity. Accordingly, the current temperature measurement can be formed using a current (HDD*DDF) value in equation 3 as:

$$i = (Y - (HDD \times DDF)) + Z \tag{3.2}$$

The equation models the current value of an indoor sensor *i* as a function of *Y*, Heating degree day days, degree day factor, and temperature difference *Z*. The analysis successfully identified building-specific values for *Y* and *Z*, which, when combined with real-time *HDD* obtained from the weather station, and *DDF* values, yield live sensor readings for the indoor temperature. However, it is anticipated that given the dynamic boundary conditions introduced in the literature chapter, it is anticipated that this equation may need a calibrating variable respectively.

Given the observed linear interpolation among historical data, this argument was further developed by adopting a linear interpolation equation. The goal was to simplify the methodology for the wider application. Accordingly, the developed equation was:

$$Y = X_t + (Y_t - X_t) \times \left(\frac{Y_t}{X_t} \right) \tag{3.3}$$

Where X_t is a reference sensor and Y_t is a secondary sensor at a specific time.

Establishing a correlation relationship between the reference sensor X and secondary sensor Y under different conditions of X has practically reduced the number of sensors. This finding is considered significant in decreasing the number of sensors, particularly in open-plan spaces that require multiple sensors. The simplified equation provided a high level of accuracy that contributed to the wider-scale application of this theory. Accordingly, secondary sensors can be phased out from the LCA inventory while still providing real-time high-accuracy measurements depending on one reference sensor and their historical measurements.

3.7 Implications of Phasing Out Indoor Monitoring Sensors on LCA

The phasing out of indoor monitoring sensors while providing higher accuracy measurement can have dual implications on the LCA of buildings. On one hand, this shift contributes to a reduction in the embodied carbon associated with the sensors as part of the LCA inventory. On the other hand, high-accuracy sensing measurements assist in optimised energy performance and subsequently maintaining well-being standards. Accordingly, assuming the operational phase of the case study zone spans 60 years, calculating embodied carbon associated with the sensors and their battery followed the equation presented in the literature:

$$E = \sum_{i=1}^{n}(C_i \cdot K_i) + C_f + C_t + C_c \tag{3.4}$$

Where *E* is the total amount of embodied energy in the sensor, expressed in KgCo2, *ei* is the embodied energy of each material, *ji* is the amount of material used, *ef* is the energy incorporated into the additional sensing system, *et* the energy needed for the transport of materials and mobility of workers, and *ec* correspond to the energy incorporated from the Batteries replacements.

As acknowledged in the literature chapter, a virtual sensing system comes in cloud computational form of its carbon footprint. Comparatively, given the advanced science in reducing carbon footprints from data centers, it is assumed that moving to virtual sensors has less environmental impact. In addition, the applicability of clear guidance on virtual sensors has more environmental benefits, including practical and feasible adoption.

3.8 Summary

This chapter has outlined the adopted methodological approach to address the research objectives through the posited research questions introduced in the introduction chapter. The methodology was carefully designed to ensure a robust and systematic approach to phasing out carbon emissions and embodied carbon in indoor sensor applications. Initially, the chapter introduced the rationale for adopting a multiple mixed-methods approach, combining quantitative LCA with qualitative case studies to provide a comprehensive understanding of the environmental impacts associated with indoor sensors' applications. The methodology was detailed, explaining the data collection process and also the modelling approaches followed. Moreover, this chapter describes the data collection, process, analysis, and interpretation. As such, statistical tools and software used in the analysis were identified, emphasising transparency and universality of the research findings. In conclusion, the methodology chapter has established a solid foundation for the theoretical background of this thesis before empirical validation. The subsequent chapters will present the results of the analysed data, discussing the implications of the findings in the context of environmentally responsible buildings.

Chapter 4 | Results and Validation

This chapter addresses the various points presented earlier and provides the research findings and their implications on the case study zone. Following that, a discussion on how these results answer the research questions in the context of a generalised framework will be presented in the following chapter. As such, the results presented here are case-specific, to provide answers to the main research questions:

- *Which criteria should be considered to select and prioritize the indoor environment parameters necessary to conduct dynamic life cycle assessment, taking into account a wide range of configurations, including occupancy schedules and geographical location?*

- *What is the minimum number of physical sensors and their optimal positioning to provide accurate dynamic accounts of indoor environments?*

- *Can virtual sensors replace physical sensors while ensuring data accuracy and reducing direct and indirect environmental impacts?*

In response to these questions, the chapter demonstrates the resulting analysis for the simulations and numerical modelling followed. Accordingly, it provides insight into indoor environment parameters' characterisation, optimal sensors positioning, and virtualised sensors in the context of performance and reliability.

4.1 Indoor Environment Parameters' Characterisation

To characterise indoor environment parameters of the highest influence on energy consumption and well-being, the methodology followed the multifaceted approach outlined in the previous chapter. Following the SRI results, The boundary conditions of the EnergyPlus model were augmented by SRI assessment results for optimised outputs. The SRI containing energy consumption data has also been used for cross-validation for the energy model for more granularity.

4.1.1 Smart Readiness Assessment

As established in the literature section, the SRI assessment can guide the deployment of indoor monitoring sensors by highlighting the level of performance in current building services in relation to energy efficiency and occupant well-being. As such, By providing initial this customised approach aims at gathering the data that is most relevant for energy efficiency and occupants' well-being. It further aids in granulating energy model input data while providing cross-validation for the models' output. The SRI assessment for the case study zone was conducted through a tailored approach. The evaluation was specific to the room's total floor area and its activity type, however, additional elements included were not taken into consideration. The assessment focused on three key functionalities—namely, heating, cooling, and additional HVAC system and services components with breakdown results in Table 4.1. In more details, a comprehensive review of the building's existing systems was undertaken, focusing on key areas such as HVAC, lighting, and shading controls. This involved gathering data on the existing technologies, their automation capabilities, and how they interact with the building's occupants. Subsequently, the building was evaluated using the SRI criteria, which categorize smart functionalities into key domains such as energy efficiency, flexibility, and occupants' comfort. Following that, specific weighting indicators related to the indoor environment parameters such as heating, cooling, and illuminance were identified. This step was crucial in defining indoor environment parameters of interest to sensing.

Table 4.1: Detailed SRI Scores for Building Systems

System	Energy Efficiency	Flexibility and Energy Storage	Comfort	Convenience	Health, Well-being and Accessibility	Maintenance and Fault Prediction	Information to Occupants
Heating	13%	0%	20%	20%	0%	0%	0%
Domestic Hot Water	80%	75%	0%	60%	0%	50%	67%
Cooling	0%	0%	0%	0%	0%	0%	0%
Ventilation	33%	0%	33%	33%	67%	100%	100%
Lighting	33%	0%	50%	50%	0%	0%	0%
Dynamic Building Envelope	0%	0%	0%	0%	0%	0%	0%
Electricity	80%	67%	0%	40%	0%	50%	78%
Electric Vehicle Charging	0%	0%	0%	0%	0%	0%	0%
Monitoring and Control	0%	0%	0%	0%	0%	0%	0%

These scores were then aligned with SRI impact criteria which resulted in 28% of the overall smart readiness level. The assessment revealed a decreased level of smartness in the heating domain, despite showing an increased level in the cooling domain Figure 4.1. This highlights the need for targeted interventions in the heating domain, particularly by deploying indoor monitoring sensors.

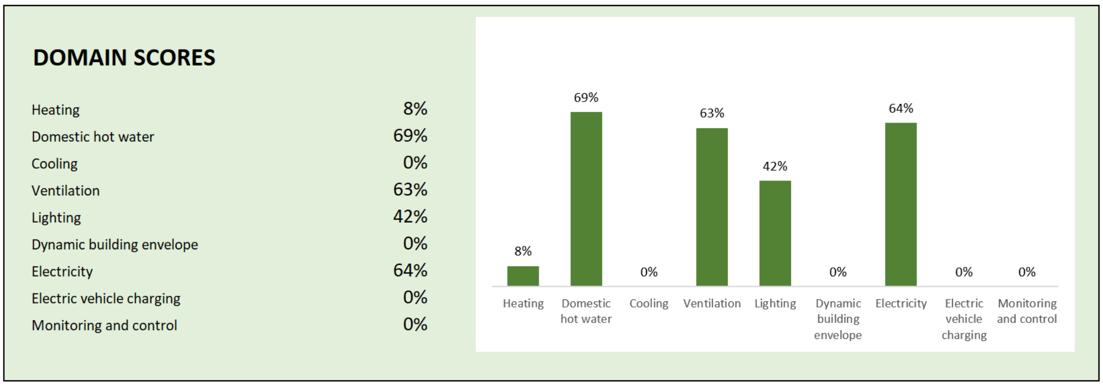

Figure 4.1: SRI Domains' Scores of Indoor Parameters

Further investigation into how these scores impact on indoor environment's energy efficiency and occupants' well-being showed variable levels of reflections Figure 4.2. The decreased energy efficiency level is understood to be caused by the low heating score being 16%, which subsequently affected the comfort score. Moreover, the high cooling score can be attributed to the combined mechanical and natural ventilation system. However, this can be another indicator to consider AIQ sensors to address possible poor IAQ as a result of natural ventilation.

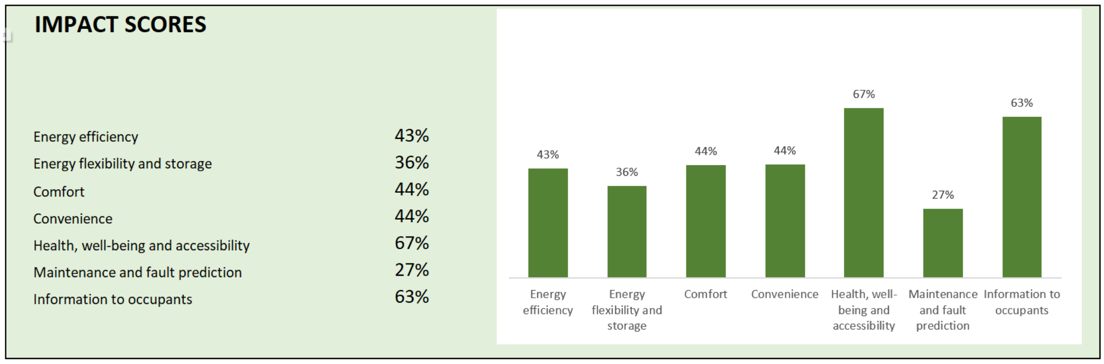

Figure 4.2: SRI Impact Scores

According to these results, multiple indoor environment parameters were identified. However, as mentioned, this is a preliminary result to enhance the energy model. Along this path, the next subsection will demonstrate the results from the energy simulation model.

4.1.2 Energy Simulation

The energy simulation was conducted using EnergyPlus for the 350 m² total area of the zone BIM model. Different indoor parameters were simulated with a focus on multiple boundary conditions also enhanced by the SRI assessment results, as can be seen in Table 4.2. This strategy aimed for a higher resolution picture of the indoor environment parameters of the highest influence on energy consumption and well-being impact. The simulation was run to show hourly energy consumption of different boundary conditions and monthly simulation.

Table 4.2: Input Parameters for EnergyPlus Model

Category	**Parameter**	**Description**	**Unit/Format**
Zone	Zone area	Total floor area	350 m²
	Zone height	Total height of the zone	6 m
Thermal properties	Wall U-value	Overall heat transfer coefficient of the external walls	0.26 W/m²K
	Roof U-value	Overall heat transfer coefficient of the roof	0.25 W/m²K
	Window U-value	Overall heat transfer coefficient of the windows	0.55 W/m²K
	Infiltration Rate	Rate of air leakage through the building envelope	1.0 ACH (Air Changes per Hour)
Schedules	Occupancy Schedule	Time-dependent schedule for building occupancy	Fractional value (0 - 1)
	Lighting Schedule	Occupancy-based sensors	Fractional value (0 - 1)
	Equipment Schedule	Time-dependent schedule for equipment use	Fractional value (0 - 1)
	HVAC Operation Schedule	Terminal AHU	VRF
	Heating Setpoint	Desired indoor temperature during heating	19 °C
	Cooling Setpoint	Desired indoor temperature during cooling	22 °C
	Ventilation Rate	Rate of fresh air supply	8 L/s/person
	Lighting Power Density	Power used for lighting per unit area	3.5 W/m²
	Equipment Power Density	Power used by equipment per unit area	2.0 W/m²

The energy simulation results revealed high dynamic interplay within the indoor environment, particularly during typical winter daytime hours. The analysis of the heat balance of the internal partitions showed a notable decrease, indicating a reduction in heat transfer between internal spaces. This is understood because the adjacent spaces are rarely occupied and thus unheated. The relative humidity showed a decrease with increased heat loss from the glazing indicating closed windows. Consistently, the decrease in fresh air influx during this period suggested limited ventilation, due to the closed windows. The results also showed increased solar gain through the glazing, highlighting the contribution to space heating. Additionally, external infiltration experiences an uptick during daytime hours, which possibly, can be weighted by the observed increase in solar gain as illustrated in Figure 4.3.

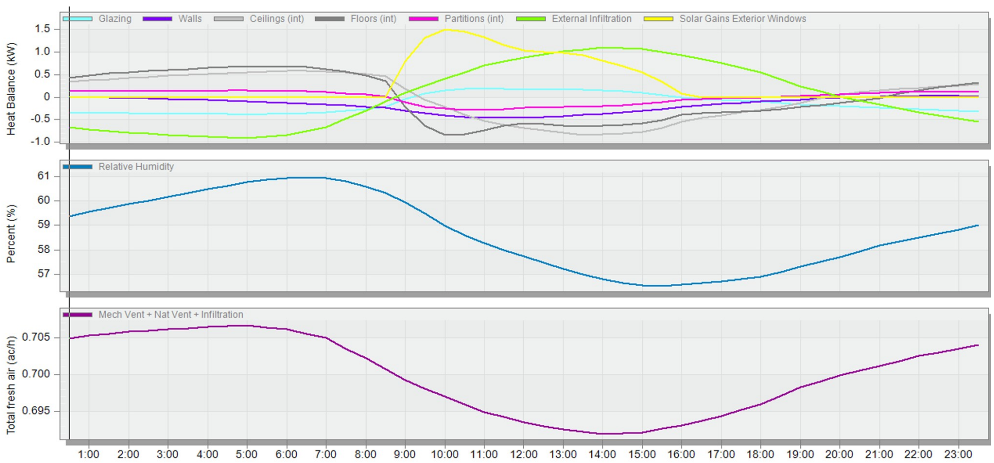

Figure 4.3: Typical Winter Day Heat Balance

Despite the natural ventilation and infiltration during the Autumn season, a notable difference between inside air temperature and outside dry bulb temperature was shown. This is understood due to the increased occupancy and heat gain during daytime hours. However, the inverse proportion observed between relative humidity and external ventilation under peak occupancy hours can indicate poor IAQ as can be seen in Figure 4.4. While this conclusion can be contradicted by the increased mechanical ventilation, high air velocity can increase air shear forces carrying particulate matter. Therefore, both cases indicate poor IAQ.

The summertime showed a similar result in inverse proportion between relative humidity and ventilation, mainly due to natural ventilation. In addition, the cooling showed slight efficiency in response to outside dry bulb temperature as illustrated in Figure 4.5. Consistently, both sensible cooling and total cooling consist of humidity decrease emphasising the role of natural ventilation. Opposite to winter time, the highlighted role of natural ventilation may indicate improved IAQ, however, the case

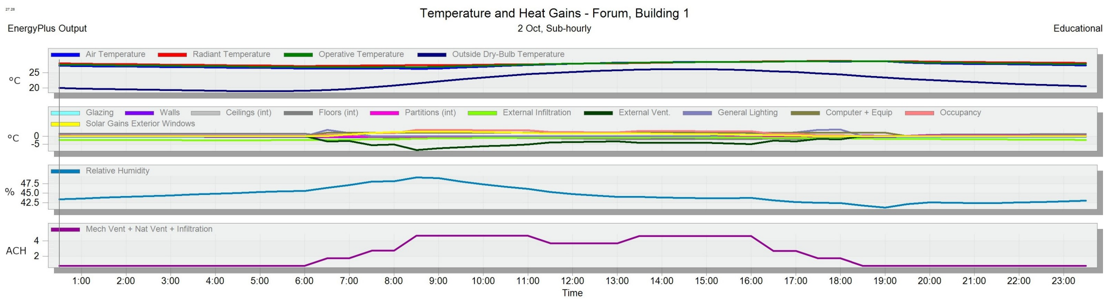

Figure 4.4: Inside temperature implications on IAQ

study is located in a densely crowded urban location can still suggest otherwise. It is also notable that the indoor environment showed notable adaptation for the indoor air temperature in response to the increased outdoor dry bulb temperature during daytime hours.

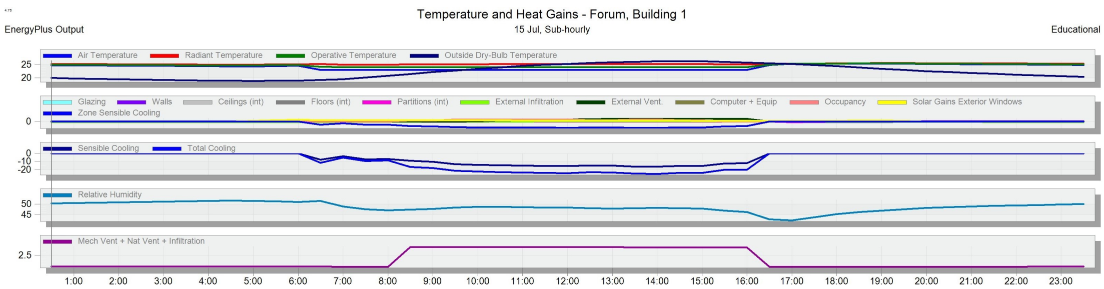

Figure 4.5: Typical Summer Day Temperature, Humidity, and Heat Gain

Despite the observable heat loss from the external walls in winter, the inside surface temperature showed 14 °C against subzero degrees for the external surface as can be seen in Figure 4.6. The thermal resistance for the external walls was observed in the increased external convection coefficient. The decreased internal coefficient is logical considering the partitions that separate the case study space from adjacent heated spaces. These results reinforce the previous results in terms of indoor temperature consistency. However, further investigation into the difference between indoor and outdoor temperatures during winter time is needed.

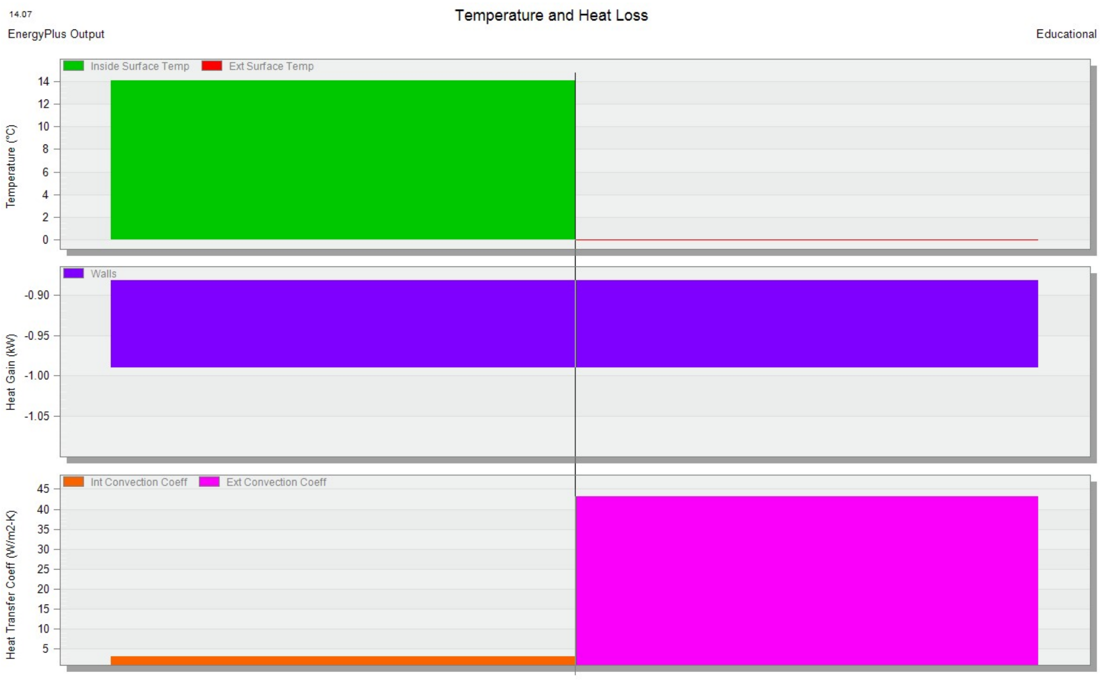

Figure 4.6: Behaviour of Indoor Temperature Under Cold Outside Temperature

To investigate the difference between inside and outside temperature, the results showed a notable difference between the outside dry bulb temperature and inside air temperature despite the outside temperature being at subzero degrees. In particular, to achieve 20 °C inside air temperature, the sensible heating indicated 15.5 °C as can be seen in Figure 4.7.

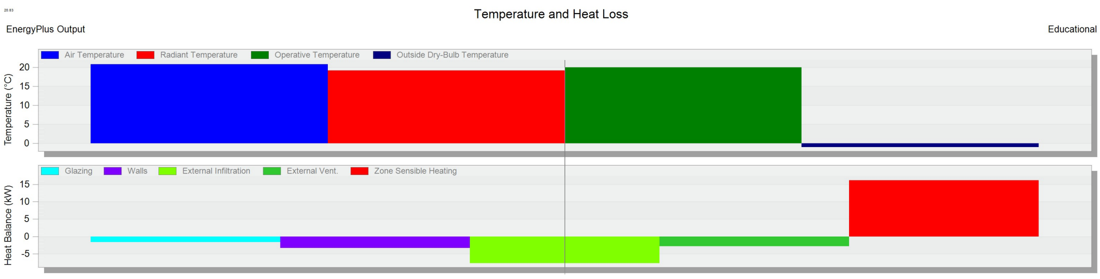

Figure 4.7: Sensible Heating Temperature

In contrast, the summer season during July, showed a proportional relationship between indoor temperature and relative humidity as can be observed from Figure 4.8. In addition, despite the total fresh air supplied partly with natural ventilation, it is notable that indoor temperature records are higher than outside dry bulb temperature. While the simulation showed an indication of windows shut down during daytime, it is observable that there is an increase in occupancy heat gain, mainly indicating the role of individual control in windows opening. This particular result is another emphasis on the importance of monitoring the IAQ.

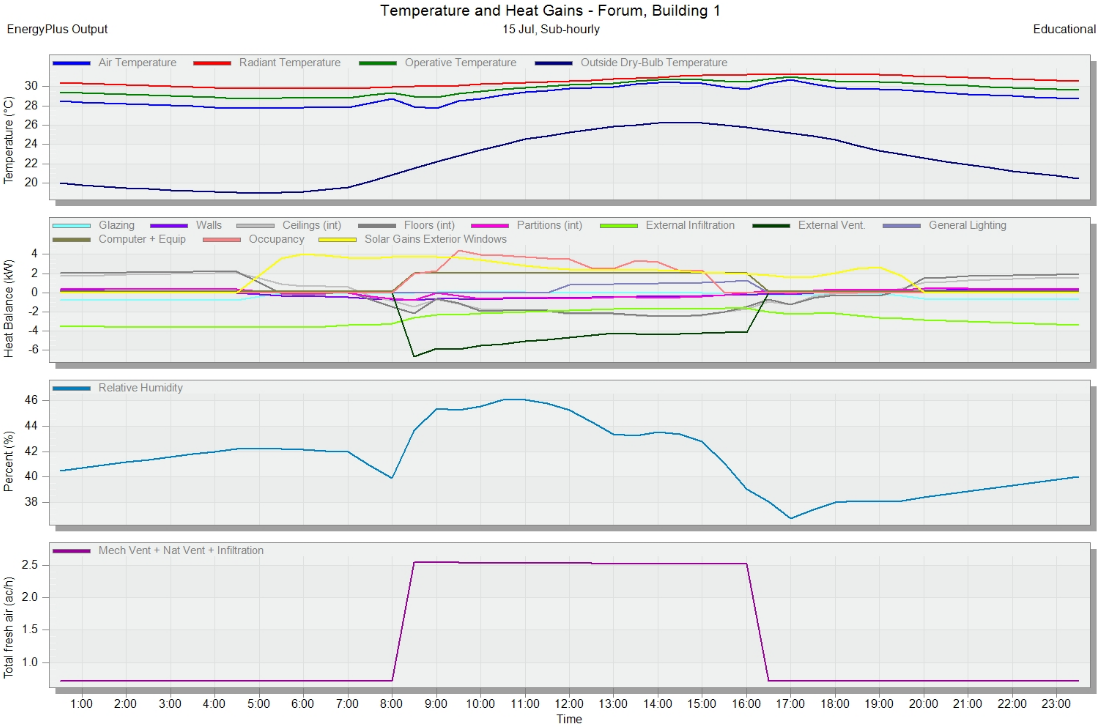

Figure 4.8: Temperature and Heat Gain Versus Cooling Load

Overall, the energy simulation results can be interpreted sequentially to address key factors influencing energy efficiency and occupants' well-being. Based on the influence of significance, the indoor environment parameters are humidity, temperature, IAQ, and pressure, as seen in Figure 4.9.

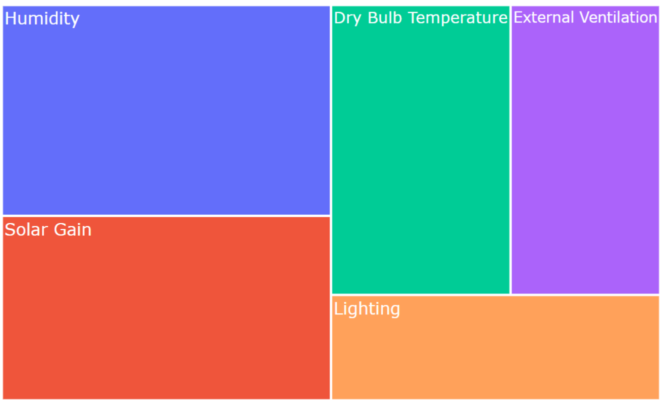

Figure 4.9: Parameters of Highest Influence on Energy Efficiency and Well-being

The high thermally resistant space envelope, with large glazing windows, allowing solar gain has positively reflected on the heating load as can be seen in Table 4.3. Moreover, given the applied boundary conditions of 20, 100, and 150 occupants, the heat gain from occupants contributed to a notable decrease in the heating load compared to the cooling load. In comparison, the indoor base temperature extracted from the simulation indicated 12.7 °C, which is slightly below the standard UK 15.5 °C. With the highlighted heat gains, changes in occupancy profile can cause indoor temperature fluctuation with variable heating demand across a typical winter day. In contrast, the increased cooling load, compared to the heating load, is also notable for the increased occupancy number and equipment heat gains. despite the natural ventilation, the individually controlled windows are understood to be responsible for temperature increase during a typical July summer day. This individual control issue can also introduce more dynamism within indoor air velocity, ppm, and CO2.

Table 4.3: EnergyPlus Model Results Showing Electricity Consumption of Indoor Parameters

Parameter	**Electricity (kWh/m^2)**
Lighting	39.02
Heating	10.22
Cooling	13.34
Other	15.41
Total	77.9

As can be seen from the table, the heating energy is less than the cooling energy. This is justifiable because the occupancy and equipment heat gains are also significant contributors to the heat gain. similarly, the lighting contributes to increased temperature through heat gain. These factors are therefore essential contributors to the indoor temperature. For instance, high occupancy density and lighting heat gains during winter can save more energy on heating. Conversely, these heat gains contribute to increased cooling load during summertime. This explicitly means that the dynamics of occupancy presence is an important element to consider when determining the indoor base temperature.

In summary, it is important to highlight that the fresh air showed a notable increase during summertime as a result of natural ventilation. This observation signals that indoor air quality and air shear forces may change due to the introduced natural air in the indoor space. As such, outdoor air temperature, speed, and particulate matter levels can all contribute to the sensing measurements of behavioral change during the natural ventilation season.

The energy simulation results were then cross-referenced with the energy simulation model as illustrated in Figure 4.10. Hence, the assessment revealed a decreased level of smartness in the heating domain, despite showing an increased level in the cooling domain. This highlights the need for targeted interventions in the heating domain, particularly through the deployment of indoor monitoring sensors. As a result, the low heating score with high cooling nominated indoor monitoring sensors to measure temperature, humidity, IAQ, particulate level, and gas levels.

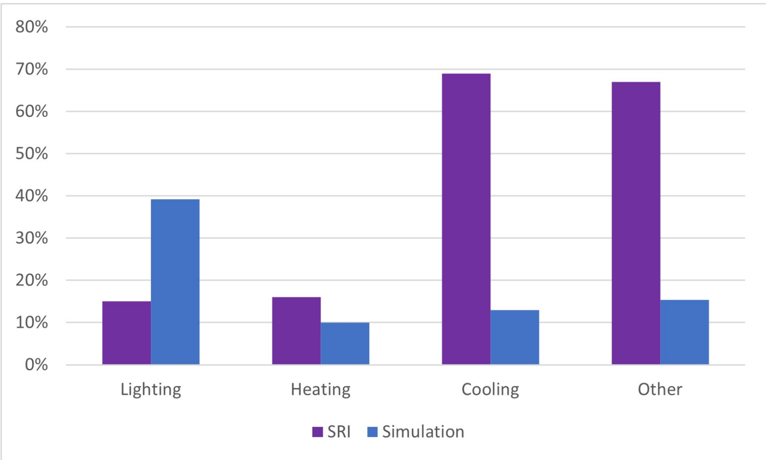

Figure 4.10: SRI Assessment Results Versus Energy Model Results

The SRI assessment results strongly correlated to the EnergyPlus model results, emphasising the characterised domains. It's therefore, lighting, heating, and cooling are the main indoor parameters domains that influence energy performance. However, to fully answer RQ1, it is important to acknowledge the multiple dimensions of heating and cooling domains. As established in the literature, heating and cooling interrelate with IAQ, CO2, and particulate matter. Building upon this, the next section will demonstrate the resulting indoor environment parameters.

4.1.3 Indoor Environment Parameters' Definition

This subsection concludes the results in answering RQ1 "Which criteria should be considered to select and prioritize the indoor environment parameters necessary to conduct dynamic life cycle assessment, taking into account a wide range of configurations, including occupancy schedules and geographical location?".

Given that the SRI results showed various impacts on energy consumption and occupants' well-being, the energy simulation has further confirmed these findings in the previous sub-section. Even though the health and well-being domain achieved 67%, both comfort and convenience achieved under 45% score. Reflecting these values on the energy simulation results, the heating domain showed increased energy efficiency of 10% of the overall consumption despite the low SRI score. This has also been understood that the space heating is based on LPHW radiator system. However, the cooling domain was slightly increased in energy consumption but its SRI score is disproportionately consistent when compared to heating. These particular results highlight the significant role of natural ventilation in the space. As established previously, the indoor parameters concerning the IAQ, humidity, and particulate matter are vital to the well-being impact. This indication is further evident by the low comfort and convenience SRI scores. As such, main three factors were identified to influence indoor environment conditions, namely (external conditions, (b) daytime, and (c) Occupancy, as illustrated in Figure 4.12.

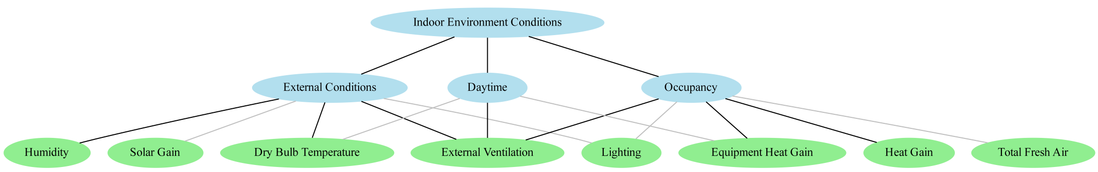

Figure 4.11: Implications on Indoor Environment Conditions

Based on these results, the indoor identified parameters are, (a) temperature, (b) IAQ, (c) humidity, (d) pressure, (e) particulate matter, and (f) CO2. Hence, this indoor environment parameters identification to guide indoor sensors' audit in the next section.

4.2 Quantifying Embodied Carbon of Indoor Monitoring Sensors

As outlined in the methodology, the BME680 wireless indoor sensor was adopted for it is high accuracy and multi-functionality as it measures temperature, humidity, gas, and pressure. This multi-functional specification comes in line with the need to decrease unnecessary embodied carbon from multiple sensors. However, additional sensors are needed to measure the CO2 level and particulate matter levels. Following the same criteria, the SCD41 wireless sensor was added to measure the CO2 level, and the PMS5003 was also added to measure the particulate matter. Furthermore, selecting the three sensors considered a matching range of the supply voltage, resulting in one sensing unit, operated with one battery of Saft LSH20 Lithium Battery 3.6V D Size Li-SOCl2 LSH-20. With this perspective. According to this selection, embodied carbon assessment was carried out to cover the environmental impact of one sensing unit and associated battery consumption. The calculation aimed to forecast embodied carbon from sensors and battery consumption for an average of the building's operational phase of 60 years Table 4.4.

Table 4.4: Quantification for Embodied Carbon from One Sensing Unit Over a 60 Years Use Phase

Item	Upstream in kgCO2					Direct Operation		Downstream
	Materials acquisition	Carbon emission factor	Materials processing and assembly	Additional materials including packing	Transportation	Use Phase 60 Years		End of life of initial multiplied by replacement frequency
						Unit	Replacements	
BME680	1.6	2.2	0.546		0.17	4.516	X 6 = 27.1	0.9
SCD41	1.9		1.23		0.17	3.3	X 6 = 19.8	0.6
PMS5003	0.7		0.95		0.17	1.8	X 6 = 10.8	0.36
Saft LSH20 Lithium Battery 3.6V D Size Li-SOCl2 LSH-20	Lithium cobalt oxide -27.5%	12.9		0.5	0.17	47.47	X 240 = 11.392.8	2.246.4
	Steel - 20.2%	9.45						
	Graphite - 16%	7.5						
	Polymer - 14%	6.5						
	Copper - 9%	4.2						
	Aluminium - 5.5%	2.8						
	Nickel - 4.3%	2						
	Electrolyte - 3.5%	1.6						
Total 60 years	46.8 kgCO2							
	Annual emission from one sensor unit including 4 batteries (Batteries consumption rate based on one year)							11.698.76 tCO2

Based on the performance observation during the experiment period, the corresponding battery consumption was defined from the batteries' performance across the experiment time.

Total unit and batteries over 60 years, including end-of-life phase:

$$E = \sum_{i=1}^{n} (e_i \cdot j_i) + e_f + e_t + e_c \tag{4.1}$$

Where *E* is the total amount of embodied energy in the sensor including batteries, expressed in tCo2, *ei* is the embodied energy of each material, *ji* is the amount of energy used in manufacturing, *ef* is the energy incorporated into the additional materials including packing, *et* the energy needed for the transport of materials and mobility of workers, *ec* correspond to the energy incorporated from the Batteries replacements, ed is the embodied carbon of end of life during the downstream stage the result showed that the projected carbon accumulation over 60 years = 11.698.76 tCO2.

The sensors' identification was derived from the characterised parameters. In addition, the quantified embodied carbon was based on the manufacturer's information, furthermore, the embodied carbon for both units and batteries, essentially the frequent replacements was based on the consumption rate across the experiment period. According to these results, significant embodied carbon accumulates from one unit measuring the identified indoor parameters. consequently, this amount increases with the number of needed sensors which negatively affects the carbon trade-off of the energy and well-being optimisation process. As a result, moving to virtualised sensors is significant to achieving LCA goals of the reduced environmental impact from this inventory tool.

4.3 Optimised Indoor Sensors Positions

Building upon the literature review and the outlined methodology, this section presents the two-step outcomes of the CFD simulation and the thermal imaging. The aim is to define the optimum positioning of indoor environment monitoring sensors for accurate measurements. The results obtained from the CFD simulation and thermal imaging helped to nominate optimum locations of least influence by the surrounding environment. The subsequent subsection details the observed impacts on sensors' strategic placement and the consequential implications of specific deployment.

4.3.1 CFD Model

A BIM model of the building was developed and simplified before being imported into the CFD environment. The model included key structural and environmental details, such as the addition of extrusions to inlets and outlets, which were crucial for avoiding airflow divergence and improving accuracy. Glass wool was used to simulate the walls, floors, and ceilings, approximating insulated walls, while other materials like steel, concrete, and wood were employed to represent radiators, columns, and furniture, respectively.

The boundary conditions for the CFD model were carefully defined to simulate realistic environmental factors. Each occupant was assigned a heat generation rate of 50W to represent body heat and external airflow was simulated with an x-direction velocity of -1.884 m/s to mimic an easterly wind. The internal gauge pressure was set at 0 Pa for all interior doors and at least one outlet, while adjacent zone doors were assigned a gauge pressure of -6 Pa. The radiators were modelled with a reference temperature of 20°C and an emissivity of 0.8 to reflect their white-painted surfaces. Also, the CO2 levels were modelled by assigning scalars, with air set at 0 and CO2 at 1, allowing for detailed tracking of air quality and occupant exhalation effects.

A mesh sensitivity analysis was performed to ensure the accuracy of the simulation, with mesh densities ranging from an initial coarse mesh to a highly refined one. The final mesh, consisting of around 1.5 million cells, was selected based on achieving a balance between computational efficiency and result accuracy. This refinement process was critical for accurately capturing the flow dynamics within the space. Residuals were monitored throughout the simulation, with convergence criteria set to ensure that continuity, momentum, and energy equations dropped by at least three orders of magnitude, confirming the reliability of the results.

Concerning the CFD simulation results, the detailed setup was successful to help to answer RQ2 regarding optimal sensor placement. The setup included definitions of material properties and thermal boundary conditions such as heat, pressure, and air-driving forces within the environment. According to the energy simulation results, there was a notable influence from the surrounding spaces, and therefore, the CFD simulation considered adjacent rooms.

The effect of air velocity from surroundings highlighted increased influence of natural ventilation as can be seen in Figure 4.12.

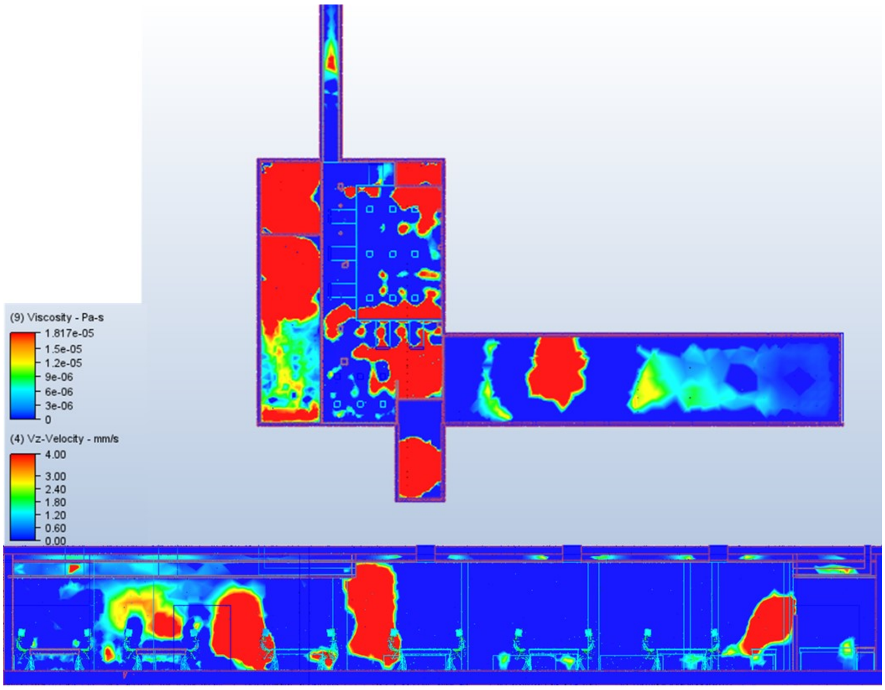

Figure 4.12: Effect of Surrounding Spaces on Air Velocity

Further investigation for the air velocity and its influence on the occupancy zone aimed at 1.8 meters high, as can be seen in Figures 4.13, and 4.14. The aim is to understand the implications of air velocity movement that may affect temperature and IAQ.

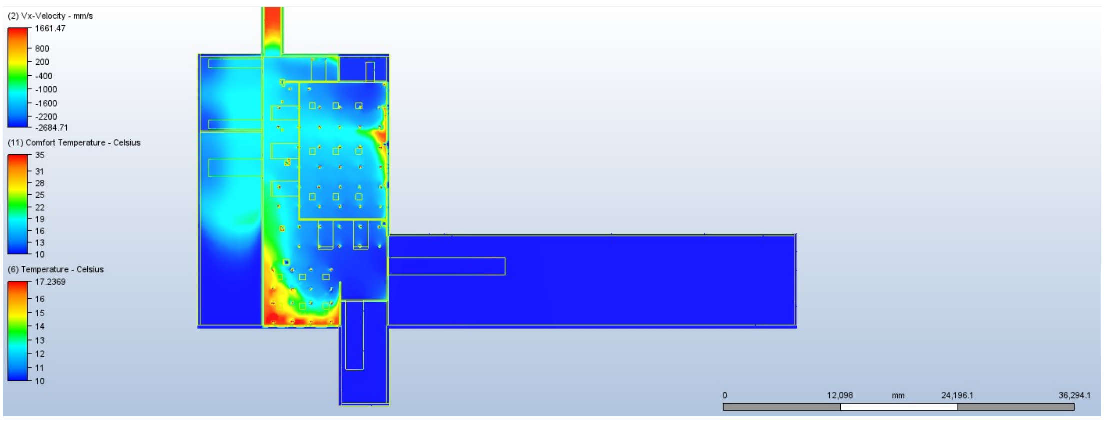

Figure 4.13: Temperature and Air Velocity At 1.8 m High-Occupancy Zone

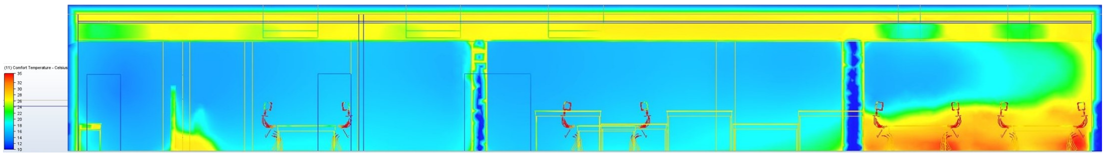

Figure 4.14: Vertical Temperature Plane

Further investigation into the effect of adjacent zones on pressure under mixed mode ventilation, a horizontal plane coupled with a vertical plane showed the increased pressure sourcing from stairwells at both sides, as well as surrounding rooms, Figure 4.15. The vertical slice showed a notable increase in CO2 in the higher atmosphere of the case study zone, indicating an unrepresentative location for the CO2 sensor. The planes also come consistent with Figure 4.12, showing the increased air shear forces at the indicated velocity.

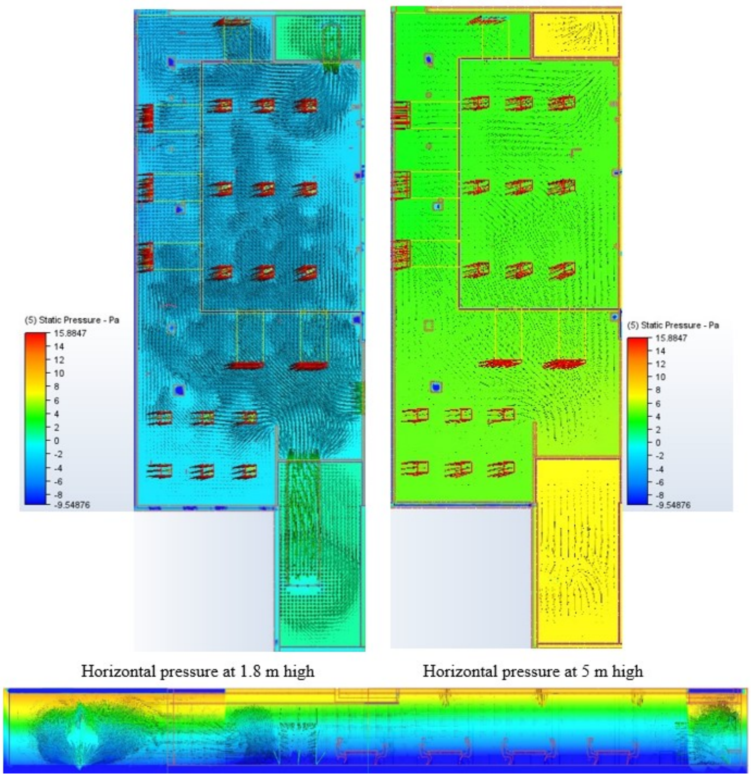

Figure 4.15: Horizontal and Vertical Pressure

Under these results, marginal changes in thermal comfort under the mixed mode ventilation can be seen on a horizontal plane of PMV in Figure 4.16.

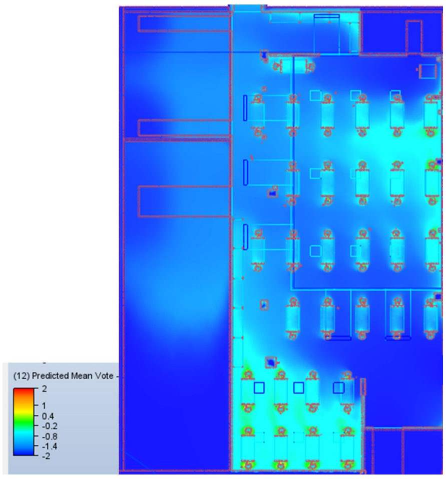

Figure 4.16: Predicted Mean Vote

In Summary, the CFD model provided a comprehensive understanding of indoor parameters fluctuation. The temperature showed notable variation by the windows' area across summer and winter seasons. Also, the air velocity showed notable shear forces closer to both entrances with highlighted pressure sourcing from the stairwells. Initially, these results suggest that areas closer to both entrances must be avoided for sensors' positioning. furthermore, the high pressure at the top atmosphere of the space indicated more CO2 concentration, particularly under mechanical ventilation while less pressure when mixed mode ventilation is used. In contrast, natural ventilation has introduced irregular air turbulence, which affects the particulate matter movement across the space. As such, there is a need to deploy more than one sensor to trace all these movements, however, for the temperature, further results of thermal imaging investigation will be demonstrated in the next subsection.

4.3.2 Thermal Imaging

While this CFD simulation result gives an understanding of the thermal and pressure distribution within the case study space, further thermal imaging was conducted. The results showed increased temperature around lighting fixtures on the ceiling, and also within the occupancy zone as can be seen in Figure 4.17.

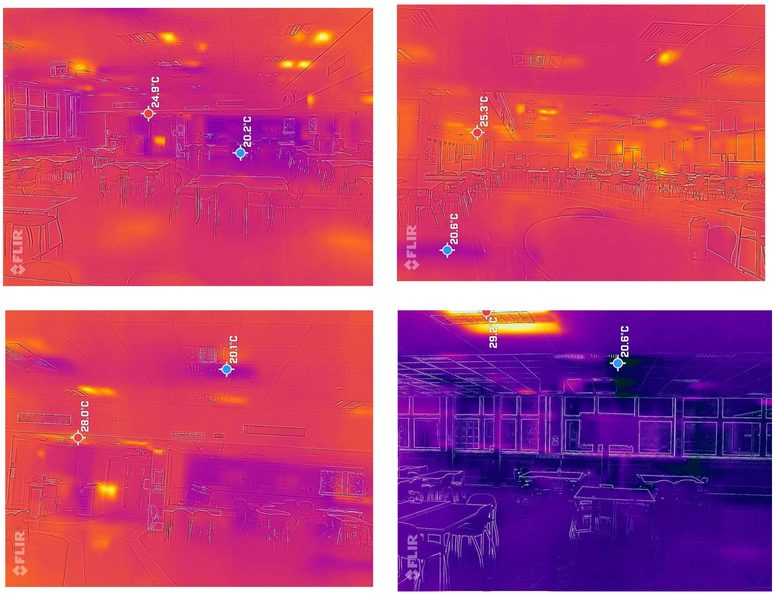

Figure 4.17: Thermal Images During May Showing Variation In Temperature Closer To Lighting Fixtures

The multi-layered approach integrating CFD simulation with thermal imaging has led to a more robust and accurate sensor positioning approach for optimal measurement accuracy. Given these results, the next section will present the optimised sensors' positioning.

4.3.3 Optimal Sensors' Positions

Based on the results obtained from the CFD simulation and thermal imaging, criteria for optimum sensors' positioning were defined as (a) temperature characteristics, including distribution, gradient, and heat gains, (b) air velocity, including vector plots, velocity magnitudes, and draft regions, and (c) pressure distribution, including HVAC effects. Accordingly, temporary sensors' positioning has resulted in the average correlation among the parameters' measurements as V, V+ 0.5, and V+1. This correlation relationship using one-year data of LORD 9 and 1, can be observed in Figure 4.18.

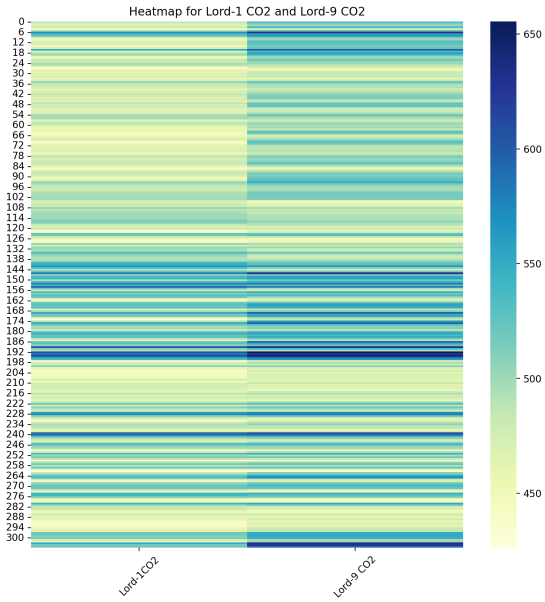

Figure 4.18: Temperature Correlation Between The Reference LORD 9 and Secondary LORD1

As such, the results nominated different optimum sensors' locations as can be seen in Figure 4.19.

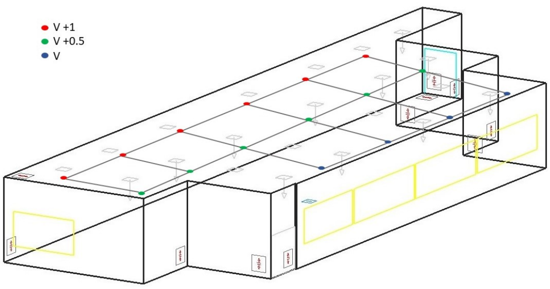

Figure 4.19: Nominated Sensors' Optimal Positioning

In determining the minimum number of sensors, six sensors were deployed, where one sensor was assigned as a reference sensor and the rest were deemed secondaries. The deployment lasted for one year to cover all the year's seasons. During this time, different data samples were taken from the sensors and compared to the outdoor parameters measured by the weather station. Daily variations in indoor temperature were closely monitored, revealing significant fluctuations that corresponds to changes in outdoor temperature levels. For instance, as outdoor temperatures dropped during the night, indoor temperatures showed a gradual decline, reflecting the building's thermal response to external conditions. To further understand the impact of outdoor conditions on building energy consumption, we analyzed the relationship between energy consumption (inferred from temperature control systems) and the mean outdoor temperature. The data revealed that lower outdoor temperatures led to increased energy usage for heating, as the building's HVAC systems worked harder to maintain the desired indoor climate, as can be seen in Table 4.5. This correlation highlights the energy required to raise the indoor temperature to a specific setpoint during a winter week. As such, this energy is a substantive element that contributes to the indoor temperature captured by the sensors.

Table 4.5: Outdoor and Indoor Mean Temperatures with Inferred Energy Consumption

Date	Outdoor Mean Temp (°C)	Indoor Mean Temp (°C)	Energy Consumption (Inferred)
2023-01-17	11.0	20.0	High
2023-01-18	12.0	20.5	Medium-High
2023-01-19	13.0	21.5	Medium
2023-01-20	10.0	19.5	High
2023-01-21	11.75	21.0	Medium

It is important to point out that the reference sensor assignment was to implement the presented equation 2.6, which will be demonstrated in the next section.

4.4 Minimum Number of Indoor Monitoring Sensors

In answering RQ2, the value of secondary sensors depends on their linear relationship with both boundary conditions and a reference sensor. Using the historical data of the deployed sensors, a linear regression ML model was approached, particularly to identify the linearity between the variables, to formulate the equation;

$$Y = \int (X) + \varepsilon \tag{4.2}$$

Where $\int$ is a fixed unknown function of $X_1, \ldots, X_p$, and ε is a random error term that is independent of X and has a mean zero.

The equation yielded promising results across various indoor environment parameters between the reference sensor and secondary sensors. Particularly, within the domains of temperature and pressure, the equation also showed a high degree of prediction accuracy when compared to actual measurements. However, the equation's performance was comparatively less accurate but still acceptable for the CO2 and IAQ parameters as illustrated in Figure 4.20. This could be attributed to the inherently challenging nature of these parameters, as they are influenced by additional factors beyond temperature and pressure.

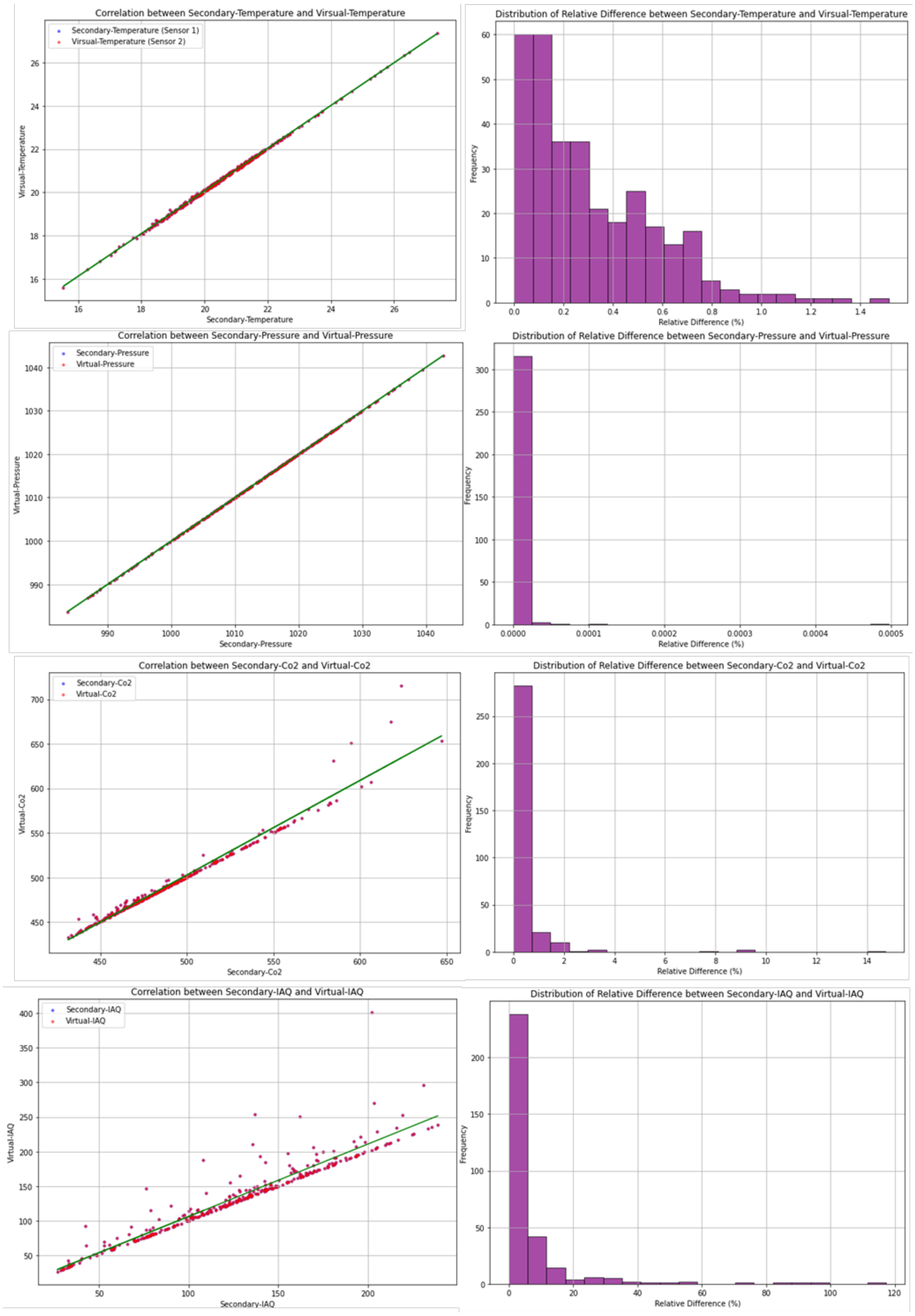

Figure 4.20: Scatter Plots for Different Indoor Parameters with Residual Error

These results represent significant findings in decreasing the embodied carbon from indoor monitoring sensors by decreasing the number of total needed units. Given a real-time reading of the reference sensor and historical data of the eliminated sensors, it is proven that high accuracy from virtual sensors is obtainable as proven by the decreased errors. Yet, for total embodied carbon elimination, the next section will demonstrate the results of transitioning to complete virtual sensors.

4.5 Transitioning to Indoor Monitoring Sensors

After decreasing the number of sensors to one sensor, this section demonstrates the findings concerning transitioning to virtual indoor sensors, for the provision of real-time measurements. The use of equation 3.2. extracted from the literature has shown significant accuracy in predicting the temperature.

$$i = (Y - (HDD \times DDF)) + Z \tag{4.3}$$

This equation models the current value of an indoor sensor i as a function of several key factors. These include the historical temperature value Y, Heating Degree Days (HDD), Degree Day Factor (DDF), and the temperature difference Z. In practice, this equation was applied by first determining the specific values of Y and Z at a given time for the building in question. These values were obtained through an analysis of historical temperature measurements that capturing the zone's thermal characteristics. Subsequently, integrating real-time HDD values from the weather station and applying the zone-specific DDF, the equation was used to predict the live indoor temperature. The results demonstrated that the equation could effectively model the temperature dynamics within the building, providing a reliable estimate of indoor conditions with a single sensor. However, given the context of the dynamism introduced in the literature chapter, the equation was further developed to include the occupancy parameter as a calibration factor. As such the equation was developed as;

$$i = (Y - (HDD \times DDF)) + Z + O \tag{4.4}$$

Where O, is the Occupancy variable.

This developed equation expands on the previous one by incorporating the occupancy factor O, which accounts for the additional heat gain from occupants within the space. This modification was necessary to enhance the accuracy of temperature predictions, especially under varying occupancy conditions. After close observation during periods of high and low occupancy profiles, this strategy resulted in more precise temperature estimates. The integration of the occupancy variable proved to be particularly effective when the predicted values from the model were compared against actual live readings from the LORD1 secondary sensor. As illustrated in Figure 4.21, the enhanced model with occupancy adjustments (Equation 4.4) yielded higher accuracy, particularly at higher temperature levels.

While this accuracy level is generally acceptable, it was observed that the model's predictions were more accurate at higher temperatures than at lower ones. This discrepancy can be attributed to the influence of changing pressure and air velocity, as demonstrated by the CFD simulation results. The CFD analysis provided insights into how these factors interact with temperature, suggesting that further refinement of the model might involve incorporating pressure and air velocity adjustments for even greater accuracy in temperature prediction.

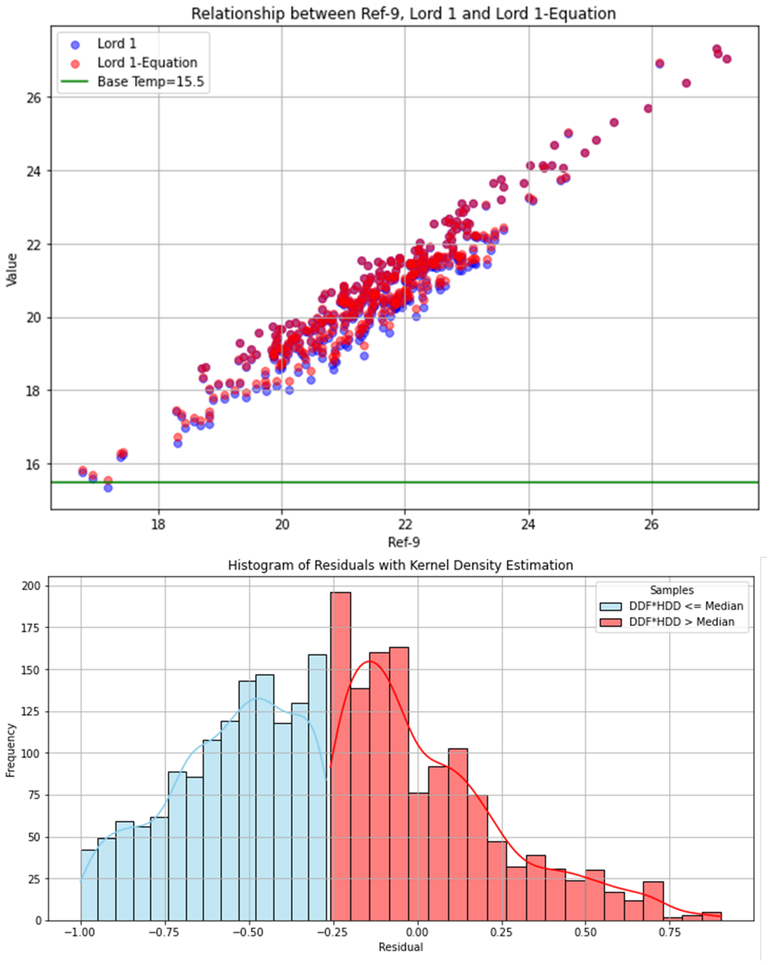

Figure 4.21: Temperature Prediction with Residual Error Using The Equation

The residual error histogram confirmed decreased accuracy on lower measurements as frequency indicates. This can further support the argument of defining a calibration value for higher accuracy. However, based on occupancy boundary conditions within the energy simulation model and observation, an occupancy profile was established and compared with the CO2, and temperature measurements. A RandomForrestClassifer model using temperature and CO2 was used. The results showed good prediction on higher and medium values of measurements, with a less accurate prediction on lower measurements, as can be seen in Figure 4.22. This is a further confirmation of the dynamic influence of the pressure and air velocity movements.

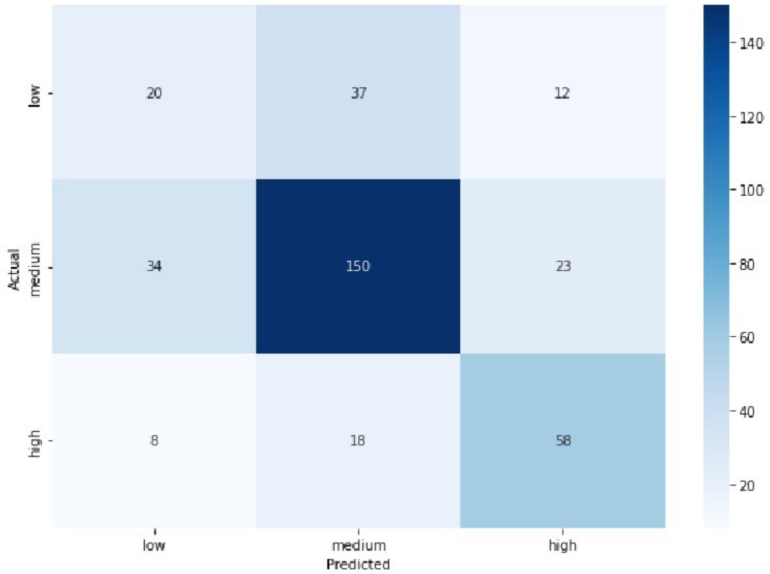

Figure 4.22: Occupancy Prediction Based on CO2 and Temperature

This initial occupancy prediction can then assist in more virtualizing for additional parameters given the identification of relevant boundary conditions. It is important to acknowledge that, due to the uncontrolled windows' opening, the methodology focused only on temperature sensing concerning total virtualisation.

To compare these results with the majority of the current literature applications, an MLP model was created. The goal is to measure the level of accuracy between these research findings to establish a solid research contribution argument. As such, the following section will demonstrate an enhanced multi-layered ML model.

4.6 MLP Model

A successful implementation of a machine learning model to predict sensors' measurements involves several key steps. This includes the data preparation containing the required inputs and also the corresponding target value. Accordingly, an MLP model was trained to predict the temperature measurement within the case study space. The historical sensors' measurements database is to be used. In addition, the HDD values were also used along with heat loss values. Also, considering that MLP models allow weighted connections between neurons, 3 occupancy profiles were adopted. These include 20 humans for low occupancy, 70 humans for medium occupancy, and 120 humans for a densely occupied space scenario. Following that, the data splitting process adopted the commonly used approach of a split ratio is 80% for training and 20% for testing. This involves training and testing the model on different subsets of the data to cover various scenarios from the data, as can be seen in Figure 4.23.

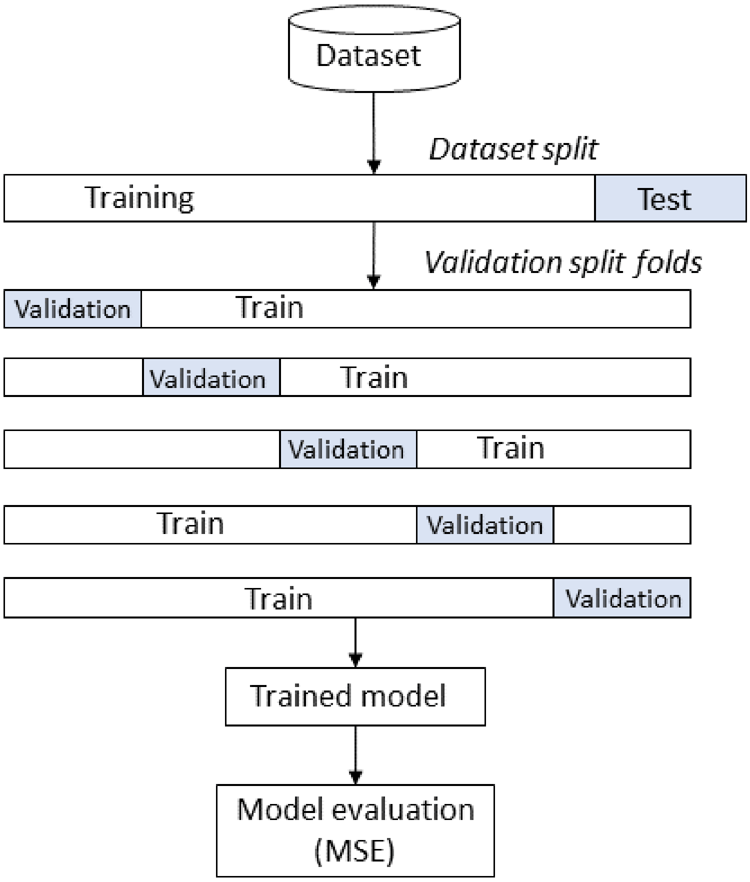

Figure 4.23: MLP Model Architecture

The model has achieved performance of MSE loss settling around 1, suggesting that on average, the model is predicting temperature values of approximately 1 unit from the true values, Figure 4.24. In general, this MSE value can be acceptable, however, considering a temperature measurement this error may not be considered as of highest accuracy. For instance, if the temperature was wrongly predicted at 1 Celcius above the maximum setpoint tolerance, automated HVAC may activated causing unnecessary energy consumption. In contrast to this research findings, the equation model showed MSE values of near zero, particularly concerning the temperature parameter. Therefore, this comparison is foundational for the premise of the adopted solution in this research.

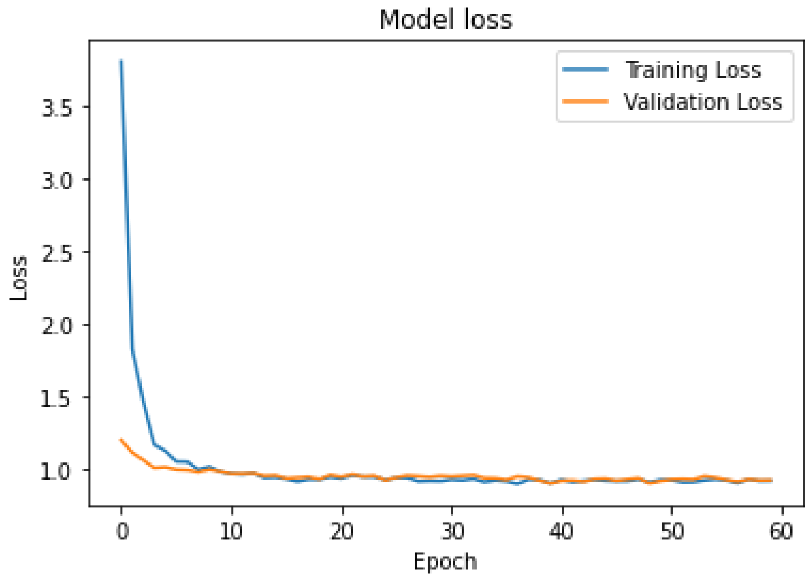

Figure 4.24: MLP Model for Temperature Prediction

It is acknowledged that more sophisticated ML models may provide more accurate predictions. However, given the complexity of the ML models, their methodology may not be affordable on a wider scale. This particular point will be further analysed in the following chapter.

4.7 Summary

By answering the research questions, the results have successfully bridged empirical data with theoretical insights to virtualise indoor monitoring sensors. In addressing RQ1, the SRI assessment emerged as integral to energy simulation for identifying and prioritising indoor environment parameters, under different boundary conditions. Similarly, RQ2 was addressed through a coupled modelling approach combining CFD simulations and thermal imaging, which provided an enhanced thermal mapping that was useful for the optimal number and placement of sensors. Using equation 2.6, the results proved high accuracy to further decrease the number of sensors to one reference sensor. Finally, answering RQ3 introduced a groundbreaking equation for transitioning to virtual temperature sensors. The predicted measurements were validated with actual measurements showing high accuracy levels. Moreover, the enhanced multi-layer ML model showed acceptable MSE values however less than the equation MSE value. As a result, the eliminated embodied carbon for the indoor monitoring sensors is a significant step in virtualising a pivotal LCA inventory component while enhancing its input data resolution.

Chapter 5 | Discussion

This chapter details the interpretation of the results in light of the proposed research questions. It also discusses their implications and reflects on the significance of this research by comparing the research findings to the existing literature. This contextualisation is also aimed at supporting the generalisability of this methodology which will be presented in the next chapter.

5.1 Implication of The Adopted Approaches

As highlighted in the methodology chapter, the adoption of a deductive approach starts with a general hypothesis and then seeks data for testing (Young et al., 2020). However, considering the need to develop a new theory concerning virtual sensors, an inductive approach is also integrated. This combination is particularly relevant given the qualitative and quantitative data used, to facilitate indoor virtual sensors. Following this path, specific theories based on the existing literature concerning existing gaps in LCA were developed. As such, the scope was defined as reducing the environmental impact of indoor energy and well-being performances.

5.1.1 Implication of The Qualitative Approach

The qualitative SRI assessment has shown useful results in defining indoor environment parameters. The indoor domain weighting definition has helped capture underlying factors affecting energy consumption. Furthermore, these weightings were particularly beneficial for cross-validation with the quantitative energy simulation results as illustrated in Figure 5.1. Although the assessment is more used for the buildings, its flexibility allowed a case-specific evaluation of the indoor parameters of the indoor space zone.

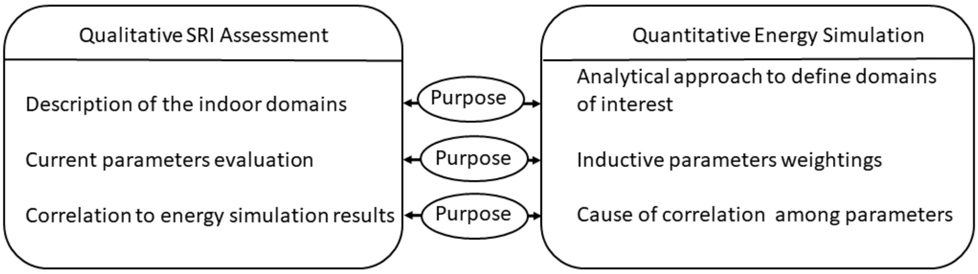

Figure 5.1: Contribution of The SRI Assessment to the Quantitative Approach

Compared to the current literature, the assessment has further enhanced the understanding of which parameters need monitoring and control. The adopted strategy of reducing embodied carbon from possible smart components can conclude a more optimised approach. As a result, the assessment implemented in this research also gives insight into unnecessary embodied carbon that may arise from new systems integration. Thus the adopted strategy can further define the energy efficiency achieved by new system additions remains conditional. The embodied carbon trade-off is, therefore, the main governor for these additions, which was mostly neglected by the majority of the current research.

Also, given the temperature variations across the space, including the ceiling surface, thermal imaging showed useful results for sensors' positioning. The combination of this qualitative method and the quantitative CFD simulation is, therefore, the base of further quantitative methods of data retrieving and analysing. This mixed-mode approach, therefore, showed useful results in defining the indoor parameters. It has also enhanced the positioning of the indoor sensors for higher accuracy measurements. Overall, while this approach was highly shaped by the research question, the combination of qualitative and quantitative approaches aimed at higher granularity results. This granularity was particularly useful, given the context of the LCA impact stated in the research questions.

5.1.2 Implication of The Quantitative Approach

Supported by the qualitative approach, the quantitative approach showed high-accuracy results. As acknowledged in the Research Design and Methodology chapter, this combination was due to the complexity of the overall approach. As a result, the qualitative-quantitative combination was also derived from the nature of the research questions. In particular, the broadness of the first research question concerning the identification of indoor parameters in the context of wide range configurations. The selection of the quantitative modeling techniques was aligned with the validation strategies. In this context, the BIM model of rich data was the foundation of the adopted approaches. This has facilitated rich data inputs concerning different scenarios for the energy simulation and later the CFD model. The energy simulation has concluded the parameters identification while the CFD model coupled with thermal imaging helped to define optimum sensors' positioning. Furthermore, the identified sensors' locations have also helped in establishing a correlation relationship among the deployed sensors which was useful for numerical modeling. As such these coupling methods highlight both static and dynamic elements to reach the final sensors' installation before the transition to virtualisation as illustrated in Figure 5.2.

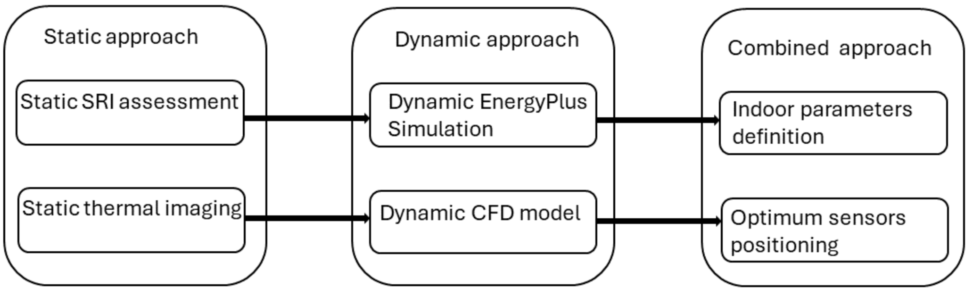

Figure 5.2: Characterisation of Coupling Strategies

Overall, given the complexity of the research questions, the combined approach has provided high-accuracy results. This accuracy was then crucial for the LCA inventory input data, aiming for optimised LCA impact. For more detailing on these results, the next section discusses the interpretation of the findings of this research.

5.2 Interpretation of The Findings

From an LCA perspective, the methodology quantified embodied carbon from the physical sensors to justify the transition to virtual sensors. Furthermore, the methodology also considered high-resolution LCA inventory input data by adopting multi-layered simulations for optimum sensors' positioning to guarantee high-accuracy measurements. The presented hypothesis showed high accuracy in predicting the indoor environment measurements on different parameters, given one reference sensor in the case study zone. As such, it saves more embodied carbon in open-plan indoor environments by decreasing the sensors to one sensor. This is particularly useful as indoor environment conditions can vary within large spaces of different characteristics such as windows, velocity magnitudes, and draft regions. In addition, the second theory concerning virtualising all temperature sensors is a significant finding, considering the validated results of high accuracy. Overall, in comparing the accuracy of the measurements from the hypothesis with the commonly used ML prediction methods from the literature, the methodology showed a notable difference in the accuracy of the measurements.

In discussing the findings of this thesis concerning the presented research questions, it is important to acknowledge that the nature of these questions dictates the selected approaches. Also, the sequential manner followed in forming the research questions was aimed at guiding the phasing out of the embodied carbon from the indoor sensor through a sequential and multi-step approach. Accordingly, the following subsections will discuss the findings of each research question.

5.2.1 Defining Indoor Environments Parameters

The first research question; " Which criteria should be considered to select and prioritise the indoor environment parameters necessary to conduct dynamic life cycle assessment, considering a wide range of configurations, including occupancy schedules and geographical location?"

The question has introduced the indoor environment parameters as being necessary to conduct a dynamic life cycle assessment. It further implied that the indoor environment parameters are part of the dynamic LCA process, which takes an input data form. As reviewed, the dynamic properties in buildings LCA are classified by their weightings, hence, the utilization of the SRI is aimed at defining the parameters of the highest influence on energy and well-being performances. However, since this weighting factor is also dynamic, the energy simulation was then conducted to investigate different performance scenarios. This investigation has helped in defining and prioritising the indoor environment parameters of the sensing interest. As such this stage is specific to the selected indoor space, therefore the parameters' weightings were constrained to the type of building, activity, and adopted setpoints. This can also infer that the SRI assessment can be more useful if it has been carried out within the scope of the intended study. Hence, as introduced in this stage, the scope is to identify indoor parameters for energy and well-being optimisation. Since the purpose of this stage is to allow suitable choices for indoor sensors, the answer to this first research question remains a prerequisite to sensors' identification. As such, according to the activity nature of the space, this step also helps to eliminate unnecessary applications for the sensors. The adopted SRI assessment sets the strategy of this case-specific approach since the assessment is flexible. However, it is important to highlight that the energy simulation cannot capture the dynamic influence of the occupants and can only simulate a fixed number of occupants, hence the simulation was conducted repeatedly for more granularity.

The occupied spaces identified from the BIM model have also contributed to the indoor parameters of interest to energy optimisation and occupants' well-being. Accordingly, the parameters' set points were prioritised. While this part of the results can represent a first layer to later identify the sensors' positioning, further simulations were carried out at a later stage to enhance this positioning.

While energy simulation is widely used across the literature, for energy optimisation purposes, the SRI assessment showed limited use. It can be understood that the SRI assessment is relevantly new and still under development. However, the defined weightings were useful in cross-validation with the energy simulation as demonstrated in the results. Therefore, a case-based SRI assessment based on indoor activity is important in defining parameters of the highest influence.

In summary, the identified parameters showed a focus on the temperature domain that reflects on heating and cooling loads. They also identified humidity, pressure, CO2, and IAQ, as linked to ventilation which may imply more energy consumption to reach optimum levels. Within this scope, the use of natural ventilation to improve IAQ, or reduce CO2 levels can result in more heating load in winter. In contrast, savings on heating load by relying on mechanical ventilation only can increase the heating load and further cause delays in restoring IAQ and CO2 levels. This interactivity among indoor parameters was the main justification behind combined monitoring for those parameters. This combination is also considered a major scenario of our existing non-domestic buildings which adds more value to this research. It is also important to highlight the notable increase in the lighting domain. This was basically because the space is also used to commute between two buildings within the campus and therefore, passers-by triggers an occupancy detection lighting system. Therefore, the study assumed unnecessary lighting monitoring and rather focused on the other parameters.

5.2.2 Identifying Indoor Monitoring Sensors

The identified indoor parameters were the main derive behind choosing the Indoor sensors. Further factors are considered in the assessment of integrating a new sensing infrastructure, including a wired or wireless sensing network. While the study decided on wireless sensors for their installation flexibility, additional criteria concerning sensors were defined. Those criteria include their coverage specifications including accuracy and multi-sensing capabilities. Compared to the literature, the majority of the studies did not consider embodied carbon accumulation as a result of a high sampling rate. As reviewed, the high sampling rate provides rich measurement data however negatively reflects on battery consumption for the wireless sensors. The selection of the sensors also followed mostly used sensors for monitoring. Also, the resulting sensing unit of different three types of sensors considered shared battery specification.

Upon sensors' selection and installation for the period of the study, the calculated embodied carbon from each sensor was projected over 60 years of an operational phase. The results showed 11.698.76 tCO2 per one sensor including battery consumption. This result highlights a significant embodied carbon considering multiple sensor installations over that period. As such, the accumulated carbon from sensors sets back the trade-off between their integration and energy optimisation purposes. Since this issue was highlighted as a main cause of LCA impact deviation, moving to virtual sensors, while providing high-accuracy measurements is a significant step toward improved LCA impact. It is important to acknowledge that virtual sensors can still accumulate carbon as the literature indicates carbon accumulation from cloud systems. However, given the reviewed research on cloud shifting, it is reasonable to assume virtual sensors have less carbon accumulation than physical sensors.

5.2.3 Defining The Optimum Positioning and Minimum Number of Sensors

The second research question "What is the minimum number of physical sensors and their optimal positioning to provide accurate dynamic accounts of indoor environments?", has two dimensions. The first dimension is the optimal sensors' positioning and the second is minimising the number of sensors. The methodology followed a multi-layer approach for optimum sensors' positioning facilitating CFD simulation and thermal imaging. Given the majority of the sensors' specifications, the CFD simulation indicated a possible influence on the sensors' accuracy. The air velocity, including air sourcing from adjacent zones and natural ventilation, can be a constant cause of pressure, CO2, and IAQ changes. Accordingly, sensors deployed in those locations may provide a false representation of the actual parameters' measurements. Furthermore, the temperature distribution showed a clear variation, particularly closer to windows in summer and also at the ceiling in winter, closer to extract ventilation openings.

While the overall CFD simulation results presented a reasonable mapping for the parameters' distribution, thermal imaging was successful in further enhancing this model. The generated images highlighted higher temperatures closer to the ceiling level. Therefore, in addition to the CFD model indicating higher CO2 concentration closer to the ceiling, thermal imaging comes as further evidence to avoid the ceiling as a possible sensor location. Different than the majority of the research, this finding is considered crucial in generating sensing measurements of higher accuracy.

According to this mapping, the six deployed sensors showed a notable correlation in their measurements. As presented, the average correlation was observed at V, V+0.5, and V+1, particularly for the temperature parameter. This correlation has further helped to establish the value of a secondary sensor as a function of a reference sensor using the presented equation. As a result, the established theory showed high accuracy in predicting a secondary sensor's measurement in an open plan large space, depending on one existing sensor. As such, a decrease of 11.698.76 tCO2 per sensor was achieved. However, it was also acknowledged that low parameters' measurements showed less accuracy, but still within minimum frequency across the sample data. In detail, the temperature showed higher accuracy indicating a stable correlation between the reference sensor and the secondary sensor. This can be understood from the fact that the space is opened to two entrances and also mechanically ventilated through a terminal AHU. This fact has also been reflected in the high accuracy of the pressure measurements across the virtual sensors. Slightly decreased accuracy was observed on the CO2 and IAQ virtual measurements. As explained in the previous chapter, the irregular natural ventilation due to individually controlled windows is the main cause behind the irregular correlation between the sensors. This fact points out that optimum results can be achieved with a higher level of ventilation control.

While this accuracy was also reliant on the CFD model and thermal imaging, the complexity of the simulation may not be universally available. Hence this issue can arguably question the methodology's generalisability. However, the simulation and thermal imaging have still concluded guidance on sensors' positioning, which will be further explained in the next chapter.

5.2.4 Defining Indoor Virtual Sensors

This subsection discusses the findings concerning the third research question "Can virtual sensors replace physical sensors while ensuring data accuracy and reducing direct and indirect environmental impacts?"

As extracted from the literature, several factors affect indoor temperature, including both external and internal factors. The external factors were highlighted as outdoor temperature, while the internal factors included thermal resistance, occupancy profile, and energy simulation boundary conditions. The approach was to first define the indoor base temperature specific to the space. Following that, the captured temperature by the sensors was used to estimate the heating capacity that maintains the temperature setpoint. This temperature value was then connected to the HDD live measurement retrieved from the weather station, formulating the equation;

$$i = (Y - (HDD \times DDF)) + Z + O \tag{5.1}$$

Where O, is the Occupancy variable.

Since the HDD and DDF are of different metrics, empirical validation was followed. The results therefore showed a notable correlation between the HDD and historical temperature sensor regardless of the time factor. This finding was understood that the HDD is a variable and therefore plays a calibration element. However, an additional variable of occupancy was added for further calibration. Along this path, different occupancy profiles were established under different temperature measurements. This strategy aimed to understand the behavior of the temperature under different occupants' numbers to enable establishing the calibration element.

The proposed equation resulted in a significant finding in virtualising indoor temperature sensors. While it only addresses the temperature parameter, this parameter affects both the heating and cooling domains. As highlighted, those domains are commonly of the highest weighting against energy and well-being. Therefore, the temperature parameter was prioritised for this investigation.

In comparison to the existing literature, the majority of the research approached ML models to predict indoor sensors' measurements. While ML can provide some level of accuracy, the applicability on a wider scale may not be obtainable for the majority of the building environment community. This fact was discussed within the literature, as the complexity of the method was highlighted as a main burden. However, to practically compare the level of accuracy from the proposed equation with ML modeling, the MLP of a regression element was investigated. The results showed acceptable accuracy however less than the results obtained by the equation.

5.3 LCA Reflection

Considering the objective of this research, the multi-layered methodology focused on phasing out the embodied carbon associated with a pivotal LCA inventory component. According to the LCA, quantifying the embodied carbon is subject to the LCA scope. However, eliminating a system component has wider benefit to the LCA impact. By virtualising wireless indoor sensors, their embodied carbon was then avoided. Moreover, the comprehensive simulation approach provided a thorough exploration of the optimum positioning of the sensors which has positively reflected on the virtual sensors' accuracy. This particular result adds more granularity to the LCA inventory sensing input data for a higher level of energy and well-being optimisation.

The optimised positions necessitated a flexibility feature of the sensors which is more achievable through wireless sensors despite their increased embodied carbon from their battery consumption, Figure 5.3. Therefore, the choice of wireless sensors was driven by their flexibility feature. In contrast, while wired sensors can show less carbon accumulation, their accuracy can be altered due to inappropriate positioning. Furthermore, the majority of existing buildings may not accommodate additional sensing components, including wiring which can also accumulate embodied carbon over the years. Hence, it is arguable that virtual sensors of high accuracy outweigh both physical wired and wireless sensors. Thus, this finding addresses a further methodology gap within the existing research.

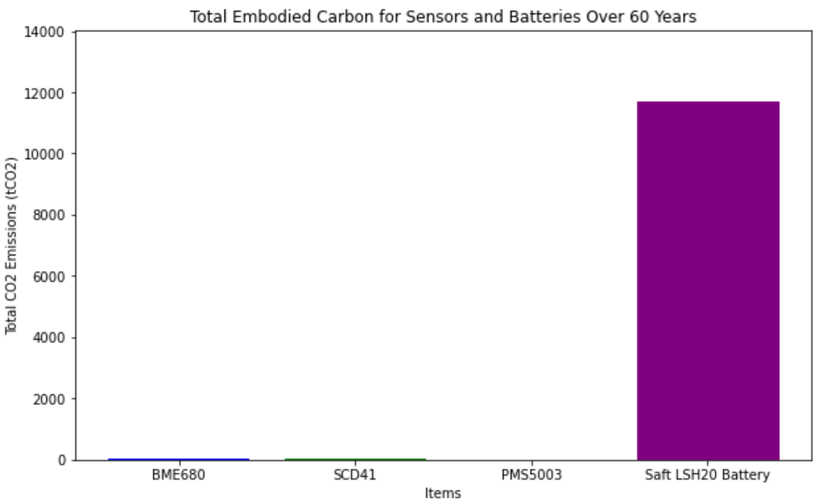

Figure 5.3: Breakdown of Embodied Carbon Among LORD Unit Components

The comprehensive simulation has helped find a correlation relationship among the deployed sensors which supported further numerical modelling. Upon defining the indoor base temperature, the integration of live HDD value has helped generate live sensing measurements across different parameters. This integration has facilitated a dynamic and responsive adaptation, resulting in more reliable sensing measurements of the indoor changing conditions. However, more dynamic factors of high influence on indoor temperature were also identified. Along this path, the use of CO2 was particularly beneficial to reflect indoor dynamic conditions upon parameters' measurements. It is also important to highlight that given the characteristics of the case study space, predicted virtual measurements were slightly increased than in reality concerning IAQ and CO2 parameters. The investigation showed that this was primarily caused by uncontrolled natural ventilation which irregularly fluctuates IAQ and CO2 levels across a typical day. While this minor error may affect sensing accuracy, it was less frequent than the data sample used. Furthermore, compared to the MLP model, the generated virtual measurements showed higher accuracy, indicating new levels of accuracy compared to existing methodologies.

5.4 Summary of Findings

The existing research notably ignored the trade-off between the embodied carbon from the indoor monitoring sensors application. As concluded from the literature, this fact can imply a significant setback to the LCA impact concerning energy optimisation. Furthermore, despite the efforts, the presented level of accuracy in sensors' measurement did not widely consider optimum positioning that provides higher accuracy results. In contrast, this research provided a breakthrough in virtualising those components phasing out embodied carbon from sensors over the entire operational phase of a building. The multi-layered and sequential approach as illustrated in Figure 5.4 has resulted in reliable indoor virtual sensors. The extensive simulations have identified indoor parameters, highlighting existing correlation relationships within a large space open plan case study zone. This correlation was evident from temporary sensors' deployment which was also used as a validation strategy from physical sensors at the final virtualisation stage.

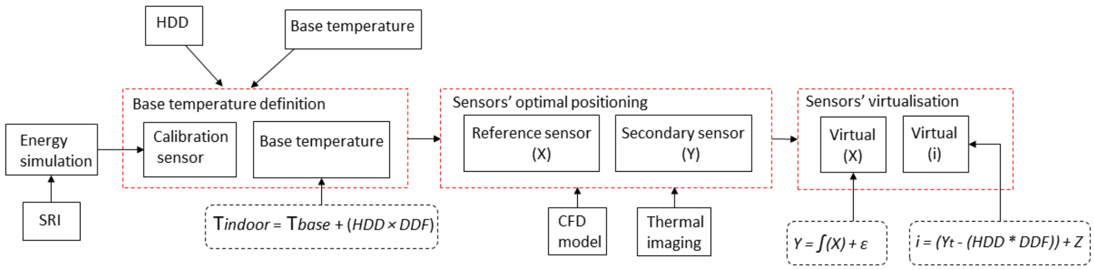

Figure 5.4: Virtual Sensors' Model

Overall, uncontrolled natural ventilation dominated the dynamic factors influencing indoor parameters' measurements. This has resulted in less accuracy among virtual CO2 and IAQ measurements, however they still maintained higher accuracy than existing ML models used in current research. While this ventilation characteristic is specific to the case study space, it gives a further understanding of the performance of this research proposal across the wider category of our existing buildings. Based on this discussion, the following section will present a generalised framework and algorithmic description of the virtual system. The aim is to guide a universal application of this research findings.

5.5 Reflection on Outcomes

Elicited from the successful results, this reflection section offers a coherent approach to the creation of virtual sensors serving as a connection between theory and practice. The overall structure is illustrated in three main phases (a) General framework, (b) System description, and (c) Overview of system algorithm. These can be broken down into detailed steps in the following sections. It also elaborates on challenges and limitations identified through the system development. The overall objective is to phase out embodied carbon from this LCA inventory component while optimising indoor energy and well-being performances.

5.5.1 Structural Layout of Virtual Sensors' System

The nature of the methodology being multi-layered necessitates a prerequisites stage. This adopted strategy aims to achieve maximum granularity in the final outputs by considering relevant data dimensions. Thus, those prerequisites elaborate on the enablers' definitions, including qualitative and quantitative data sources. They also define the system boundaries including the level of detail required by the sensors in line with the LCA scope. Furthermore, they guide the sensors' positioning and their performance characterisation for optimum sensing data resolution. Accordingly, those prerequisites can be defined as follows;

Enablers' definitions: In this stage, the energy data including BIM model is to be obtained. Subsequently, the SRI assessment is to be conducted for the targeted indoor space. While this assessment should aim at indoor parameters performance definition, it can also be used to understand embodied carbon trade-off between different levels of possible smart systems additions. The results are then further analysed using energy simulation for the BIM model to define indoor parameters of the highest influence on energy and well-being performances.

Given the building case, this weighting definition is the first layer in defining the needed indoor monitoring sensors. Accordingly, initial identification for the indoor sensors is to be carried out. Furthermore, HDD data is to be facilitated from the nearest weather station. Identifying these variables is crucial to establishing a relationship between the outdoor and indoor temperatures at a later stage. In particular, the HDD values, and heating and cooling loads from the energy simulation can both be used to define indoor base temperature. Further calibration for the indoor base temperature can also be achieved using sensors' measurements to capture additional internal influences on the indoor conditions at a later stage. As such, these influences include the effect of occupancy and internal service characteristics. Introducing the Autodesk CFD model at this stage is important to understand temperature distribution and air velocity patterns. This understanding further supports the indoor sensors definition. Coupled with thermal imaging, the resulting draft regions and temperature anomalies also help to identify suitable types of sensors and optimal positioning.

The concluded results shape the indoor environment parameters of the highest interest. They also guide sensors' definitions and optimal locations in the next steps. Given those results, the next step guides the definition of virtual system boundaries, including sensors' identification.

System boundaries: At this point, the focus shifts to specifying the sensors based on the identified parameters from the previous step. This includes the level of detail represented in the information required in the historical measurements and also the required parameters for LCA. Based on the EnergyPlus and Autodesk CFD models created from the previous step, the definition of the number of sensors follows as explained in the previous chapter. The results should then provide an optimum representation of the building energy and well-being parameters using minimum sensors in the LCA model. Additionally, embodied carbon from the sensors including battery usage across the entire operational phase of the building is to be calculated to quantify the eliminated environmental impact of the physical sensing application.

Sensors' positioning: This stage defines the optimal locations for the sensors based on the building's CFD simulation results and thermal imaging. This positioning optimisation is significant to account for the quality of the virtual sensors' measurements. It is also important that the installation period covers various occupancy profiles under different ventilation performances for higher data resolution. Therefore, it is advisable that diversity of the weather is crucial to establish a solid conclusion of the differences between the indoor and outdoor temperatures.

Subsequently, a data collection process is to be conducted. This involves creating a database of historical sensors' measurements covering different weather and occupancy profiles. Additionally, live HDD measurements are to be facilitated from a local weather station to support real-time sensors' predictions at a later stage.

System Description: After establishing data sources from the previous step, a reference sensor and secondary sensors are specified. The HDD value obtained from the weather station is then collected along with the heat loss factor for the targeted indoor space. Subsequently, a correlation between the occupancy profile and indoor parameters measurement values is to be defined. This correlation will then help to formulate the equation 2.6 function that virtualises the secondary sensors' measurements given the live reference sensor's measurements. It is also important to identify the relationship between the occupancy profile, HVAC performance, and sensing measurements for the calibration factor. Given this context, the correlation between the sensors' measurements should then be established using the presented equation 4.4.

Based on the founded function, secondary sensors can then be virtualised, providing different parameters' measurements based on one reference sensor. Following this step, virtual measurements are to be validated using live measurements from physical secondary sensors before their removal. This particular step should aim to further enhance the calibration value introduced in the equation. Similarly, the different occupancy profiles' influence on parameter measurements can also contribute to this calibration value.

Following the calibration verification, relying on virtual sensing data accomplishes a dual objective of optimising both energy performance and occupants' well-being, while phasing out sensors' embodied carbon as illustrated in Figure 6.1. Accordingly, an environmental impact assessment can be carried out using the eliminated embodied carbon associated with the sensors and the achieved results from the virtual sensors. As such, this framework offers a structured and efficient incorporation of virtual sensors, setting the stage for greener and more environmentally responsible buildings.

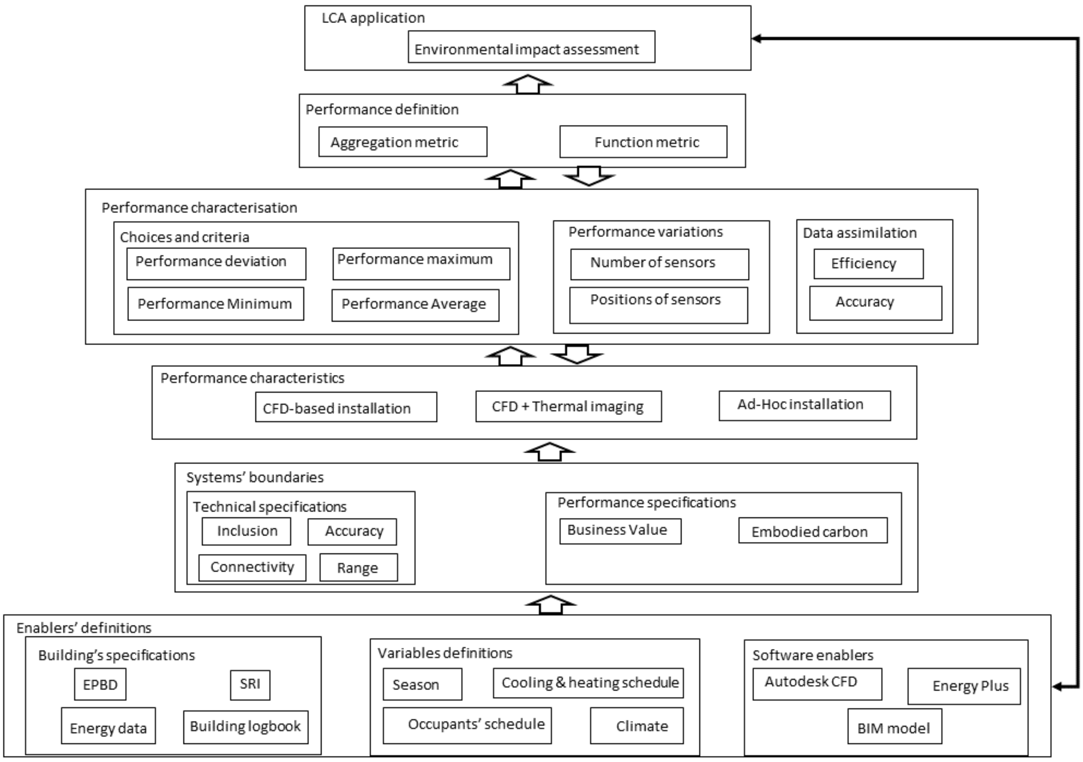

Figure 5.5: Framework for Virtual Sensors Integration

The presented framework acts as a general system architecture for virtualising indoor sensors. However, for more detail on the system's specification, the next section describes the algorithmic description of the proposed system. The aim is to provide an intelligent and predictive system for facility managers to make decisions based on the virtual sensors' measurements.

5.5.2 Computational System Description

This subsection presents a detailed description of the computational system, facilitating a user interface for facility managers. It explains the procedures involved, including the execution of the energy simulation, fetching HDD values, and utilising historical sensors' measurements stored in a database. The goal is to gather the required inputs to the equations used in the virtualisation process. In line with the defined LCA scope, this inventory input data is supported by the prerequisites stage from the previous step. The process of the prerequisites should therefore be fundamental to calibrate and improve the LCA inventory impact. Accordingly, multiple dimensions of these prerequisites were identified and can be centered around;

Scope Definition and System Boundaries: Clear outlining for the scope helps to better understand the LCA inventory input data. In more detail, this process represents the first layer in defining the system boundaries. This includes the level of detail required from the BIM model including the SRI results and the energy model. By defining these characteristics this step can then exclude unnecessary parameters to further narrow the number of sensors. Also, additional components of the prerequisites are represented in the sensors' identification including their compatible performance with the identified SRI results. The final dimension in this element is the use of the Autodesk CFD model and thermal imaging for optimum sensors' positioning.

Data Precision and Credibility: A substantive prerequisite dimension is to ensure data credibility considering the overall objective is to provide virtual sensors' measurements. This prerequisite dimension is to consider the granularity of the energy model including various boundary conditions. It should also consider the nearest weather station for high-resolution real-time HDD values. As such, this dimension is accounted fundamental to high-resolution LCA inventory input data for more accurate virtual sensors' measurements.

Functional Units Specification: To enable informative impact assessment for the proposed system, adopting consistent measurement units is substantive. Along this direction, this stage focuses on identifying relevant parameters that can later be used in sensitivity analysis. This strategy helps in assessing variations or uncertainties in certain factors that may affect the overall outcomes of the LCA. As such, this prerequisite dimension is centered around identifying the function used in equation 2.6. to calculate the value of (Y), given an (X) value. This entails;

- *Clock Synchronisation:* This factor guarantees uniform timing across the sensing network by synchronising the internal clocks of all sensors with the parent unit. This element is therefore crucial to support establishing a consistent correlation between the reference sensor and secondary sensors.
- *Sensor Sampling Frequency:* In addition to the clock synchronisation, sensors' sampling frequency should be unified across all sensors. This strategy helps to further establish a concise correlation across the physical deployment period.
- *Time Stamping:* Implementing a common timestamp format for all sensors is crucial for a useful database. As such, this strategy helps to create a cohesive database of historical sensors' measurements, allowing relevant correlation among different sensors' measurements. It is worth noting that this dimension was also useful in preparing the MLP model data that was used for accuracy comparison.
- *Overall Energy Performance Metrics:* While normalised measures are a necessity for accurate conclusions, the use of HDD of a different metric to predict Celsius values is acknowledged. However, since the empirical validation has shown a new level of accuracy, this metric is assumed valid for the context of this research.

Allocation Procedures: This prerequisite dimension involves assigning indoor set points according to the targeted parameters' categories. Following legislative guidance on these set points can present an opportunity for energy optimisation while maintaining the required level of occupants' well-being. As such, a consideration of the indoor parameters' set points can be defined per a building or zone category. moreover, in open-plan indoor zones, further segmentation can suggest different set points within the space. This particular element can then provide further energy optimisation opportunities.

Temporal and Geographical Considerations: The consideration of temporal aspects in this stage focuses on their relevancy to the defined scope. As such, the influence of the occupancy profiles and seasonal changes on the indoor environment conditions is to be established. This particular stage is fundamental to the calibration factor that will later be employed in the presented equations.

As presented, the system uses different dimensions of input data to facilitate optimum energy consumption while accommodating occupants' well-being. As illustrated in Figure 6.2, these dimensions provide multiple layers of granularity to the LCA inventory, contributing to the overall LCA impact.

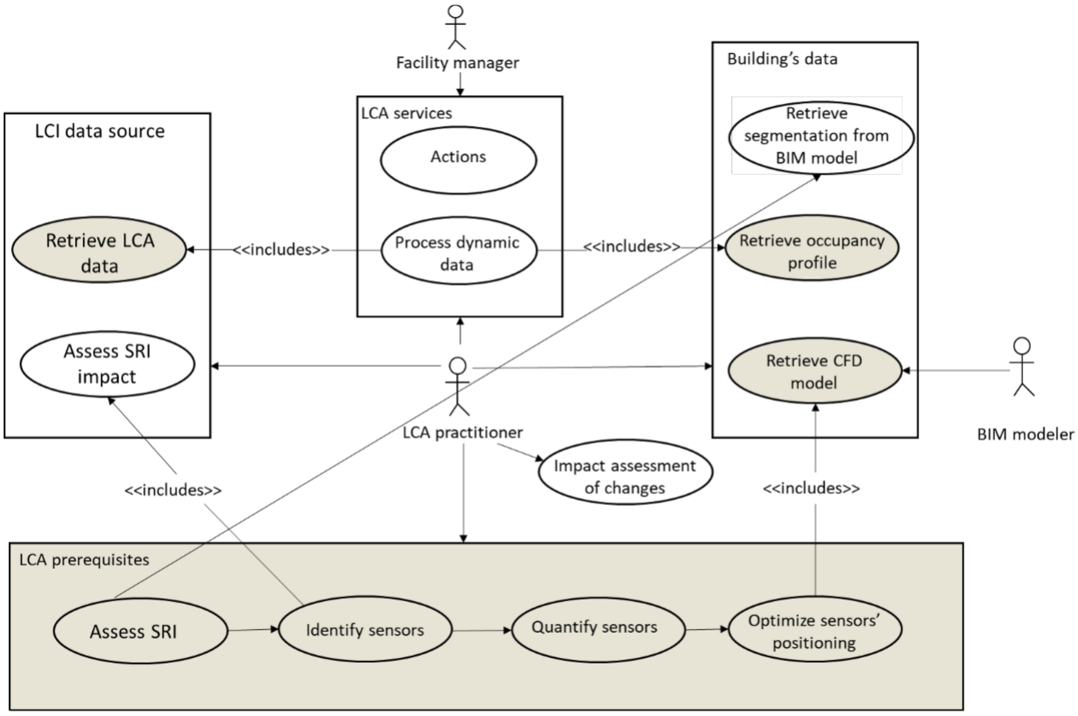

Figure 5.6: System's Use Case Diagram

For more understanding of the system architecture, the following subsection demonstrates the development of the user interface algorithm. The goal is to provide a clear, structured approach for live-streaming virtual sensor measurements. Given this structure, facility managers can then get live-streaming virtual sensors' measurements to be able to make decisions on energy and well-being performances. This facilitates timely actions given the changing scenarios of the indoor environment conditions.

5.5.3 Overview of the System Algorithm

This subsection elaborates on the algorithm system architecture. It aims to provide a detailed approach to illustrate the overall function of the system. Accordingly, it follows detailed steps in tackling the presented research problem from a practical perspective. The overarching objectives are then achieved through the combination of qualitative and quantitative considerations, as highlighted in the methodology. Along this direction, the next subsections demonstrate the adopted approach in creating the computational system. They further illustrate the system's algorithm architecture for optimum guidance.

5.5.3.1 Reflection on Research Problem

As established, the system was designed to facilitate real-time virtual indoor sensors' measurements for facility managers. Accordingly, a user interface was created for practical support in making decisions concerning energy and well-being optimisation. As such, the system's algorithm uses different input data created within the prerequisites stage as presented in Figure 6.2. These include defining the building characteristics using SRI and energy simulation and coupling the CFD model with thermal imaging for optimum positioning. Additionally, the outdoor influence was represented in the variable HDD value, which supports the real-time dimension.

Historical sensors' measurements are also part of the algorithm input data. As presented, querying a database of historical sensors' measurements is crucial to calibrating the resulting virtual measurements. This calibration factor is accounted for capturing different parameters' measurements under various indoor conditions. This includes different occupancy profiles, and seasonal changes are therefore stored in measurements' values.

Given these data, the following subsection will guide the development of a user-friendly platform to generate live virtual sensors' measurements. It provides a detailed software structure underpinning the user interface. The goal is to provide facility managers with practical applications for the proposed system, supporting their ability to make decisions on energy and well-being optimisation.

5.5.3.2 Predictive Modeling

A development of a Python script was adopted to link diverse data sources and a user-friendly interface, to enable gaining valuable insights into the live-streaming indoor environment conditions. Being an open-source programming language, including associated libraries, this approach comes in line with the applicability of the proposed framework on a wider scale.

Following data sourcing from the previous section, a Python script is to be developed leveraging the API of the EnergyPlus and the weather station. The script should also connect to the historical sensors' data to query for measurements used in the correlation process. The code should then implement the predictive equations using the data from simulation results, the weather station, and the historical sensors' database. Upon generating the virtual sensors' measurements' the values are then to appear within a Graphical user interface. For visual guidance, a detailed algorithm of this system can be seen in Figure 6.3.

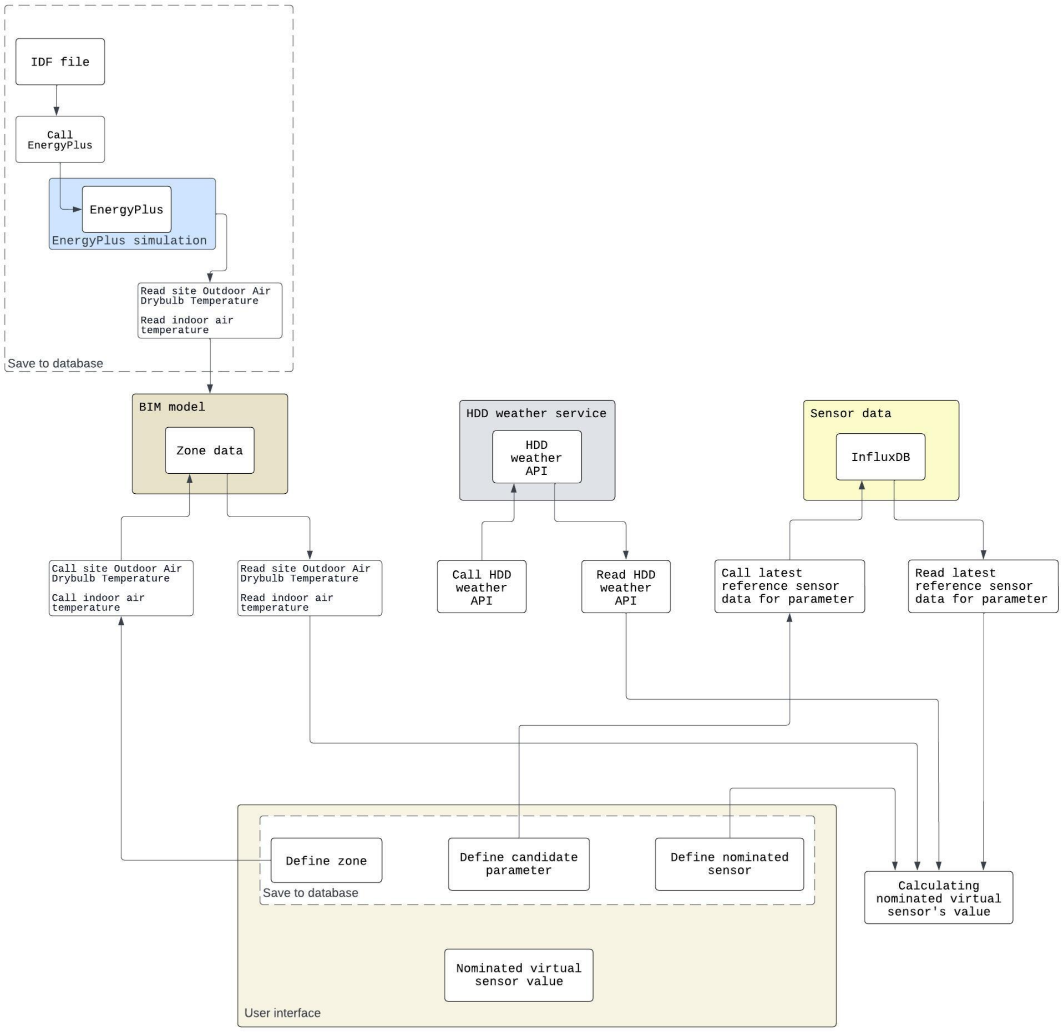

Figure 5.7: Algorithm System Architecture

While the presented algorithm architecture achieves the goal of generating virtual sensors' measurements, more elements should be considered. Accordingly, monitoring and updating the input data is crucial to maintain a continuous level of high accuracy. This issue can be centered around the usefulness of the historical sensing data given a building change of use or a service update. As such, there can be a missing element of the occupancy profile or energy system update that is not captured within the historical sensing data. Therefore, monitoring and updating data sources is crucial for a continuous level of high accuracy. This can be achieved by deploying sensors to calibrate the data.

Drawing upon the introduced framework proposal, the following section provides a recapitulation of the Key Points presented. The goal is to reiterate the practical dimension of the hypothesis, reflecting on the expected impact of the adopted solution.

5.6 Summary

In summary, the system yielded promising results for virtualising indoor monitoring sensors. Given the empirical validation, the proposed framework and algorithm architecture provide a solid solution for phasing out the embodied carbon associated with the physical sensors. Furthermore, the high accuracy of the virtual sensors also facilitates carbon emission reduction by optimising energy performance while maintaining occupants' well-being. Accordingly, the resulting approach has a dual benefit to the LCA for energy optimisation during the buildings' operational phase. The first is eliminating the embodied carbon from the LCA inventory components represented in sensors. The second objective is to reduce carbon emissions resulting from energy use by providing high-accuracy sensing measurements.

Chapter 6 | Conclusion

This chapter provides a thorough reflection on the findings of this research, concluding on the adopted hypothesis in addressing the identified problem. Accordingly, it reflects on each of the presented research questions and the corresponding findings. Furthermore, it reflects on the research contribution to the field of virtual sensors research field as part of the LCA inventory tools. The chapter also summarises possible limitations and future directions, guiding potential improvements to the presented proposal.

6.1 Research Findings

The resulting solution for the research problem presents a new shift in indoor management applications. According to the research questions presented in Chapter 1, the core contribution was to phase out embodied carbon associated with physical indoor sensors as an LCA inventory component. The approach also focused on facilitating high-accuracy real-time virtual sensors' measurements for optimum energy performance and well-being control. Following sequential steps, the hypothesis emphasised the importance of adopting prerequisites of different dimensions to tackle the research problem. This includes a wide range of configurations covering both static and dynamic factors influencing sensors' measurements. As outlined in the methodology chapter, the solution approach navigated through qualitative and quantitative data to formulate the virtual sensors system. The overall results were developed through step-by-step guidance in a generalised framework for wider application.

As outlined in the methodology, the hypothesis was developed by answering structured and sequential research questions to guide the formulation of the overall solution. Along this path, the following subsections will conclude the results concerning the presented research questions.

6.1.1 Indoor Environment Parameters' definition

The first research question was centered around setting the criteria for defining indoor environment parameters of interest to the LCA with the scope of energy optimisation during the buildings' use phase. It was structured as:

Which criteria should be considered to select and prioritise the indoor environment parameters necessary to conduct dynamic life cycle assessment, taking into account a wide range of configurations, including occupancy schedules and geographical location?

By determining the criteria for defining and prioritising the indoor environment parameters, this first research question helps to set the scope of the LCA in this research. It also implies inventory formation by considering different dynamic factors. Accordingly, a comprehensive literature review was conducted to facilitate a holistic analysis of the relevant information. The outcomes of the review pointed to several shortcomings. These include the lack of consideration of the trade-off between the embodied carbon of energy optimisation tools and the needed level of performance efficiency. As a result, the majority of the current approaches did not factor in the background and foregrounds of their proposals in defining indoor parameters.

Further literature findings concluded the case-specific approach to characterise indoor parameters of highest interest. The investigation identified a range of external weather factors influencing the indoor parameters conditions, including poor air quality and heat islands. Internally, the review identified different dynamic factors including occupancy profile, ventilation characteristics, and also the influence of the outdoor factors of weather changes. These findings were further examined in chapters 3, and 4 against different qualitative and quantitative analysis approaches to define and prioritise parameters of highest interest. Accordingly, the SRI assessment was used to identify indoor domain weightings against energy and well-being performances. This approach also helped to avoid unnecessary system upgrades that may come with extra embodied carbon. Additionally, the energy simulation further refined the understanding of indoor parameters' domain performances. The concluded results from both assessments defined the indoor environment parameters of highest interest under different performance scenarios, including weather seasons and occupancy profiles.

Given the highlighted significance of indoor monitoring and control, these findings were then used to identify the types of the needed indoor sensors. Accordingly, the following subsection will reflect on the findings in answering the second research question.

6.1.2 Defining the Minimum Number of Sensors With Optimal Positioning

The second research question asked:

What is the minimum number of physical sensors and their optimal positioning to provide accurate dynamic accounts of indoor environments?

This research question seeks solutions for highly accurate indoor environment monitoring through a minimal sensors configuration. It further considers the optimum positioning as an approach to higher accurate measurements. Moreover, the inclusion of the term “Physical sensors” implies embodied carbon dimension to the sensors’ characteristics.

Informed by the current limitations identified in the literature review from Chapter 2, a multi-layered approach was adopted to define the minimum number of sensors with their optimum positioning. In line with the identified indoor parameters from the previous step, the indoor sensors were defined. However, to provide an accountable representation of the measurements of the indoor parameters, an extensive analysis of the indoor environment was conducted. While the adopted CFD simulation exists within current literature approaches, an additional layer of granularity using thermal imaging was added. The resulting sensors’ positions were, therefore, avoided draft regions, temperature hot spots, and additional localised heat sources identified by the thermal imaging. This strategy has notably increased the accuracy of indoor sensors which was proved by temporary ad-hoc installation to check the temperature and IAQ anomalies.

Further decrease in the number of indoor sensors extended to total virtualisation concerning the temperature sensor. To reflect on the adopted approach and the results, the following subsection will address the third research question.

6.1.3 Virtualising Indoor Environment Monitoring Sensors

The third research question asked:

Can virtual sensors replace physical sensors while ensuring data accuracy and reducing direct and indirect environmental impacts?

As indicated, the comprehensive literature review has identified the influence of both external and internal factors on indoor temperature measurements. The concluded external factors recommended the use of a local weather station to track the influence of external temperature fluctuation on indoor parameters' behaviour. Accordingly, the adopted approach considered both outdoor and indoor factors in the temperature sensor virtualisation equation of:

$$i = (Y_t - (HDD \times DDF)) + Z_t + O \tag{6.1}$$

The results showed a high level of accuracy for real-time temperature measurements. According to the difference between historic sensor measurements and the occupancy profile, the real-time measurement was then generated. These variables acted as adjusting factors to provide the time dimension element, interpreting historical measurements into real-time measurements. As identified, the heating and cooling parameters are substantial domains behind energy consumption and well-being requirements. Therefore, this finding represents a breakthrough in aiding energy and well-being optimisation by providing a real-time virtual temperature sensor's measurements. For more context of these findings in the current research, the following subsections compare these results to the current research approaches.

6.2 Impacts on Existing Theories

This section contrasts this thesis's findings with the existing research. The goal is to reflect on the adopted approach within the context of current research. Accordingly, the comparison approach is centred around two main elements. This includes the methodological variances and the flexibility and adaptability of the presented theories. A conclusion of those variances can then enhance the overall understanding of the applied improvements and also Thesis development.

6.2.1 Methodological Variances

Compared to the existing methodologies, the majority of current research showed a notable focus on adopting ML approaches, including black box and grey box modelling. As highlighted, ML models imply complexity, and therefore, are not affordable for the wider scale application. Furthermore, the absence of addressing unpredictable scenarios including weather changes and real-world occupancy profile dynamics was evident. This particular element showed notable improvements to the results when considered in this Thesis development. However, part of the research indicated high-accuracy results of different ML models, but with less clarity on facilitating high-accuracy historical sensing data. This was mainly centred around optimum sensors' positioning, which is significant for providing more representative measurements of the overall indoor conditions. Moreover, the reviewed research also showed less consideration for the age of historical data. This shortcoming lacks the weather dimension, essentially seasonal influences on the indoor conditions.

It is important to reflect on the various sensors' sampling rates adopted by the current research. on one hand, this approach facilitated highly accurate sensors' measurements. On the other hand, the approaches did not address the accumulation of battery consumption concerning wireless sensors. This issue was further highlighted in this Thesis, indicating high battery consumption associated with the high sampling rate. As a result, the accumulation over an entire building's operational phase can further deviate from the anticipated LCA impact. Accordingly, avoiding the accumulation of carbon from battery consumption by virtualising indoor sensors was fundamental to optimised LCA impact.

Overall, following the data collection, an MLP model was approached to cross-validate the presented hypothesis. Despite the both applications adopted multiple real-life scenarios, including occupancy profiles and weather data, the results showed observable differences in accuracy. The MSE of the MLP settled around 1 Celsius which is considered significant for a temperature measurement. In contrast, the result of the adopted hypothesis showed near-zero error. Further analysis of the virtualised IAQ and CO2 results indicated the role of individual-controlled windows on their accuracy level. While the ML models can further be improved by integrating more enhanced calibration of the occupancy dynamics, their complexity remains a practical challenge. Along this direction, the following subsection further reflects on the applicability of this Thesis in the context of current research.

6.2.2 Flexibility and Adaptability

The sequential development of this Thesis presented a comprehensive yet applicable methodology for virtualising the indoor sensors. The adopted tools are therefore considered alternatives to complex ML modelling approaches. These tools provided an enhanced foundation of indoor parameters' definitions and subsequently sensors' selection and positioning. In contrast to the existing research, this approach introduced a new dimension to the sensors' virtualisation represented in adopting a prerequisites stage. In summary, compared to the existing research, the flexibility and adaptability of this Thesis can be classified as:

Relevance of Adopted Approaches: Building on the existing knowledge was foundational to establish the relevance of this Thesis. With this background, this research has explored new boundaries of the indoor environment for high-accuracy sensors' measurements. The adopted contextualisation of the quantitative modelling by the qualitative assessments' results ascertained the overall relevancy to the research impact. The effectiveness of this strategy was evident through the cross-validation of the SRI assessment and the energy simulation in defining and prioritising indoor parameters. Further CFD simulation and thermal imaging informed optimum sensors' positioning. Furthermore, using a real-world case study over a year helped to formulate a better understanding of how to solve unexpected scenarios. As a result, this approach provided a universal infrastructure from where different types of buildings can be assessed.

Overall, the formulation of the hypothesis was guided by multiple prerequisites, drawing insights from diverse resources, to reach optimum solutions. In this context, the following subsection reflects on the relationship between the adopted theories and expected practice.

Bridging Theory and Practice: The theoretical stance behind the presented equation was one of the main findings in this Thesis. In this context, the adopted real-world case study space demonstrated how the presented theories can be applied in practical settings. This approach was mainly aimed at testing the presented theories under different challenges. As highlighted in the previous subsection, the selection of the adopted tools aided the input data formation of high resolution. Compared to the existing research landscape of ML modelling, these tools presented notable simplicity in approaching the results.

Overall, the presented prerequisites provided comprehensive guidance in understanding and analysing the dynamic interplay among the LCA inventory input data. According to the LCA scope in this Thesis, the identified dynamism within the indoor changing conditions was sourced from real-world scenarios, over a year of data collection. This particular consideration has provided enhanced relevancy in tackling what-if scenarios. For more reflection on the research contribution, the following section addresses this Thesis's contribution to the field of research.

6.3 Research Contribution

The proposed hypothesis successfully eliminated unnecessary embodied carbon associated with indoor sensors. This benefit was achieved by phasing out physical sensors while providing credible real-time measurements' accuracy. As a result, this approach was significant in formulating a high-resolution LCA inventory within the relevant LCA scope. Along this direction, the contribution of this Thesis can be addressed in three main categories, including theoretical, methodological, and practical contributions. These contributions can be summarised in the following subsections.

6.3.1 Methodological Contribution

The development of this thesis provided a structured and sequential approach leading to sensors' virtualisation. The introduced prerequisites and cross-validation using the SRI assessment results and energy simulation have factored in enhanced indoor parameter identification. Further CFD simulation and thermal imaging also contributed to optimum sensor positioning for high-accuracy measurements. The resulting sensors' measurements were then used to establish a correlation between secondary sensors and one reference sensor which showed a high level of virtual measurements.

6.3.2 Theoretical Contribution

The theoretical contribution evolves around developing an integrated framework for virtualising indoor sensors. This contribution can be summarised into two main contributions

Integrated Methodology: As presented in Chapter 2, the conventional methods were the main reason for the LCA impact deviations. Building on this knowledge, the combination of qualitative and quantitative approaches resulted in a holistic approach that goes beyond conventional methods. As a result, the adoption of two data analysis dimensions resulted in a step-by-step cross-validation framework. Accordingly, the contribution was therefore useful in formulating the LCA input data of high resolution. These include the first two contributions of:

- A holistic definition of the indoor environment parameters of interest.
- The definition of optimum indoor sensors' positioning.

Innovative Sensor Virtualization Model: The observed dynamic interplay between outdoor and indoor conditions was substantive to formulate the founded equations. As a result, the first equation contributed to the decrease in the number of needed sensors, while the second equation contributed to the total virtualisation for the temperature sensor. Accordingly, the third and fourth contributions are:

- Finding the equation for defining the minimum number of indoor sensors:

$$Y = X_t + (Y_t - X_t) \times \left(\frac{Y_t}{X_t}\right) \tag{6.2}$$

- Finding the equation to virtualise all indoor temperature sensors:

$$i = (Y_t - (HDD \times DDF)) + Z_t + O \tag{6.3}$$

The developed equations represent a ground base for virtualising indoor sensors. The defined dynamic elements, which are interpreted to the adopted variables can therefore be replaced to adapt this framework to different buildings. As a result, a significant benefit of reducing embodied carbon associated with physical sensors' performance can further enhance the LCA impact.

6.3.3 Practical Contribution

The structured methodology also offered a new concept of virtual indoor sensors as part of the LCA inventory. This inventory feature was found significant in eliminating embodied from two elements. The first is associated with the physical sensors' and their corresponding battery consumption across the entire buildings' use-phase. The second category of the decreased embodied carbon is the high accuracy of virtual measurements. Compared to current research, the achieved level of accuracy was a product of the optimum positioning and the integration of the proposed equations at a later stage. Accordingly, the fifth and sixth contributions were:

- Phasing out embodied carbon associated with physical sensors.
- Optimising energy performance during buildings' operational phase by facilitating high-level accuracy of indoor parameters measurements.

The simplified framework presents a practical methodology as an alternative to the complex ML models. The compared results of the MLP model to this Thesis findings proved the reliability and applicability of the presented framework. However, these results were also faced with challenges of limitations. Accordingly, the next section will reflect on the identified limitations of this Thesis' findings. It further reflects on future work based on the concluded results.

6.4 Limitations and Future Work

While the proposed framework yielded promising results, two limitations affecting virtual sensors' accuracy were observed. Those limitations were understood to result from both short-term and long-term changing conditions. It is important to acknowledge that those limitations are also a present challenge in the existing research. However, this Thesis has still provided higher accuracy levels compared to the current research field.

- **First Limitation:** The first was mainly associated with fast dynamic changing conditions. This includes the fast-changing occupancy profile dynamic. The reason is that this Theis adopted 3 main occupancy profiles, namely, low, medium, and high occupancy profiles depending on the scheduling activity. As a result, the computational time shifting between medium and high occupancy profiles showed a decreased accuracy on the presented RandomForrest diagram as can be observed in Chapter 4. However, it is still arguable that the developed theory can present significant benefits to buildings with fixed occupancy numbers.

- **Second Limitation:** The second limitation is that the established virtual sensors' accuracy can be altered by a building change in use across the operational phase. This issue may not be present with the physical sensors application as they instantly capture the new indoor boundary conditions. As a result, the changing occupancy profile can increase the overall heat gain altering temperature values. Furthermore, a high occupancy profile can also increase the CO2 levels and also affect the IAQ parameter. This issue was observable when correlating the occupancy profile to the temperature, CO2 and IAQ levels.

Based on the observed results and the identified limitations, future work is recommended. The goal is to guide further enhancement of the effectiveness of the framework under short and long-term changing conditions. Accordingly, these recommendations include:

- **Enhancing the Occupancy Calibration Factor:** To enhance the virtual measurement accuracy, additional optimisation to the occupancy calibration factor is needed to address the fast-changing occupancy profiles. This recommendation can then improve the prediction, particularly on higher values of parameter measurements as presented in Chapter 4.

- **Introducing New Boundary Conditions:** This limitation can be addressed by updating the historical sensors database to include the newly introduced conditions. It is assumed that deploying sensors to capture these new conditions is arguably less in embodied carbon reduction given the comparison of services update to the deployment of the sensors covering the entire operational period.

- **Testing the Theory Across Wide Range of Different Buildings:** Testing and developing this Thesis theory in different types of buildings is highly recommended. The examination of how different occupancy activities interact with the building structure and indoor parameters' characteristics can help to classify the buildings according to specific characteristics. This classification can then provide pre-defined datasets from which a generalised framework for the presented theory can be developed.

6.5 Closing Remarks

The existing research knowledge was of a significant benefit to develop this Thesis approach. The research showed different methodologies dimensions in the adopted approaches which was useful to develop the prerequisites of the presented framework. As a result, this Thesis has presented a more simplified and applicable framework for the wider benefits. The structured cross-validation approach provided higher virtual sensors' measurement accuracy compared to complex ML approaches. This strategy proved effective, particularly in answering the presented research questions. Given the high-accuracy results, the established equations are another breakthrough in the virtual sensors field. Accordingly, the overall contribution resulting in phasing out physical sensors is a practical elimination of a pivotal LCA inventory component that implies embodied carbon. As such, the trade-off between indoor sensors and their impact on LCA is compared to a decreased embodied carbon, mainly, associated with the computational system. However, given those significant results, more work is needed to be done. This work is mainly centered around enhanced occupancy profile dynamic calibration factor. Therefore, this thesis is considered a proof of methodology within the field of generating virtual indoor sensors' measurements.

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