A Novel Approach to Life Cycle Assessment for Early-Stage Design of Low-Carbon Buildings

by

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M.Sc. University of Tehran, 2016

B.Sc. MEng, Iran's National University, 2008

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Abstract

Building design processes are dynamic and complex. The context of a building project is manifold and depends on the context, climatic conditions and personal design preferences. Many stakeholders may be involved in deciding between a number of possible designs defined by a set of influential design parameters.
Building LCA is the state-of-the-art way to provide estimates of the building carbon content and environmental performance of various design alternatives. However, setting up a simulation model can be labour intensive and evaluating it can be computationally unfeasible. As a result, building simulations often occur at the end of the design process instead of being an influential factor in making early design decisions. Given this, the growing availability of machine learning algorithms as a potential method of exploring analytical problems has lead to the development of surrogate models in recent years. The idea of surrogate models is to learn from physics-based models, here a building LCA model, by emulating the simulation outputs given the simulation inputs. The key advantage is their computational efficiency in terms of accuracy and time. They can produce performance estimates for any desired building design within seconds, while in physics based modeling hours maybe needed to run the analysis. This shows the great potential of surrogate modelling to innovate the field. Instead of only being able to assess a few specific designs, entire regions of the design space can be explored, or instant feedback on the sustainability metrics of building can be given to architects during design sessions.

This PhD thesis aims to advance the young field of building LCA surrogate models. It contributes by: (a) developing a parametric model capable of whole design space exploration, to solve the issue of lack of building LCA data and (b) deriving surrogate models that can process dataset of building carbon results and estimate the associated impact on building performance. The result of this study can assist architects, engineers, researchers and policy makers both by provided results and also the proposed methodology to integrated LCA in strategic and early-stage decision making in the design process.

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Finally, I am immensely grateful for the unwavering support from my family. Maman, Baba, and my sister have provided so much for me since the very first day of my life. A heartfelt thank you to Mohammad, my caring and loving spouse, who has stood by my side patiently every step of the way. Thank you!

Mahsa S. Torabi

July 2024

Introduction

Building design comprises different stages. As we progress through the process, the amount of information and data about the building increases, making performance assessment more deterministic and accurate. A similar trend is observed regarding the cost of changes. The earlier changes are implemented in the design, the lower the cost and resource use (time, effort, funds, etc.). Changes in the early stages also have a greater impact on improving building performance. As shown in the graph below, the early stages of design are critical for implementing changes that achieve the highest impact and lowest cost. However, due to the lack of information in the early stages, conducting performance studies and evaluations is difficult and sometimes not feasible.

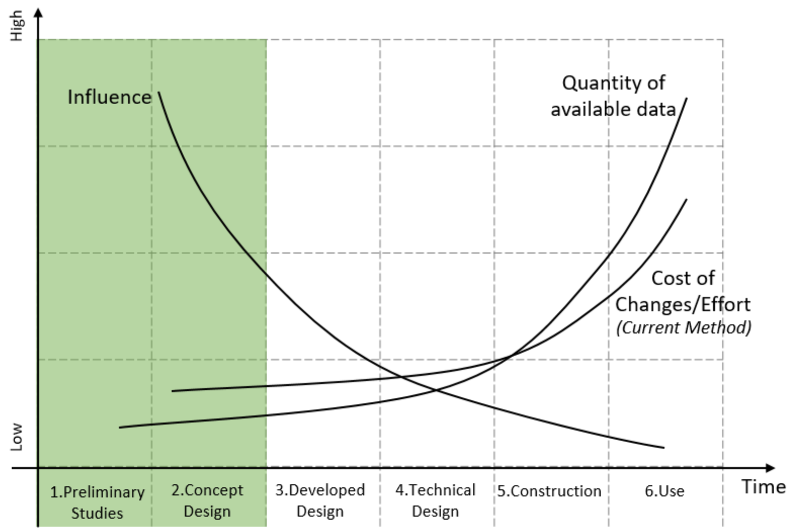

Fig1- Cost versus impact of changes during design process compared to data availability

An overview of building LCA tools shows that conventional tools are mainly applicable in the later stages of the design process. This is primarily due to the data-intensive nature of these tools, which require significant input data from the user. Recent tools, however, have managed to shift LCA from the detailed design stage to design development by integrating architectural models into LCA tools. These tools can read information and automatically extract input from 3D models, expediting the modeling process and allowing for the early assessment of environmental indicators. However, these tools can only assess a design and cannot provide insights for decision-making in the very early stages—known as the concept design stage. In other words, while recent advancements in tool development can facilitate early evaluation of a building's environmental impacts, they do not assist in making informed decisions. Therefore, we aim to develop a tool that facilitates low-cost, high-performance concept design that capitalizes on the potential of the early stages.

A more detailed review of the ecosystem of building LCA tools reveals that different tools exist in this area, and new tools are emerging to address evolving sustainability questions and stakeholders' needs. Regardless of their focus, methodology, or scope, these tools are not fully compatible with the design process. To apply LCA results in early-stage design decision-making, we need a tool that can generate an unlimited number of iterative results to allow for assessment following numerous design changes. These results also need to be rapid and instantaneous to show the changes in performance to the architect and enable them to move forward in the design process. As the graph illustrates, there is a gap in the ecosystem of building LCA tools that we aim to address in this research.

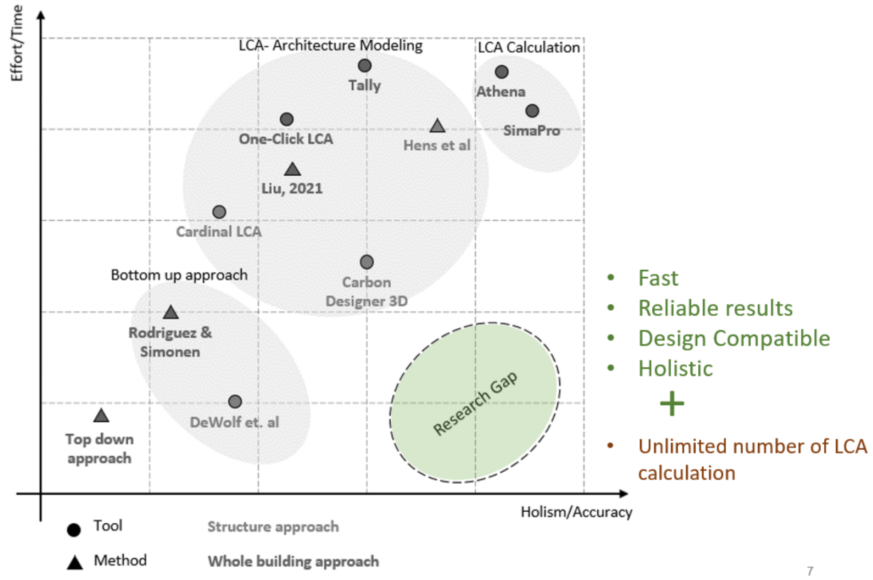

Fig2- Comparison of LCA tool per time and accuracy and the identified gap for design adaptable LCA tool

In this research, we aim to develop a tool that provides LCA results in the early stages of design. This tool is intended for use during the design process and is specifically designed to address the lack of data in the early stages and handle the associated uncertainties. It is meant to assist architects in making informed design decisions to achieve a low carbon footprint and meet stringent sustainability targets. By using this tool, the design process is performance-driven from the early stages, allowing for higher levels of carbon savings.

The tool is comprehensive, enabling architects to monitor changes in carbon emissions resulting from design modifications and evaluate trade-offs between embodied and operational carbon. It is also flexible enough for more technical users, offering accurate results by incorporating real data from the industry. This reflects the current technological potential in construction and the materials available on the market. Usable by architects, designers, engineers, and policymakers, this tool aims to reduce the carbon content in the built environment and help meet sustainability goals.

List of Publications

The research conducted throughout the course of my PhD studies has been published in high-ranked, international scientific journal or conference proceedings. In total I have contributed with four journal papers, of which one was published and three are submitted or ready for submission, and two published conference papers, in the proceedings of the eSIM conferences.

The papers are sorted in order of time conducted and appearance in the thesis; secondary publications are included in the appendix.

- P1: Torabi, M. Simonen, K. Evins, R., 2024, A Review of Building LCA Tools Ecosystem: Gaps and Trends. [Journal Paper, Ready for submission]
  MT defined the methodology, conducted the data collection, analysed and compiled the findings and wrote the paper. KS conceptualized, reviewed the methodology and revised the manuscript RE revised the manuscript.

- P2: Torabi, M. and Evins, R., 2021, September. An LCA Framework to Prioritize Carbon-Sensitive Measures in Residential Building Design. In *Building Simulation 2021* (Vol. 12). IBPSA. [Conference paper, Published]
  MT conducted the data collection, analysed and compiled the findings and wrote the paper. RE revised the manuscript

- P3: Torabi, M. and Evins, R., 2024. Towards net-zero carbon buildings: Investigating the impact of early-stage structure design on building embodied carbon. *The International Journal of Life Cycle Assessment*. [Journal paper, Published]
  MT conducted the data collection, analysed and compiled the findings and wrote the paper. RE revised the manuscript.

- P4: Torabi, M. and Evins, R. What Matters the Most in Designing Low-Carbon Buildings in Canada? [Journal paper, Ready for submission]
  MT conducted the data collection, analysed and compiled the findings and wrote the paper. RE revised the manuscript.

- P5: Torabi, M. and Evins, R. A machine learning-based surrogate model to approximate building carbon footprint in early stages of design. [Journal Paper, Ready for submission]
  MT conducted the data collection, analysed and compiled the findings and wrote the paper. RE revised the manuscript.

MT conducted the data collection, analysed and compiled the findings and wrote the paper. RE revised the manuscript.

Secondary publications

- P1: Torabi, M. and Evins, R., 2021, September. Evaluating Building Carbon Footprint in Concept Design Stage. In *Building Simulation 2023* (Vol. 18, pp. 2252-2259). IBPSA. [Conference paper, Published]

  MT conducted the data analysis and compiled the findings and wrote the paper. RE revised the manuscript.

Key Contributions

The key contribution of this thesis is providing a tool for early-stage assessment of building carbon footprint to support design decision making in uncertain space of early-stage of the project. In order to reach this goal, an extensive literature review has been done in each step to equip the methodology with the state-of-the art findings and build upon that. The literature shows that current LCA tools has some significant gaps for utilization in strategic planning and early stage design. The goal of this study was to address these gaps by providing a design-integrated LCA tool which was reached through a five-stage method as explained below. Therefore this study focused on developing LCA tools that are holistic in terms of scope, data self-sufficient, transparent and modifiable in terms of data, flexible and generalizable in term of application and fast, iterative with real data in terms of results.
The path leading to development of the tools is a five-step methodology as follows:

Building LCA tool review [P1]: The field of LCA is young and evolving. With more stringent policies and social awareness, more and more LCA tools are developed to support questions from groups of stakeholders through building life span. In the first step a hybrid analysis of LCA tools was conducted. The reviewed tools are live LCA tools, with Building scope analysis for application in North america. Also a 35 metric characterization framework was developed to evaluate tools against. This tool characterization framework (TCF) was built upon previous studies on LCA tools and also based in intake survey from EPA PODlLCA stakeholders which include architect, engineers, researchers, policy makers and tool developers. The results of this study showed significant trends in development of tool. While the recent trends are invaluable and helpful in better sustainability assessment, current ecosystem of tools still lack significant gaps. As a first contribution we provided a guide on current tools and their scope, features, outputs and potential application which assist growing LCA community in informed-selection of LCA tool. Secondly we identify main trends in tool evolutions as well as shortcoming to be used in conceptualization of LCA tool developed in this study.

LCA Scope definition [P2]: one of the main gaps identified in ecosystem of tools was inconsistency of LCA tools scope. Therefore to define the scope of our LCA tool a research has been done to identify the main conytributors of building LCA in terms of building elemnt scope. The results showed that unlike recent trends of excluding systems due to lack of data and complexity of their design, building mechanical , structural and enclosure all have significanyt impact of building carbon and can not be excluded from a holistic LCA. Moreover the results show that operational emissions can not be excluded from study even in low carbon intensive regions of Canada, due to deep impacts of EC and OC and trade-offs. Therefore as the second achievement the scope of LCA model was defined to include building mechanical, structural, operational and enclosure emissions. The results also shows the significant dominance of structural system on building EC.

Structural design; a pitfall for architects [P3]: Despite buildings are known as a consistent system, there is a segregated approach to design buildings by systems. In this regards building structural systems are difficult for architect to assess and predict due to complex structural behavior and lack of intuition. Given the high impact of building structure on carbon footprint, there couldn't be a robust LCA- design tool unless a sophisticated structural module is included. Therefore in the thirst step, we focused on developing generative structural module to design, evaluate and optimize structural system and report structural material assessment. This module include foundation design parameters such as load bearing capacity and density of soil as well as superstructure design parameters that are related to design (Bay, height, material, etc) under static and dynamic loads based on Canadian building code. In this study, 8200 structure for a design project was generated and the most influential parameters on structure carbon was identified, also the role of building footprint geometry was assessed to provide architect a sense of impactful factor on structural carbon.

What matters the most? Prioritization [P4]: Having the structure LCA generative developed, in the fourth step we developed the parametric LCA model by adding modules for mechanical, operational and enclosure as well as geometry. This generative model, allows user to explore the whole design space and automatically generate scenarios and assess their total carbon footprint. Also due to the influence of climate on building OC as well as the extending the scope to other cities in order to include design trade-off on different context, we analysed the same scenarios across 7 Canadian cities with different climate, heating degree days and grid carbon intensity. The results of this study were analysed to identify the main proprieties for designers and architects when design net-zero buildings to reach their sustainability goals. Aside from the independent use of the model, the results of this study is used to bridge the lack of LCA data for surrogate model.

Surrogate-based LCA benchmarking [P5]: while the parametric model was capable in generating design solutions and assessing carbon impacts, it was computationally heavya time consuming to generate results out of available data, therefore in order to generalize the performance of LCA tool a leaning model was developed. To do so after reviewing the literature of ML in LCA, two algorithms that have most compatibility and performance for training based on multi parameter dataset were selected. Then bothe were trained and tested. The results show great accuracy of predicted results. Use of this model provide fast, reliable resuts for a wider range of parameter inputs and reports carbon data instantly which is a great tool for iterative design integrated LCA tool. This step would put the las piece in this research path

Appendix

Rule of thumbs assessment for building carbon footprint [P5]: Intuition in performance assessment is crucial skill for architects, however with spread use of building performance tools, architects have long let that assessment to tools however they are not able to provide inside for concept buildings. Similar to designing windows and imagining how bright the space will be, architects need rule of thumbs to design for modifying building geometry o reach low-carbon content. However, this field is young and calculation-intensive and architects do not have the intuitive skillset to assess carbon content of concepts. In this step of the research we developed the geometry-generative module of our LCA parametric model. We looked at 162 scenarios that were generated using Design space exploration and LCA was calculated. The important achievement of this study was proving insight on a measure to evaluate building LCA based on their very early concept geometry. This results discover a direct correlation between the building's perimeter/VFAR and its carbon footprint emerged, offering a useful metric for early carbon estimations.

Novelty

This research aims to contribute to the state-of the art in sustainability design by integrating LCA into building performance assessment. In order to make the tool applicable in early stage of design and to be insightful for decision making rather than carbon reporting the tool needs to have these features.

- **Data:** Data is a fundamental issue in LCA tools. Accurate and reliable LCA can only be achieved with high-quality data. In addition to accuracy the variety of material in the dataset is also important. This research benefits from a rich dataset of local EPDs that provide reliable data for conventional materials. Moreover, the dataset is open to customization and user can input their local EPD or in case of using private data they can edit the LCA dataset.

- **Flexibility:** There is a need for access to the underlying assumptions and methodology, so that the user can have control over the calculations and change the assumptions associated with scenarios and calculations per needed. In this research all the assumptions in the LCA analysis are open to modification by users.

- **Results:** Current tools mainly generate results in the form of numbers or charts. Previous studies have shown that in order for user to use LCA data in design, the results should be translated in a visual form of graphs or images. This study uses a visualization module to translate LCA results in form of building 3D images as well as interactive dashboard to facilitate working with data and filtering scenarios. Also use of interactive scatter plots, bar charts and parallel coordinates allow used to filter data and generate meaningful results

- **Holism:** Most tools can generate results based on specific stages and can not calculate WBLCA impact assessment. Moreover in terms of building scope, they are mainly focusing on a few of are building components and exclude the rest. This is while important building components with higher emissions such as structure and foundation are simply neglected. There fore there is a more holistic approach to building LCA both in LCA scope and building scope.

- **Real-time results:** In order to use the LCA results for design decision making, there is a need for instant reporting that can reflect the changes in impact following a design modification. Additionally the results should be generated iteratively and in unlimited number of scenarios to allow architect to explore design space and a selected section of that with more detail in order to get to the final design. The tools generated in this study can provide countless results that can support architects in decision making.

- **Interoperability:** Another missing part in current LCA tools is lack of interoperability. The tool generated in this study, by integration in parametric design tool facilitate data exchange between design tools and analysis tools which not only makes the tool easy to use but also eliminate risk of data loss and in consistency in modeling.

This research by identifying the gap in the literature and current tools, aims to extend mentioned limitations and develop LCA tools for mitigating building carbon through utilizing impactful early decisions.

Chapter 1- Building LCA Tools Review: Gaps and Trends

Building LCA Tools: Current Landscape and Future Trends

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Abstract

This paper reviews building LCA tools for supporting the net-zero and carbon absorbing building design. The study provides a comprehensive review of the LCA tool ecosystem, with detailed analysis of tools features, functions and applications. The goal of this study is first to identify the trends and gaps in the LCA tool ecosystem in the North American building sector, as well as identifying their potential and limitations in integrating recent innovations in building sectors into LCA frameworks. For carbon absorbing building design. Lastly this paper provides an overview of tools features and scope of work to assist growing LCA community stakeholder in selecting proper LCA tools. This paper conducts a comprehensive review on the most crucial and demanded tool features from the literature and surveyed a diverse group of stakeholders to identify their needs and questions from LCA analysis results to make a characterization framework. Then a list of active LCA tools in North America's building sector was selected and evaluated against TCF. The results show some dominant trends of simplifying LCA modeling for different users and tools self-sufficiency by providing data with different granularity. This trend has helped LCA earlier in the decision making, however tools still face some significant gaps for design decisions making especially in early stages. Additionally the results show the recent tools focus on carbon and aim to include the whole building for LCA analysis. The results also indicate inclination towards including sources of carbon capture in form of novel materials or technologies as well as natural strategies, however that's still in early stages and the approaches are simplistic which required more elaborated methods and data to make carbon capture analysis feasible. This research can inform future studies and support architects and engineers in their efforts to create a sustainable carbon-positive built environment.

Keywords: building LCA tool, Carbon positive buildings, Design stage, Early-stage LCA, Tool Review

1-Introduction

1.1 Background

In recent decades, global agreements have increasingly emphasized the urgency of addressing climate change by mandating emission reductions across the world. As a result, national sustainability targets have been established to lower emissions in all sectors, including the construction industry. The imperative for more sustainable building practices, driven by the common consensus to mitigate climate change, has spurred a demand for progressive research aimed at reducing the carbon footprint of buildings.

With the benefit of recent advances,this transition has evolved from the pursuit of low-carbon buildings to the emergence of zero carbon buildings, and more recently, to the innovative concept of carbon-negative buildings (Kuittinen et al., 2021). This evolution is often inspired by the introduction of new bio-based that have the capacity to sequester and store carbon in long life building materials (Ganguly et al., 2020). While this approach holds significant promise in addressing the climatic impacts associated with buildings, current Life Cycle Assessment (LCA) tools have not kept pace with these advancements. Consequently, there exists a gap in effectively integrating newly developed materials and innovative building designs into practice, despite their potential to mitigate emissions in built environments (Dervishaj & Gudmundsson, 2024a).

Furthermore, as the construction industry continues to explore novel materials and building solutions to meet sustainability goals, there is a growing need for tools that can seamlessly integrate these innovations into LCA frameworks in the future. Traditional LCA tools often struggle to accommodate the complexity and diversity of new materials, thereby hindering their ability to accurately assess the environmental implications of alternative building designs.

Against this backdrop of evolving methodologies and emerging challenges, this paper aims to address these gaps by defining a comprehensive Tool Characterizing framework (TCF) using both literature and stakeholders ideas, to study existing LCA tools and identify their contribution and shortcoming in facilitating the assessment of novel low carbon and carbon storing materials. Additionally, by compiling a database of Whole Building Life Cycle Assessment (WBLCA) tools and assessing them against the established framework, this project will contribute to advancing the state-of-the-art in sustainable building practices. Through this collective effort, stakeholders can make informed decisions, promote best practices, and ultimately pave the way towards a more sustainable built environment.

Goals:

The primary goal of this paper is to assess the current ecosystem of LCA tools and assess the gaps in their functions to assess carbon-negative building design

Objectives:

1. Explore digital technologies in the area of building LCA through an exploratory search to evaluate their potential application for assessing the development of carbon-storing buildings.
2. Develop a comprehensive Tool Characterization Framework (TCF) to dEPICt the landscape of LCA tools and evaluate their features.
3. Analyze and compare existing building LCA tools to determine their scope, effectiveness, and limitations in supporting and assessing the design of carbon-negative buildings.

1.3 Literature review

In the area of building LCA tools, numerous research has been conducted in recent years. That is merely due to more stringent sustainability targets set by policymakers that motivate other stakeholders to demand more efficient sustainability digital tools that aids in achieving project objectives (Dervishaj & Gudmundsson, 2024a; DeWolf et al., 2023). On the other hand, there are still many growing aspects to building sustainability that warrant further investigation such as the impact of novel technologies and new materials, true extends of system boundary for building footprint, end-of-life scenarios, and novel design styles all of which present opportunities for advancement in the realm of sustainability tools (Bari et al., 2022; DallaMora et al., 2020; Dervishaj & Gudmundsson, 2024a; Säwén et al., 2024). In this regard, in recent years, several researchers have targeted the landscape of LCA tools, and investigated their features, aiming to identify trends in developing digital tools. In this section, we highlight the literature review findings to identify the cutting-edge knowledge and trends in the field of Build LCA tools and find areas to contribute to this topic.

Another topic that has attracted the attention of LCA practitioners, researchers and developers is in-depth analysis of specific features of tools and the extent of granularity associated with that. For example, Darvishaj and Gudmundsson in a study reviewed 252 peer-reviewed papers and 17 LCA tools to find recent advancements in addressing circularity in building performance assessment. They found that LCA has dominated the sustainability assessment of buildings leaving large areas for implementation of circularity in tools. They compare tools based on their framework and some features. They found that despite several Circularity indicators have been proposed in the literature, these metrics remain underdeveloped in current tools, with only a few implementations like in Rhino Circular(University et al., 2020) and Circular EcoBIM(EcoBIM", 2022). This research has provided a more comprehensive list of tools and a more extensive comparison of tools' features compared to previous research which shows the inclination in the research community towards exploring the landscape of sustainability tools. Results of this comparative study in this research can be of assistance for tool selection. Authors also found four main research trends in previous studies with the focus on sustainability digital tools:

- Integrations to BIM or Parametric model
- Predicting Bill-of-Material
- The use of computational methods
- Characterization of LCA tools for practitioners (Dervishaj & Gudmundsson, 2024a).

In another paper, Holberg and his team reviewed 39 LCA tools and focused on reporting and visualization of results in LCA tools. Their findings show a great variety in visualization methods. By matching them with common LCA goals they provided a structured basis for future developments. Most LCA tools employ classical graphical representations for presenting LCA results such as pie charts and barcharts, which, according to their findings, are inefficient for communicating results to stakeholders. This is whilst there is a potential for facilitating the interpretation of LCA results and collaborative design processes by using other sorts of graphical content such as combining different kinds of visualizations within the design environment, interactive dashboards, and immersive technologies, such as virtual reality (Hollberg et al., 2021).

Another dominant trend in LCA tool reviews focused on integration of LCA models in computational models. This trend has three secondary streams. The first topic that has received vast attention is reviewing BIM-LCA integrated tools and comparing them in terms of database, level of development, scope, etc. For example in a research Dolla Mora et al. proposed an analysis of the research published between from 2007 to 2019,regarding the integration of BIM-LCA as a methodology whereby the BIM approach can support and simplify data management for LCA analysis. The analyzed 39 research and tools found that one of the major problems is the lack of available LCA software integrated in BIM tools (DallaMora et al., 2020). Similar research investigated various aspects of integration of BIM and LCA ((Hollberg et al., 2020; Obrecht et al., 2020; Soust-Verdaguer et al., 2017; Wastiels & Decuypere, 2019). BIM-LCA integration remarkably marks the most popular topic for researchers; however this is not the only evolving type of LCA tools.
Other secondary trend in LCA tool studies is integration of parametric modeling and LCA that proposed tools such as Bombyx(Basic et al., 2019), BHoM, Tortuga (Thumfarth, 2016), Cardinal LCA(Chen et al., 2021), OneClickLCA (Apellániz et al., 2021). Parametric LCA tools are thriving and expanding due to open-source architecture of grasshopper that makes creating new tools easy and free. Lastly, In addition to developed tools, numerous researchers have developed their multi-objective optimization model that aims to guide design towards reaching lowest environmental impacts while satisfying other design objectives. For example, Kiss and Szalay developed a parametric multi-objective optimization approach to minimize the environmental impacts of different building systems, including envelope, heating, and energy systems (Kiss & Szalay, 2020). In another research Manni et al. developed a parametric multi-objective optimization model to minimize the embodied carbon and maximize solar irradiation by varying building geometry and orientation (Manni et al., 2020). Płoszaj-(Płoszaj-Mazurek et al., 2020) et al. built a parametric machine-learning model to predict carbon footprint using basic design parameters such as wall area, roof area, and height. Lastly, Wang et al. developed a trade-off optimization-based framework for thermal comfort, and environmental impacts and cost of building envelope (Wang et al., 2020).

1.4 Novelty

With a review on the research background of research on LCA tools, several gaps are identified:

1. **Extensiveness of studied tools:** it is understood that despite growing numbers of research and expanding literature, only a few studies provide detailed review on the scope and features of LCA tools and majority of research focused on specific tools or explored a narrowed section of ecosystems. Most of the comparative studies found in the literature encompass less than 5 tools leaving the rest of the tools unexamined. The papers with good number of studied tools has focused on a few features. Consequently, many of the novel and promising tools with high potentials remained

unexplored. To bridge this gap in the literature, in this study we studied and evaluated the comprehensive landscape of active LCA tools in March 2024.

2. **Holism in defining TCF:** Another aspect of novelty of this study is the holism in defining the TCF that was developed for in-depth analysis and evaluations of the tools in current study. This TCF is developed by incorporating promising previous findings through literature and also adding other measures for comparing the tools in order to assess their applicability in carbon-absorbing building design. The scope of this research is tailored to practical LCA tools that are focused on building level analysis and are compatible with local LCA datasets and methods in North America.

3. **Adaptability of tools for carbon negative buildings design:** Lastly, this study will focus on another noticeable gap in the literature which is the functionality of current LCA tools for progressive generation of carbon-absorbing buildings. After the comprehensive literature review of paper and snowballing more references, authors were unable to find any research that addressed development of novel zero or negative carbon materials in building LCA research, therefore, in this review we analyze tools from this aspect too

The results are summarized and reported to aid stakeholders, including designers, architects, engineers, owners, real estate professionals, and LCA practitioners, in selecting appropriate tools from the broad ecosystem of LCA tools. Additionally, this research supports stakeholders in effectively identifying their options by understanding tool functions, limitations, and scope. Moreover, besides assisting users in making informed decisions about tool selection, the findings of this paper highlight literature gaps for improving LCA tools and enhancing carbon absorption design in the buildings and construction sector.

2- Method

To address objectives of this paper a five-step methodology is proposed. **Step1** started by exploring the current topics and research questions in the area of zero-carbon built environment. The result of this exploration highlighted that at the time of preparing this paper, the some of the most important research topics are building circularity, cradle-to-grave LCA, interoperability of tools, BIM-integration of LCA tools, parametric LCA, carbon storing materials, early stage LCA, rapid LCA and etc. Exploratory search in the area of the latest topic LCA leads to defining the umbrella keyword of “Building LCA Tools” that covers all the recent research topics.
Based on that keyword in **Step 2**, a systematic search has been done to find state-of-the-art research in the area of “Building LCA tools” and previous research on reviewing ecosystem of tools. In this stage, ScienceDirect as one of the leading sources for scientific and technical research to retrieve recent projects was used. The focus of this search was on recent research in the area of Building LCA that was published in the course of 2020 till March 2024. Other criteria for selecting relevant research were limiting the papers to include the keyword, be original research or review articles and be in English which resulted in to 22 papers. In the next round by filtering papers based on relevancy to the topic of this research and limiting the scope to Building-scale LCA, 15 articles were shortlisted that represented the state-of-the-art achievements in the area of this paper.

In **Step 2**, further analysis was conducted on the selected papers to extract data from literature with two goals:

- To identify the contribution of the previous papers to analyze the ecosystem of LCA tools by identifying the methodology and framework used to evaluate, compare, and scrutinize the landscape of LCA tools
- Identify recent trends and gaps in this area.

In addition to the literature, some other features were added to evaluate the complaint of current LCA tools for addressing application of new material and technological construction methods in environmental analysis. Collected information along with adding additional features resulted in defining a holistic Tool Characterization Framework (TCF) according to the aim of this study which is discussed later in this section.

In **Step 3**, the list of current Building LCA tools was selected for further analysis. In order to assure, latest LCA tools in the dynamic and evolving context of tool developments are included, similar to the previous step, we used a hybrid search method to cover different type and formats of tools. The search sources, along with criteria and list of tools are discussed in the Methods section.

Having the TCF defined in **Step 2** and the main LCA tools identified in the **Step 3**, in **Step 4** we aimed to test and evaluate the tools to illustrate different aspects of current LCA tools landscape, which are shared in details in the Results section. The ecosystem of the tools along with their features, functions, limitations and scopes are identified in this stage and discussed in Result section. Lastly, in **Step 5** with having a glance on the tools ecosystem, the gaps of the LCA tools are identifies to highlight the areas for future research to achieve better LCA tools and lowest-carbon Built environment in the future.

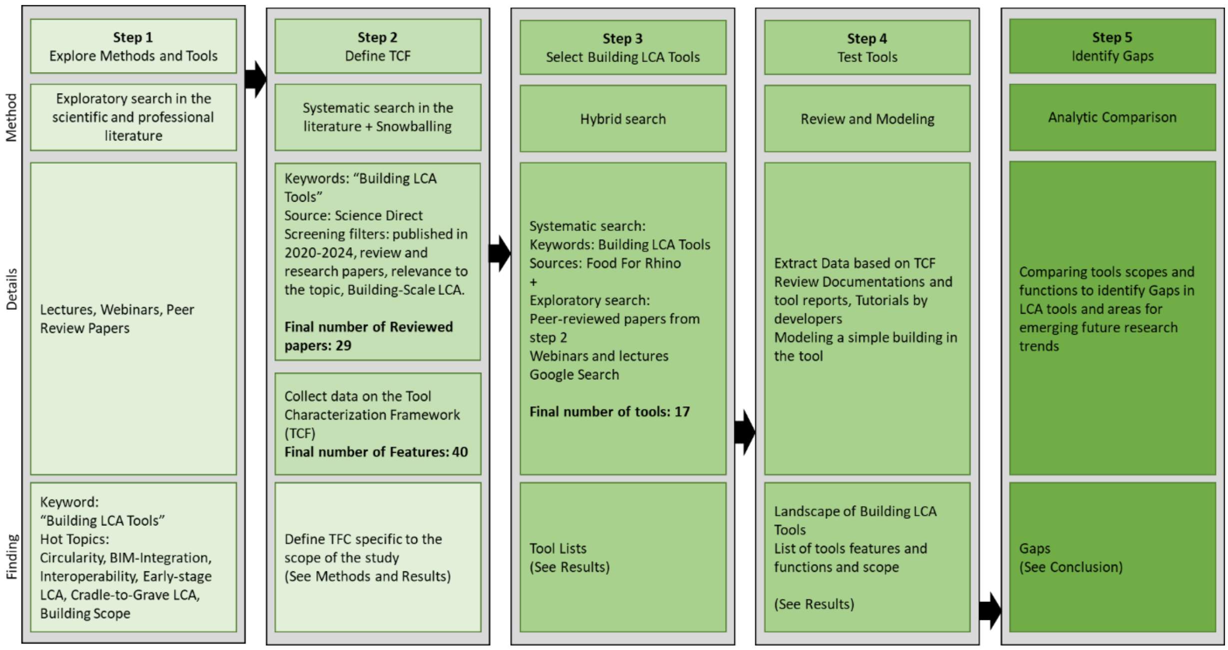


Fig.1- Research methodology and Steps

2.1 Tool Characterization Framework:

2.1.1 Background of TCF

In order to define the TCF that holistically highlights the landscape of LCA tools, we started by reviewing the literature. This is done aiming to learn about previous findings and achievements and equip the research method with the state-of-the art efforts to enhance the performance of LCA tools. Although the search in the literature reveals no research on carbon storing buildings and appropriate LCA tools for this purpose, still literature shows recent advancement in analysis of LCA tools with similar goals that can be beneficial to the objectives of this study. Below are findings of the literature review. With a review of the literature, the authors could extract two different methods that substantiated the two different approaches to TCF:

The first group of researches on TCF, focused on stakeholders opinion for extracting TCF. This method is fairly applied in innovative aspects of LCA to cover the lack of literature. The goals of this group of research is mainly on developing new LCA tools or models for better analysis. The data collection methods that are most common in these groups are surveys or interviews that inquire tools, features and functions from the stakeholder, such as direct tool users and other groups of stakeholders that use the results of these tools such as architects, engineers and procurement crew.
For example in a study Holberg et. al. developed and tested a framework for user centric development of a new user friendly LCA tool. They incorporated stakeholders' ideas in defining the tool requirements and evaluated the tool success based on feedback from the same group of stakeholders upon using the prototype tool in the Swedish context. The results encompass insight on tool features that Architects, engineers and real estate professionals agreed upon. Results also show that the users' expectations of an LCA tool can be satisfied well when the requirements are integrated from the very beginning (Hollberg et al., 2022). In another research DeWolf collected data on European LCA tools and databases through literature review, surveys/interviews (DeWolf et al., 2023).

Other groups are the researchers that aim to understand the ecosystem of current LCA tools with intention of informed tool selection based on their applicability and features and scopes. Therefore, unlike the first group that pursued the goal of developing a new tool/ model, this group would like to understand the landscape of tools to use them in the most effective way to meet sustainability goals of their projects. This can be for either designing low, zero or negative carbon building, pursuing certificates, incentives, and credentials. The method that this group chooses is using a predefined TCF after slight modifications and expansion of features and use that for comparing LCA tools (DallaMora et al., 2020; Nguyen & Pishdad-Bozorgi, 2023; Prideaux et al., 2022; Säwén et al., 2022) .

In a recent similar paper, 13 grasshopper tools were classified based on their modeling approach and then were compared based on nine characterization features of required knowledge, geometry input, default settings and adaptability, modeling level, output of results, intended application, data source, LCA modules, and impact categories in addition to GWP. Using that TCF the authors then evaluated four tools (Bombyx, Cardinal LCA(Chen et al., 2021), BHoM, and Tortuga(Thumfarth, 2016)), providing an overview of the tools scope for designers to use LCA tools in their design process (Säwén et al., 2022). This research provides insightful details on early-stage LCA tools, however, due to a limited number of investigated features and less than a handful of studied tools the application of results for properly selecting LCA tools are limited .In this study, tool characteristics were adopted from a previous study (Hildebrand & Linda, 2018) and expanded to the framework for LCA design tools. Similarly, Nguyen and Pishdad-Bozorgi refined a framework for deep analysis of LCA tools with regards to design and development application. By reviewing 15 papers with existing TCF between 2009-2021and based on a previous work by (DallaMora et al., 2020) a new TCF was developed. In this TCF features such as the Design stage, Development Level, Integration Tools, Impact categories, learning curve, Database, LCA phase, and Reporting results are included. Then they applied this framework in comparing three mainly used LCA tools in North America, Tally, Athena, and EC3 (Nguyen & Pishdad-Bozorgi, 2023). Despite the benefits of the applied approach of expanding a previous framework is helpful in identifying contributing tool features, the limited number of investigated tools in both papers has limited the generalization of results. Moreover, in both studies, the proposed framework has limitations with respect to post-LCA analysis. The two studies have adopted two different references as the initial underlying framework and refined them with two different focuses with fairly similar goals and eventually reported two TCFs that have noticeable similarities approaches despite they landed on the fairly similar characterizations which indicates the reliability of results.

Each methods has advantages and in order to build upon the literature and also expanding that to meet the needs of stakeholders, a combination of both methods can be used. For example, in a paper, DeWolf et al. collected four Level(s)-compliant LCA tools and four databases used in Europe for WBLCA and developed a TCF for analyzing their characteristics based on a set of criteria. Their methods for setting TCF included a literature review, surveys/interviews, and the co-creation of criteria for the categorization of tools and databases. The results provided a TCF of four categories and 12 criteria including:

- Comprehensiveness (construction-specificity, system boundaries & scope, indicators, modeling granularity)
- Robustness(methodological adherence to Level(s) and EN standards, data quality, transparency, and verification)
- Interoperability (accessibility, data exchange and interoperability, cost, training, and support)
- Additional information (DeWolf et al., 2023).

This research contributed to the literature by defining a comprehensive TCF according to the research question. However, in terms of examining the application of TCF, it suffices to use of four tools (OneClick LCA, GaBi, SimaPro,OpenLCA) and left a wide section of tools landscape, consisting of more novel and innovative tools, out of the scope of their investigation. Additionally, this research focused only on EU tools and neglected the implication of TCF to North American tools.

In this research we deploy a hybrid method to define the TCF; we first conduct reviewing literature and elaborating on existing TCF. Then we use Stakeholders opinion in improving the TCF especially for deploying novel materials and technological construction methods. The details methodology is discussed in this section.

2.1.2 Defining TCF

Tool features in the literature

As mentioned earlier, to find existing TCF a systematic search followed by snowballing was deployed. As the results, six recent TCF has been identified and their framework has been broken in to single identifiable features. The TCF from the literature has some overlaps, and also different wording for the same tool feature. In order to extract unique, distinct and relevant features the description were reviewed and the TCFs were homogenized which resulted in 32 features. In the next step, the listed features from the literature were reviewed and filtered by their relevance to the topic. As mentioned in the literature the relevance topics are application to LCA tool on building-scale and supporting design of net-zero or negative buildings. Moreover the features needs to be clear, unique and measurable. By applying filtering criteria 23 features were selected. To benefit from the literature we summarized previous research and their proposed TCF in the table below.

Table 1- Collected features from the literature

Criteria	Description	Acceptable values	Reference
Intended use	Specify the purpose of the development and use of the tool.	Education, design evaluation, complete assessment	(Säwén 2022)
Indicators	Full or partial coverage of impact indicators	GWP, Ozone Depletion, Smog potential, Euthrophization, acidification, Human Health effect, or others	(Säwén 2022) (Nguyen 2023)
LCA Stages	Life cycle stages, geographic information,	A1-A3; A4-A5; B1-B7; C1-C4; D	(Säwén 2022) (Nguyen 2023)
Building Element	Parts or whole building	Structure, Envelope, Interiors, HVAC	(DeWolf 2023)
Design Stage	Refers proper application of the tool in three Schematic design, Design developement, Construction	schematic design, design development, construction documents, bidding, and construction administration.	(Nguyen 2023)
Database	Digital data includes environmental information for building materials	LCI, EPD, Athena, ICE, Ecoinvent, etc.	(Nguyen 2023)
Control	Possibility to adapt the built-in predefined settings.	High, moderate, low	(Säwén 2022)
Interoperability	Import and export possibilities	Y/N	(DeWolf 2023)
Modelling level (default Scenarios)	Where one can start an LCA. Are there predefined materials, component and/or building specifications	Material, component, building Level	(Säwén 2022)
Visualization of results	Visualization of LCA results. The results processed into a report, charts and or surface colouring (hotspot)	Report, charts, surface colouring	(Säwén 2022)
Format	Software format	Web interface, Standalone, BIM plugin, Rhino/GH plugin, Spreadsheet, etc	(DeWolf 2023)
Cost	Free or commercial price	Free, Subscription-required	(DeWolf 2023)
Geographic information	Where the tool was developed	Country Name	(DeWolf 2023)

Methodological adherence to standards	Alignment	Standard Name	(DeWolf 2023)
Development, management, and updates	Continuous update of the tool and customer service to users	Y/N	(DeWolf 2023)
Operational Carbon	The ability of the tool to calculate energy consumption and operational carbon	Y/N	(Dervishaj 2024)
Circularity	use of Circularity Index	Y/N	(Dervishaj 2024)
Flexibility on Database	Enables change of databases	Y/N	(Säwén 2022)
Flexibility on LCS	Enables change of LCS	Y/N	(Säwén 2022)
Use of Private Material	allow adding material	Y/N	(Dervishaj 2024)
Optimization	multi-objective optimisation using genetic algorithms (or similar)	Y/N	(Dervishaj 2024)
Hotspot Analysis	Aggregation of assessment results, enabling user to identify areas for potential improvement.	Y/N	(Prideaux 2022)
Uncertainty Analysis	focuses primarily on data uncertainty rather than uncertainty related to user inputs	Y/N	(Prideaux 2022)

Tool Features from the Stakeholders

As mentioned before, the author could not find any research that evaluates the landscape of LCA tools from the lens of negative carbon buildings. Therefore there was a need to add features corresponding to new carbon absorbing material/buildings and technological construction methods in the TCF. To do so, we referred to stakeholders' opinions and the opinion of groups of AEC experts comprised of designers, LCA practitioners, researchers, engineers, faculty professors specialized on developing new sustainable materials were collected. The expert groups were asked about their expectations from a LCA tool for carbon absorbing building design and performance assessment. They were also asked about the challenges of novel material utilization in a carbon-negative building design. Their brainstorming ideas included a range of factors from modeling interface to interoperability and post-LCA analysis offered by ideal LCA tools. After collecting brainstorming ideas, processing and summarizing them, the tool features from stakeholders was listed as Table.2. Then TCF from literature TCF from stakeholders were compared which showed some similarity and overlaps. Following unifying the similarities and wording, the holistic TCF from the both sources were prepared containing 33 features, with clear definitions. Also to ensure consistency in data collection and analysis, categorized default responses for each feature is provided.

Table 2- Collected features from the Stakeholders

Criteria	Description	Acceptable values
Biogenic Carbon	Calculate carbon storage benefits for biogenic materials	Reported Separately/Reported in module A & C
Transportation Impact	Calculate/estimate transportation impacts	Y/N
End-of -Life emissions (EOL)	Calculate/estimate end-of-life emissions	Y/N
Circularity	Calculated Circularity	Not Included, Percentage, MCI, BCI, CEV, CEIP
LCA A-C scope	Calculate cradle-to-grave LCA impacts using static LCA	Y/N
Carbonation	Calculate carbonation impacts	Y/N
Use of Radiative Forcing	Calculate GWP using dynamic Radiative Forcing Method	Y/N
Design alternatives	Compare current and future scenario versions of same formulation [differnt design Alternatives according to Monica]	Y/N
Baseline Comparison	Compare with incumbent material or baseline building	Y/N
Contribution analysis	Perform a contribution analysis	Y/N
Dynamic-Static LCA comparison	Compare dynamic LCA vs static LCA results	Y/N
Hotspot analysis	Perform a material-scale? hotspot analysis [highlighting which processes or materials in an LCA add up to the top 80% of impacts according to Monica]	Y/N
Customized A5	Enable customized scenarios to calculate/estimate construction impacts	Y/N
Customized C	Enable customized EOL scenarios	Y/N
Custimized Circularity Impact	Enable customized scenarios to calculate/ estimate circularity impacts	Y/N
Use of open-source LCI library	Select upstream material and process data from an open-source LCI library	Y/N
Use of Private Data	Allow user to input user-defined LCI data	Y/N
A4 Default Scenario	Provide default transportation scenarios	Y/N
C Default Scenario	Provide default end-of-life scenarios and data	Y/N
B4 Default Scenario	Provide default building component lifespan/use scenarios	Y/N
Baseline OC	Estimate Baseline Building Operating Energy LCA Impacts	Y/N
Electricity Emissions	Provide default electricity	Y/N
Equipment emissions	Provide default equipment	Y/N
Fuel emissions	Provide default fuel data	Y/N

2.2 LCA Tool Selection

2.2.1 Criteria for Tool Selection

After defining the TCF, the list of LCA tools have been identified. The criteria for including tool is :

- Live tool: at least one update biennially since 2022
- Building-Scale LCA: Any tools that can be utilized to conduct LCA analysis specifically for buildings on building scale, excluding tools that focus on building systems (such as structure, mechanical systems, envelope, etc.)
- Applicable for projects in North America
- Availability of tools and documentation in English,

In order to find the list of tools a hybrid was conducted. In the first step the search started by a systematic search by exploring FoodforRhino (2 tools), IBPSA best directory (0 tools) , Dynamo Packages (0 tools) and Autodesk app store using the “LCA” keyword. The exploration in step one showed the advent of increasing number of dashboards and web-based tools in recent years in the area of building LCA in comparison to stand-alone tools. As there is no repository to gather web based tools and dashboards, in the second step of search, an exploratory search was conducted using the same keyword through Google search. After finding the tools and applying selection criteria – number of tools have been selected for analysis.

In addition to parametric plugins, to explore independent tools such as web-based, standalone, and spreadsheets a detailed exploratory Google search was conducted using the same keyword. Sampling includes government, academia, and commercial software; a representation of free, open-source and closed-source options; and a selection of BIM-LCA, web-based, and standalone software. The tools that were found through peer-reviewed paper searches during **Step 1** were also added. Through using all selection method after applying inclusion filtering 17 building LCA tools were selected.

2.3 Tool Evaluation

Having the TCF from **Step 2** and List of tools in **Step, 3** we started reviewing and testing with the goal of collecting data on their main features and functions. We evaluated the tools through two methods; primarily through published documentation or tutorials in English by the tool developer. For the accuracy of data collection other references with authors other than the developers were excluded. Secondly, if enough data on documentation were not available, we collected required data by contacting developers, requesting demo and modeling simple buildings, exploring the modeling interface and generated initial results to examine the tool feature according to the TCF. The results of this stage are further discussed in the Results section.

3. Results

The results show that the number of active tools in the ecosystem of building LCA tools has increased at a progressive rate in recent years. This necessitates closer look at tool features and potential, in order to facilitate selection of correct tools for project sustainability goals.

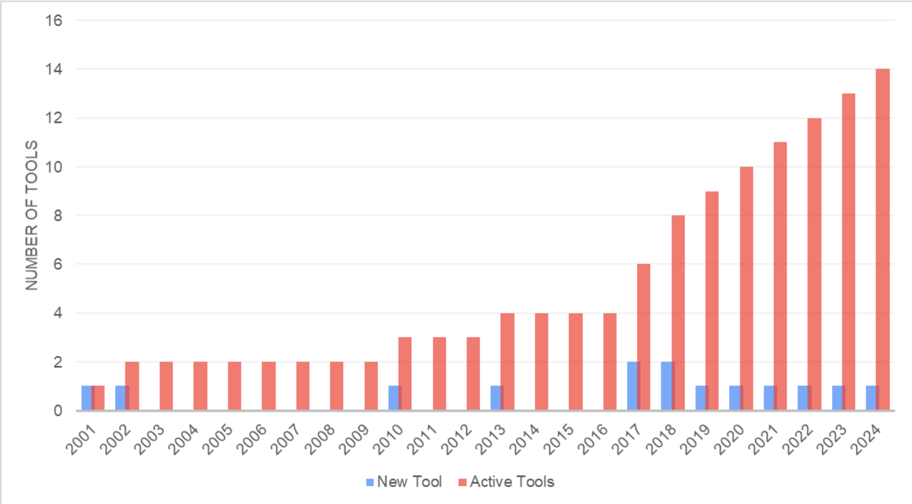


Fig. 2- Evolutionary trend of LCA tool development

The following sections present the analysis and a brief description of the reviewed LCA tools by the evaluation across the selected TCF. This section discusses general features of the tools, their application, embedded data, reported outputs and analysis.

3.1 Tool Features

3.1.1 Intended use:

This feature investigates the intended application of the tools per TCF as discussed in section 2. The results show that most of the tools have more than one potential application.
Precursor and renowned tools (such as Tally and athena) provide detailed analysis that is helpful for material selection in later stages of the design and do not provide simplified LCA, suitable for educational use. This is while more recent tools tried to mitigate the data-dependency and complexity of traditional LCA which facilitated design and even educational use which will be further discussed in section 3.2.2.
It is rare to see that a tool provides all three uses, from educational use which requires fast and less data LCA, to detailed assessment which has a complete and detailed list of inputs. The only example is One Click LCA which aims to meet needs of different walks of audience by providing different tools with different levels of accuracy, holism and required inputs. For example One Click LCA has planetary, carbon designer 3D which can be used for educational purposes, while they have the building LCA tool for detailed analysis and procurement.

3.1.2 Tool Format

The results show that web-based tools are the most common type of tools. This is due to using ever increasing capacity of cloud computing for fast analysis. Moreover, web based tools are accessible and work across different platforms which makes them an ideal choice for a collaborative working environment. Moreover, in previous study web based tools are

considered as the most user friendly format for building design tool (Dervishaj & Gudmundsson, 2024b)
One another note, it is observed that most of the tool developers provide their product in different formats. With less inclination towards standalone tools, BIM and GH plugins have been respectively the next choices for LCA tool developers. These plugins facilitate connection to other building modeling tools and provide most of the required input data by reading data from the architectural model. It also helps maintain modeling consistency and reduces risk of modeling error, the same architectural/analytical model is used for LCA analysis as well as other performance simulations.
With increasing use of BIM, the majority of developers prefer BIM over GH for integration. The latter is more popular with tools that are aiming to provide design-oriented analysis while BIM is more popular with tools that aim at detailed analysis. Excel is the least popular plugin due to less common use in the design community and compatibility with the design process.

3.1.3 Building Scope

Regarding the building scope, all tools cover the building envelope which has historically been the first and most-addressed building component in LCA tools, followed with interiors. Most of the tools also cover structure emissions, however they use different approaches. Some tools use per capita values for assessing structural emissions (Ex. Cove tool, Building Pathfinder, Autodesk forma, EPIC, etc) while other tools rely on user inputs to define structural elements and then on they can calculate material and caused emissions (Example, Athena Impact estimator, Tally, Bombyx, BHoM, etc). Emissions associated with building MEP, however, have received the least attention. Just very recently One Click LCA has launched a tool to estimate MEP emissions based on data of as built buildings and the review results shows that more effort in this area is needed to bridge the gap of assessing building MEP in WBLCA

Table 3- Summary of general features of the tools

		Tool Features																		
Tool	Year first developed	Intended Use			Tool Format					Building Scope				Life Cycle Stage						
		Educational	Design Comparison	Complete assessment	Stand-alone	Web-based Tool/Dashboard	BIM plugin	GH Plugin	Excel	Structure	Envelope	Interiors	MEP	A1-A3	A4	A5	B	Op. Carbon	C	D
One Click LCA-tool suite	2001	X	X	X	-	X	X	X	-	X	X	X	X	X	X	X	X	X	X	X
Athena Impact Estimator	2002	-	X	X	X	-	-	-	-	X	X	X	-	X	X	X	X	X	X	X
etool	2010	-	X	X	-	X	-	-	-	X	X	X	-	X	X	X	X	X	X	X
Tally	2013	-	X	X	-	-	X	-	-	X	X	X	-	X	X	X	X	X	X	X
Cove Tool	2017	X	X	-	-	X	X	X	-	X	X	X	-	X	-	-	X	X	-	-
Building Pathfinder	2017	X	X	-	-	X	-	-	-	X	X	-	-	X	X	X	X	X	X	-
Autodesk Insight	2018	-	X	X	-	X	X	-	-	-	X	X	-	X	-	-	-	X	-	-
Bombyx	2018	X	-	-	-	-	-	X	-	-	X	X	-	X	X	X	X	-	X	-
BHoM	2019	-	X	-	-	-	X	X	X	X	X	X	-	X	-	-	-	-	-	-
EC3	2020	X	X	-	-	X	-	-	-	X	X	X	-	X	X	X	-	-	-	-
EPiC	2021	X	X	-	-	X	-	-	-	X	X	X	X	X	X	X	X	X	X	-
CARE	2022	X	X	-	-	X	-	-	-	X	X	X	-	X	X	X	X	X	X	-
Autodesk Forma	2023	X	X	-	-	X	X	-	-	X	X	X	X	X	-	-	-	-	-	-
REAL Tool	2024	X	-	-	-	X	-	-	-	X	X	X	X	X	X	X	X	X	X	X

3.1.4 Life Cycle Scope

In terms of lifecycle scope, A1-A3 as the base LCA stage is covered in all tools. Limited number of tool encompass has cradle-to-cradle approach and encompass module D. Almost half of the studied tools have a cradle-to-grave approach which satisfies their application for design and certificate reporting. the results show that all tools

In reviewing the methodology of tools, inconsistency in addressing A4 and A5 is observed. Some tools have fixed inputs of distance and means of transportation, such as athena and Tally, while others consider that as a fraction of upfront carbon, such as EPIC. Other groups of tools allow users to define a more realistic transportation scenario and consequent emissions (ex. One Click LCA, ETool and EC3). Studies have shown that when a user can define transportation means theA4 emission is higher than what estimated in the codes and standards [ref].

For **A5** some tools include waste of material in their methodology and some tools consider both equipment use and waste. Some tools consider that as a fraction of upfront carbon and others might multiply area.

Simplifications are also observed in **B** emissions, which limits the refurbishment emissions to the lifespan of materials regardless of real retrofit scenarios. Therefore, B emission is underestimated and can be higher by considering real scenarios. For example, in a retrofit, if the inner material layer or an element needs replacement, all covering layers should also be replaced, which is not reflected in the tools. In other words for B emissions tools should adopt an element-based approach meaning that the life of an assembly is defined by the shortest life of any of the layers [?]

Most of the tools also do not allow integrating **new technologies** of harvesting energy and see the embodied operational balance. EPIC is one of the newly developed tools that allow users to define PV arrays and see the added EC and savings in OC. Insight and REAL tool also provide renewable options in modeling and report total carbon considering its impact on embodied and operational carbon.

3.2 Tool Application

3.2.1 Design stage application

The results show good compatibility of tools with the construction stage, which includes modifications in material selection for a better environmental performance. Studied tools also showed fairly good compatibility for application in the design development stage. Changes in this stage have low impact on BOM, therefore for generating new results, the same model can be used with minor modification.

On the contrary, tools that provide insight for the concept stage are limited. There are two categories of tools that target concept stage LCA, concept stage calculator, and provide a range or achievable threshold of emissions based on provided information. Good example of this group of tools is EPIC, REAL and Building Pathfinder, while their scope is different they can provide a rough estimation of carbon footprint based on project use, area, location, structural system or in the first two use of renewable energy, etc. the more information provided, the more accurate the results are, however with minimum data the tool is still capable of estimating building carbon, which inevitably might have some discrepancies.

There is another group of tools that can provide concept LCA results, but unlike calculators, they are design oriented and provide early stage concept results. Unlike the previous group, these tools have a design interface and allow users to change the most fundamental parameters such as building geometry, dimensions, and form that impacts BOM. They also provide real time LCA results per changes in design. Forma, Bombyx, Cove tool are examples of this group. These tools allow architects to choose between millions of alternatives, by estimating emissions in the concept stage.Autodesk forma is a good example of an early stage LCA tool that allows users to draw real-time impacts. Covetool also has identified the need for LCA design tool and allows user to benefit from an interoperability between design and carbon analysis

It is noteworthy to mention that these two groups have been referred to interchangeably by terms such as “early stage LCA tools. While their fundamental differences, make them able to serve different stakeholders, answer different design questions in the early stage of the project.

3.2.2 Modeling level

In response to the need to simplify LCA and reduce data dependency of models, more tools have steered direction from user-dependent data to tool-sufficient data. This has been observed in tools by shifting from requiring BOM and providing material carbon factor to calculate total carbon towards providing high-level assumptions such as building benchmark emissions and emission of building element per capita and requiring users to select from the list. For example COVE tool uses ASHRAE for defining scenarios and Forma has its own defined scenario from which the user can select. On a different approach, EPIC tool uses CLF benchmark study for building-level emissions values. Bombyx also provides two modeling levels due to the double LCA approach in the tool. The top-down approach gives the option of selecting several inputs to categorize the building and assess carbon emission, while the bottom-up approach gives users the option of defining the building element from the underlying materials.

3.2.3 Connection

Connection of LCA modeling tools with other tools, provide users with the option of using the same model for different analysis as well as LCA, ensuring consistency in modeling as well as saving time and effort in modeling. Connection between tools exists in two level: import/export and Interoperability which are discussed in this section

3.2.3.1 Import Export

One level of tools connection is a one way data transfer that LCA module reads or write data from and to other tools. Typically in the ecosystem of LCA tools, BOM is read from design tools and the results are written in spreadsheet or pdf reports. The results of this study shows that almost all tools have the option of reading and writing. The most common tool to connect with LCA tools is Revit. As the BOM report is embedded in the BIM tool, developers have paid special attention to use this potential for solving the challenge of input data for LCA models. Import from the BIM tool can be done in the form of uploading gbxml-IFC models. Import from GH model however is less common due to less elaborated reports or export models and specifically lack of material reporting option in this platform.

Reading BOM from excel is also common in LCA tools. In terms of writing to other tools Excel is the best option for writing the results followed by pdf format for exporting reports.

3.2.3.2 Interoperability

Another level of tools connection, which requires live data transfer and two way stream of data transfer, is called interoperability. Interoperability is defined as the “ability of two or more systems or components to exchange information and to use the information that has been exchanged" (ISO, 2013). The case of interoperability in ecosystems of LCA tools is scarce to find. BHoM tool is one and only pure example of interoperable tool that links BIM, GH, excel to to benefit from the advantages of each tool which resulted in a functional tool for upfront carbon analysis in design. Another example is the One Click LCA BIM integration. While this tool provides over 20 integration of AEC tools to its server, BIM integration is the most advanced one. While in other integrations data is read from software to One Click LCA server for conducting LCA analysis, in BIM integration there is a two-way connection between the two tools, enabling users to open one click in the BIM environment and get instant results while changing the building design.

The value of interoperability is better understood, when compared to simple connection of import/output. For example Autodesk Insight provides detailed LCA results, however, it only reads from the analytical model in BIM and after uploading the analytical BIM model to the server, runs carbon analysis. Therefore, in case the tool is used for design, the process needs to be repeated for every iteration, which limits instant, live results and makes it impossible to use in early stages.

GH tools show better interoperability with the host platform compared to BIM-based tools. LCA tools that are run on GH (OneClick LCA, Bombyx, BHoM, Covetool, etc), aims to benefit from the potential of GH in reporting real time results. Therefore there is operability between the LCA module and the parametric building model. For BIM based tools, however, the gist of connection is reading BOM and transferring that to LCA module, which means one way data flow from BIM to LCA model. As this connection is weaker and does not require back and forth data transfer, BIM based tools work with import and lower interoperability is needed in general.

Table 4- Summary of tool application data

	Tool Application												
Tool	Design Stage Compatibility				Modelling Level (Default Scenarios)			Interoperability			Reads / Writes to		
	Early Stage Carbon Estimator	Early Design Application	Design Developement	Construction	Material	Element	Building	BIM	GH / Rhino	Excel	BIM	GH / Rhino	Excel
One Click LCA-tool suite	X	-	X	X	X	-	-	X	-	-	X	X	X
Athena Impact Estimator	-	-	X	X	X	-	-	-	-	-	-	-	X
etool	-	-	-	X	X	-	-	-	-	-	X	-	X
Tally	-	-	X	X	X	-	-	-	-	-	X	-	X
Cove Tool	-	X	X	-	X	X	X	-	-	-	X	X	-
Building Pathfinder	X	-	-	-	X	-	-	-	-	-	-	-	-
Autodesk Insight	-	-	X	X	X	-	-	-	-	-	X	-	-
Bombyx	-	X	X	-	X	-	X	-	-	-	-	X	-
BHoM	-	X	X	X	X	-	-	X	X	X	X	X	X
EC3	-	-	X	X	X	X	-	-	-	-	X	-	X
EPiC	X	-	-	-	-	X	X	-	-	-	-	-	-
CARE	X	-	-	-	-	X	-	-	-	-	-	-	-
Autodesk Forma	-	X	-	-	-	X	-	-	X	-	X	X	-
REAL Tool	X	-	-	-	X	X	X	-	-	-	-	-	-

3.3 Data

3.3.1 LCA reference data

In terms of data, tools have used different resources. Majority of the tools use an exclusively compiled dataset of LCA data compiled from different LCIs and EPDs. This includes tools such as Athena, Tally, EPIC, REAL tool, etc. Another group of tools which includes recently developed tools is using the EC3 EPD dataset. EC3 has solved the issue of lack of data in LCA tools to some extent by providing a bank of EPDs that can be filtered based on location and thermo-physical features that facilitate access to data. Open API which is available to public also promoted integration of EC3 databank in new tools such as EPIC, Cove tool, BHoM, Insight, etc. More transparency in terms of data is seen in recently developed tools, such as EPIC, REAL tool, CARE unlike Athena that is not transparent in terms of their data.

3.3.2 New Material

More and more tools are facilitating the use of new materials in LCA studies. This feature is needed by industry to quantify and analyze the benefits of using novel materials in building LCA. Utilization of new tools in LCA tools, is currently done by the option of adding new materials and exists in several tools. For example in tools such as EC3, REAL tool, Insight and Forma, in case the environmental impacts are available users can define the new material by inputting environmental impacts or upload the EPD and assign that as material to building components. The challenge of using new materials in LCA, however , is having that data available in the first place. Among the studied tools only two tools would assist users in generating LCA data for a novel material that does not exist in their dataset. ETool allows users to prepare the EPD of their new material and change the scenarios and assumptions in calculating impact to reflect project conditions. One Click LCA also provides inputting new materials through two methods: either importing new material EPD and or using its tools for new cementitious or wood base material to assess their embodied environmental impacts. Athena also allows defining new concrete mixes. While these tools provide a method to define new material beyond the materials in EPD bank, they are still in early stage and do not include methods for addressing novel materials or technologies.

3.4 Customization and flexibility

The results of this tool review show that a great number of tools have fixed scenarios or assumptions for LCA stages. As Table 5 indicates, among the studied tools, the majority of the tools do not provide customizable scenarios for calculating A4, A5,B4 and C emissions.
The emissions associated with **A4** can vary significantly according to the distance and means of transportation. In other words, a predefined fixed A4 scenario that represents average distance and common means of transport can not necessarily represent the material acquisition in a project and may cause a remarkable inaccuracy. Another method for calculating A4 emissions is considering transportation emission as a fraction of total floor area or upfront carbon. Among studied tools One Click LCA, eTool and EC3 provide options to edit A4 emissions by defining distance, adding legs of transport. Tally allows editing distances only while EPIC allows input per sqm emissions associated with A4 abd A5. Other tools in this study use fixed assumptions and do not provide the customization.

The same is true about end of life (**module C**) scenarios. In this stage the rate of recycling and waste management should be editable in order to provide users with the option of evaluating carbon saving at the end of life span as well as draw insight on upfront vs. end of life emission tradeoffs. The studied tools however show that the C module is the least flexible module for customization. This can be due to the uncertainty and variation of materials and pertaining EOL scenarios. One Click LCA allows the user to select EOL scenario from a list according to the material type. It also benefits the avoided carbon by using reused components and subtracting the carbon intensity from upfront carbon.
Regarding construction emission (A5), however, the diversity of approaches is greater compared to any other life cycle stage. Inconsistency associated with this stage arises from the diversity of system boundaries. Some tools (such as EPIC and One Click LCA) cover emissions from demolition of existing buildings on site as well as two other conventionally accepted components of A5: waste rate (A5w) and machinery emissions (A5a). Other tools only include one of the two A5w or A5a. One Click LCA allows user edit only waste rate. On the other hand EC3 and Tally allows users to define machinery energy consumption associated with A5. On the other hand, more tools allow users to change the life span of material which impacts the B4 module. Most of the tools do not allow users to choose the LCI for carbon intensity of Material.

Table 5- Summary of tool application data

	Data							Customization							
Tool	Database				Utilizing Open Source LCI?	Choice of Database allowed?	Private data allowed?	Can Change A4 Scenario	Can Change A5 SCenario	B3/B4 Default Scenario	Can Change EOL Scenario	Estimated OC	Input Electricity Emissions	Input Equipment Emissions	Input Fuel Emissions
	EPD	Exclusive Dataset	EC3	GaBi											
One Click LCA-tool suite	X	X	-	-	-	X	X	X	X	X	X	-	-		-
Athena Impact Estimator	-	X	-	-	-	-	-	-	-	-	-	-	-	-	-
etool	X	-	-	-	-	-	X	X	X	X	X	X	X	X	X
Tally	-	-	-	X	X	-	-	X	X	X	-	X	-	-	-
Cove Tool	-	-	X	-	-	-	X	OS	OS	X	OS	X	-	OS	-
Building Pathfinder	-	X	-	-	-	-	-	-	-	-	-	-	-	-	-
Autodesk Insight	-	X		-	X	X	X	OS	OS	OS	OS	X	-	-	-
Bombyx	-	X	-	-	-	-	X	-	-	OS	OS	-	-	-	-
BHoM	-	X		-	X	-	X	OS	OS	OS	OS	OS	OS	OS	OS
EC3	X	-	-	-	X	-	X	X	X	-	-	OS	-	X	X
EPiC	-	X	-	-	X	-	-	X	X	X	-	X	X	-	-
CARE	-	X	-	-	X	-	-	-	-	X	-	X	-	-	-
Autodesk Forma	-	X	-	-	-	-	-	OS	OS	OS	OS		OS	OS	OS
REAL Tool	-	X	-	-	X	-	-	-	-	-	-	X	-	-	-

3.5 Outputs

3.5.1 Environmental Impacts

The results show that all the studied tools include Global Warming potential in their analysis output, however the other TRACI indicators are less regarded in the ecosystems of tools. Athena Impact Estimator, Tally, One Click LCA and eTool have the most various impact categories in their results. As the Table 6 shows, recent tools , such as BHoM, EC3, forma, Insight, Cove tool, EPIC , Care, focus more on carbon, excluding other indicators from their scope. Most of the studied tools used TRACI as they are in the North American context. One click LCA and eTool can include other environmental impacts such as CML.

3.5.2 Biogenic Carbon

In terms of biogenic carbon analysis, half of the tools report the carbon savings through using bio-based materials separately, while others include that in A1-A3 and C (if included) emissions. EPIC tools has a more stringent approach towards carbon saving accounting through using wood based material. Only use of wooden material in this tool won't lead to carbon saving and the user is asked to confirm if the materials is responsibly supplied. In accordance with ISO 21930. Responsibly supplied wood is determined if it is necessarily sourced from a transparent and traceable supply chain and either has a growing carbon stock or is certified, recycled or reclaimed material. By having these conditions biogenic carbon will be deducted from total carbon. Moreover this tool has the option to include softscape and estimate carbon absorption of adjacent green space.

3.5.3 Circularity

The results show that in the current ecosystem of North American tools, circularity report is addressed only in one tool. The reason can be found in regulations and standards that mandates and requires circularity assessments in Europe, while in North America circularity is optional and not required. Among the studied tools Only One Click LCA has a simplistic approach towards Circularity by reporting the percentage of recycled, reused or renewable percentage of the mass in a materials. While this input wouldn't impact A1-A3 emissions, it is used in circularity indicators. REAL tool and EPIC also allows users to choose the recycling percentage which will impact the upfront and end of life emissions. None of the studied tools use circularity indicators such as Building Circularity Index (BCI) or Circular Economic Value (CEV).

3.5.4 Output format

Output format may vary a lot based on the tools . The most popular format used is graphs. Stacked bar charts and pie charts facilitate hotspot and contribution analysis (Real tool, One Click, Tally, EPIC, Covetool, CARE). Also for design scenario comparison bar charts have been used (One Click LCA, Athena.). While previous studies have shown the impact of using color coding in reporting results in the building sector, only three tools of Forma, Insight and Bombyx provide color coding output in order to show the impact intensity of building components. Use of parallel coordinate in building pathfinder allows users to explore options by easily filtering and selecting scenarios and providing instant reporting. One Click LCA and EC3 use sankey diagrams to show multi-level contribution analysis and allow users to customize the graph and report desired variables. EC3 uses boxplot to show the uncertainty associated with the impact as well as showing the achievable and conservative threshold, which shares 80th and 20th percentile of available EPDs respectively and potential in carbon reduction by material selection.
Most of the tools use different formats for reporting the results with most common as graphs, to tables (Athena, tally) or downloadable reports (Athena, Tally, eTool). This feature accommodates the needs of different users. However, the tools that are developed on other plugins (BHoM and Bombyx) normally rely on generating solely numbers and leave visualization of results to underlying features of the host tool.

Table 6- Summary of tool output

	outputs												
Tool	Environmental Indicators								Outputs format/Visualization				Time Series
	GWP	Acidification	Euthrophication	Smog	Human Health	Ozon Depletion	Biogenic Carbon Reported Separately?	Circularity	Graphs	Report	Tables	Color-Coding	
One Click LCA-tool suite	X	X	X	X	X	X	X	Percentage	X	X	X	-	-
Athena Impact Estimator	X	X	X	X	X	X	X	Not Included	X	X	X	-	-
etool	X	X	X	X	X	X	X	Not reported	X	X	X	-	-
Tally	X	X	X	X	X	X	X	Not reported	X	X	X	-	-
Cove Tool	X	-	-	-	-	-	-	Not reported	X	X	X	-	-
Building Pathfinder	X	-	-	-	-	-	-	Not reported	-	-	X	-	-
Autodesk Insight	X	-	-	-	-	-	-	Not reported	X	X	X	X	-
Bombyx	X	X	X	-	-	-	X	Not reported	-	-	-	X	-
BHoM	X	-	-	-	-	-	-	Not reported	-	-	-	-	-
EC3	X	-	-	-	-	-	X	Not reported	X	X	X	-	-
EPiC	X	-	-	-	-	-	X	Not reported	X	-	-	-	X
CARE	X	-	-	-	-	-	-	Not reported	X	-	-	-	X
Autodesk Forma	X	-	-	-	-	-	-	Not reported	X	X	X	X	-
REAL Tool	X	-	-	-	-	-	-	Not reported	X	-	-	-	X

3.6 Analysis

3.6.1 Design comparison

Majority of the tools (10 out of 14) provide **design comparison** options. This feature has been present in both older and newer tools. A closer look to the tools that excluded that feature, REAL tool and Pathfinder, shows that this analysis is excluded as the scope of analysis in these tools targets very early estimation based on building general features and not the design scenarios. Therefore as the “building design” does not exist in that stage they do not have design comparison features. The other two tools, Bombyx and BHoM, were developed on GH and depended on the features of the host tool to draw comparison on other scenarios. The motivation for tool developers toward this analysis is rooted in providing insights for design developments purposes as well as sustainability certificates reporting. CARE tool is developed based on the concept of comparison in decision making. This tool provides insight and estimated carbon emissions, in three scenarios of continued use, new construction or retrofit for a building.

3.6.2 Benchmark Analysis

Comparison of building scenarios allow architects to make design decisions and select the lower-carbon intensive scenarios, however, both scenarios can have relatively high carbon content and the comparison does not result in reaching low-carbon content possible. Benchmark analysis allows architects to compare their design with other similar buildings. This analysis requires a rich dataset of similar buildings and compares the project carbon footprint in the range of similar buildings’ output. Currently, this analysis is only provided by the EPIC tool. This tool uses the results of CLF Carbon Benchmark study (CLF, 2022) and can report the comparison of building total carbon along similar buildings per life cycle stages and included building elements. Cove tool can report benchmark analysis only for operational carbon. Covetool offers two methodologies for benchmark comparison. With little information on building use, location and standard to comply with, this tool can calculate energy consumption and resulting carbon emission to be compared with project B6 emissions as for operational carbon benchmark analysis. Additionally, this simple shoebox model can be defined with more data regarding building enclosure and geometry to calculate more accurate operational carbon estimations.

3.6.4 Hotspot Analysis

In order to report the most impactful components to building environmental impact, LCA tools use different hotspot analysis. The results show that environmental impacts breakdown by building components is the most common way of identifying contributors. Another popular hotspot analysis is impact breakdown by material. Lastly, tools use life cycle stages for impact break down.

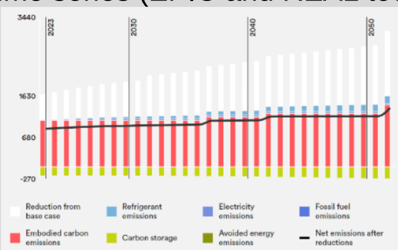
Results show that tools use different hotspot analysis each best suited for analysis in one stage of the project. For instance, the results of LCS hotspot analysis can be best useful for fundamental decisions in very early stages of the project through analyzing tradeoffs of different strategies. For example, tools that have LCS emissions breakdowns can help architects and other project stakeholders have a clear idea of carbon savings by using new materials, novel construction techniques, renewable energies or even master planning open space and comparing that to typical scenarios.

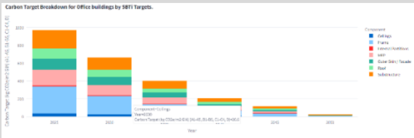
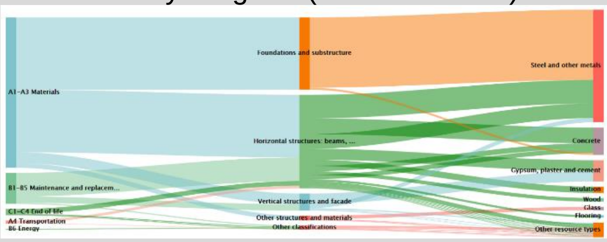
Component-level hotspot results can be best used at the design development stage. These results can show the most contributing components and help architects know the area of focus for cutting emissions through design refinement and development. Material-level hotspot analysis on the other hand can be helpful in the detailed design stage and help comparing use of different materials and find the lowest achievable emissions through material selection.

A new method of reporting LCA results is impact breakdown by component in annual granularity (EPIC tool) or decade granularity (REAL tool). The time series reporting provides a better understanding and deeper level of details that of building emissions throughout years and building life. Another remarkable feature is in one click LCA tool which allows users to merge any desired type of hotspot analysis to find the impacts and define the hotspot for further work towards carbon reduction which allows users to gain desired insight from the results.

Some tools aim to provide more insight on LCA results by combining the results of contribution analysis in the same graph in order to help users better identify the hotspots and area of focus. As the chart below shows, EPIC and REAL combine component impacts and life cycle stage in the timeseries chart and OneClick LCA allows users to see the breakdown of emissions per component, material and LCS in one sankey diagram.

Table 7- Novel hybrid hotspot analysis results by combining common methods in LCA tools

<table>
<tr><th colspan="3">Hotspot Analysis</th></tr>
<tr><th>Material-Level</th><th>Component-Level</th><th>LCA stage</th></tr>
<tr><td></td><td colspan="2">Time series (EPIC and REAL tool)

</td></tr>
</table>

<table>
<tr><td></td><td>
</td></tr>
<tr><td colspan="2">Sankey Diagram (One Click LCA)

</td></tr>
</table>

3.6.5 Uncertainty

Uncertainty analysis is another important requested analysis by stakeholders. The reason is that due to variation of materials in the market and their different carbon footprint, users are interested in knowing the achievable ranges of carbon footprint by using different level of carbon intensity of materials. This analysis requires a range of materials and quantifying emissions in case of using other materials with different carbon factors. EC3 provides such analysis, thanks to its extensive and growing EPD bank that can calculate project carbon as well as the range and achievable and conservative reduction by using typical materials or low carbon materials in the market. ETool also has a meticulous approach towards uncertainty by assigning default uncertainty factor to project, material quantity and carbon data. In defining material environmental impacts, eTool allows users to define uncertainty factors manually. The results also indicate that none of the tools have utilized Radiative forcing or dynamic LCA in their analysis.

Table 8- Summary of tool analyses

	Analysis							
Tool	Use of Radiative Forcing	Design Alternatives Comparison	Benchmark comparison and reporting	Hotspot Analysis: Material	Hotspot Analysis: Component	Hotspot Analysis: LCS	Dynamic-Static LCA comparison	ncertainty Analys
One Click LCA-tool suite	-	×	-	×	×	×	-	-
Athena Impact Estimator	-	×	-	×	×	×	-	-
etool	-	×	-	×	×	×	-	×
Tally	-	×	-	×	×	×	-	-
Cove Tool	-	×	-	-	×	-	-	-
Building Pathfinder	-	-	-	-	-	-	-	-
Autodesk Insight	-	×	-	×	×	-	-	-
Bombyx	-	-	-	-	-	-	-	-
BHoM	-	-	-	-	-	-	-	-
EC3	-	×	-	×	-	-	-	×
EPiC	-	×	×	×	×	×	-	-
CARE	-	×	-	-	-	-	-	-
Autodesk Forma	-	×	-	-	×	-	-	-
REAL Tool	-	-	-	-	×	-	-	-

4. Discussions

A review on the studied tools and the collected data shows remarkable trends in development of tools in recent years. There are also some gaps identified which can be the topic of future development for reaching zero-carbon goals and proceed to carbon positive buildings which can be implemented by accurate and reliable LCA tools.
It seems that with respect of standards and certificate requirements on carbon, more and more tools, especially recent tools are targeting GWP and exclude other indicators from their results,
Which shows the flexibility and adaptation of the ecosystem of LCA tools to match the needs of the industry. It also indicates the impact of policies in forming the need and therefore future LCA tools.

4.1 Tools Self-sufficiency

As the results show, the ecosystem of LCA tools is moving towards early-stage carbon assessment due to the influence of early stage decisions and in response to previously identified gaps in the literature. The new trend is observed in supporting self-sufficiency of the tool so that the LCA analysis can be done in different project stages as needed including early stages when less data is available. This new trend is also changing LCA tools to be used by not only sustainability consultants and LCA practitioners, but various groups of stakeholders. Unlike older tools that managed LCA complexity and data intensity by limiting the LCA stage scope or included building elements, new tools are addressing the challenge of data dependency in LCA by providing data for users.in different forms including default values, lists of scenarios to select from, average values, pertaining standards as default scenarios, benchmark values, etc. In case the user is using LCA in early stages, the default values can be used to draw results and in case analysis is conducted in later stages of the design, the tools accept as much project-specific data as available. A good example of the tools forming these trends are EPIC, REALtool, eTools and EC3. This has transformed LCA analysis tools from data intensive models that could not handle any missing data into flexible tools with versatile design applications.

In tools that are developed based on a host tool, such as plugins and add-ons, it is observed that these tools are moving towards independence, which means being self-sufficient and less dependent on host tools. This is observed by changing to web applications in recent updates that made the tool interface independent from the host tool. Development of web based tools or adding a web-based interface for existing tools is becoming a dominant trend. This facilitates utilizing cloud computing, data-driven machine learning technique in the area of LCA.

4.2 LCA integration in design space

Another trend is observed in tools that bridge the gaps of design stage compatibility. While the first trend of data sufficiency would facilitate fundamental decision making, in design scope LCA tools are still not fully compatible with design process application. Most of the tools do not have a design interface or the needed interoperability to work closely with a design tool. Some tools such as Forma, Insight, Bombyx and BHoM LCA tool kit have targeted the mentioned gap; they are still facing some limitations that impact their application in design and to assess the whole building LCA. For example, operational carbon of the design (in contrast to benchmark eui and OC) or embodied - operational tradeoff have been neglected in these tools due to their limited scope. While Covetool has addressed this gap by incorporating B emissions, it lacks end of life emissions and also emissions of an important component of building, MEP, is also excluded from the study. In summary, despite recent valuable tool development in the area of LCA integration into design, there is still a need for holistic LCA tools. A design-integrated tool that encompasses the whole building as a cohesive system through its complete life span, that allows users to design the building through informed tradeoffs and prioritizations.

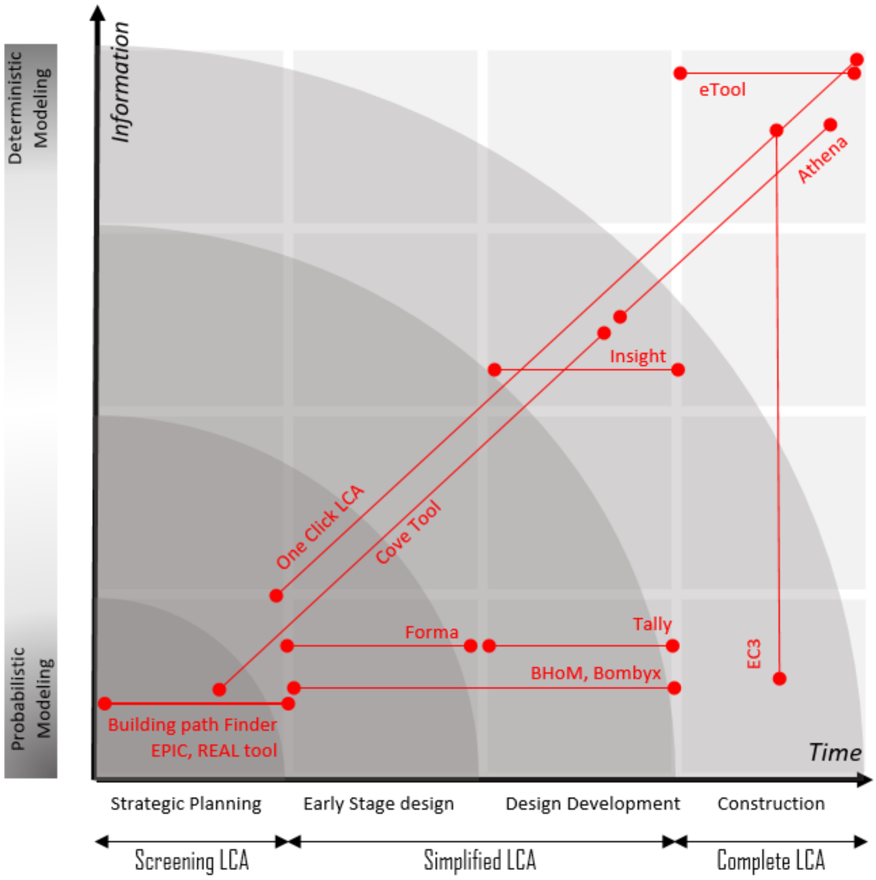


Fig. 3-Studied tools in terms of design stage application

4.3 Carbon capture and LCA tools

As mentioned in the results section, the evolutionary trend of LCA tool developments shows that more tools are providing users with options to quantify avoided carbon through design. Some recent tools allow users to estimate carbon reduction potential through using design strategies such as planted roofs, harvesting renewable energies on site, green space design etc. This trend pursues quantifying avoided carbon through design decisions however the results identifies a gap in this area. Currently most of the LCA tools accept uploading new materials however Majority of these tools allow only uploading LCA data for new materials and they do not assist users to quantify the impacts of a new material, building assembly or compare potential savings to an industry average equivalent. The tools that provide users with this option are rare in the current ecosystem of tools and more tools are needed to allow users to quantify carbon capture potential through utilizing novel and nature-based materials. Another potential method to bridge this gap is connecting EPD generators, material assessment modules to building assessment tools. As novel materials are a new source of carbon reduction through absorption it is expected that more tools would include this option.

4.4 Data

Despite recent advancements and LCA tools developments, data has remained an important challenge. For more comprehensive LCA analysis in the building sector, there is a need for more LCA data that is free and publicly available. LCIs can be one solution to this challenge. That represent the North American construction industry. In terms of using generic LCA data, ICE has long been a reference for construction materials emissions in the European context. EPIC is the same for Australia, however, in the North American context, there is a gap for free construction data. USLCI is a free carbon database that is not for construction purposes. Still there is a need for such data with focus on the construction industry.

Another gap in building LCA associated with data is lack of data in MEP emissions. This section of building emissions can make up for a great portion especially in the demolition stage due to refrigerants however due to lack of MEP data, it is the least regarded building system in LCA tools. Providing EPD data by manufacturers as well as industry average data by the research community can significantly contribute to bridging this gap. Another challenge in this regard is associated with estimating MEP systems material which requires further research on the built MEP material quantity in different typologies of buildings.

4.5 Simplification

The review of tools show that most LCA tools are focused on A1-A3 stages, which result from more and more available data and available EPDs, however, other stages are either excluded from the study or calculated with simplistic and unmodifiable assumptions. Therefore, there is a significant need for incorporating more LCS in current tools and having WBLCA tools. Special attention should be drawn to end of life (module C) as well as module D. specially for assessing circularity and design for disassembly potential incorporating module D and C is crucial. Assessing added carbon and saving through retrofit and deciding between retrofit or rebuild for a project is another important question that current tools can not address well. However, by elaborating on module B emissions this can be answered. Current methodologies also has underestimated module A4 emissions. The scenarios also do not reflect today's global procurement and supply. More data in defining different transportation scenarios and distances should also be taken into account in future tools. The results of this review shows that recent tools are aiming to cover these steps and there is a need for more research in these areas to provide data and realistic market scenarios to facilitate developments of WBLCA tools.

5. Conclusion

This paper presents a review and comparative analysis of the current state of LCA tools in the context of a sustainability assessment in the built environment. The study aimed to identify trends in the evolution of LCA tools and plugins and identify the gaps for future research to support NetZero and carbon positive building design. The introduction of the paper highlights

the role of building LCA tools in facilitating the reduction of environmental impacts and promoting net-zero and carbon-absorbing carbon building design. As these goals are embedded within carbon reduction targets and progressive sustainability goals, they are demanded by large groups of stakeholders. To respond to this need new LCA tools have been developed and the ecosystem of building LCA tools has grown over the past decade. Therefore, there is a need in analyzing the tools and by showcasing their capabilities, unique functions and outputs, provide guidance for the stakeholders to select the proper tools. In the literature review section, previous research in studying and evaluating LCA tools were reviewed and the most pertaining findings were reviewed. In the methods section, a new tool characterization framework was defined for the means of this study which integrated the most crucial features from literature as well as additional criteria from stakeholders for investigating the tools. The findings of this study identified the main features and potentials of the current ecosystem of LCA tools. The discussion section shows the main trends and directions that were adopted to meet the needs of stakeholders. Also, we highlight the gaps and present recommendations for further development.
In this review we found that remarkable advancement in recent years have been made in developing LCA tools. New tools can provide insight for deployment of fundamental strategies in early stages. Design integrated LCA tools also need further development to provide insight for design decision making through fast, flexible and reliable LCA results in early stage design to achieve project sustainability targets. They also adapted to the new formats to utilize the new methodologies and computation capacities for high performance LCA models. LCA tools also show the recent trend of pushing system boundaries to include site landscape and green roof carbon savings which is an crucial stage in addressing carbon positivity and balancing out other stage emissions to reach net-zero targets. Tools has recognized the need to include new materials and technologies in their analysis, however further work is needed to meet this need for designing carbon absorbing buildings in future.

Despite recent advancements, the ecosystem of LCA tools faces numerous areas for future advancement. The study suggests that the ecosystem of LCA tools require the adaptability to incorporate state-of-the-art material and assemblies in their analyses to quantify carbon reduction potentials. Tools need more interoperability with EPD generators or LCA engines to quantify the carbon capture feature of novel materials and technological assemblies. Additionally, design and decision making could be further integrated in more comprehensive LCA tools. Moreover building LCA analysis can support addressing critical questions based on building performance by incorporating holistic approach and realistic data. LCA tools have the potential to support the sustainable transition of the construction sector from low carbon to carbon positive built environment. However, further developments are still needed for digital tools to allow for a comprehensive evaluation of environmental footprint, carbon capture, and other sustainability aspects.

6. References

Apellániz, D., Pasanen, P., & Gengnagel, C. (2021). A Holistic and Parametric Approach for Life Cycle Assessment in the Early Design Stages. *SimAUD 2021*.

Bari, R. D., Horn, R., Bruhn, S., Alaux, N., Saade, M. R. M., Soust-Verdaguer, B., Obrecht, T. P., Hollberg, A., Birgisdottír, H., Passer, A., & Frischknecht, R. (2022). Buildings LCA and digitalization: Designers' toolbox based on a survey. *IOP Conference Series: Earth and Environmental Science*, *1078*(1), 012092. https://doi.org/10.1088/1755-1315/1078/1/012092

Basic, S., Hollberg, A., Galimshina, A., & Habert, G. (2019). A design integrated parametric tool for real-time Life Cycle Assessment – Bombyx project. IOP Conference Series: Earth and Environmental Science, *323*(1), 012112. https://doi.org/10.1088/1755-1315/323/1/012112

Chen, J., Kharbanda, K., & Loganathan, H. (2021). *Cardinal LCA* (0.0.1).

CLF. (2022). *CLF WBLCA Benchmark Study v2 - Carbon Leadership Forum*. https://carbonleadershipforum.org/clf-wblca-v2/

DallaMora, T., Bolzonello, E., Cavalliere, C., & Peron, F. (2020). Key Parameters Featuring BIM-LCA Integration in Buildings: A Practical Review of the Current Trends. *Sustainability*, *12*(17), 7182. https://doi.org/10.3390/su12177182

Dervishaj, A., & Gudmundsson, K. (2024a). From LCA to circular design: A comparative study of digital tools for the built environment. *Resources, Conservation and Recycling*, *200*, 107291. https://doi.org/10.1016/j.resconrec.2023.107291

Dervishaj, A., & Gudmundsson, K. (2024b). From LCA to circular design: A comparative study of digital tools for the built environment. Resources, Conservation and Recycling, 200, 107291. https://doi.org/10.1016/j.resconrec.2023.107291

DeWolf, C., Cordella, M., Dodd, N., Byers, B., & Donatello, S. (2023). Whole life cycle environmental impact assessment of buildings: Developing software tool and database support for the EU framework Level(s). Resources, Conservation and Recycling, *188*, 106642. https://doi.org/10.1016/j.resconrec.2022.106642

EcoBIM", "Circular. (2022). *Circular EcoBIM*. https://circularecobim.eu

Ganguly, I., Pierobon, F., & Hall, E. S. (2020). Global Warming Mitigating Role of Wood Products from Washington State's Private *Forests*. Forests, *11*(2), 194. https://doi.org/10.3390/f11020194

Hildebrand, & Linda. (2018). Hildebrand, Linda & Bach, Rebecca. (2018). A Comparative Overview of Tools for Environmental Assessment of Materials, Components and Buildings. In *sustainable and resilient building design: approaches, methods and tools* (pp. 143–157). BK Books.

Hollberg, A., Genova, G., & Habert, G. (2020). Evaluation of BIM-based LCA results for building design. *Automation in Construction*, *109*, 102972. https://doi.org/10.1016/j.autcon.2019.102972

Hollberg, A., Kiss, B., Röck, M., Soust-Verdaguer, B., Wiberg, A. H., Lasvaux, S., Galimshina, A., & Habert, G. (2021). Review of visualising LCA results in the design process of buildings. *Building and Environment*, *190*, 107530. https://doi.org/10.1016/j.buildenv.2020.107530

Hollberg, A., Tjäder, M., Ingelhag, G., & Wallbaum, H. (2022). A Framework for User Centric LCA Tool Development for Early Planning Stages of Buildings. *Frontiers in Built Environment*, *8*, 744946. https://doi.org/10.3389/fbuil.2022.744946

Kiss, B., & Szalay, Z. (2020). Modular approach to multi-objective environmental optimization of buildings. Automation in Construction, *111*, 103044. https://doi.org/10.1016/j.autcon.2019.103044

Kuittinen, M., Zernicke, C., Slabik, S., & Hafner, A. (2021). How can carbon be stored in the built environment? A review of potential options. *Architectural Science Review*, 1–17. https://doi.org/10.1080/00038628.2021.1896471

Manni, M., Lobaccaro, G., Lolli, N., & Bohne, R. A. (2020). Parametric Design to Maximize Solar Irradiation and Minimize the Embodied GHG Emissions for a ZEB in Nordic and Mediterranean Climate Zones. *Energies*, *13*(18), 4981. https://doi.org/10.3390/en13184981

Nguyen, T. D., & Pishdad-Bozorgi, P. (2023). A Review of Life Cycle Assessment Tools for Measuring the Environmental Impact of Building and a Decision Support Framework for Choosing Among Them. *EPIC Series in Built Environment*, *4*, 816–806. https://doi.org/10.29007/pcmw

Obrecht, T. P., Röck, M., Hoxha, E., & Passer, A. (2020). BIM and LCA Integration: A Systematic Literature Review. Sustainability, 12(14), 5534. https://doi.org/10.3390/su12145534

Płoszaj-Mazurek, M., Ryńska, E., & Grochulska-Salak, M. (2020). Methods to Optimize Carbon Footprint of Buildings in Regenerative Architectural Design with the Use of Machine Learning, Convolutional Neural Network, and Parametric Design. Energies, 13(20), 5289. https://doi.org/10.3390/en13205289

Prideaux, F., Allacker, K., Crawford, R. H., & Stephan, A. (2022). A review of embodied life cycle assessment tools used to support the building design process. IOP Conference Series: Earth and Environmental Science, *1122*(1), 012031. https://doi.org/10.1088/1755-1315/1122/1/012031

Säwén, T., Kalagasidis, A. S., & Hollberg, A. (2024). Critical perspectives on life cycle building performance assessment tool reviews. *Renewable and Sustainable Energy Reviews*, *197*, 114407. https://doi.org/10.1016/j.rser.2024.114407

Säwén, T., Magnusson, E., Kalagasidis, A. S., & Hollberg, A. (2022). Tool characterisation framework for parametric building LCA. IOP Conference Series: Earth and Environmental Science, 1078(1), 012090. https://doi.org/10.1088/1755-1315/1078/1/012090

Soust-Verdaguer, B., Llatas, C., & García-Martínez, A. (2017). Critical review of bim-based LCA method to buildings. *Energy and Buildings*, *136*, 110–120. https://doi.org/10.1016/j.enbuild.2016.12.009

Thumfarth, M. (2016). *Tortuga-LCA in grasshopper*. https://www. food4rhino.com/en/app/tortuga-lca-grasshopper

University, C. C. L., Cornell, Heisel, F., & Becker, C. (2020). RhinoCircular: Development and Testing of a Circularity Indicator Tool for Application in Early Design Phases and Architectural Education. *2020 AIA/ACSA Intersections Research Conference: CARBON*, 154–159. https://doi.org/10.35483/acsa.aia.fallintercarbon.20.24

Wang, R., Lu, S., Feng, W., Zhai, X., & Li, X. (2020). Sustainable framework for buildings in cold regions of China considering life cycle cost and environmental impact as well as thermal comfort. *Energy Reports*, *6*, 3036–3050. https://doi.org/10.1016/j.egyr.2020.10.023

Wastiels, L., & Decuypere, R. (2019). Identification and comparison of LCA-BIM integration strategies. IOP Conference Series: Earth and Environmental Science, 323(1), 012101. https://doi.org/10.1088/1755-1315/323/1/012101

ISO, I. (2013). 25964-2: 2011 Information and Documentation-Thesauri and Interoperability with Other Vocabularies-Part 2: Interoperability with other vocabularies. International Organization for Standardization.

Kiss, B., & Szalay, Z. (2020). Modular approach to multi-objective environmental optimization of buildings. Automation in Construction, *111*, 103044. https://doi.org/10.1016/j.autcon.2019.103044

Manni, M., Lobaccaro, G., Lolli, N., & Bohne, R. A. (2020). Parametric Design to Maximize Solar Irradiation and Minimize the Embodied GHG Emissions for a ZEB in Nordic and Mediterranean Climate Zones. *Energies*, *13*(18), 4981. https://doi.org/10.3390/en13184981

Nguyen, T. D., & Pishdad-Bozorgi, P. (2023). A Review of Life Cycle Assessment Tools for Measuring the Environmental Impact of Building and a Decision Support Framework for Choosing Among Them. *EPIC Series in Built Environment*, *4*, 816–806. https://doi.org/10.29007/pcmw

Obrecht, T. P., Röck, M., Hoxha, E., & Passer, A. (2020). BIM and LCA Integration: A Systematic Literature Review. Sustainability, 12(14), 5534. https://doi.org/10.3390/su12145534

Płoszaj-Mazurek, M., Ryńska, E., & Grochulska-Salak, M. (2020). Methods to Optimize Carbon Footprint of Buildings in Regenerative Architectural Design with the Use of Machine Learning, Convolutional Neural Network, and Parametric Design. Energies, 13(20), 5289. https://doi.org/10.3390/en13205289

Prideaux, F., Allacker, K., Crawford, R. H., & Stephan, A. (2022). A review of embodied life cycle assessment tools used to support the building design process. IOP Conference Series: Earth and Environmental Science, *1122*(1), 012031. https://doi.org/10.1088/1755-1315/1122/1/012031

Säwén, T., Magnusson, E., Kalagasidis, A. S., & Hollberg, A. (2022). Tool characterisation framework for parametric building LCA. IOP Conference Series: Earth and Environmental Science, *1078*(1), 012090. https://doi.org/10.1088/1755-1315/1078/1/012090

Soust-Verdaguer, B., Llatas, C., & García-Martínez, A. (2017). Critical review of bim-based LCA method to buildings. *Energy and Buildings*, *136*, 110–120. https://doi.org/10.1016/j.enbuild.2016.12.009

Thumfarth, M. (2016). *Tortuga-LCA in grasshopper*. https://www. food4rhino.com/en/app/tortuga-lca-grasshopper

University, C. C. L., Cornell, Heisel, F., & Becker, C. (2020). RhinoCircular: Development and Testing of a Circularity Indicator Tool for Application in Early Design Phases and Architectural Education. *2020 AIA/ACSA Intersections Research Conference: CARBON*, 154–159. https://doi.org/10.35483/acsa.aia.fallintercarbon.20.24

Wang, R., Lu, S., Feng, W., Zhai, X., & Li, X. (2020). Sustainable framework for buildings in cold regions of China considering life cycle cost and environmental impact as well as thermal comfort. *Energy Reports*, *6*, 3036–3050. https://doi.org/10.1016/j.egyr.2020.10.023

Wastiels, L., & Decuypere, R. (2019). Identification and comparison of LCA-BIM integration strategies. IOP Conference Series: Earth and Environmental Science, 323(1), 012101. https://doi.org/10.1088/1755-1315/323/1/012101

Chapter 2- LCA Contributions Study

An LCA Framework to Prioritize Carbon-Sensitive Measures in Residential Building Design

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Abstract

Building design involves numerous trade-offs between several design objectives that span multiple aspects with diverse effects on building subsystems. Hence, low-carbon building design requires a comprehensive understanding of varied factors and their range of impact on building emissions throughout the building life cycle. Previous research often focuses on one building component at a time. This research devises an LCA framework that provides a holistic overview of all building subsystems in the Whole Building Life Cycle Assessment. The methodology integrates a sensitivity analysis entailing conventional material selection and construction details for the building envelope, the heating/cooling system and the structure of the building. The methodology is demonstrated for a midrise residential building in the city of Vancouver. Results indicate that certain timber buildings both in structure and envelope have the lowest environmental impact and heat pumps are the most effective heating systems to provide comfort with the lowest whole building emissions.

Keywords: Sensitivity Analysis, Life cycle Assessment, Embodied emissions, Low-carbon building design.

1. Introduction

Climate change has intensified over the past decades and has turned into a threat to human life. Special attention has been placed on greenhouse gases (GHGs) since their accumulation in the atmosphere is the primary cause of climate change. In British Columbia, policies are set to cut greenhouse gas emissions by 40 percent by 2030 and to net-zero by 2050 (Toronto & Dulmage, 2018). AEC (Architecture, Engineering, and Construction) makes up to 25% of national emissions, therefore, construction and operation of buildings is an important contributor to global GHG emissions (Torabi & Mahdavinejad, 2021). In the field of low-carbon building design, building operations have historically been the largest contributor to GHG emissions; however, embodied emissions (EE) have been gaining in importance in recent years. This is mainly due to reductions in operational emissions (OE) achieved through the decrease in the carbon intensity of electricity and improvements in building energy systems. In British Columbia, the share of EE and OE in building whole life cycle emissions are roughly equal. EE has received scant attention in the research community as the top priority has been operational energy, therefore, there is a huge potential to mitigate buildings emissions by tackling EE, and it is growing to be more and more important (Engineering Net Zero, 2021.; Toronto & Dulmage, 2018).

In this study, firstly, the impact of building subsystems on EE is investigated. Secondly, as a building is defined as a system, changes in each component would impact other subsystems and result in the overall efficiency of the building. Therefore, no design decision can be evaluated correctly unless the impact on energy demands and building occupants is investigated. In this study, the most important contributor of building carbon footprint is investigated considering scenarios for structural and envelope design and heating options.

2. Background

Life Cycle Assessment (LCA) of buildings is a fast-growing research area with a number of publications that have more than doubled in recent years (Jusselme et al., 2020; Torabi et al., 2022). Historically OE was considered the most influential part of building emissions and consequently the research focus was drawn to tackling OE. In recent years however, with advances in in renewable energy extraction, efficient buildings and decarbonized energy sources, OE has been controlled significantly. This has results to steering attention towards the impact of EE in cutting whole building emissions, as there is huge potential in this overlooked issue.

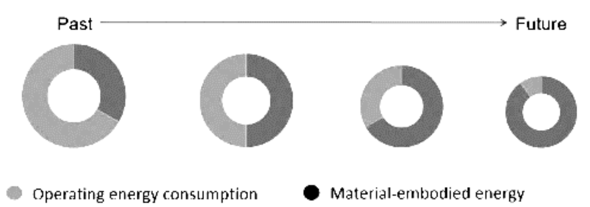

Figure 1- trend in life cycle energy/carbon in buildings from (Embodied Carbon in Construction, 2017)

Previous research shed light on the carbon footprint of a single components of the building individually. They have conducted an in-depth analysis of EE through variables in a subsystem. For example, to investigate EE of structure, DeWolf in a comprehensive study calculated structural emissions associated with different building archetypes. In her calculation, she considered different structural systems and materials according to local constructions. She also has reported the level of uncertainty associated with structural design in whole building emissions (De Wolf, 2017).

Similarly, in a research Schneider et al investigated the impact of structure on building environmental impact. They concluded that exchanging reinforced concrete for a wood structure reduces total GHG emissions by 25%, which emphasizes the importance of structure on building carbon footprint(Schneider-Marin et al., 2020). Similarly, the impact of Hvac systems in building EE has been addressed. Rodriguez addressed the EE associated with heating and cooling equipment and their distribution systems with a focus on the Northwest Pacific market (Rodriguez, 2019a). Similar research has been done in other regions (Kiamili et al., 2020).

The impact of envelope in whole building emissions is also investigated in several studies. In the study carried out at the Norwegian University of Science and Technology EE in single-family house was studied. Analysis was done according to the current standards in Norway (TEK 17), using an LCA approach. The study examines various insulation types and thicknesses in search of the most effective combination for lowering the lifetime emissions of the building. The study also identifies the part of the building envelope where additional insulation is most efficient in reducing the lifetime greenhouse gas emissions of the building. This study shows that the calculated GHG emissions vary inversely proportionally with the material quantities in building envelope. (Totland et al., 2019)

Although previous research clarifies emissions resulted from subsystems of a building in detail, they neglect multi-aspect, complex and interwoven impact of subsystem on one another and on whole building emissions. In other words, the goals of these fragmented studies are not mutually independent but closely related and interplaying with each other and some of them are even in a trade-offs. Therefore, a research gap is observed in addressing whole building emissions with a holistic approach.

To address this research gap, it is important to consider the impact of components on whole building emissions as one building with low EE can have high OE which over all dimmish all savings in manufacturing and construction phase. On contrary, all savings in OE through building life span might not justify huge EE of over-insulated passive building in design and construction phase. This shows the importance of adopting whole approach to EE modeling in LCA studies.

To adopt a holistic approach to whole building emissions, the initial is to identify the priorities. This can be defined as materials or systems that contribute the most to a building's emissions. Knowing the range of carbon-intensity associated with building components can help architects and engineers manage time, effort, and cost more effectively in projects and helps them to come up with better designs for lowering building total environmental footprint.

3. Methodology

The model for this research is developed in Rhino and Grasshopper and takes local data from Environmental Product Declarations (EPD)s as input data. All input data including thermos-physical characteristics of the materials, material EE, energy grid carbon intensity, and other required information are compiled and imported in an excel-sheet which in this report is called "Source Data File".

3.1. LCA Scope

The scope of this study is cradle to gate, covering stages A1-3, B6 of the building life cycle according to EN 15978 that encompasses production, manufacturing and building operation until end of life. The functional unit to evaluate scenarios is Kg or tonnes of CO_{2eq} and the life span of the building is 60 years. Figure.1 illustrates the LCA analysis scope.

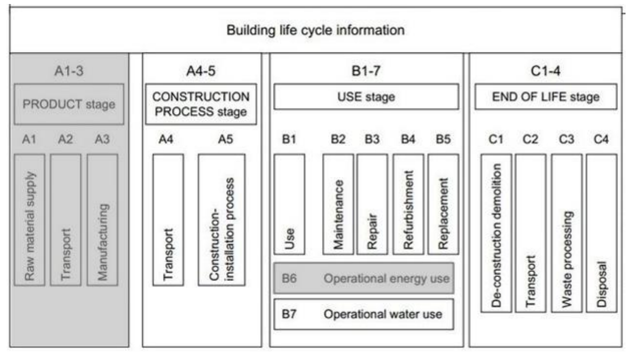

Figure 2- LCA Scope of this study from (CEN, 2011)

3.2. Modeling Framework

The model developed in this study to evaluate EE and OE is comprised of four modules to report emissions associated with building envelope, structure, heating system, operational energy consumption. As mentioned previously energy consumption and associated emissions is calculated to determine the impact of changes in building envelope and heating system on lifetime emissions. The figure below, illustrates 45 studied scenarios.

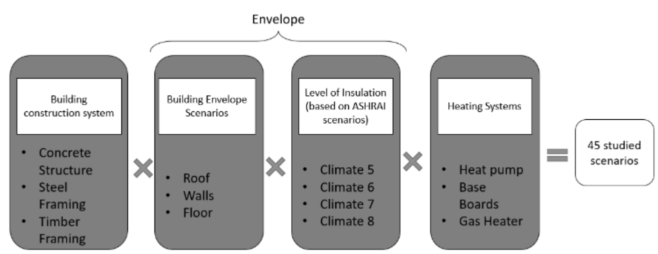

Figure 3- Scenario definition

3.2.1.Envelope

The envelope section of the model uses the construction details based on construction sets of ASHRAE 2019. The city of Vancouver is in climate 4, however, due to inclination to highly insulated buildings for new constructions in Vancouver, ASHRAE constructions from climates with higher heating demand were used for modeling in order to cover the higher level of insulation.

Table 1- Building envelope options

Envelope component	Studied ASHRAI Scenarios	Normalized EE ($KgCo_{2eq}/m^2$)
Wall	Typical Insulated Wood Framed Exterior Wall-R20	15
	Typical Insulated Exterior Mass Wall-R13	74
	Typical Insulated Metal Building Wall-R23	114
	Typical Insulated Metal Building Wall-R26	118
Roof	Typical Wood Joist Attic Floor-R48	12
	Typical IEAD Roof-R32	44
	Typical Insulated Metal Building Roof-R35	50
	Typical Insulated Metal Building Roof-R39	56
Floor	Typical Insulated Carpeted 8in Slab Floor-R5	63
	Typical Insulated Carpeted 8in Slab Floor-R8	65
	Typical Insulated Carpeted 8in Slab Floor-R10	68

3.2.2.Structure

The structure is estimated to be a concrete, steel, or wooden framing structure according to conventional structural systems in BC. In this study the result of a study on structure mass is used (Roynon, 2020). The concrete structure features in situ columns and flat slabs (400 mm), the steel option has composite decking (120 mm) with a steel frame, and the timber building uses a glulam frame with primary beams, secondary beams and CLT floors (100 mm). All designs include a concrete core and pad foundations.

The detail of structure mass for three structure systems is tabulated in Table2. The emissions were calculated using the LCI dataset (Hawkins et al., 2021; Oladazimi et al., 2020).

Table 2-Embodied energy and emissions of structural systems

Structural Material	Structure Emissions Intensity ($kgCO_{2eq}/m^2$)	EE ($MtCO_{2eq}$)
Concert	384	2.48
Steel	275	1.78
Timber	187	1.2

3.2.3.Heating system

For heating system systems, conventional heating systems were defined based on literature. To calculate the EE of heating systems, EE of equipment was calculated, as well as distribution systems (Planning, 2019). Emissions associated with equipment was calculated using the list of materials from EPDs and previous studies. Similarly, emissions for distribution system was calculated using a similar case study(Pease & Jayati Chhabra Zahra Zolfaghari Member ASHRAE, n.d.; Shah et al., 2008; Zheng et al., 2016).

Table 3- The components of the three heating and cooling systems

Heating system	Fuel consumption	Central appliances	Distribution system
Electric baseboard	Electricity	Baseboard	-
Residential Heat pump-no cooling	Electricity	Heat pump Fan coil unit	Ductwork
Gas heater	Natural Gas	Furnace	Ductwork

3.2.4.Operational Emissions

As mentioned previously, this research is focused on reducing WBLCA with a focus on EE; however, due to the significant impact of OE on WBLCA, this parameter is also simulated. To be more detailed as firstly OE comprises almost half of WBE, and secondly, it is deeply affected by the parameters forming EE, in a holistic approach to WBLCA both EE and OE should be monitored.

In this model, first model according to designated construction system, envelope and heating system is updated, then energy consumption for each scenario is calculated using EnergyPlus in honeybee. Lastly, emissions associated with energy consumption is calculated in grasshopper using carbon-intensity information provided by BC Ministry of Environment (Ministry of Environment and climate change strategy, 2022). This information is embedded in model using "Source data file".

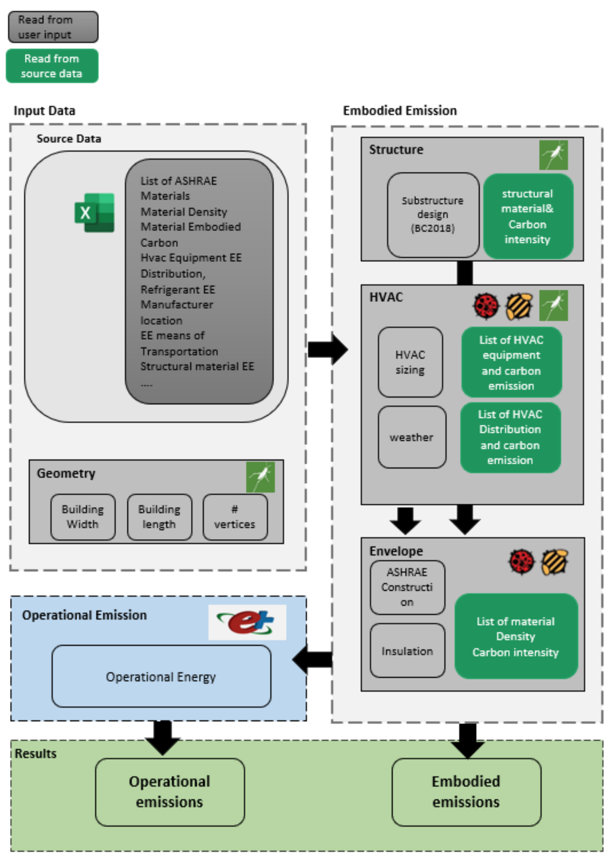

Figure 4- Modeling framework showing inputs and outputs of the four modules

The novelty of this research is mainly, in its holistic approach which aims to bridge the marked gap of disaggregated LCA studies in the literature. Outputs of this model shows the real impact of each design decision on whole life-time emissions of building which can help architects to make principal decisions in sustainable design consciously. Secondly, as this model is developed in parametric space, it can be best coupled with form finding modules in architectural software and provide accurate results on building environmental output instantly during early stages of design. Lastly, considering thermos-physical features of building in each design iteration, results of this modeling approach, shows the major carbon emitter in design alternative and shed light on next steps of back-and-forth process of design to reduce carbon footprint of the building.

3.3. Case Study

The case study building is a residential building in Vancouver. The building footprint is a 36*36 square with 4 residential units. The building

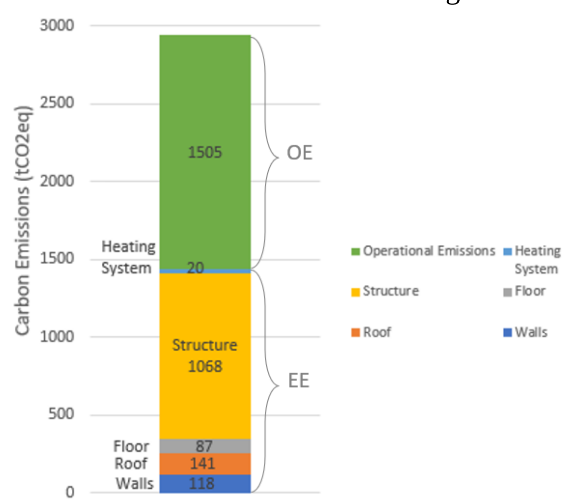

Figure 5-Average OE and EE of studied cases and main contributors

enclosure has window-to-wall ratio of 20% on all facades. Building is facing south. The building has 5 storeys with spans of 9 m and an imposed loading of 5 kN/m^2 . For this building, 45 scenarios with different construction systems (defining structure and envelope layers) was modelled. Further, different level of insulation was investigated to including code minimum and better-insulated buildings. Finally, conventional gas and electricity-consuming heating systems was defined in model. The EE of building was calculated and to monitor the impact of building component design on OE, energy consumption was also modelled coupling model to EnergyPlus. The EE, OE and whole building emissions is reported in Figure 8.

4. Results

British Columbia has one of the cleanest electricity grids in Canada, Therefore, the majority of buildings' carbon footprint is EE. Figure 5 illustrates the proportion of average EE versus OE for 45 studied scenarios of this study while Figure 8 shows the amount of EE and OE in each scenario. As the figure shows, due to the low carbon intensity of electricity in BC, average EE dominants OE, however, in some scenarios EE dominates OE and in some others, they share an equal share in building total emissions. It can be understood from the graphs EE associated with the structure is the main factor in building EE, which makes up for more than half of building EE. Envelope emissions is the second contributor to building EE, which is comprised of roof, wall and floor emissions. Wall EE grows to be more significant in highrise while in midrise and lowrise buildings the impact of the roof is more significant due to the high emissions of roof insulation, especially in colder climates.

4.1. Envelope and structure

Figure 8 reveals the result of carbon footprint in 45 studied scenarios in this study. As the figure shows OE in all scenarios are roughly similar with a 5% discrepancy, however, their EE can vary remarkably according to building characteristics and material selection. Buildings with concrete structures have noticeably higher EE than OE which is due to the high carbon intensity of reinforced concrete. Concrete structure buildings have also higher EE in comparison to buildings with steel and wooden framed structure. The difference between OE and EE amounts is minimum in buildings with wooden framing. Having lower EE for timber reduces buildings carbon footprint significantly.

4.2. Heating System

Figure 6 shows the energy efficiency of three studied heating systems in providing comfort conditions for the studied building. As it can be extracted from the figure, considering thermal behavior of building envelope due to varied insulation of building enclosure, scenarios with heat pumps for heating report less energy consumption and consequently lower OE. In the next place, electric baseboard and gas heater are reported with 13% and 17% increase in OE. It is worth mentioning that the ranks of heating systems in terms of EE is showing another pattern, with electric baseboards with the least EE followed by gas heaters and heat pumps with the highest EE. The reason can be found in the self-sufficiency of electric baseboards from the distribution system to convey hot fluid to the equipment, while heat pumps need distribution systems as well as transmission equipment such as fan coils that justify higher EE.

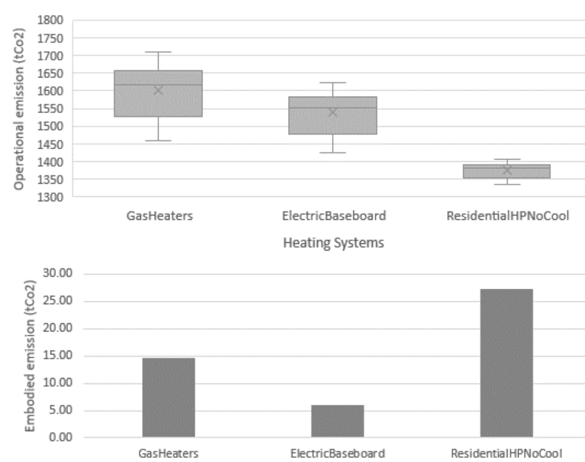

Figure 6- Comparison of Heating systems in terms of EE and OE

5. Discussion

The results of this study show the importance of structure in building carbon emissions in residential buildings. Studying the impact of structure on building EE shows that using high-carbon-intensity structural material can increase building emissions by up to 53%. Comparing the total emissions of the scenarios reveals that, timber framed structure not only provides a stable structure with lower emissions, due to high thermal resistance of wood, but these buildings also have better thermal performance and report lower energy consumption and OE. The results of this study show that wooden structures can be a good option for midrise residential buildings.

Similarly, envelope design and material selection play a significant role in building total emissions. Among the factors of the building envelope, walls and roof make up a noticeable portion of envelope emissions, which shows the priorities of building detailed envelope design in low carbon design to architects and engineers.

In terms of heating system, the scenarios show that electricity and gas consuming equipment and required distribution systems makes up 8% of EE. This amount might be significant using refrigerant based equipments and should be furthered investigated according to heating and cooling systems of the project. The comparison of EE and OE buildings according to heating systems shows that although heat pumps have remarkable higher EE in comparison to other options, due to its energy efficiency and lower OE it is the best option for residential heating system among studied scenarios.

Verification of results

In LCA studies, results cannot be evaluated using real data as real time emissions measurements are not possible. To be more detailed, as emissions factors for building material and equipment result from a chain of processes both within and outside construction project, it cannot be modelled in real condition (Ao et al., n.d.; Ciroth & Becker, 2006; Laurent et al., 2020).

Therefore researchers must verify results by first assuring the accuracy of model and calculations and then by using the results of similar studies for comparison. Therefore, to make the most reliable results of model, the calculations and outputs of modules where controlled separately and in conjunction. Secondly, the result of this study were compared to similar previous studies, each of which investigated EE of a single subsystem of the building (de Wolf, 2014; Hollberg et al., 2016; Rodriguez, 2019b). The results show good compliance to similar studies and therefore can be reliable for estimating carbon footprints of residential buildings in city of Vancouver and similar regions. The calculations for OE and EE are checked separately for correctness. The results can be checked in different layers, according to their objective and subject:

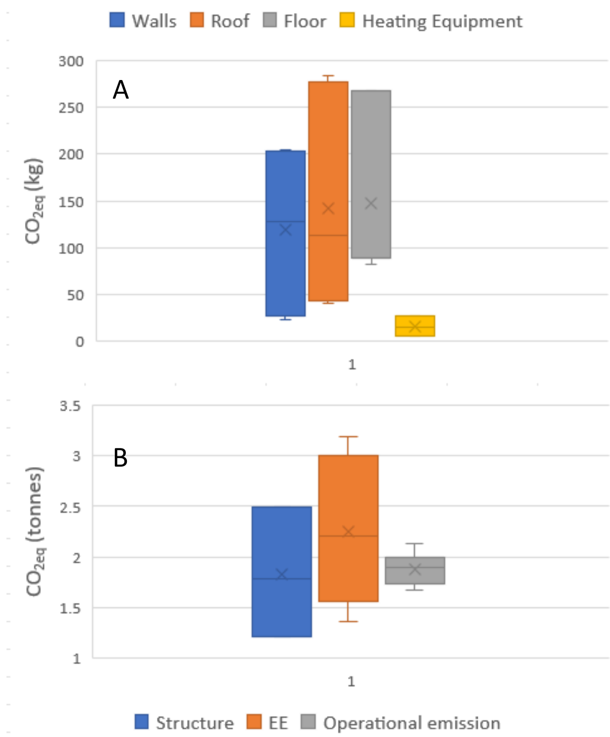

Figure 7-A) Deviation in EE of Envelope components and Heating systems. B) Deviation in EE of structure, EE, and OE in studied scenarios

6. Conclusions

In reducing building emissions through design, architects and engineers need to know the main contributors to dedicate time and effort to better decisions in those sections. Due to uncertainty in design and construction, there might always be changes. However, managing building emissions could be conducted easier and more effectively by determining the priorities in building emissions and the range of influence of each subsystem.

The result of this study reveals information on EE and OE of feasible construction scenarios for a typical residential building in Vancouver. The dependent variables are building structure options, envelope design, and conventional heating systems. The results show that with the benefit of low carbon energy use in BC, today EE is more important than before. Also, the structure is identified the most significant impact on building emissions and the lowest design solution for this case study is wooden frames building with the highest insulation and heat pump heating system. Total emissions can be increased to 53% in the scenario with concrete structure, lowest insulation, and gas heater.

7. References

Ao, S.-I., Douglas, C., Grundfest, W. S., & International Association of Engineers. (n.d.). *World Congress on Engineering and Computer Science : WCECS 2016 : 19-21 October, 2016, San Francisco, USA*.

CEN. (2011). *EN 15978 Sustainability of Construction Works - Assessment of Environmental Performance of Buildings - Calculation Method*. *436*.

Ciroth, A., & Becker, H. (2006). Validation - The missing link in life cycle assessment towards pragmatic LCAs. In *International Journal of Life Cycle Assessment* (Vol. 11, Issue 5, pp. 295–297). https://doi.org/10.1065/lca2006.09.271

de Wolf, C. (2014). *Material quantities in building structures and their environmental impact Chair of the Department Committee on Graduate Students*.

De Wolf, C. (2017). *Low Carbon Pathways for Structural Design : Signature redacted Signature redacted Signature redacted*. *June*, 212.

Hawkins, W., Cooper, S., Allen, S., Roynon, J., & Ibell, T. (2021). Embodied carbon assessment using a dynamic climate model: Case-study comparison of a concrete, steel and timber building structure. *Structures*, *33*, 90–98. https://doi.org/10.1016/j.istruc.2020.12.013

Hollberg, A., Jürgen, I., Prof, R., Linda, I., & Knaack, I. U. (2016). *A parametric method for building design optimization based on Life Cycle Assessment*.

Jusselme, T., Rey, E., & Andersen, M. (2020). Surveying the environmental life-cycle performance assessments: Practice and context at early building design stages. *Sustainable Cities and Society*, *52*(January 2019), 101879. https://doi.org/10.1016/j.scs.2019.101879

Kiamili, C., Hollberg, A., & Habert, G. (2020). Detailed assessment of embodied carbon of HVAC systems for a new office building based on BIM. *Sustainability (Switzerland)*, *12*(8). https://doi.org/10.3390/SU12083372

Laurent, A., Weidema, B. P., Bare, J., Liao, X., Maia de Souza, D., Pizzol, M., Sala, S., Schreiber, H., Thonemann, N., & Verones, F. (2020). Methodological review and detailed guidance for the life cycle interpretation phase. *Journal of Industrial Ecology*, *24*(5), 986–1003. https://doi.org/10.1111/jiec.13012

Lavalin. (2021). *Engineering Net Zero*. https://www.snclavalin.com/~/media/Files/S/SNC-Lavalin/download-centre/en/report/canada_enz-technical-report_en.pdf

Ministry of Environment and climate change strategy. (2022). *New methodology for calculating electricity emissions and updated reporting requirements for Electricity Import Operations*.

Oladazimi, A., Mansour, S., & Hosseinijou, S. A. (2020). Comparative life cycle assessment of steel and concrete construction frames: A case study of two residential buildings in Iran. *Buildings*, *10*(3). https://doi.org/10.3390/buildings10030054

Pease, P., & Jayati Chhabra Zahra Zolfaghari Member ASHRAE, P. (n.d.). *Planning for net zero by 2050, what HVAC system interventions will today's code minimum commercial buildings require?*

Rodriguez, B. (2019a). *Embodied Carbon of Heating, Ventilation, Air Conditioning and Refrigerants*. *April*, 33–35.

Rodriguez, B. (2019b). *Embodied Carbon of Heating, Ventilation, Air Conditioning and Refrigerants (HVAC+R) Systems*.

Roynon, J. (2020). *Embodied Carbon, Structural Sensitivity Study*.

Schneider-Marin, P., Harter, H., Tkachuk, K., & Lang, W. (2020). Uncertainty analysis of embedded energy and greenhouse gas emissions using BIM in early design stages. *Sustainability (Switzerland)*, *12*(7). https://doi.org/10.3390/su12072633

Shah, V. P., Debella, D. C., & Ries, R. J. (2008). Life cycle assessment of residential heating and cooling systems in four regions in the United States. *Energy and Buildings*, *40*(4), 503–513. https://doi.org/10.1016/j.enbuild.2007.04.004

Torabi, M., Labbafan, S., & Farajnia, B. (2022). Data for electricity consumption, thermo-physical characteristics of residential buildings in Tehran. *Data in Brief*, *40*. https://doi.org/10.1016/j.dib.2022.107813

Torabi, M., & Mahdavinejad, M. (2021). Past and future trends on the effects of occupant behaviour on building energy consumption. *Journal of Sustainable Architecture and Civil Engineering*, *29*(2), 83–101. https://doi.org/10.5755/j01.sace.29.2.28576

Toronto, O., & Dulmage, S. (2018). *EMBODIED CARBON WHITE PAPER EXECUTIVE SUMMARY*.

Totland, M., Kvande, T., & Bohne, R. A. (2019). The effect of insulation thickness on lifetime CO2 emissions. *IOP Conference Series: Earth and Environmental Science*, *323*(1). https://doi.org/10.1088/1755-1315/323/1/012033

Walker, M., Lopez, D., Teshnizi, Z., & Pilon, A. (2020). *POLICY REVIEW OF CARBON-FOCUSED LIFE CYCLE ASSESSMENT*.

Zheng, M., Fang, R., & Yu, Z. (2016). Life Cycle Assessment of Residential Heating Systems: A Comparison of Distributed and Centralized Systems. *Energy Procedia*, *104*, 287–292. https://doi.org/10.1016/j.egypro.2016.12.049

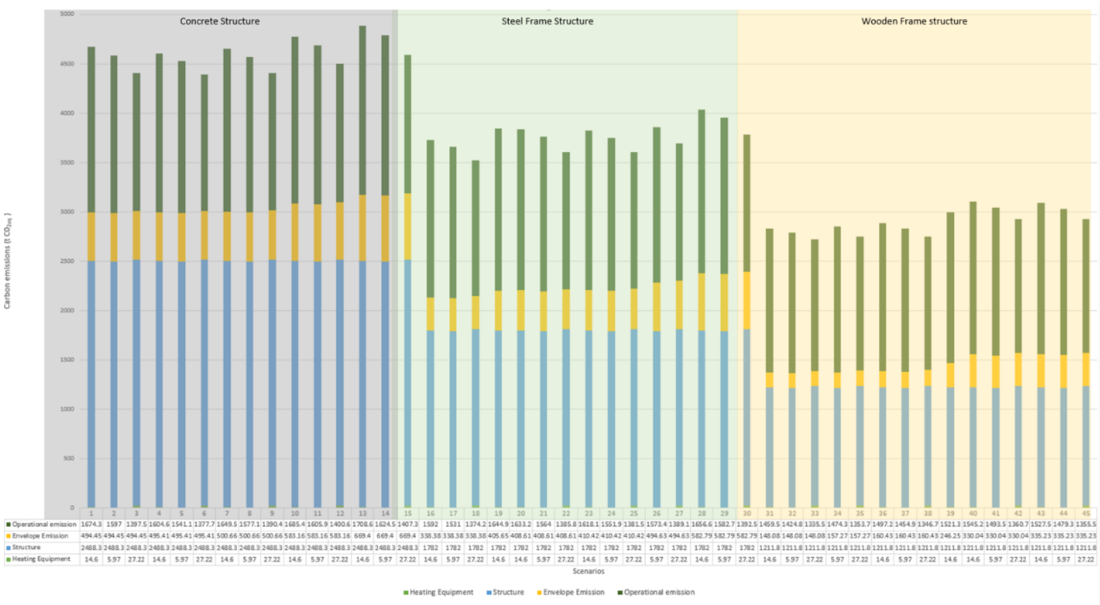

Figure 8- Embodied and operational emissions of studied scenarios

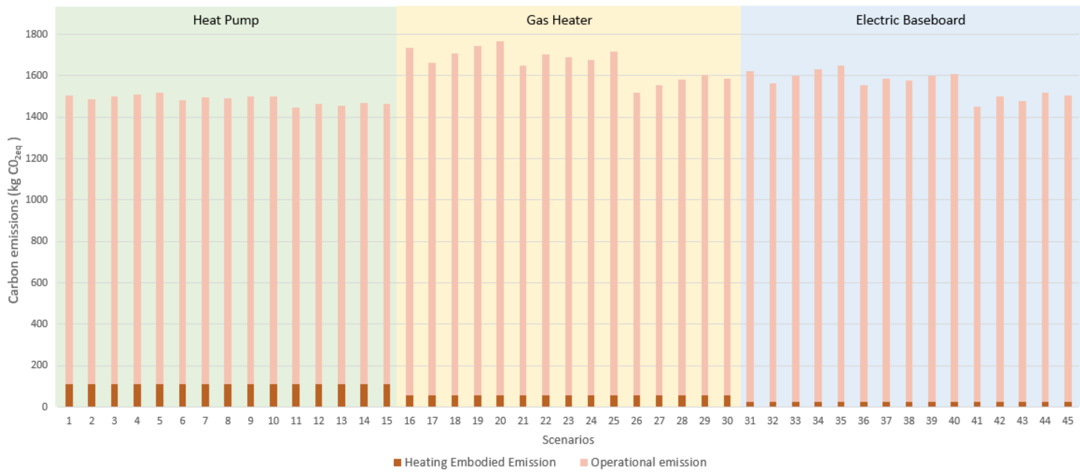

Figure 9- The impact of heating system on embodied and operational emission

Chapter 3- Structural Parametric LCA Model

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BUILDING COMPONENTS AND BUILDINGS

Towards net-zero carbon buildings: Investigating the impact of early-stage structure design on building embodied carbon

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Abstract

Purpose This study tries to fill a gap in early-stage design and incorporate LCA results in design from early concept formation. This research aims to find the most influential parameters in building embodied carbon (EC) in early-stage design and suggest a range of their impact so that the architects can navigate their design process towards low-carbon intensive solutions. As the structure is the main contributor to building EC, the impact of structural parameters on mitigating EC of residential buildings was studied.

Methods This research introduces a novel design exploration method for concept-stage life cycle assessment (LCA) to analyze over 8200 design solutions. Parametric modeling was employed to explore structural design variations for a multi-unit residential building on Vancouver Island, Canada. The study focused on eight key structural design parameters, with a comprehensive analysis of the resulting EC for both the structure and foundation. The study encompasses the A1–A3 stages of the building life cycle, and the findings were presented through a design-oriented dashboard for comparative assessment.

Results and discussion The results of this study reveal that material and structural system choices exert the most significant influence on EC. Furthermore, the number of stories and building footprint geometry play pivotal roles. In low-rise buildings, geometry holds a higher impact, while in taller structures, the number of stories assumes greater significance. For steel and wood structures, floor-to-floor height emerges as a crucial factor in designing low-carbon buildings while the impact in concrete structures tends to be lower. The study challenges a prevailing misconception. It demonstrates that the normalized EC of the structure slightly decreases with an increase in the number of stories, for a given area. This decrease is attributed to material consumption savings achieved by minimizing structural components. This insight facilitates achieving lower carbon thresholds in taller structures with compact forms. Additionally, the study underscores the advantages of symmetrical and compact footprints in achieving lower carbon emissions.

Conclusions and recommendations This research provides a free web-based tool for estimating the carbon footprint of the structure for concept design decision-making. To achieve the lowest possible carbon footprint, the study strongly advocates for using wood as the structural system, coupled with minimization of floor-to-floor height and span length. As the results show compact and symmetrical footprint shape contributes to lowering building carbon footprint. While variations to compact and symmetrical footprints do impact structural EC, their influence may be outweighed by prioritizing other design goals. The study highlights the dominance of structure over substructure in total carbon footprint within the scope of studied buildings, suggesting similar research in other regions and for underground structures. Additionally, future investigations should explore carbon savings through recycling and biogenic carbon at the end-of-life stage, thereby further reducing building emissions. This research equips designers, architects, and engineers with essential insights to make informed decisions at the concept design stage, advancing sustainable building solutions from inception.

Keywords Early stage LCA · Life cycle assessment · Structure embodied carbon · Low-carbon building · Design exploration

1 Introduction and background

Considering the increasing repercussions of climate change on human life, dramatic reductions in greenhouse gases are required since their accumulation in the atmosphere is the primary cause of climate change (Lucon et al. 2014). In this

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regard, Canada as one of the top per capita emitters is committed to decreasing its GHG emissions by 30% below 2005 levels by 2030, in line with a worldwide response to climate change (Government of Canada 2019).

The building sector is an important component of global and national GHG emissions, representing roughly 40% of global carbon emissions (International Energy Agency. & Global Alliance for Buildings and Construction 2019). GHG emission within buildings, which is often quantified with carbon emission, consists of two main components: operational carbon (OC) and EC. The first quantifies emissions resulting from energy consumption by the occupants during operation, and the latter indicates the emissions associated with construction including material production, manufacturing, transportation, and construction activities. OC has historically been the largest contributor to building greenhouse gas (GHG) emissions and has been the main objective in low-carbon research. However, due to recent promising achievements such as grid decarbonization and improvements in building energy systems, building OC accounts for only 19% and 11.5% of global (Norouzi et al. 2023; Lucon et al. 2014) and Canadian (Hammad et al. 2018) emissions through a building life cycle (Pereira and Posen 2020) leaving EC a relatively untouched topic with high potential for reducing building carbon (Fig. 1). Today, EC accounts for 9–50% of building life cycle GHG emissions in North America which indicates the shift of interest from OC to EC in sustainable communities (Ibn-Mohammed et al. 2013; Zolfaghari and Jones 2022; Torabi et al. 2022a, b).

Another factor that highlights the importance of EC is the enormous future need for new construction, which captures huge carbon in building stock.

Between now and 2060, the building industry is predicted to undertake 230 billion m^2 of new construction worldwide. That means the number of buildings we currently have worldwide should double over the next four decades (UN Environment and International Energy Agency 2017). While it is important to look at the cumulative emissions over the lifetime of a building, it also matters when the emissions take place. What makes it alarming is the time value of carbon; once a building has been constructed, the embodied carbon has already been emitted, and the emissions will actively impact the climate for the next decades and centuries. In other words, when the new constructions are done, a high amount of carbon is captured, and there is no way to reduce EC. The same is not true for OC, which could be reduced in the future by scaling up renewable energy generation in the grid, retrofitting, and using efficient equipment (Pak 2019).

2 Literature review

A review of the literature shows that EC has been quite untouched compared to the rich research background on OC. This necessitates more research focusing on total carbon reduction through EC as it has a high potential for impact in the fight against climate change. To identify the main contributors to EC, numerous research studies have focused on the underlying components of EC in recent years. A research study by Tolia explored different archetypes of residential and commercial buildings showing that current structure, mechanical systems, and envelope are correspondingly the top three components of the building. EC makes up for 72%, 21%, and 7% of total EC in a typical single-family home with a low level of insulation. The results reveal that by carbon-sensitive building design coupled with high insulation and high-performance mechanical systems, the share would change to 44%, 40%, and 16% (Tolia 2020). In a similar study, Torabi and Evins show that structure makes up more than 50% of EC in midrise residential buildings followed by envelope and heating systems (Torabi and Evins 2022a). The high environmental impact of the building structure is due to the high mass of materials within the building's structure, as the structure is often the heaviest part of the building. Secondly, materials used in building structures are carbon-intensive materials with long industry processes; reinforced concrete, steel, and processed wood such as cross-laminated timber (CLT), oriented strand board (OSB), and parallel strand lumber (PSL) are the most common materials (Hammond and Jones 2008).

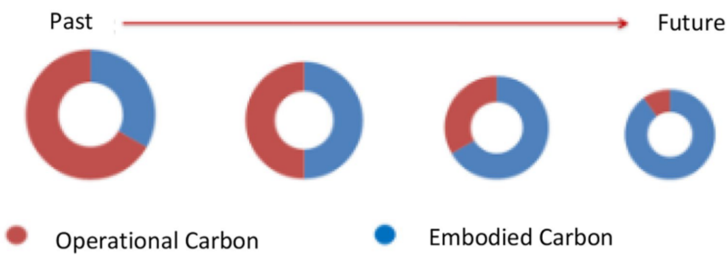

Fig. 1 Share of EC and OC in building embodied energy/carbon (Pak 2019)

To decrease the carbon footprint of building structures, the embodied carbon should be analyzed in the early stages of design, as the structure of the building mimics the early conceptual form of the building. Lower carbon impacts can be achieved; the design process aims for environmental efficiency from the early stages. Unfortunately, this cannot be achieved easily with the current tools. With current methods, the environmental impact of buildings is assessed through the LCA framework. This framework is mainly dependent on numerous and various input data mostly on the physical characteristics of design that are known to the designer not sooner than the final stages of design. At that stage, fundamental changes in design are hard and expensive; therefore, architects and designers need a novel method to analyze the environmental footprint of structures in the early stages that provide them with insights into the carbon footprint of their schematic design. Having quantified LCA results in the concept stage can help architects and engineers choose low-impact design alternative concepts, which can further develop a low-carbon layout.

2.1 LCA and structural design

The major part of the LCA literature is focused on building materials and envelopes because the current methods of conducting LCA are material-oriented with a focus on later stages of design. However, before this, major design decisions have already been made, and only minor changes are possible. Consequently, the building structure, as the first building subsystem to be designed, has a big impact on EC. Therefore, in recent years, with the need to lower building carbon significantly, attention has been shifted to the EC of structure.

Research has shown that early-stage decisions can make a huge difference in building performance and environmental outputs. In a research study, Hollberg showed that by conducting LCA and setting environmental objectives, the early-stage building design process can reach higher efficiency with lower cost and effort (Hollberg 2016). Figure 3 compares the impact of design decisions made in different design stages and compares the pertaining impacts and required effort. As the graph shows, the influence of design alterations in the early stages is high on project performance and it drops logarithmically, suggesting that in the latter stages, negligible changes can be achieved through design (Andersen et al. 2021; Gibbons and Orr 2020; Wang et al. 2021). The efficient methods should focus on making LCA feasible in the early stages when no data on building features and bills of material are known. This is an ambitious goal that can make great carbon saving through design and can only be attainable through integrated design and LCA modeling.

The current method of implementing LCA in structural formation is the traditional bottom-up approach facilitated by utilizing data on the carbon intensity of materials from the literature. De Wolf et al. signified the application of this method by analyzing the data obtained from over 200 buildings. The results show that the amount of building embodied CO_2 emissions equivalent (CO_2eq) varies in the range of 150–600 kg CO_2eq/m^2 per year of building lifetime (De Wolf et al. 2014). Simonen et al. evaluated 1150 buildings, reporting a significant share of CO_2eq emissions, which is in the range of 10–1082 kg CO2eq/m^2 per year (Simonen et al. 2017). These variations show the inaccuracy of prescriptive recommendations in LCA and show the necessity of more accurate building LCA methods based on a building's features.

2.2 Current LCA tools and gaps

In terms of tools to conduct LCA, currently, EC associated with building structure is measured through calculations based on late-stage design data. For instance, Athena Impact Estimator, as one of the first and highly regarded LCA tools, provides detailed calculations using numerous detailed input data for structure and reports of EC as well as other environmental impacts. These tools, however, do not consider dynamic forces such as wind and seismic load or soil conditions in calculations. Similarly, EC3, a new web-based LCA tool, requires a bill of materials as the input for structural emission calculation, which is hard to get in the early design stages. Another recent tool, Cardinal LCA, aims to bridge this gap by linking the design model to the EC3 server and feeding data from the design model directly into the calculation engine. This tool is suitable for the design development stage of the building when the structure is determined and the bill of materials is provided. Other tools, such as one-click LCA, EC3, and Tally, first linked to parametric and the latter linked to BIM models, can read structural material quantity but require structure definition to conduct LCA calculations and face the same challenge; however, they are not designed to be iterative, and changes in design require redoing the LCA calculation process, which makes LCA time- and energy-intensive.

It can be concluded that recent LCA tools and methods have identified the research issue in LCA correctly; however, they have not succeeded yet in addressing the issue completely. In other words, recent methods are imitating the same pattern of older tools in conducting LCA which is based on vast input data, but they managed to do that earlier in the design process compared to older methods. The progress in new tools is similar to extracting input data from the architectural model and transferring it into the LCA module as input instead of traditionally requiring the user to input the bill of material. This recent trend in developing LCA methods/tools targets early-stage design LCA, but in practice has shifted LCA from the technical design stage to the design development stage and leaves the gap between current methods/tools and early-stage LCA untouched. Figure 2 summarizes and compares recent research and state-of-the-art tools in structural LCA, highlighting the research gap in the research literature.

In one of the few research studies on applying LCA to the design process, embodied carbon in tall timber structural systems is investigated at the design stage. The framework lets the designer compare designs from the structural, aesthetic, and embodied carbon performance (Zaraza et al. 2022; Hens et al. 2021). The results show that structure design can have a 15% difference in emissions, which resulted from early-stage decision-making (Hens et al. 2021). Despite good contribution by addressing LCA in design, the results are very case-specific and cannot be used in similar research. Still, results and suggested design outputs explicitly show that there is a high potential to reduce building EC through design using the same material. It is anticipated that the future of low-carbon buildings is rooted in developing design-integrated- LCA tools.

2.3 Uncertainties in the LCA process

The early planning phases play a crucial role in the future performance of a building throughout the building life cycle—where the potential for design improvement is high at a very low cost (Liu 2021; Rodriguez 2019). Bogenstatter points out that early design stages determine up to 80% of building operational costs, as well as environmental impacts (Kovacic and Zoller 2015). Currently, the construction industry is facing a challenge/problem that other industries have experienced like a lack of information, data, and appropriate tools for the early planning phases (Torabi and Mahdavinejad 2021). Therefore, investors and planners are increasingly requiring planning tools for supporting decision-making, which would enable the calculation and simulation of life cycle analysis in the early planning phases. This new method should be design-linked to make LCA and design interwoven in the same space. More importantly, it also should be fast and accurate and provide reliable results even with low input data.

Hollbert et al. evaluated the application of a BIM-LCA tool to estimate the embodied global warming potential (GWP) throughout the whole design process of a real building. The results show that the embodied GWP during the design phase is misleadingly assessed and can be twice

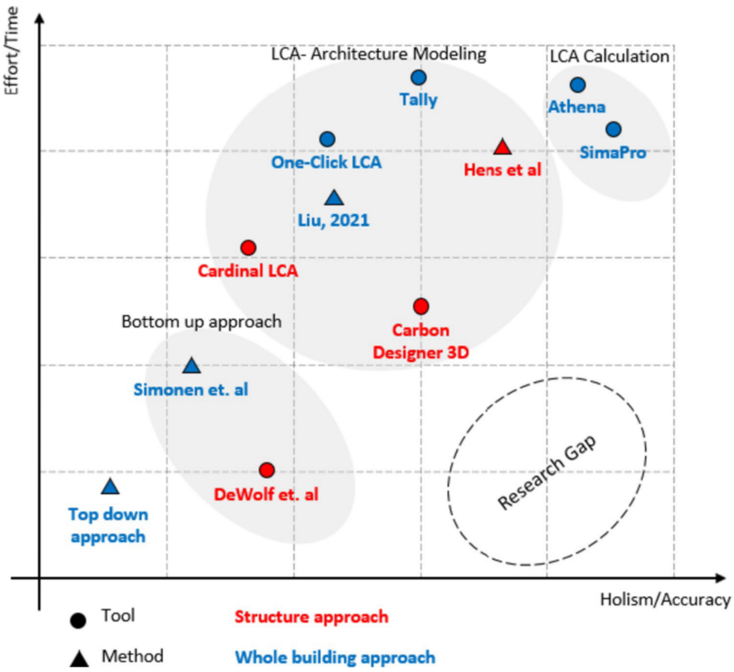

Fig. 2 Research landscape showing existing tools and methods and the research gap that this research addresses

as high as for the final building. They concluded that the reason for changes can be mainly attributed to the inadequate use of LCA in early-stage design decisions and the inability of tools to quantify the environmental assessment during the design process (Hollberg et al. 2020).

2.4 Sources of inaccuracies in LCA

Researchers have always had to simplify real conditions in modeling to save time and computation power. Additionally in LCA studies, not all required data are determined; therefore, to address missing data, sometimes defaults or inaccurately defined data were used which has resulted in the inaccuracy of the results. In the following section, we address variables that are influential on building environmental impact but are generally less commonly discussed.

2.4.1 Loads

The building structure is designed to convey the internal and external loads to the foundation; therefore, the most important factor in designing the structure is load, and accuracy in defining loads is a preliminary success factor in simulating real conditions. Despite this, the majority of studies on structure-related emissions aim to simplify the imposed loads in different ways due to their complexity. This is mainly by excluding dynamic loads and designing the structure according to static loads only. For instance, in a study by Skullestad et al., the mass and pertaining emissions to the structures have been investigated. In this study, the imposed loads are live, dead, and snow loads (Skullestad et al. 2016). This can be acceptable for areas with a low risk of earthquakes and high wind speeds; however, the same pattern is observed in structure design and EC in high-risk areas too (Hawkins et al. 2021; Ytrehus 2015; López-Mesa et al. 2009). The reason for this common simplification can be found in the predictability of static loads. Unlike dynamic loads, static loads are easy to accurately simulate and are clearly defined in the literature. On the contrary, dynamic loads depend highly on the location and can change significantly from case to case. In some areas with low seismic risk, wind load dominates lateral forces, and the intensity and direction should be defined in the early stage structural design; while in other regions, the impact of the earthquake is greater and dominates the wind load. In a recent study, the Massachusetts Institute of Technology (MIT) structural model for a wide range of buildings was modeled with related emissions and costs reported; however, due to limitations in load definition, the amount of carbon footprint might be underestimated (Liu 2021). Despite being a promising method, considering an influential parameter such as lateral loads in structural design places a gap between simulated results and real structure. This not only does not assist design but also can mislead the designer to reach low carbon targets.

2.4.2 Foundations

Similar to loads, the foundation is over-simplified in some studies. In many pioneer studies, the weight of the foundation and associated emissions were considered out of scope, leaving the super-structure as the main objective (Hens et al. 2021). In other studies, the impact of the foundation was investigated with a simplified approach. Liu's research designed foundations according to per capita static load from the literature. As a result, all designs, from a high-rise building with a small footprint to a low-rise building, would have identical foundations, as long as they have similar total floor area. This is a good example that highlights the discrepancy resulting from oversimplification and indicates the importance of accuracy in LCA modeling.

2.4.3 Soil condition

A similar pattern is observed in soil condition. The authors of this study could not find a tool or research that has investigated the impact of soil on embodied emission of foundation and structure. This is due to the wide range of soil and depending on the density and soil bearing capacity (SBC) material quantity and emission can vary a lot. This might not be an issue in a case study as the location and soil are known, but studies with multiple locations have neglected this parameter either.

2.5 Research gaps and novelties of this work

Most of the literature on structural embodied emissions is dedicated to high-rise commercial buildings. Meanwhile, low-rise and midrise residential buildings have received scant attention, and more research in this area is needed. Therefore, in this research, midrise residential buildings are studied due to their vast frequency.

From the literature review, it is understood that there is a gap in research literature in addressing LCA in the early stage of design in order to evolve and optimize structural design. This gap can best be bridged by a novel method with the following features:

- Design compatible: LCA tools should be deployable in close connection with existing design processes and decision-making. LCA results should be derived from the design while also addressing changes in design to reflect environmental outputs within the design process. Therefore, the method should be capable of providing fast results to allow the designer to make back-and-forth adjustments in the design process feasible.

- Accurate: considering real conditions and all influential impacts. Provide fast yet reliable results in order to be incorporated into the design process.
- Holism: to reach good accuracy, a new method should be capable of considering all design objectives and influential factors simultaneously. Despite current methods, the results should not be case-specific to let architects and engineers see other options in design as well.
- Uncertainty: considering limited input data availability at the early stage, this method should be capable of handling uncertainties in order to prevent suboptimal design decisions.

This research aims to tackle these issues, which have resulted in a fragmented LCA analysis and design process. The initial results of this research showcase the benefits of parametric design, scenario analysis, iterative decision-making, and accurate data gathering. A wide range of design solutions can be explored, and large embodied carbon savings can be achieved through better-informed early-stage decision-making.

3 Methods

To investigate the impact of building structural design on EC, data on a wide, comprehensive range of structures are required. Due to the reasons mentioned before, simulating thousands of design solutions using common tools was not feasible. Therefore, for the purpose of this study, a new method of conducting LCA was developed. In this method, a design exploration approach was deployed, which investigated the whole design space. LCA calculations were conducted for all solutions with inputs and outputs recorded, creating a database of all feasible designs and corresponding EC values. The result provides fast yet reliable insights for design decision-making and can be repeated unlimited times (Fig. 3). This method is a front-loaded task that requires time and energy in the conceptual stage but guarantees fast and accurate LCA reports in later stages and is compatible with any alterations to the design.

3.1 Workflow

The LCA method of this study was developed in a parametric design environment and comprises three main modules: problem formulation, structural design, and LCA calculations.

The process starts with problem formulation and defining ranges for design parameters. This study aims to analyze all feasible design solutions for a low to midrise multi-unit residential building project, located in Victoria, British Columbia. The building has a total area of 5000 m^2, with the range of acceptable design parameters outlined in Fig. 5. In this study, 8209 design combinations were modeled and analyzed.

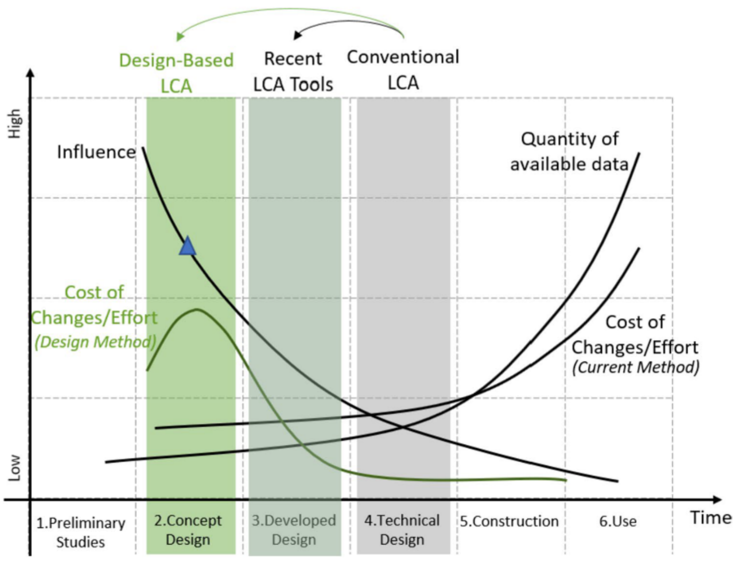

Fig. 3 Conventional versus recent LCA tools and design-based LCA. Opportunities to reduce embodied carbon emissions decrease as the design process progresses

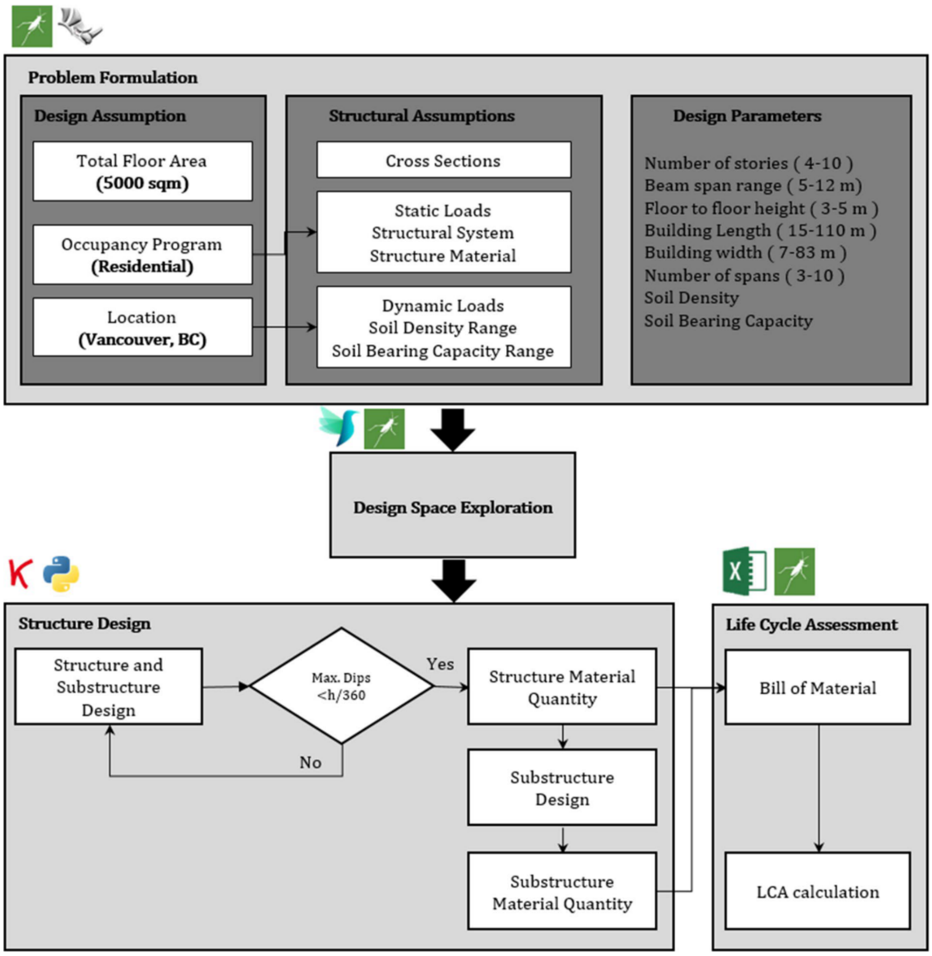

Fig. 4 The workflow of the new method and related software integrations. The design parameters listed in the top right box are varied in the subsequent design space exploration

In the majority of similar research, the EC of the structure is limited to the super-structure, and the impact of the foundation was ignored. In this study, however, the total EC covers both the super-structure and foundations. Moreover, to model a realistic range of variables, such as soil density and SBC were defined and varied to cover the range of local soil classifications. Finally, a range of cross-sections was defined according to structural material. This allows the structural design module to optimize the mass while keeping maximum displacement below the acceptable threshold. The scope of the LCA calculations covers stages A1–A3 of the building life cycle according to EN 15978 which encompasses production and manufacturing (EN 15978:2019), which covers manufacturing and production of materials. The carbon factors were extracted from Hammond and Jones (2008) with the functional unit being $kgCo_2eq/m^2$. These and other values that are selected based on the case study example can easily be changed to represent other scenarios.

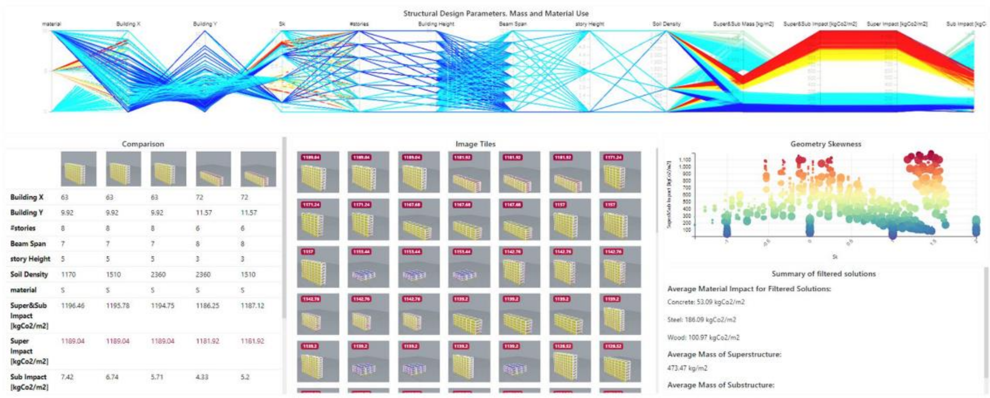

Fig. 5 Dashboard interface

4 Results

In this study, 8209 design variations were studied. To efficiently screen design parameters and compare results, a design-oriented dashboard was developed to generate comprehensive emission reports. The dashboard presents design parameters such as building length and width, structure material, number of stories, span length, floor-to-floor height, soil density, and load-bearing capacity (Fig. 4). Regarding the outputs, this web-based tool can report the mass and carbon footprint of the super-structure and foundation for a specific design solution or a group of selected scenarios. Figure 5 shows an interface of this dashboard providing building structure concept design along with LCA reports iteratively and instantly for design purposes.

By filtering and comparing the results of structural design and LCA using a design-oriented dashboard, insights on the impact of structure on building carbon footprint are provided which can be helpful for the concept design stage of the buildings. In the following paragraphs of this section, the impact of the eight design parameters, i.e., building length, width, structure material, number of stories, span length, floor-to-floor height, soil density, and load-bearing capacity on the structural carbon footprint is discussed, and solutions for lowering building carbon footprint through concept design are provided.

Table 1 Embodied carbon of structural materials

	Structural material	Embodied carbon ($kgCo_2eq/kg$)
1	Concrete	0.159
2	Steel	1.7
3	Mass Timber	0.65

4.1 Variation in structural material

In general, two dominant trends are observed in the results regarding building materials: one for concrete and another similar trend for steel and wood. The reason can be rooted in the structural behavior of structures based on material properties as steel and wood excel in tension, while concrete excels in compression. The other factor that differentiates these two categories is the load transfer mechanism of connections which are rigid and joint connections, respectively.

Another important issue in reviewing the results is the background data in calculating the EC of the structure based on the estimated mass of the structure. Embodied carbon is a factor that is a function of the mass and carbon intensity of material. In this study, the first is calculated using simulation and the latter is extracted from the life cycle inventory (Hammond and Jones 2008). The carbon intensity used to calculate the EC of structures is based on Table 1. It is noteworthy that different EC for materials can be used, depending on the location, scope of the study, and manufacturing process. In this study, we considered virgin material and the UK average; therefore, the EC of steel is noticeably higher than concrete and timber which resulted in a higher EC range for steel alternatives. The result can be slightly different depending on the local/national EC of material.

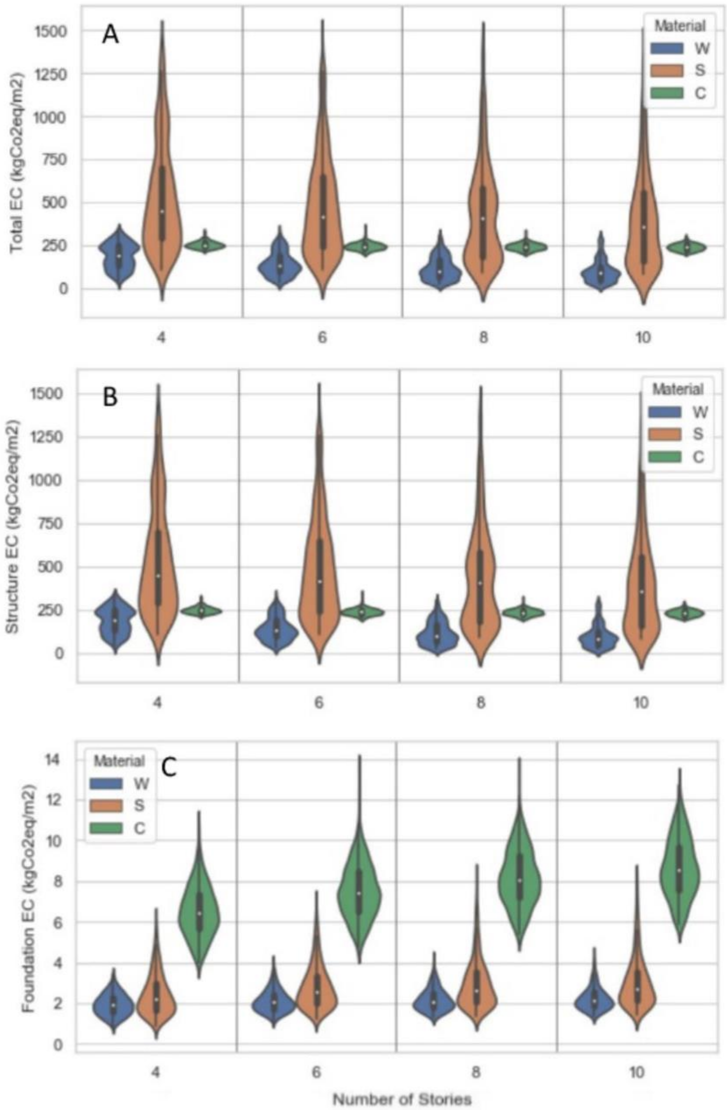

Fig. 6 Structural embodied emissions plotted by the number of stories for **A** the total structure, **B** the super-structure, and **C** the foundation

4.2 Variation in the number of stories

In this study, the impact of building height, on a building's environmental footprint, is investigated by changing the number of stories and floor-to-floor height. The results show that by increasing the number of stories in low and midrise buildings, the normalized EC reduces. This pattern is observed both in total EC and EC associated with the superstructure. EC in the foundation, however, shows a reverse pattern of a rising carbon footprint with an increasing number of stories. The underlying reason can be found in the degree of freedom of structural design using concrete, steel, and wood.

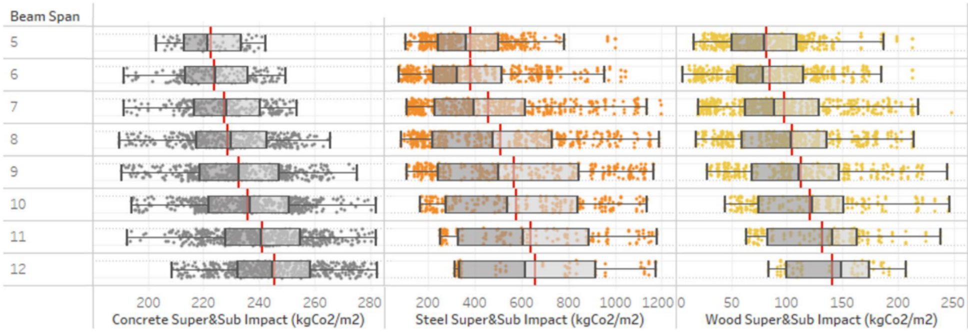

Fig. 7 Structure total EC per material per span length

Taller buildings tend to be exposed to higher seismic forces, especially in the upper stories, which increases the risk of collapse. Therefore, to provide a sufficient resisting moment in response to lateral forces, deeper and heavier foundations are required. Also, for a given area in higher buildings, the footprint area is smaller, and the pressure is higher; therefore, a more robust foundation is needed. These two factors lead to an increase in material use and corresponding EC in the foundation as a result of the increase in building height. Ultimately, in the studied buildings, the building super-structure exerts a significantly greater influence compared to the foundation. Consequently, the overall impact of the building structure aligns with the trends in the super-structure. It is noteworthy that the rate of change is not the same in the three materials studied. In steel and wood structures, the normalized EC tends to decrease by 33% and 26%, respectively, whereas in concrete structures, the decrease is only 7% when comparing a 10-story building to a 4-story building.

Figure 6 shows the EC associated with the whole structure as well as the super-structure and foundation per number of stories with more detail. As the graph shows, the average total EC decreases slightly by increasing the number of stories in steel and wood. As mentioned in the material section, the observed trend in Fig. 6 can be related to the statics of materials and mechanisms of load transfer in connections. This is rooted in the number of components involved in the load-bearing mechanism. For a given total area, a higher number of stories means a smaller footprint and fewer structural components. Given higher seismic load in the higher building, this means that fewer structural components are exposed to higher load and should provide high resistance which necessitates higher structural performance.

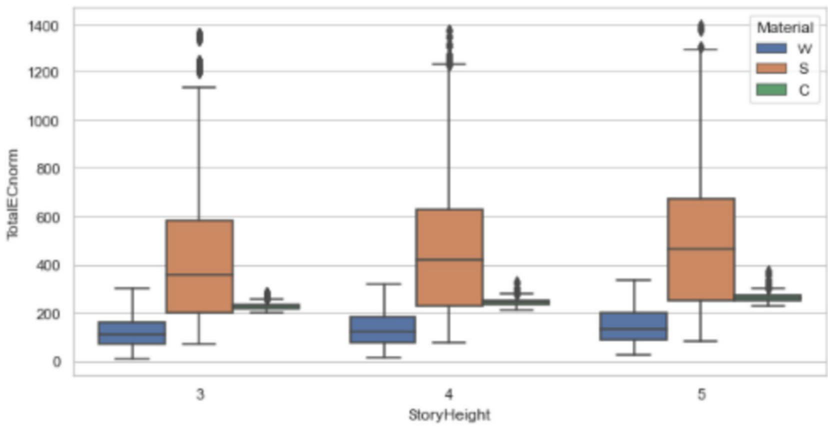

Fig. 8 Structure EC per story height

As the number of structural components is lower, the material consumption is lower, and therefore EC associated with total structure and substructure is lower in buildings with a higher number of stories compared to low-rise buildings with a wide footprint. Therefore, in a higher number of stories, fewer structural component is observed, with higher performance and lower material consumption in total which will lead to lower EC of the structure.

4.3 Variation in span length

In this section, the impact of span length on the mass of the building structure and EC is discussed. Figure 7 shows the total EC of structure by span length in three studied material categories. The red line also indicates the average EC in each span length. As the figure illustrates, an increase in building EC is observed by an increase in span length. This increase however is of different rate with steel, concrete, and wood with highest to lowest rate. On average, EC increases by 3.5% per added story, while this number in concrete structures is 1.7% and 5.5% per story. This highlights that the wood structure's carbon footprint can be reduced in lower stories while the other two materials show less sensitivity to the number of stories.

4.4 Variation in story height

Story height was another studied parameter that influenced EC. Unlike other parameters with multiple patterns, in all design solutions by increasing story height, the average normalized EC of the structure increased; the rate of change, however, was different. The average normalized EC for concrete, steel, and wood show 16%, 21%, and 19% increases respectively for a change in story height of 3 m to 5 m. As anticipated due to the vulnerability to buckling of steel and wood structures, in higher floor-to-floor heights, this weakness should be tackled by increasing the cross-sections, which adds to the material use. In concrete structures, however, better resistance against buckling is observed. Therefore, lowering story height can reduce building EC remarkably. Figure 8 reports the structure EC according to story height and materials.

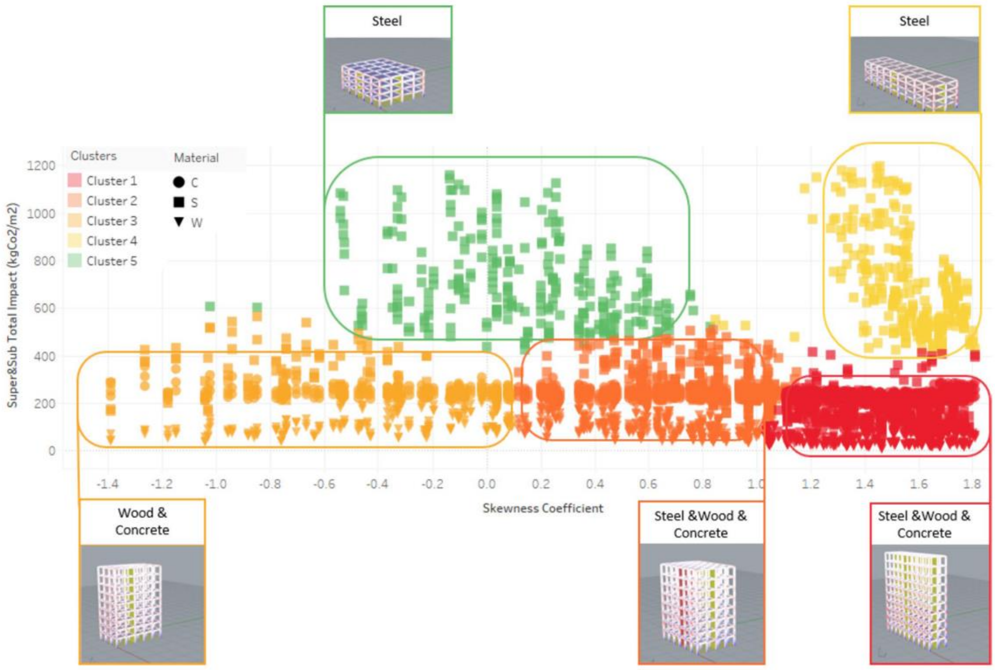

Fig. 9 Design solutions based on skewness and total EC

Table 2 Details of clusters based on footprint geometry and EC

Clusters	Number of solutions	Average Sk	Super & subtotal impact ($kgCO_2/m^2$)
Cluster 1	4392	1.4644	149.94
Cluster 2	3150	0.68211	209.57
Cluster 3	1521	−0.46632	214.19
Cluster 4	828	1.5573	693.46
Cluster 5	801	0.1293	701.1

4.5 Variation in building geometry

To quantitatively categorize the geometry in all scenarios, the skewness coefficient (Sk) was defined according to the equation below, where X is the building length and Y is the building width. Positive values of Sk show skewness of footprint in the X direction and negative amounts show skewness in the Y direction. Building footprint shapes close to a square have a low magnitude of Sk, around 0.

$$\mathrm{Sk} = \frac{X - Y}{(X + Y)/2}$$

The graph below shows the impact of geometry on the total EC of structure for three materials. By categorizing all studied buildings, the EC result can be clustered into five clusters based on Sk and the number of stories. As can be inferred from the Fig. 9 and Table 2, the lowest normalized EC is associated with wooden structures in all ranges of skewness. As shown in Fig. 9 the highest EC is observed in clusters 4 and 5. These two clusters pertain to lower buildings with larger footprints with correspondingly highest amount of Sk ($1.2 < \mathrm{Sk}$) or midrange amount of coefficient ($-0.45 < \mathrm{Sk} < 0.45$). The graphical representation of cluster 4 refers to structures with high skewness in the X direction, and cluster 5 summarizes structures with more compact footprints, ranging from square ($\mathrm{Sk} = 0$) to a rectangle with a ratio less than golden ratio ($|\mathrm{Sk}| < 0.45$).

Results of the first three clusters show that for each of the three studied materials, there are a number of possible scenarios with low EC. A closer look reveals that buildings with skewness in the X direction (cluster 1) have the lowest EC, followed by square forms (cluster 2), and lastly buildings with skewness in the Y direction (cluster 3). In other words, buildings with skewness aligned with seismic load direction (X direction, as defined in the Karamba model), tend to engage more load-bearing members for lateral resistance, which distributes the load on a larger part of the structure and increases structure performance and subsequently decreases material consumption. Therefore, two identical buildings with constant Sk can have different carbon footprints regarding their alignment to lateral loads. This can be influential in the early stages of design especially in areas with high wind load as the average speed and direction are known. In early-stage seismic design, however, defining the load direction can be challenging.

It can be understood from the graph that structural material has the highest impact on the structure's carbon footprint. In the next place, a number of story plays a significant role in setting limits on structure carbon content. Geometry should be the third priority of architects for lowering structure carbon footprint.

Figure 10 shows the normalized total EC per story and in the range of Sk. A general trend of increasing EC with an increase in Sk is observed in the class of material and number of stories, which shows the symmetrical forms have the lowest EC resulting from their structure. EC starts to rise as the skewness of the form increases, and the magnitude of Sk increases in either direction. This is more noticeable in steel and wood where the fluctuation

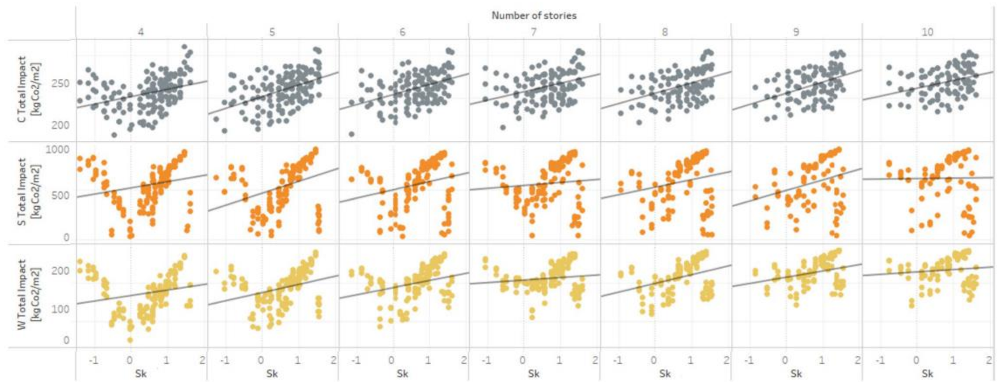

Fig. 10 Total EC per story versus skewness coefficient Sk

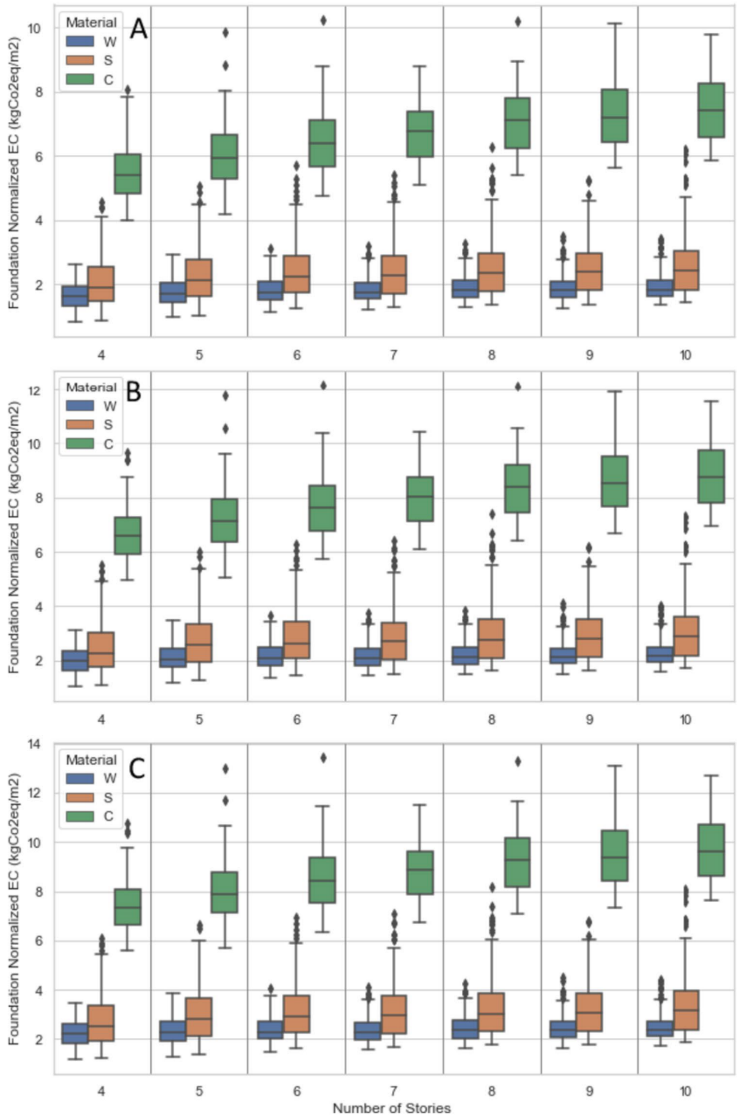

Fig. 11 Foundation EC with respect to the number of stories and soil density. **A** 2360, **B** 1510, and **C** 1170 kg/m^3

of EC is higher compared to concrete structures with the same design parameters. Setting the design condition of a minimum of three spans in one direction limits the range of spans in the *Y* direction and therefore the Sk in higher stories does not reach – 1.

The graphs in Fig. 10 also show that the impact of geometry is higher in low-rise buildings and subsides as the number of stories increases. In shorter buildings, geometry plays a more significant role due to the higher number of structural members and connections which leads to higher material consumption and thus EC.

4.6 Foundations

One of the less regarded subjects in this topic is the impact of foundations on EC. In this study, three of the most common soil types on Vancouver Island are used for modeling and estimation of sub-grade material use in the conceptual stage of design. As the graph below shows highest EC of foundations refers to concrete structures followed by steel and wood, which is rooted in the same pattern in the mass of concrete structure compared to steel and wood. It also shows the direct correlation of foundation EC and the number of stories (Fig. 11). In taller buildings due to higher moments imposed by lateral forces, deeper and stronger foundations are required, and the impact increases as the number of stories increases. The rate of increase is higher in concrete structures followed by steel structures. The increase rate of EC by the number of stories in wood structure is meaningfully lower due to the low mass of wooden structure compared to the other two types.

4.7 Recycling and local EPD

The figure below compares structure versus foundation emissions for the studied scenarios. As can be inferred from the graph, a steel structure has the highest structural impact due to the high carbon intensity of steel, regarding the scope of this study which is A1–A3 (Fig. 12). Steel structures are relatively light compared to concrete structures and therefore have light foundations with lower emissions. On the other hand, concrete structures are the heaviest, but due to the

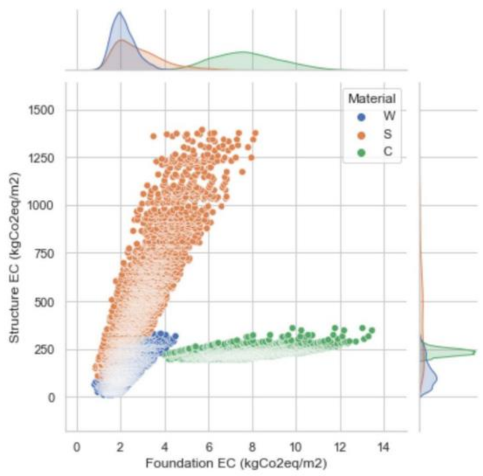

Fig. 12 EC related to the structure versus the foundations for the three structural materials

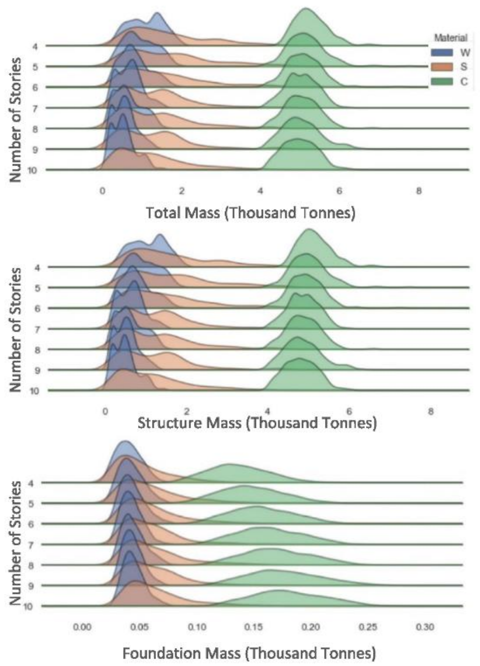

Fig. 13 Mass distribution for the total building, the structure, and the foundation based on material and number of stories

lower carbon intensity of reinforced concrete according to the LCI, they show lower structure-related emissions. However, they are by far the heaviest structures, and consumed mass can add to their emissions if considering end-of-life emissions (module C of the building life stage).

Another noteworthy issue is that the results might be different when considering the recycling potential of steel which would drop the carbon intensity remarkably with regard to carbon savings at the end of life. Similarly, with recycled material content and additives in concrete, the embodied emissions can differ significantly in different regions. Therefore, depending on the scope of the studies, it is suggested that the local embodied carbon of materials be fed into the tool for more accurate results when running LCA calculations (Fig. 13).

5 Conclusions

This study aims to bridge the gap of carbon footprint analysis in the early stages of design. To reach this goal, a design exploration method for concept-stage LCA was proposed to investigate the resulting changes in structure carbon by changing 8 main structural design parameters. In this study, over 8200 design solutions for a multi-unit residential building were parametrically modeled, and the related EC of the structure and foundation were calculated.

The results of this study can assist architects and engineers in building form-finding and concept formulation based on carbon emission reports. The novel tool developed in this study manages the uncertainty and lack of data existing in the early stage of design. Unlike conventional LCA tools that report the carbon footprint of a near-final design with limited space for alteration, this study provides carbon reports in concept stages empowering architects to drastically change their design based on carbon footprint analysis. The results of this study provide LCA results far earlier in the design stage than conventional methods. In this paper, the impact of fundamental design parameters and the range of their influence on building carbon footprint is also discussed, thereby educating the designer on the impact of design modification on the total carbon footprint of the building. The results were reported in the form of a design-oriented dashboard to provide insight into design solution comparison.

With regard to the scope of LCA analysis, which covers the A1–A3 stages of the building life cycle, the results show that the most influential design decision is the material and structural system which can change the possible range of EC for the design fundamentally. In the next step, the number of stories dictates the structure of carbon impact. The third influential parameter is the building geometry and skewness of the building footprint especially in low-rise building. The results show that the impact of geometry is higher in low-rise buildings, while in higher buildings, the number of stories plays a significant role. In steel and wood structures, floor-to-floor height can also be of high importance in designing low-carbon building. The result of this study challenges a common misconception in estimating building EC in the early stages. The results show that for low to midrise residential buildings the normalized EC of the structure reduces slightly by increasing the number of stories due to savings in material consumption achieved by minimizing the number of structural components. This can facilitate achieving a low carbon threshold in a higher number of stories with relatively compact building form. The results also show that lower carbon emissions can be more achievable via symmetrical and compact footprints.

Finally, to achieve the lowest possible carbon footprint of the structure, the results strongly suggest using wood for the structural system with the lowest floor-to-floor and shorter span length possible. Other factors are also impactful in structure EC, but their impact can be outweighed in favor of other design parameters.

The results of this study show the dominance of structure over substructure within the study scope for Vancouver Island; however, similar research with underground and in other regions should be conducted. Another topic for future investigation is studying carbon savings at the end-of-life through recycling and biogenic carbon in lowering building emissions from the main contributor of building carbon footprint, structure.

5.1 Future work

In this study, schematic structural designs across a wide range of scenarios were investigated. Considering the wide scope of the design space, this goal was only attainable with some simplifications that should be further analyzed in future studies. In this study, the impact of reinforcement on structural resistance was not considered, and the ratio of rod to concrete was considered to be constant. However, with optimized reinforcement, lower EC in concrete structures might be attainable. The impact of industrially processed wood also can be the topic of future studies. In terms of a typical structural design workflow, the complex behavior of earthquakes and multidimensional seismic load should be further discussed. In conclusion, given the close interdependence of the substructure and super-structure, along with diverse influential regional factors such as soil-bearing capacity (SBC), density, building type, and function, it is recommended to undertake additional investigations, especially for buildings beyond the scope of this study.

Regarding LCA scope, the authors highly recommend considering emissions in modules C and D in future work. Emissions associated with end-of-life can be high for structures with rigid connections and low for joint connections, which could impact the results. The potential for reuse and recycling all of materials should be taken into account in future studies.

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Data availability The data utilized in this study is available upon request. Interested parties may reach out to the corresponding author for access to the dataset.

Declarations

Competing interest The authors declare no competing interests.

References

Andersen CE, Rasmussen FN, Habert G, Birgisdóttir H (2021) Embodied GHG emissions of wooden buildings—challenges of biogenic carbon accounting in current LCA methods. Front Built Environ 7(August):1–15. https://doi.org/10.3389/fbuil.2021.729096

De Wolf C, Iuorio O, Ochsendorf J (2014) Structural material quantities and embodied carbon coefficients: Challenges and opportunities. In: Griffin C, Mollner J (eds) Proceedings of the 5th annual school of architecture symposium. 5th annual school of architecture symposium - sustainable structures: the intersections of structural systems and green buildings, 16-18 Apr 2014, Portland State University, Portland, OR, USA. School of Architecture, Portland State University, pp 309–328

European Committee for Standardization (2019) EN 15978:2019 sustainability of construction works - assessment of environmental performance of buildings - calculation method. CEN-CENELEC Management Centre, Brussels

Gibbons OP, Orr JJ (2020) How to calculate embodied carbon. IStructE Ltd

Government of Canada (2019) National inventory report 1990–2017. https://www.canada.ca/en/environment-climate

Hammad AW, Akbarnezhad A, Oldfield P (2018) Optimising embodied carbon and U-value in load bearing walls: a mathematical bi-objective mixed integer programming approach. Energy Build 174:657–671. https://doi.org/10.1016/j.enbuild.2018.05.061

Hammond G, Jones C (2008) Inventory of carbon & energy (ICE) version 1.6a, Bath, UK

Hawkins W, Cooper S, Allen S, Roynon J, Ibell T (2021) Embodied carbon assessment using a dynamic climate model: case-study comparison of a concrete, steel and timber building structure. Structures 33:90–98. https://doi.org/10.1016/j.istruc.2020.12.013

Hens I, Solnosky R, Brown NC (2021) Design space exploration for comparing embodied carbon in tall timber structural systems. Energy Build 244. https://doi.org/10.1016/j.enbuild.2021.110983

Hollberg A, Genova G, Habert G (2020) Evaluation of BIM-based LCA results for building design. Autom Constr 109. https://doi.org/10.1016/j.autcon.2019.102972

Hollberg A (2016) A parametric method for building design optimization based on life cycle assessment (Doctoral Thesis). Bauhaus. https://doi.org/10.25643/bauhaus-universitaet.3800

Ibn-Mohammed T, Greenough R, Taylor S, Ozawa-Meida L, Acquaye A (2013) Operational vs. embodied emissions in buildings - a review of current trends. Energy Build 66:232–245. https://doi.org/10.1016/j.enbuild.2013.07.026

IEA (2019) Global status report for buildings and construction 2019. IEA, Paris. https://www.iea.org/reports/global-statusreport-for-buildings-and-construction-2019

International Energy Agency & United Nations Environment Programme (2018) 2018 global status report: towards a zero-emission, efficient and resilient buildings and construction sector. https://wedocs.unep.org/20.500.11822/27140

Kovacic I, Zoller V (2015) Building life cycle optimization tools for early design phases. Energy 92:409–419. https://doi.org/10.1016/J.ENERGY.2015.03.027

Liu J (2021) Early design stage building lifecycle analysis (LCA) of cost & carbon impact (Master's Thesis). Massachusetts Institute of Technology. https://hdl.handle.net/1721.1/140196

López-Mesa B, Pitarch Á, Tomás A, Gallego T (2009) Comparison of environmental impacts of building structures with in situ cast floors and with precast concrete floors. Build Environ 44(4):699–712. https://doi.org/10.1016/j.buildenv.2008.05.017

Lucon O, Zain Ahmed A, Akbari USAH, Bertoldi P, Cabeza LF, Graham P, Brown M, Henry Abanda F, Korytarova K, Urge-Vorsatz D, Zain Ahmed A, Akbari H, Bertoldi P, Cabeza LF, Eyre N, Gadgil A, DD HL, Jiang Y, Liphoto E et al (2014) Climate change 2014: Mitigation of climate change. contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change. Chap Buildings, Cambridge, UK and New York, NY

Norouzi MS, Labbafan S, Farajnia B, Torabi M, Norouzi MR (2023) Dataset on environmental impacts and costs of energy consumption in educational buildings in Iran. Data in Brief 51. https://doi.org/10.1016/j.dib.2023.109606

Pak A (2019) Embodied carbon: the blindspot of the buildings industry. Canadian Architect. Retrieved on 26/2/2026. https://www.canadianarchitect.com/embodied-carbon-the-blindspot-of-the-buildings-industry/

Pereira L, Posen ID (2020) Lifecycle greenhouse gas emissions from electricity in the province of Ontario at different temporal resolutions. J Clean Prod 270. https://doi.org/10.1016/j.jclepro.2020.122514

Rodriguez B (2019) Embodied carbon of heating, ventilation, air conditioning and refrigerants (Doctoral Thesis). University of Washington. http://hdl.handle.net/1773/44736

Simonen K, Rodriguez BX, De Wolf C (2017) Benchmarking the embodied carbon of buildings. Technol Archit Des 1(2):208–218. https://doi.org/10.1080/24751448.2017.1354623

Skullestad JL, Bohne RA, Lohne J (2016) High-rise timber buildings as a climate change mitigation measure – a comparative LCA of structural system alternatives. Energy Procedia 96:112–123. https://doi.org/10.1016/j.egypro.2016.09.112

Tolia R (2020) Assessing the embodied emissions of building to the energy step code. UBC sustainability scholars report

Torabi M, Mahdavinejad M (2021) Past and future trends on the effects of occupant behaviour on building energy consumption. J Sustain Archit Civ Eng 29(2):83–101. https://doi.org/10.5755/j01.sace.29.2.28576

Torabi M, Evins R (2022a) An LCA framework to prioritize carbon-sensitive measures in residential building design. In: eSim 2022: 12th Conference of IBPSA-Canada. IBPSA-Canada. https://publications.ibpsa.org/conference/paper/?id=esim2022_269

Torabi M, Labbafan S, Farajnia B (2022b) Data for electricity consumption, thermo-physical characteristics of residential buildings in Tehran. Data Brief 8(40):107813. https://doi.org/10.1016/j.dib.2022.107813

Wang Z, Liu Y, Shen S (2021) Review on building life cycle assessment from the perspective of structural design. J Asian Archit Build Eng 20(6):689–705. https://doi.org/10.1080/13467581.2020.1807989

Ytrehus E (2015) Investigating the "CO2-premium" for building height. Norwegian University of Science and Technology, NTNU. http://hdl.handle.net/11250/2349754

Zaraza J, McCabe B, Duhamel M, Posen D (2022) Generative design to reduce embodied GHG emissions of high-rise buildings. Automat Constr 139:104274. https://doi.org/10.1016/j.autcon.2022.104274

Zolfaghari Z, Jones J (2022) A multi-variable building energy optimization: assessing the role of energy efficient lighting technology in changing the optimal window-to-wall ratio in an office building. Int J Sustain Energ. https://doi.org/10.1080/14786451.2022.2118276

Chapter 4- Whole Building LCA Model

What Matters the Most in Designing Low-Carbon Buildings in Canada? Tradeoff Between Embodied and Operational Carbon in Early Stage Design

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Highlights

- Results show the high impact of local grid carbon intensity in defining the order of importance of design parameters and the extent of their impact on building carbon footprints.
- In Canadian cities with a low grid carbon emissions intensity, the most influential design decisions are structural configuration and mechanical system choice, followed by three parameters (window-to-wall ratio, geometry and level of insulation) that have roughly equal level of importance.
- In cities with high grid carbon emissions factors, design priority should focus on mechanical systems design, structural design, window-to-wall ratio, level of insulation and geometry, in that order.
- Regardless of the location, informed decisions in designing mechanical and structural systems can reduce total lifetime carbon emissions significantly in early stages of design and assist architects in meeting sustainability targets.
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Abstract

Reducing global greenhouse gas emissions is a crucial sustainability target around the world. The ambitious sustainability thresholds that have been defined for the building sector can only be achieved through carbon-sensitive design from the beginning. Multiple design parameters, their impacts on building performance, along with embodied and operational carbon tradeoffs makes comparing design alternatives in the uncertain context of concept design difficult for architects. Tools and methods often focus more on either operating efficiency or material selection rather than assisting architects in making holistic carbon-sensitive design decisions.

In this research, a design-compatible methodology for low-carbon buildings was developed by using design exploration methods and parametric LCA calculations. The model was run for seven Canadian cities, resulting in over 20,000 design scenarios to capture a broad range of potential solutions. The study investigates the most influential design parameters in relation to the varying carbon intensity of grid electricity. The results show that despite the significant impact of climate, Grid Carbon Intensity (GCI) plays the most crucial role in defining building design priorities in order to optimize for total life carbon impacts. The results also indicate that mechanical and structural systems play a significant role in building carbon footprint. The results also show that in cities with high grid carbon factors, optimizing window-to-wall (WWR) ratio, level of insulation and geometry can contribute the most to reducing carbon footprint. Conversely in cities with low GCI, structural material and mechanical systems selection are highly impactful and all other factors play a marginal role.

Keywords: Life Cycle Assessment, Embodied Carbon, Operational Carbon, Building Carbon Footprint, Early-Stage LCA, Design parameters, Design Space Exploration, Sensitivity Analysis

1. Introduction

The urgency to mitigate climate change, emphasized by the IPCC, calls for substantial reductions in greenhouse gas (GHG) emissions to limit global warming to 1.5–2°C [1]. Despite international pledges, a significant disparity persists between projected emissions and targets. Among major contributors to GHG emissions, the building sector stands out, accounting for 37% of global emissions and 36% of worldwide energy consumption in 2020 [2] . While this presents a formidable challenge, it also signifies a critical opportunity for transformative change.

With increasing importance of building sustainability, efforts to address this issue have led to the emergence of various codes and methodologies aiming to set ambitious goals to reduce emissions and promote sustainable building practices [3]. However, existing approaches often focused on optimizing material choices during the construction stage, overlooking the broader implications and fundamental impact of early-stage design decisions on the carbon footprint of the building [4], [5]. Recent discussions highlight the need for a paradigm shift towards considering building carbon footprints at the early stages of design and planning. However, integrating carbon considerations into early-stage design poses significant challenges due to inherent uncertainties [6], [7], [8], [9], [10].

Previous research has tried to answer the question of design priorities for low-carbon building design during the conceptual design phase, however, the majority of them had a simplistic approach to design by either defining a limited number of design variables or limited range of accepted values. Table 1, summarizes some of the most related recent research. They also diminished the impact of trade-offs between embodied-operational carbon trade-offs and their interwoven impact on building total carbon by incorporating one of the two or estimating OC by per capita values instead of project base, energy consumption and carbon estimations [11] .

Another gap that limits the applicability of previous studies for Canadian built environments is that the impact of harsh cold climates, codes and conventional building construction and energy sources has not been fully addressed for the Canadian building sector. Therefore there is a need to provide clear prioritization for low carbon built environment design in Canada.

Our study addressed these challenges by identifying the key areas in design that exert the most influence on building environmental impacts, particularly in the context of the Canadian building sector. Focusing on cold climates and diverse GCI in major Canadian cities, we determined design priorities conducive to reducing building carbon emissions during the early stages of design. Specifically, we concentrated on fully electrified, high-performance buildings, aligning with guidelines and municipal recommendations for the future of Canadian built environments.

As part of our research, we developed a design-compatible method for early-stage Life Cycle Assessment (LCA) to assist in fundamental decisions. Targeting architects and engineers conscientious of their projects' carbon emissions, our research aim to inform architects and engineers in building design process, and support them in reaching their low carbon goals.Through this study, we filled existing gaps in the literature and provide actionable insights for achieving low-carbon building designs in Canada.

2. Literature Review

The literature review achieved three outcomes. Firstly, by identifying state-of-the-art research and their findings, gaps in the literature that impedes finding influential design parameters in building design were identified. Additionally, this review identified appropriate modeling methodologies to assess building environmental impacts in early stages of design.

Lastly, from the literature two sets of design parameters were selected; first the design parameters that were proven in the literature to have high influence on building total life carbon (TC) were selected, to be evaluated to see if they have the same level of importance for Canadian buildings. Secondly the influential parameters that have received less attention in the literature due to difficulties in modeling have been identified to see if they have meaningful impact of building life carbon and to what extends. These parameters were then used as inputs to the modeling framework developed for this study to evaluate their level of impact for low carbon building design in the Canadian context. We also use the previous research to define a reasonable and practical range of values for each parameter.

2.1 Comparison of different modeling approaches for building performance assessment in during design

Given the growing awareness of the impact of design in impacting the carbon footprint of the buildings, researchers have employed diverse approaches to address embodied carbon in early stages of design in recent years. With a review of the literature, three main methods for this purpose have been identified which are summarized in the following sections.

2.1.1 Scenario-Based models

Some projects have approached the impact of design decisions on building carbon footprints by evaluating case studies and comparing them. These research works aim to identify the impact of either a specific material or technology or a limited set of design strategies on building sustainability performance. This is mainly conducted by describing a limited range of scenarios with similar parameters and quantifying the impact of changes on the building's TC (Total Carbon) by varying one parameter. As an example, Tolia examined 5 scenarios defined based on the British Columbia's high performance operational energy code, the 'step code' and calculated the potential carbon reduction through changes in building insulation, HVAC systems, and fuel type (Tolia, 2020). In another study, Lukic et al investigated the embodied energy and greenhouse gas (GHG) emissions of a residential multi-story timber building with an increase in height. To do so they performed LCA for four scenarios with an integrated approach that considers structural behavior and includes connectors and fasteners (Lukić et al., 2021). Similarly, Hawkins et. Al explored the implications for structural design decisions by comparing three scenarios of concrete, steel, and timber options for a typical medium-rise building structure. They used dynamic life cycle assessment to convert greenhouse gas emission histories to key climate impacts using a simple dynamic model [12]. In a recent study, scenario-based models were utilized to compute and analyze the energy, carbon emissions, and embodied water in four university buildings [13].

These researches provide information on the effectiveness of design measures and their conclusions are based on a high level of detail in modeling within the scope of the study. These methodologies are primarily employed to demonstrate the impact and performance of emerging building technologies. However, due to their narrow scope and limitation in generalization of results, such studies have become less common in recent years, owing to advances in computational capabilities enabling a broader range of studies with more generalizable results.

2.1.2 Design Optimization

The other methodology is the single or multi-objective optimization approach that aims at the lowest-carbon-intensive scenarios within the design space according to the goals of the study. This research has a wider range of parameters and objectives and better reflects the complexity of design decision-making and scope of the design space. In the research stream, energy use, carbon emissions, cost (Schwartz et al., 2022), and other environmental impact categories have attracted the most research interest (Gagnon et al., 2019a, 2019b; Hammad et al., 2018; Hollberg, 2016; Kamazani & Dixit, 2023; Kovacic & Zoller, 2015a, 2015b; Verbeeck & Hens, 2007.; Zolfaghari & Jones, 2022).

While optimizing quantitative objectives have been widely addressed in the literature, interestingly recent advancements in computational modeling and performance assessment made optimizing even qualitative variables feasible. For example, carbon footprint and the view of the conceptual building form have been optimized to reach the lowest carbon and highest view score using multi-objective optimization implemented by parametric models [14]. In another study, Kaitouni et al. developed a parametric digital workflow in the Grasshopper environment to evaluate the energy performance and indoor thermal and visual comforts in a nearly Zero-Energy office building (Idrissi Kaitouni et al., 2024).

Design is a complex issue with several influential parameters with different weights and impacts that can change simultaneously and dynamically. The goal of Multi-Objective Optimization (MOO) is to satisfy multiple design objectives in an optimum design solution. Therefore, while these methods are more generalizable than the scenario-based method, their scope is still limited to the number of objectives and default values/ranges for the parameters which may result in leaving a range of high performance scenarios unexplored [15].

2.1.3 Design Exploration

The last approach is design exploration, which investigates the whole design space meticulously by measuring the objectives for each possible design solution within the design space. The advantage of this method is managing the uncertainty associated targeted variable (here, total life carbon) in early-stage design as the whole design space has been explored (Marsh et al., 2023). The downfall, on the other hand, is the time and computation-heavy calculations. This method facilitate selecting the scenario that best satisfies design objectives by providing a clear and deterministic understanding of all possible scenarios within the design space. Unlike the other two methods, in design exploration, designers have full control over selecting the design strategies based on outputs and performance metrics and there are no possible solutions with unknown results. Therefore, this method provides better understanding of design options compared to two previous methods and also manages the uncertainty that exists in optimization [16]

These benefits overcome the gaps in previous methods and make DSE an appropriate method for integrating LCA into early-stage design. This method has been used to investigate the impact of structural design parameters on building carbon footprint of high-rise mass timber buildings (Hens et al., 2021). In another study the DSE has been utilized in early stage design to quantify the impact of building subsystems on the carbon footprint of a commercial building [10]. In another study, a DSE-based model was developed to report the embodied carbon of building structures in early stage design by exploring all structural design parameters.

Due to the complexity of carbon assessment in conceptual structure design, this method has been of assistance to architects in design decision-making [10], [17]. In this regard, previous studies deployed approaches to simplify calculations in order to overcome this challenge. For example, in a study DES has been applied to investigate the impact of building form on carbon emissions of a building with six potential geometries. The method evaluated the whole design space however, operational carbon calculation was conducted on per capita basis, which would neglect the impacted enegy consumption by design modifications and therefore limit the ability of assessing the EC-OC interactions. [18]. To overcome the challenges associated with DSE, in another study, Li et al. reviewed and proposed different methods of guided DSE and compared them in terms of their performance [16]. They proposed that guided methods , such as near optimal DSE, Representative DSE and Local DSE, can overcome the time-intensity of the unguided DSE method by parting design space and excluding less efficient scenarios; however, this simplification would leave a part of design space unexplored. Therefore, while these methods can answer specific design questions, they are not design compatible as they leave a remarkable number of scenarios unexplored and they face some deficiency in addressing uncertainty.

Fig. 1 provides a diagram for comparing the main features of three mentioned methods in addressing building performance for design integration. With respect to all applied methods in the literature and the benefits, limitations and shortcomings associated with them, DSE shows the highest compatibility with the design process and can be integrated better in design. This is mainly due to both breadth of studied scenarios as well as the accuracy of modeling and deterministic results in each scenario. Due to these features the results of the DSE model are more generalizable and are useful for architects to steer the design progress to reach low TC. As this method assesses all scenarios, it is time intensive in application. On the other hand as the performance of all scenarios are available to the user, it is the best and most accurate method for decision making. On the other hand scenario-based modeling, May only evaluate a few scenarios for modeling and performance assessment which yield results faster but due to the uncertainty associated with unstudied scenarios cannot be a reliable decision making method. Optimization methods are between the two.

Fig.1 shows the main characteristics of the four design-integrated performance assessments. In this diagram, the methods are also compared based on the resources required, indicated by color, and the radius of the circles illustrates the suitability of each method for decision-making in the early design stage, balancing determinism and comprehensiveness of the results. The vertical axis represents the extent of the studied sections of the design space, indicating the generalization of the results to the whole space. The horizontal axis reflects the expected determinism of the results within the study scope. For example, in scenario-based modeling, a limited number of scenarios are examined, leading to a specific and restricted section of the overall design space being investigated. However, since the scenarios are modeled directly, the results are deterministic and reliable. In other words, this method provides deterministic insights for a limited section of design space, which cannot be helpful for design decision making beyond the studied scenarios.

In contrast, optimization-based methods involve exploring multiple scenarios, which allows for a larger section of the design space to be investigated. However, due to unexplored segments of the space, there is a risk of missing potentially better solutions, making the results less deterministic. Lastly, DSE investigates all scenarios within the space, resulting in the highest level of comprehensiveness. Unlike optimization-based methods, DSE evaluates all scenarios and explores the whole design space, leading to deterministic results. This method shows the highest compatibility with decision making due to the extent of explored space along with determinism of results, however the method is time-intensive and demands computation resources.

In this study by deep understanding of advantages and limitations of design performance assessment methods we aim to define the modeling process that provides the highest compatibility with early-stage decision making. Our goal is to develop a modeling framework that explores the whole design space efficiently and generates reliable results on building total carbon emissions of different designs.

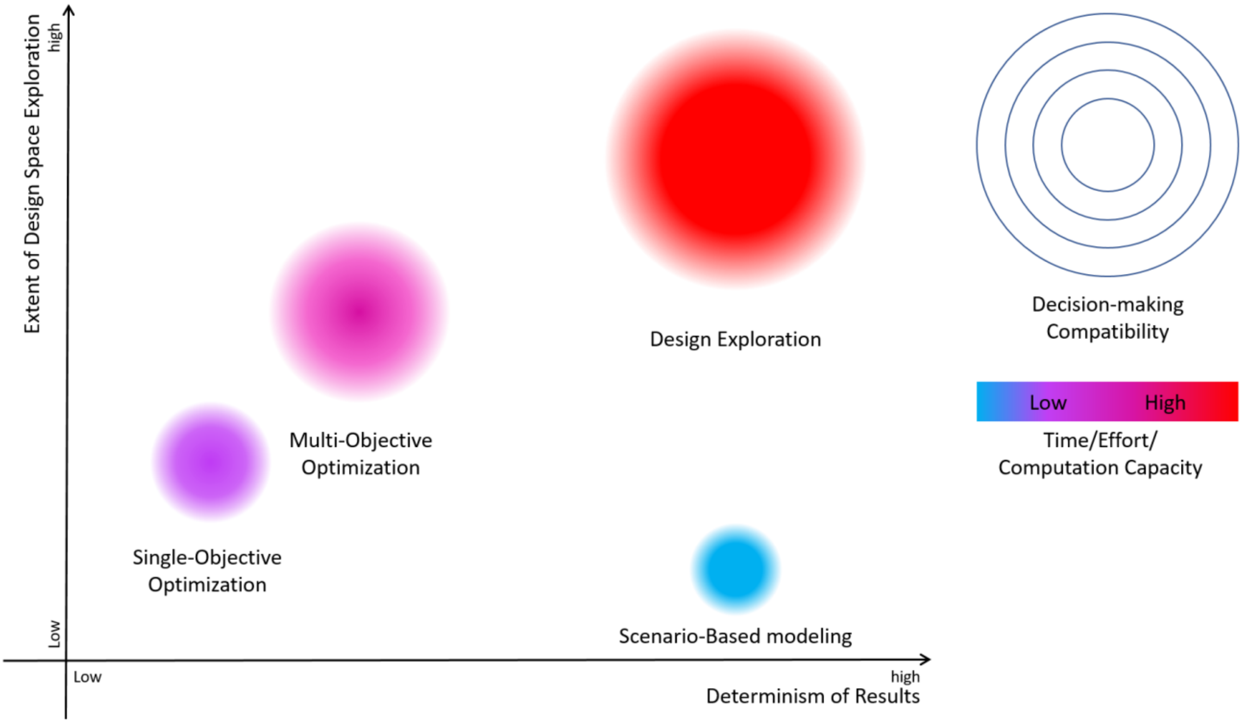


Fig. 1- Diagram comparing main characteristics of methods for evaluating performance of design alternatives

2.2 Analysis of the different design parameters used in literature

2.2.1 Parameter selection

In the next step, the literature was investigated to explore the most impactful early-stage design parameters on building total life carbon Literature shows that a great portion of research on this topic focuses on design parameters' influence on building energy consumption and therefore they targeted Energy Use Intensity (EUI) as their objective leaving buildings' OC and EC impacts out of the scope of the study. In this literature review we focused on studies that aim to investigate the impact of design parameters on building total life carbon.

An exploratory search has been done to explore the recent research in this area and identify which parameters are frequently studied and find specific research on those that we identified as important design parameters for early stage design. Table 1 shares the results of the study. We aim to identify the design variables by the highest impact according to previous studies that have been proved to be impactful on building carbon. The results of a previous review identified the most influential design parameters on building LCA and revealed that twelve design variables had the most impact on building environmental impact. These parameters includes: building aspect ratio, window-to-wall ratio, shading area, building orientation, number of floors, building shape, floor area and floor-to-floor height, have an impact on a building's life-cycle environmental impacts, types of building components, sizes of building components, types of building materials, and thickness of building materials [19]. Therefore in this study we selected a list of variables that are both associated with early stage design and are also playing an important role on building performance in cold climates.

Table 1- Summary of the literature review on early stage low-carbon design, comparing scope, method and measures.

Reference	**Design Parameters**													**Methods**	**LCA stage**	**Building Scope**	**Building Type**	**Measures**						**Location**
	Geometry	Orientation	Area	WWR	Window material	Envelope material/assembly	Level of Insulation	HVAC	PV	Sharing	Structure	Occupancy	Infiltration					EC	OC	Cost	Energy Consumption	Embodied Energy	Solar Radiation	
[20]	X			X	X	X			X					MOO	A1–A5, B4, and B6	Envelope, Structure, HVAC	a single-family house	X	X				X	Oslo, Norway
[21]				X	X	X				X				MOO	A-C	Envelope, HVAC	Multi-story apartment building	X		X				Hungary
[22]		X			X	(X) Only Wall								MOO	unknown	Envelope	Medium office building (ASHRAE benchmark model)	X				X		Texas, USA
[23]	X			X	X	X					X	X	X	DSE	A1-A5	Envelope, Structure	midrise to high rise, residential or office	X		X	X			Singapore, Singapore Lagos, Nigeria Kiev, Ukraine Cairo, Egypt Shanghai, China London, UK
[24]	X					(X) Only Wall	X	X						DSE	A-C (B6 excluded)	Envelope, HVAC	Apartment	X	X					Potsdam, Germany
[25]				X		X					X			Scenario-based modeling	A-D	Envelope, Structure	Mid-rise office	X			(X) Fuel Consum	X		Charleston, South Carolina.

																					ptio n			
[26]	X			X	X	X	X							MOO	A1-A3	Envelope, HVAC,	Mid-rise exhibition hall	X	X	X	X			Tenjin, China
[27]	X	X		X		X		X					X	MOO	Not stated	envelope, PV design	Mid-rise residential building	X	X		X			Accra, Ghana
[28]		X	X	X	X	X	X				X			MOO	A1-A3	Envelope, Structure, Interior, renewables (PV), HVAC	Multifamily building	X	X	X	X			Bhubaneswar (hot and humid), New Delhi (composite), Jodhpur (hot and dry)

WWR= Window to wall Ratio

LCA Scope= Stages of building life cycle which is materials manufacturing (A1-A3), construction (A4,A5), use and maintenance (B), and end of life ©, Beyond the scope emissions(D) [29]

Building element= Included elements and studies components of the building which can include; Structure, Envelope, HVAC, Interior, etc.

X Included (X) Partly Included

2.2.2 Range and value selection

As the DSE generates and calculates the performance of each scenario, defining the realistic range for parameters is crucial. The literature review shows the commonly acceptable ranges for parameters. However as this amount is highly impacted by the area and design convention, the collected data on values/ranges has been double checked by practice for studied cities. All parameters along with their values and ranges are specified in Table 2 and has been used for developing the parametric model used in this research.

2.3 Gaps identified in prior work and novelty of this paper

The majority of papers in the area of performance assessment in the early stage of design focused on consumption and building TC have received less attention. With a closer reviewer on current literature on early-stage decision-making for embodied carbon several gaps are observed. One of the gaps is the approach to energy consumption and reducing the operational section of TC. A common approach is to simplify energy assessment, as mentioned in the previous section that leaves the question of the real-time and accurate impact of building design features on operational carbon.

Secondly, this paper incorporates the impact of climate in a more realistic way. Previous research shows building emissions can change depending on design features in different cities but the range of investigated climates mainly covered mild to warm and moist climates. Given the impact of climate on building performance and emissions (Gauch et al., 2023). a gap is observed in addressing design priorities in the cold and very cold climate of Canada. Similar to climatic conditions, another factor that is dependent on the location, the GCI can range significantly and thus can have a significant impact in defining low TLC design priorities. The literature shows uneven attention to areas with low grid carbon when EC would likely have a higher influence on TLC results.

Thirdly, the variety of design parameters and their range has received a simplified approach and in some of the studies a limited number of design variables were considered or the ranges were very limited due to aforementioned computation constraints. Therefore, there is a need for an study that addresses a wide range of design parameters with realistic ranges that correctly reflect the diversity of design decisions faced by industry.

The main aspect of novelty of this paper lies in its applicability and design compatibility of the applied method to address total life carbon in the early stage of design. We aim address this for major Canadian cities considering their contextual features such as grid carbo intensity and climate. Moreover, we aim to answer the question using DSE method that can be incorporated in the design process and is flexible in terms of objectives, therefore it can be utilized in a design problem to satisfy various design objectives.

3. Methodology

In this study we deployed a design space exploration (DSE) tool to investigate a the whole set of design options and identify the most influential design parameters on building TC. To do so, a space of over twenty thousand scenarios in seven major Canadian cities was investigated. This study is focused on fully electrified mid-rise commercial buildings. The figure below shows the methodology deployed in this study.

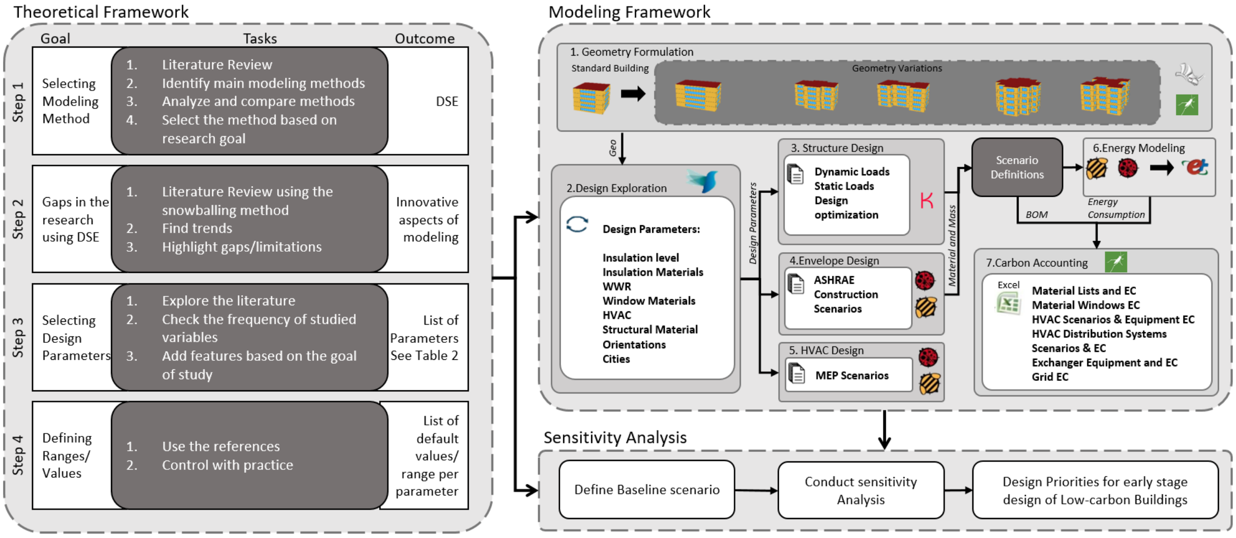


Fig.2 -Research Theoretical and Modeling Framework

3.1 Design Parameters

For this study, an eight-dimension design space was defined with eight design parameters and conventional ranges. This resulted in 2,880 design iterations per city. This analysis was done for seven major Canadian cities to find the most impactful design priority to reach the lowest building TC across different cities. In total 20,160 design solutions were generated using the modeling workflow and EC, OC, and TC for each scenario were calculated. Table 1 lists the design parameters and the ranges defined for each parameter.

Table 2-Design Parameters, ranges and discretization used in this model

	Design Parameter	Secondary Parameter	Range	Number of values
1	Geometry		Square, Sq+, SqH, Rec, Rec +, RecH	6
2	Envelope	Level of Insulation	code-minimum High Insulation	2
		IGU	Double glaze-Aluminum Triple glaze-Aluminum	2

		WWR	0.25 0.5	2
3	Structure Type		Concrete, Steel, and wood	3
4	HVAC system		Packaged rooftop heat pump VAV AHU w/ PFP Terminals DOAS + VRF DOAS ERV	4
5	Orientation	Azimuth	-60, -30, 0, 30, 60	5
6	Cities		Vancouver, Edmonton, Winnipeg, Saskatoon, Toronto, Montreal, Halifax	7
	Total			**20,160**

3.1.1 Geometry

The base model is a typical standard 3-storey commercial building in the city of Vancouver with a square footprint and total floor area of 3075 m^2. To investigate the impact of early-stage form finding five variations of base model were included; elongated form which is the same area of a rectangle footprint. For each type, 2 other variations were also developed: protruded geometry with a protrusion in the façade (type plus) and a cavity geometry with negative protrusion in surfaces (type X). All types have the same total floor area footprint area and occupancy profile. See figure X below that outlines the variation in geometry.

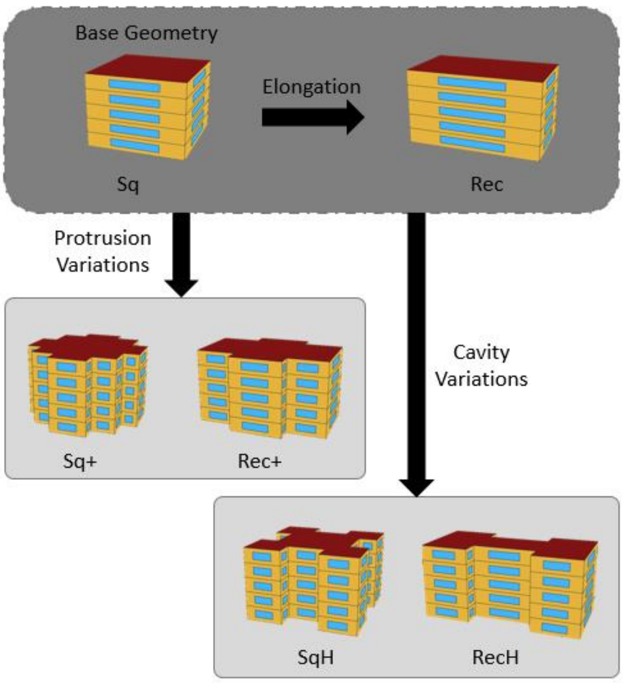


Fig. 3- Variation of geometry

3.1.2 Envelope

To simulate the design options that impact envelope EC, different insulation levels and insulation materials were defined. Also due to the impact of the transparent envelope on TC, WWR and Insulating Glass Unit (IGU) number of glazing layers varied among studied scenarios

To include the range of insulation levels, code-minimum insulation based on ASHRAE guidelines [30] was modeled for each city. Also to reflect scenarios with better thermal behavior, construction details for the colder climate were modeled to reflect user choice of higher insulation to mitigate energy loss through enclosure. For example, the City of Vancouver is located in a mixed climate zone (zone 4) based on ASHRAE guidelines (American Society of Heating, 2019). To study the environmental impact of conventional enclosure construction details for zone 4 were considered as scenarios with code-minimum insulation. Then, to model highly insulated enclosure construction details for cold climates (zone 5) were also modeled which in this study is referred to as high-performance scenarios (refer to Table 1). For windows, two high-performance common insulated glass units (IGU) were studied, double and triple paned. Also, to model different variations of the transparent envelope, two WWRs were investigated: a conventional WWR of 0.25 and a more transparent option of 0.5.

3.1.3 Structure

For this study framing structure with three materials of concrete, steel, and mass timber was selected and the impact of structural material selection on building EC was calculated. It is noteworthy to mention that other design parameters such as bay length, floor-to-floor height, number of stories, etc. can affect structure design and its impact on building carbon footprint, however, due to the scope of this study, they are considered as control variables. Default values for structural design are as Table 3. The design loads are extracted from the British Columbia Building Code 2018 [31]. The impact of structural parameters on the embodied carbon of the building was discussed in detail in another paper by authors [17]].

Table 3- Design assumptions and input for structural automatic design

	Design parameter	Value
1	Structural material	Reinforced Concrete, Steel and mass timber
2	Bay	6-8 m (depending on the geometry)
3	Floor-to -floor height	3.5 m
4	Live load	4.8 kPa (First Floor) 2.4 kPa (upper floors)
5	Dead load	3.1 kPa (Concrete Structure) 2.4 kPa (Steel Structure) 1.5 kPa (Mass Timber structure)
6	Snow load	3 kPa (average for Canada)
7	Lateral forces	5 kPa (average for low-risk areas)

3.1.4 HVAC systems

To correctly reflect the various available options for building an HVAC system, two conventional and two high-performance scenarios were selected. To select the HVAC scenarios, the results of a previous study by Rodrigues recommend a list of HVAC systems for a mid-rise commercial building. This study reveals per capita lifetime carbon values for listed HVAC scenarios that includes equipment, distribution systems as well as refrigerants [32]

- packaged rooftop heat pump,
- Variable air volume Air Handling Units with Parallel fan powered Terminals (VAV AHU w/ PFP)
- Dedicated Outside Air Systems with (DOAS + VRF)
- Dedicated Outside Air Systems with Energy Recovery Ventilators (DOAS ERV)

3.2 Life Cycle Data and Methods

The scope of this study covers A-C stages of building life cycle according to EN 15978 (CEN, 2012) to study EC, OC and the tradeoffs between the two. The goal is to calculate and compare the TC of functionally equivalent design scenarios to identify the most impactful design parameter on a building's environmental impact. All investigated scenarios are structurally stable, have the same area of 3075 m2 and satisfy ASHRAE building code requirements over the 60 years life span of the building. The functional unit is kgCo2/m2 of total area for the life span of the building. Carbon intensity of materials is extracted from EPDs.The EPDs are comparable in terms of life cycle stages (A1-A3), environmental impact indicator (GWP), and their method (EN 15804). Declared units are either in SI units or converted to kgCo2eq/kg material using information published in the EPD. For GWP per material see Appendix 1.

To calculate other life cycle emissions, City of Vancouver embodied Carbon guidelines. In absence of carbon impact per life cycle stage, the following methodology may be used as an interim solution to report TC [33]:

- Construction process stage – transportation to the construction site (module A4) impacts shall be assumed equal to 4% of the A1-A3 impacts;
- Construction process stage – construction (module A5) impacts shall be assumed equal to 6% of the A1-A3 impacts;
- Use stage (modules B1-B5) impacts shall be assumed equal to 10% of the A1-A3 impacts; End-of-life stage (modules C1-C4) impacts shall be assumed equal to 5% of the A1-A3 impacts.

To calculate operational Carbon, for each scenario energy consumption was calculated using energy plus model couples with the parametric model. The grid carbon intensities (see Appendix 2) were extracted from Canada’s National Inventory Report (Canada. Environment and Climate Change Canada, 2023) and used to calculate OC for the life span of the building.

3.3Modeling Workflow

The modeling workflow of this study consists of a chain of software and tools to investigate design variations and related energy modeling as well as LCA calculations associated with scenarios within the design space. The parametric model developed in this study is capable of generating a physics based model for each scenario within the design space. In this space, the parameters are the dimensions of space and their values/ranges are the length of each dimension which is explored through DSE. To explore the complex and multidimensional design space, this parametric model first generates geometrical models in Rhinoceros and Grasshopper based on the six defined footprint geometries (module 1). To ensure all scenarios are generated and the whole design space is explored Colibri plugin was used in module 2. In module 3 which is the structure module, the building structural system is designed based on building form and analyzed using Karamba 3D for structural stability under static and dynamic forces and optimizing cross sections (Architekten & Airport, 2011). After generating design scenarios, in module 4, they are translated into energy models using ladybug tools. This module will simulate weather conditions for each city and define envelope assemblies with respect to ASHRAE 2019 requirements and defines thermophysical features of materials (Smith & Gill, n.d.), in module 5 the HVAC scenario are assigned to models to prepare energy model for module 6, in which the model is translated into an IDF file ready for energy modeling and predicting energy consumption using Energy Plus [34]. In the last module of this modeling pipeline, bill-of-material is extracted from the model and further LCA calculations are conducted to quantify EC associated with structure, envelope, and HVAC systems. Also the energy consumption reported in form module 6 which is in the form of EUI, is first used to calculate energy demand annually and for building lifetime. Then, by using GCI (see Appendix 2) predicted energy consumption is used to calculate OC. Lastly all the input and outputs are exported for data preprocessing, analysis and visualization. The modeling framework in Fig 2 depicts the modeling process.

3.4 Sensitivity Analysis and Benchmark

The sensitivity analysis method used in this study is one-factor-at-a-time (OFAT) sensitivity analysis that was feasible through availability of data on EC and OC of all scenarios. This method has higher accuracy compared to other sensitivity methods such as Multi-Way or Global Sensitivity Analysis because it isolates the impact of a single variable, minimizing the complexity and potential interactions that could obscure the direct relationship between input and output, thus providing more precise insights into the effect of individual parameters [35], [36]. In this method one parameter varies at a time while the others remain constant and have equal value of the base scenario. To use the OFAT sensitivity analysis, a base model should be defined to measure the changes in TC against that. The benchmark developed for this analysis is the scenario with the first value for the design parameters in Table 1.

4. Results

4.1 Location, Climate and Grid Carbon intensity

As a result, over 20 thousand scenarios were modeled and the OC, EC and TC were calculated. The figure below shows the distribution of EC, OC and TC across studied cases. As the whole design space exploration method was adopted, similar scenarios were studied in different cities and consequently the range of EC is similar in all cities. The only difference in the studied scenarios is the envelope insulation according to the ASHRAE requirements per region. On the other hand, the range of OC shows significant variation, which makes TC vary significantly across different cities. The graph below shows the average EC, OC and TC of studies scenarios along with carbon intensity of the grid. As fig. Shows there is a strong correlation between GCI and average TC of studied scenarios per city. Cities such as Calgary, Halifax and Saskatoon with high GCI have significantly higher average TC, while scenarios studied in Toronto, Vancouver, Montreal and Winnipeg with almost decarbonized grid, have remarkably lower average TC. In this study, we call the former groups HGC (High Grid Carbon) and the Latter LGC (Low Grid Carbon). The results show that in LGC cities ,despite cold climate and high Heating Degree Day (HDD), the OC is negligible due to carbon decarburization leaving EC as the main contributor to building TC. However in HGC cities, OC still dominates EC's share in building TC. Given the variation in expected TC across different cities and with respect to different role of EC and OC in influencing building TC, It is expected that different design parameters will be impactful to reduce building TC and the level of their impact also be different per city.

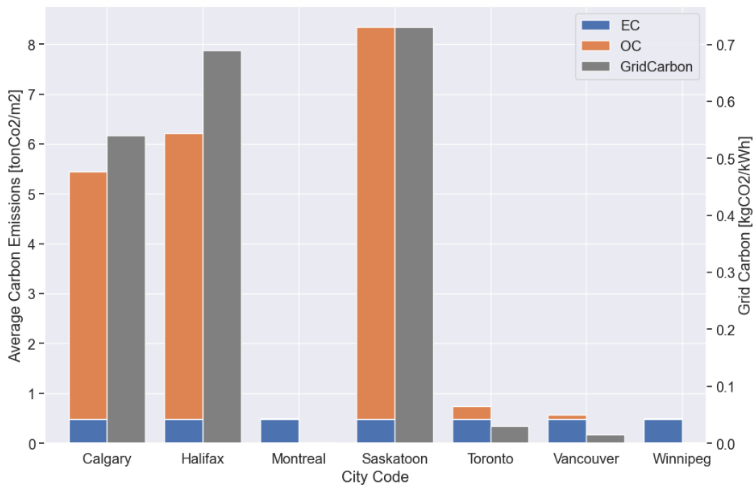


Fig. 4- Comparison of average EC, OC and TC and GCI per city

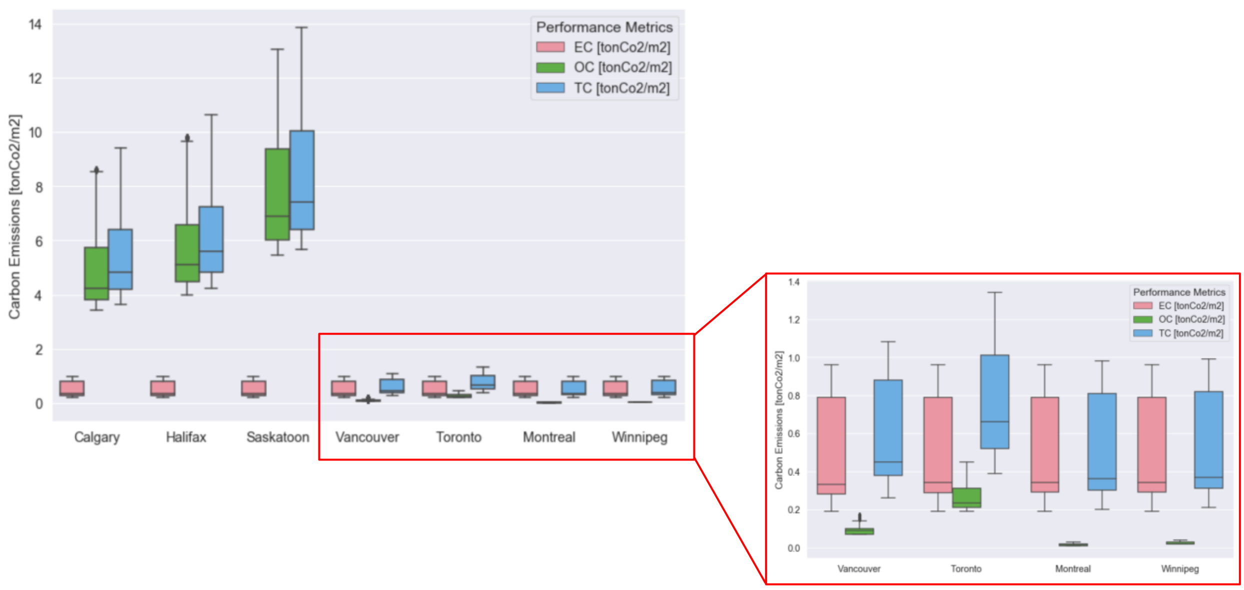


Fig. 5- Range of building EC, OC and TC, per city

The results show that the impact of GCI is dominant on the climate and heating demand. For example in Winnipeg with extremely colder climate (zone 7) and coldest climate among studied cities, reports lowest bound of TC, due to the almost decarbonized grid carbon intensity. This is more meaningful when compared to TC of buildings in Toronto, which has warmer climate (zone 6), or even Vancouver with the warmest climate among studied cities (Zone 4). Both cities report higher bound of TC despite milder climate and lower energy consumption. This example shows that the impact of sever climate and high energy demand can be outweighed by low GCI, therefore, the first question for architects in defining design priorities and expected TC for low-carbon building, first refers to carbon intensity of source of energy. Although architects are not in control of GCI, by pinpointing the impact of GCI on building TC and by using the results of this study they will be able to identify the area of focus in design for cutting carbon by knowing the most influential design factors and the extent of impact.

4.2 Geometry

Another design priority aiming to lower the building carbon footprint is building geometry. As Fig. 6 shows compact shapes, such as squares, generally result in lower EC, EUI, and TC across all cities. Geometry shows a higher impact on building TC in HGC cities rather than LGC cities. The reason is that the shape of the building footprint impacts building interaction with EUI, and changes in EUI in HGC cities, impacts TC significantly due to the importance of OC. On the other hand in LGC cities, an increase in EUI would not affect TC much due to the importance of EC.

Fig.6 shows the trend of changes in TC by geometry. As a reminder all studied geometries have the same area but due to cavities or protrusion their perimeter is different according to Appendix 3. Among all studied geometries, the square which is the most compact shape among all variations has lowest EC, EUI, and TC across all cities, on the other hand, shapes with most protrusions such as SqrX, RecX and RecH has the highest EC, EUI and TC. The same pattern is observed across all cities regardless of their grid carbon factor, HDD and climate.

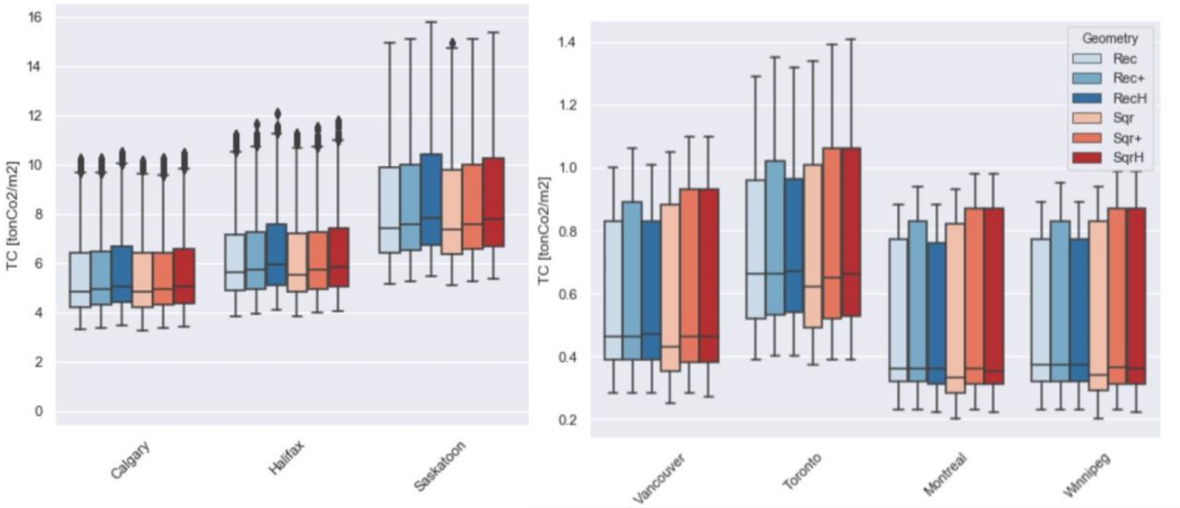


Fig 6- The impact of geometry on building TC in studied Cities

It is important to note that due to the significant difference in TC bounds across HGC and LGC cities, the changes in TC should not be solely considered. Because the TC in LGC is far lower than HGC cities and it might seem that changes in geometry are not impactful in cutting carbon. Appendix 4 shares the results of minimum and maximum and average TC reported per geometry per city. As the results show by changing the geometry of the building in HGC cities can change the TC on average by %5, while in LGC this change is %7, therefore it is concluded that while geometry does not show remarkable potential for reducing building YC compared to other design parameters, it is still important in reducing TC specially in HGC cities.

4.3 Structural Material

The results show significant impact of structural material on building TC in all cities. As the graphs in Fig. 7 show, in all cities mass timber structure has the lowest TC while steel structure has the highest TC. While the trend in both LGC and HGC is similar, the magnitude of TC fluctuations is significantly different.

In HGC cities due to dominance of OC and relatively limited impact of EC on building TC, the choice of structural material would not impact TC more than 13%. On the contrary, as the Table 4 shows, in LGC cities the material choice affects TC remarkably and can increase TC to more than double. Therefore architects should be cautious of selecting structural material when designing buildings in LGC regions. This underscores the critical role of structural material in managing building TC, particularly in regions with low grid carbon intensity.

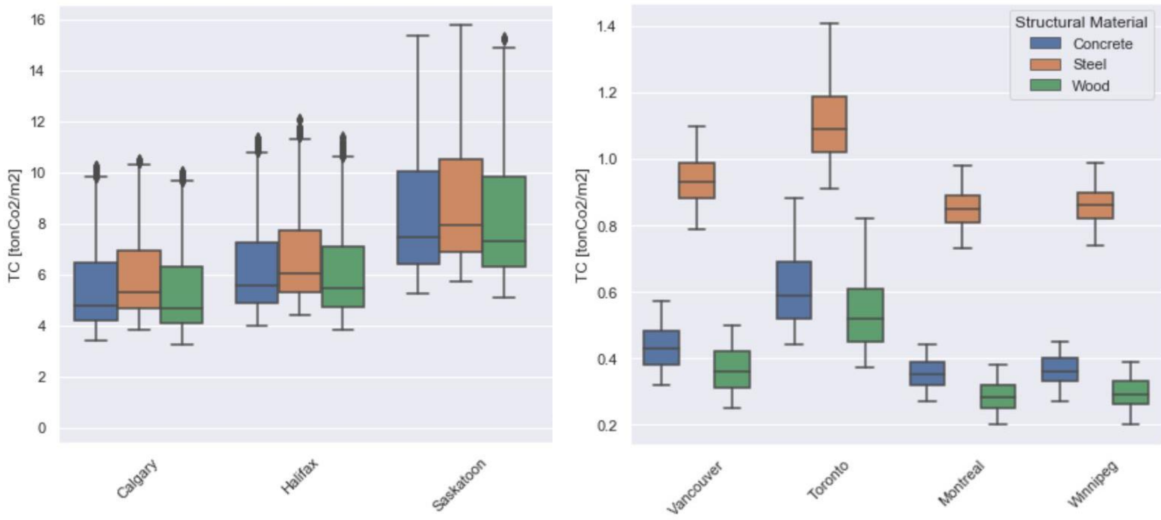


Fig. 7- TC range per structural materials

4.4 Window Design

In this study the window design has been classified under two design parameters, WWR and type of IGU. Since heating is a concern in Canadian buildings, a high WWR is less common. Therefore, a WWR of 0.25 was considered typical, while a WWR of 0.5 was used to represent more transparent designs. Also as the windows are typically a source of heat loss, IGUs with high thermal resistance (such as double and triple-pane windows) are used (see Appendix 1). For this purpose, two and three pane windows with Thermal break aluminum frame have been used.

The analysis shows that while lower WWR reduces EUI and OC, the choice of IGU has a limited impact on TC, suggesting that typical double-pane windows are adequate for carbon reduction in Canadian climates and using triple pane IGU will only increase the EC without noticeable benefits in reducing OC.

4.4.1 WWR

The results indicate that the trend in TC changes with WWR is consistent across all cities and climates. As the Fig.8 shows across all studied regions, lower WWR contributed to lower TC while higher WWR leads to higher TC.However, the extent of impact of WWR on changes in TC is different across studied cities. In HGC cities using lower WWR has a remarkable positive impact on lowering TC due to the importance of OC and direct impact of WWR on EUI. Therefore in cities with high GCI special attention should be placed on less transparent enclosure design to lower building carbon footprint. It is important to note that these results are based on highly efficient IGUs, which still do not justify high WWR in cold regions with high GCI from a carbon perspective. Therefore it is expected that by using typical GUI for higher WWR, will increases building TC.

Thus, in LGC cities, while lower WWR buildings still report lower TC, the difference is less significant and may be outweighed by other design considerations. Compared to HGC cities and it can be neglected in virtue of satisfying other design goals. In summary, optimizing WWR is particularly critical in HGC cities due to its substantial impact on TC.

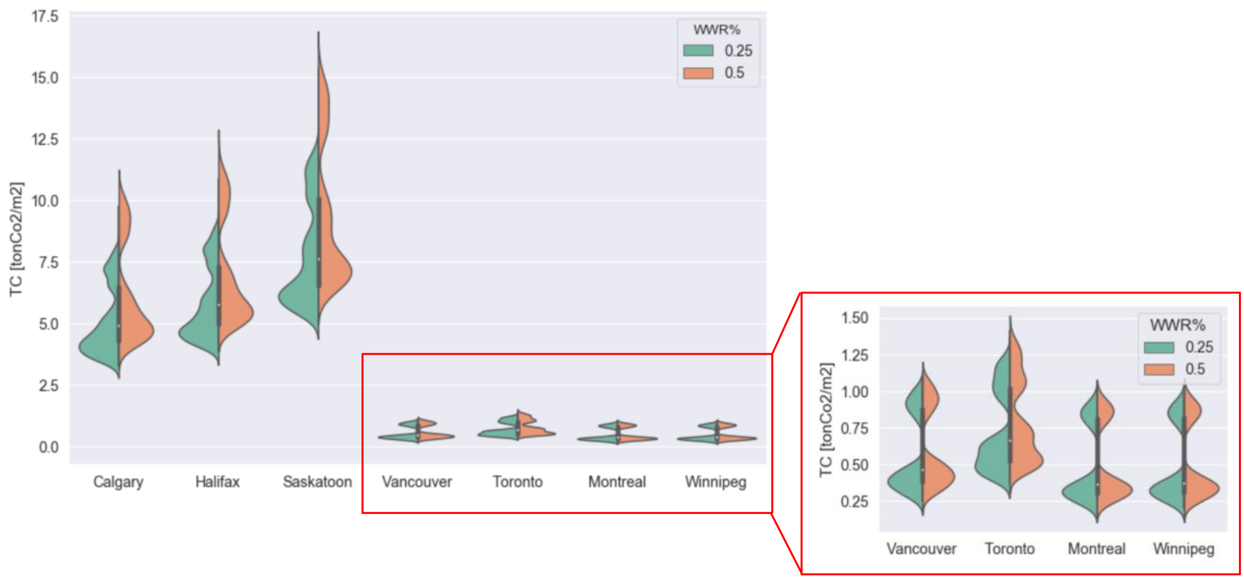


Fig. 8- EC, OC and TC range per WWR

4.4.2 Window Material

On the contrary to the trend observed with WWR, the use of different IGUs shows limited impact on building TC across all cities. Notably, the results show that using three-pane IGU results in lower TC compared to using two-pane IGUs. This difference is more noticeable in HGC cities than LGC cities. However, use of more efficient IGUs compared to the impact of other design parameters, shows only a marginal difference in TC (see Fig. 11). To be more detailed, while three-pane windows can reduce EUI and cause reduction in OC, they are more carbon intensive and therefore these two impacts are overall balanced out. It is concluded that typical two-pane windows perform well in reducing building TC and additional thermal resistance for building IGU is hardly justifiable given the minimal additional benefit in Canada's climate.

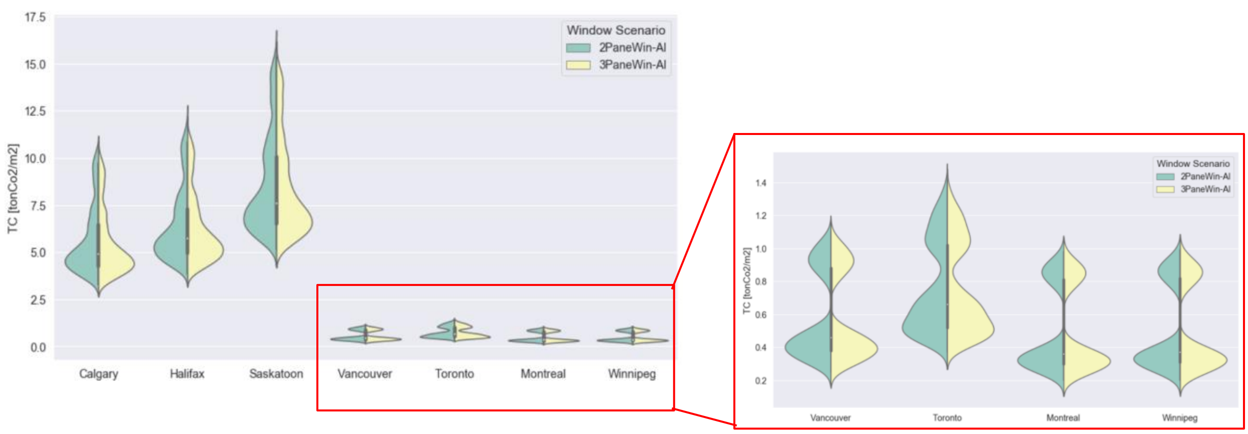


Fig 9- IGU material and WWR per city

4.5 Insulation Level

In this study two levels of insulation were used: code-minimum insulation that satisfies the requirement of climate according to ASHRAE and a voluntary one-step higher level of insulation. For example for the city of Vancouver which is located in region 4, insulation levels for climate region 4 (mix climate) and 5 (cool climate) were modeled.

The results show a consistent trend of TC reduction with higher levels of insulation. As higher insulation results in lower EUI and OC, this trend is more noticeable in HGC cities. In this study fiberglass was used as the insulating material (see Appendix 1). As fiberglass is not a carbon-intensive material, increased use does not contribute significantly to EC. However, it is impactful in reducing OC. Overall, a higher level of insulation is recommended in all cities, with a more pronounced impact expected in HGC cities.

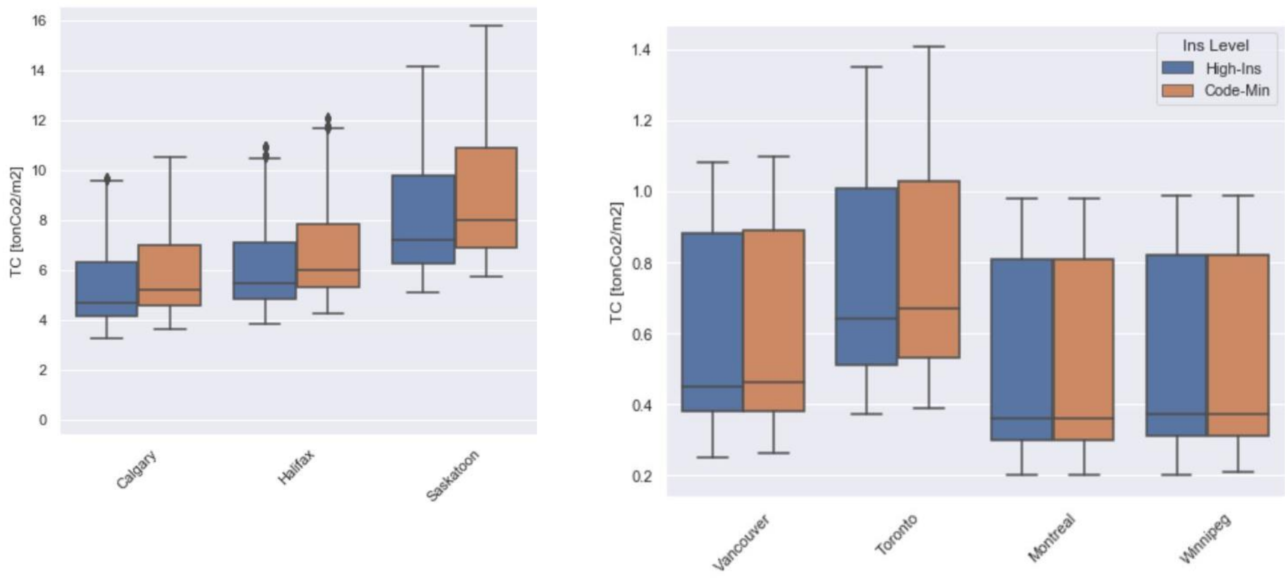


Fig. 10-Range of Total Carbon per area by Insulation level per city

4.6. HVAC Systems

HVAC systems have a dual impact on building TC, influencing both EC through the carbon intensity of materials and OC through energy efficiency. The correct selection of HVAC systems is an important decision in all studied cities. In HGC cities, the impact of HVAC systems on EUI and therefore OC affects TC substantially. In LGC cities, while OC is negligible compared to EC, HVAC selection still shows a significant impact on TC due to the carbon intensity of equipment, distribution systems, and refrigerants. For instance, high-efficiency HVAC systems significantly reduce OC in HGC cities, whereas in LGC cities, selecting low-carbon HVAC components is crucial. Overall, the role of HVAC systems in both energy consumption and material carbon intensity makes them a critical factor in reducing TC across various climatic conditions.

4.7 Orientation

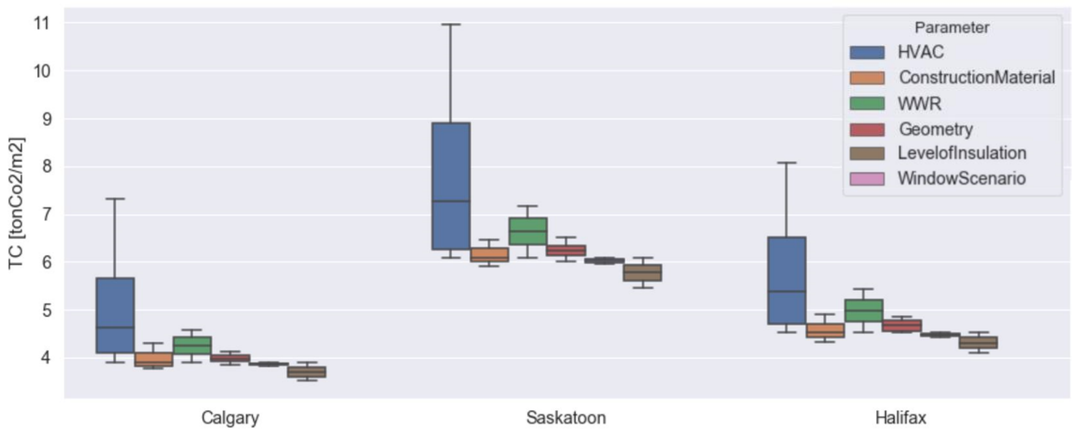
Orientation mainly affects solar gain and, to a lesser extent, conduction due to wind direction, both of which impact energy consumption, OC, and consequently TC . Given the high performance of building enclosures with efficient windows and opaque surfaces, the impact of orientation on thermal transmittance is minimal in the studied scenarios. This will diminish the influence of building orientation on building TC. The results indicate a negligible impact of changing orientation in LGC cities and a slightly higher, but still limited, impact in HGC cities. Therefore, the results shows that orientation of the building does not play a significant role in TC of thermally efficient buildings. Given the advanced thermal efficiency of modern building envelopes, orientation's role in TC reduction is secondary to other design considerations like HVAC systems and structural materials.

5. Discussion

The graph below shows the range of changes in building TC in HGC and LGC cities. As the graph shows, in HGC cities higher ranges of TC are observed. The results show that design priorities change in cities based on contextual conditions. In other words, the potential of reducing building TC by design parameters, changes significantly across Canadian cities. Our findings highlight the dominant role of GCI in determining building TC range, as well as determining design parameters with the highest potential in reducing TC.

In HGC cities, due to the dominance of OC over EC, design parameters that directly impact EUI have the most potential for reducing TC. The results show HVAC scenarios play the most significant role in building TC. Secondly, the design process should focus on lowering TC by reducing WWR, increasing insulation levels, selecting less carbon-intensive structural materials, and opting for compact geometry.

In LGC cities however the same parameters show quite different level of influence on building TC. In these areas, due to dominance of EC in building TC, Structural material is the most influential parameter and selecting bio-based material can decrease TC significantly. In the next place, more efficient HVAC scenarios can play an important role in reducing building TC. The third place, WWR, geometry and insulating level shows potential in reducing building TC which is by far of lower potential compared to Structural material and HVAC scenarios. Other factors such as window material and orientation do not show meaningful impact on TC range.



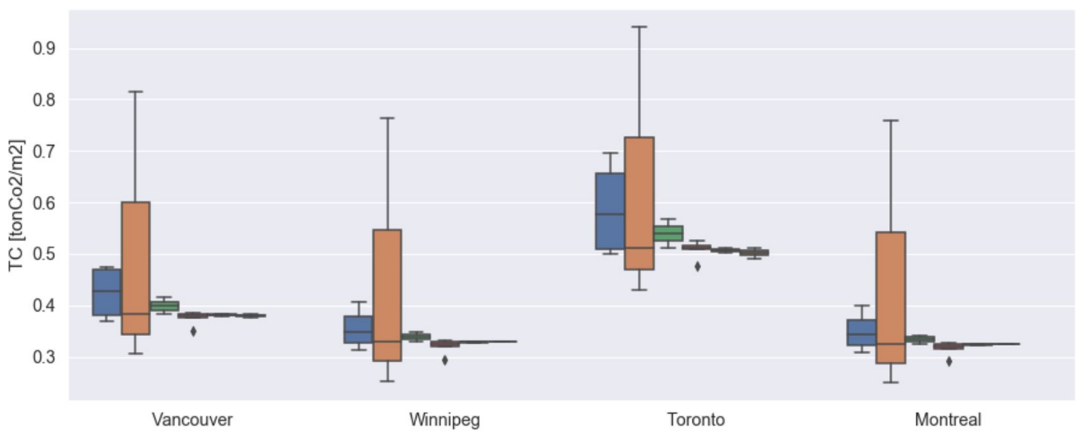


Fig. 11-Range of Total Carbon per design parameter

In Cities with LGC, a totally different weight of design parameters are observed for low-carbon building design in the cold climate of Canadian cities. In these cities the importance of OC is balanced by grid low impact, therefore parameters related to EC plays the most important role, namely structural material. Therefore, the results show this ranking for influence of design parameters. As it can be inferred from Fig. 11, in LGC cities due to near zero grid carbon emission, design priorities that affect EC are in higher priorities. The most significant impact comes from selecting structural material, due to significant mass of structure and therefore, resulting EC. Secondly, architects are advised to consider an optimized HVAC system. Next priorities are very similar in terms of extent of impact which includes WWR, Geometry and insulating material. Insulation materials and window scenarios due to balancing impact in reducing OC by increasing EC show marginal impact on building total carbon in cities with LGC.

The results also indicate the same features for the scenario with lowest TC in all cities. Buildings with mass timber structure which have compact form and lower WWR and are ventilated using high efficiency HVAC systems have the lowest TC reported. Conversely, if the design objective supports using a form with more protrusion, concrete construction and higher transparency for enclosure, therefore higher TC from the building should be expected.

The results also show that some parameters that previously were considered to have significant impact on building TC have lower impact in buildings with high-performance construction even in cold climates. For instance, in buildings with highly-insulated enclosure, due to use of efficient components and subsystems, tolerance in TC is managed which allows freedom for creativity to satisfy other design objectives. On the contrary some design parameters have been neglected while they play a crucial role in the current low-carbon building design field. An example is the HVAC systems in buildings that play a significant role both in OC, especially in cities with HGC, and also in EC. This impact will be more significant in larger scale projects with more complex HVAC systems. This is while the literature shows that HVAC has been considered out of scope or left as a controlled variable to simplify LCA analysis in the design stage. The same is true for structural systems of the building.

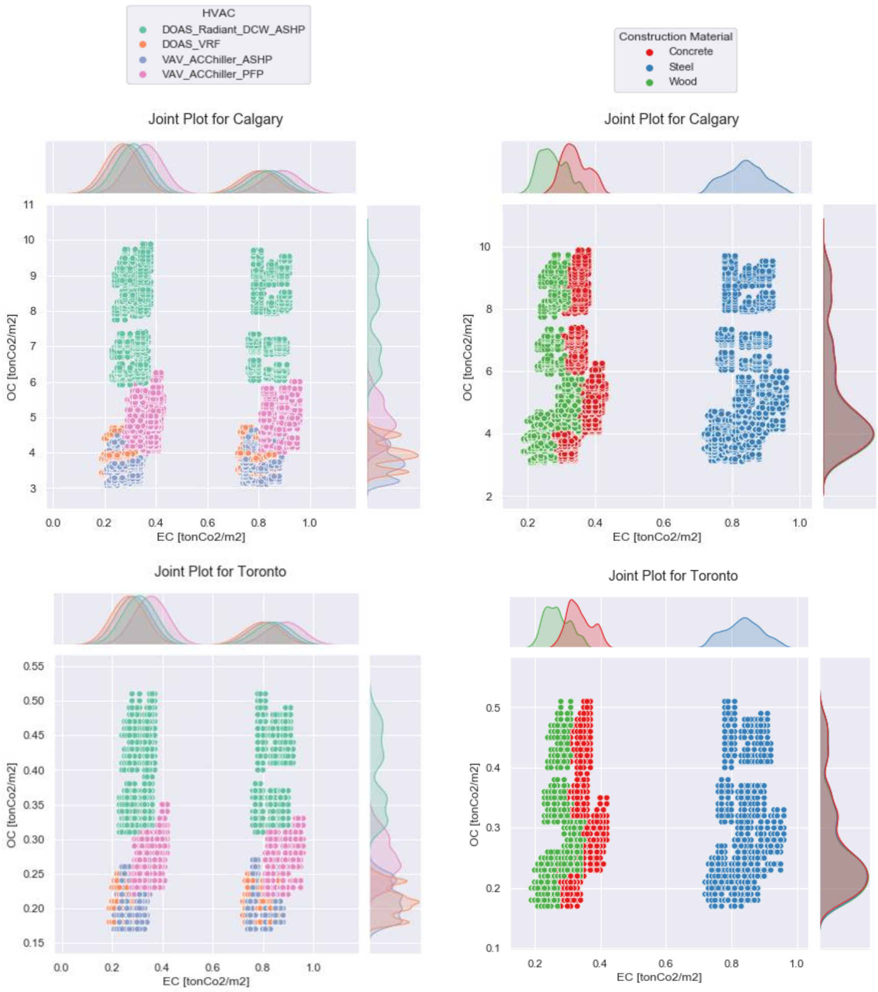


Fig. 12- the impact of first two influential design parameters on building TC in example LGC and HGC cities

6. Conclusions

In this research we aim to answer the question of what matters the most regarding total life cycle carbon emissions when designing low carbon buildings across Canadian cities. This research evaluates more than 20,000 parametrically generated building designs across seven major Canadian cities with four different climates and substantially various GCI factors. Considering climate and GCI, the results show significant differences in expected range of TC for building across studied regions. The difference mainly stemmed from GCI which showed an underlying impact on EC and OC tradeoff. The results also indicated that the similar design outputs can have substantially different TC depending on the design decisions and therefore architects should be aware of their design impact and potential of each design parameters in order to reach their sustainability targets.

The results of this study reveals clear distinction and influential impacts of design parameters on building TC across investigated cities. In summary architects are advised to be mindful of the high impact of HVAC choices as well as structural materials on the building carbon footprint. WWR is the third parameter with the highest potential for carbon reduction across all cities. The next priority for carbon reduction should be design decisions associated with geometry, level of insulation in HGC. Other factors such as window material and orientation of building however show lowest potential for reducing TC and should be regarded with more flexibility in favor of other design objectives.

The results of this study can assist architects in setting TC expectations more realistically and identify the hotspot area for carbon reduction through design. This study focuses on Canadian climate and uses local GCI for LCA calculations, however, the results can be applied to similar climates with comparable GCI, providing valuable guidance for architects worldwide in the pursuit of low-carbon building designs.

References

[1] IPCC, "Climate Change 2021: The Physical Science Basis," Cambridge University Press, 2021. [Online]. Available: https://www.ipcc.ch/report/ar6/wg1/#FullReport.
[2] U. N. E. Programme and Olhoff, "The Heat Is On – A World of Climate Promises Not Yet Delivered," in *United Nations Publication*, 2021. [Online]. Available: https://wedocs.unep.org/20.500.11822/36993
[3] A. R. G. Garzon *et al.*, "A Comparative Analysis of Five Forest Certification Programs," *Forests*, vol. 11, no. 8, 2020, doi: 10.3390/f11080863.
[4] A. Hollberg, D. Kaushal, S. Basic, A. Galimshina, and G. Habert, "A data-driven parametric tool for under-specified LCA in the design phase," *IOP Conf. Ser.: Earth Environ. Sci.*, vol. 588, no. 5, p. 052018, 2020, doi: 10.1088/1755-1315/588/5/052018.
[5] J. Basbagill, F. Flager, M. Lepech, and M. Fischer, "Application of life-cycle assessment to early stage building design for reduced embodied environmental impacts," *Build. Environ.*, vol. 60, pp. 81–92, 2013, doi: 10.1016/j.buildenv.2012.11.009.
[6] S. Basic, A. Hollberg, A. Galimshina, and G. Habert, "A design integrated parametric tool for real-time Life Cycle Assessment – Bombyx project," IOP Conf. Ser.: Earth Environ. Sci., vol. 323, no. 1, p. 012112, 2019, doi: 10.1088/1755-1315/323/1/012112.
[7] D. Apellániz, P. Pasanen, and C. Gengnagel, "A Holistic and Parametric Approach for Life Cycle Assessment in the Early Design Stages," in *SimAUD 2021*, 2021.
[8] J. Basbagill, F. Flager, M. Lepech, and M. Fischer, "Application of life-cycle assessment to early stage building design for reduced embodied environmental impacts," Build. Environ., vol. 60, pp. 81–92, 2013, doi: 10.1016/j.buildenv.2012.11.009.
[9] A. Kanyilmaz, V. H. Dang, and A. Kondratenko, "How does conceptual design impact the cost and carbon footprint of structures?," *Structures*, vol. 58, p. 105102, 2023, doi: 10.1016/j.istruc.2023.105102.
[10] M. Torabi and R. Evins, "An LCA Framework to Prioritize Carbon-Sensitive Measures in Residential Building Design," in *eSim 2022: 12th Conference of IBPSA-Canada*, 2022.
[11] Y. Zhou, V. WY. Tam, and K. N. Le, "Sensitivity analysis of design variables in life-cycle

environmental impacts of buildings," *J. Build. Eng.*, vol. 65, p. 105749, 2023, doi: 10.1016/j.jobe.2022.105749.
[12] W. Hawkins, S. Cooper, S. Allen, J. Roynon, and T. Ibell, "Embodied carbon assessment using a dynamic climate model: Case-study comparison of a concrete, steel and timber building structure," Structures, vol. 33, pp. 90–98, 2021, doi: 10.1016/j.istruc.2020.12.013.
[13] M. K. Dixit and P. P. Kumar, "Embodied impacts of buildings from energy-carbon-water nexus perspective: A case study of university buildings," *Clean. Energy Syst.*, vol. 7, p. 100108, 2024, doi: 10.1016/j.cles.2024.100108.
[14] Y.-S. Tsay, Y.-C. Yeh, and H.-Y. Jheng, "Study of the tools used for early-stage carbon footprint in building design," *e-Prime - Adv. Electr. Eng., Electron. Energy*, vol. 4, p. 100128, 2023, doi: 10.1016/j.prime.2023.100128.
[15] R. Evins, "A review of computational optimisation methods applied to sustainable building design," *Renew. Sustain. Energy Rev.*, vol. 22, pp. 230–245, 2013, doi: 10.1016/j.rser.2013.02.004.
[16] J. Li, X. Bi, and W. Yang, "Suggestions for solution space exploration in the early stage of architectural design based on a literature review," IOP Conf. Ser.: Earth Environ. Sci., vol. 1078, no. 1, p. 012039, 2022, doi: 10.1088/1755-1315/1078/1/012039.
[17] M. Torabi and R. Evins, "Towards net-zero carbon buildings: Investigating the impact of early-stage structure design on building embodied carbon," *Int. J. Life Cycle Assess.*, pp. 1–16, 2024, doi: 10.1007/s11367-024-02287-w.
[18] A. Hollberg, N. Klueber, S. Schneider, and J. Ruth, "expanding Boundaries - A Method for Evaluating the Environmental Life Cycle Potential of Building Geometry – A. Hollberg, N. Klüber, S. Schneider, J. Ruth, D. Donath," 2016. doi: 10.3218/3774-6_96.
[19] Y. Zhou, M. Ma, V. WY. Tam, and K. N. Le, "Design variables affecting the environmental impacts of buildings: A critical review," *J. Clean. Prod.*, vol. 387, p. 135921, 2023, doi: 10.1016/j.jclepro.2023.135921.
[20] G. Lobaccaro, A. H. Wiberg, G. Ceci, M. Manni, N. Lolli, and U. Berardi, "Parametric design to minimize the embodied GHG emissions in a ZEB," *Energy Build.*, vol. 167, pp. 106–123, 2018, doi: 10.1016/j.enbuild.2018.02.025.
[21] B. Kiss and Z. Szalay, "Sensitivity of buildings' carbon footprint to electricity decarbonization: a life cycle–based multi-objective optimization approach," Int. J. Life Cycle Assess., vol. 28, no. 7, pp. 933–952, 2023, doi: 10.1007/s11367-022-02043-y.
[22] M. A. Kamazani and M. K. Dixit, "Automated Thermal Zoning and Multi-Objective Optimization of Embodied and Operational Energy and Carbon Emissions of Buildings," in *ASCE Inspire 2023*, 2023.
[23] H. L. Gauch, C. F. Dunant, W. Hawkins, and A. C. Serrenho, "What really matters in multi-storey building design? A simultaneous sensitivity study of embodied carbon, construction cost, and operational energy," *Appl. Energy*, vol. 333, p. 120585, 2023, doi: 10.1016/j.apenergy.2022.120585.
[24] A. Hollberg, N. Klüber, S. Schneider, and J. Ruth, "expanding Boundaries - A Method for Evaluating the Environmental Life Cycle Potential of Building Geometry – A. Hollberg, N. Klüber, S. Schneider, J. Ruth, D. Donath," 2016, doi: 10.3218/3774-6_96.
[25] M. Z. Esteghamati, H. Sharifnia, D. Ton, P. Asiatico, G. Reichard, and M. M. Flint, "Sustainable early design exploration of mid-rise office buildings with different subsystems using comparative life cycle assessment," J. Build. Eng., vol. 48, p. 104004, 2022, doi: 10.1016/j.jobe.2022.104004.
[26] H. Yu, W. Yang, Q. Li, and J. Li, "Optimizing Buildings' Life Cycle Performance While Allowing Diversity in the Early Design Stage," *Sustainability*, vol. 14, no. 14, p. 8316, 2022, doi: 10.3390/su14148316.
[27] M. K. Ansah, X. Chen, and H. Yang, "A holistic environmental and economic design optimization of low carbon buildings considering climate change and confounding factors," *Sci. Total Environ.*, vol. 821, p. 153442, 2022, doi: 10.1016/j.scitotenv.2022.153442.

[28] D. Satola, A. Houlihan-Wiberg, and A. Gustavsen, “Global sensitivity analysis and optimisation of design parameters for low GHG emission lifecycle of multifamily buildings in India,” Energy Build., vol. 277, p. 112596, 2022, doi: 10.1016/j.enbuild.2022.112596.
[29] *American Institute of Architects* (AIA), “AIA Guide to Building Life Cycle Assessment in Practice,” Jan. 01, 2010, American Institute of Architects. [Online]. Available: https://content.aia.org/sites/default/files/2016-04/Building-Life-Cycle-Assessment-Guide.pdf
[30] ANSI/ASHRAE/IES, “ANSI/ASHRAE/IES 90.1-2019: Energy Standard for Buildings Except Low-Rise Residential Buildings,” 2019, *American National Standards Institute (ANSI)*. Accessed: Mar. 13, 2024. [Online]. Available: https://webstore.ansi.org/standards/ashrae/ansiashraeies902019
[31] B. Columbia, “British Columbia building code 2018,” 2018, *British Columbia Ministry of Municipal Affairs and Housing*. [Online]. Available: https://free.bcpublications.ca/civix/content/public/bcbc2018/?xsl=/templates/browse.xsl
[32] B. Rodriguez-Droguett, “Embodied Carbon of Heating, Ventilation, Air Conditioning and Refrigerants (HVAC+R) Systems,” University of Washington, 2019.
[33] C. of Vancouver, “City of Vancouver Embodied Carbon Guidelines v0.2 - FINAL DRAFT,” Jan. 01, 2023.
[34] U.S. DOE, *EnergyPlus*TM. USDOE Office of Energy Efficiency and Renewable Energy (EERE), Energy Efficiency Office, 2017. [Online]. Available: https://www.osti.gov/biblio/1395882
[35] Y. Zhou, M. Ma, V. WY. Tam, and K. N. Le, “Design variables affecting the environmental impacts of buildings: A critical review,” J. Clean. Prod., vol. 387, p. 135921, 2023, doi: 10.1016/j.jclepro.2023.135921.
[36] A. S. Silva and E. Ghisi, “Estimating the sensitivity of design variables in the thermal and energy performance of buildings through a systematic procedure,” J. Clean. Prod., vol. 244, p. 118753, 2020, doi: 10.1016/j.jclepro.2019.118753.
[37] G. of Canada, “Emission factors and reference values.” Accessed: Apr. 10, 2024. [Online]. Available: https://www.canada.ca/en/environment-climate-change/services/climate-change/pricing-pollution-how-it-will-work/output-based-pricing-system/federal-greenhouse-gas-offset-system/emission-factors-reference-values.html

Appendix 1- Material Carbon intensity

Table 1- List of materials and emissions per tonne

Building Element	Material Name	A1-A3 Carbon [KgCo2/tonne]	Density [kg/m3]	Reference
Structure	Steel	2624	7870	cqd.io/e/ec3m4n2058
Structure	Rebar	813.1	7830	cqd.io/e/ec3ux61jxj

Table 2- List of materials and emissions per m3

Building Element	Material Name	A1-A3 Carbon [KgCo2/m3]	Thickness [m]	Density [kg/m3]	Reference
Structure	Reinforced Concrete (with %3 of weight rebar)	572.3	-	2400	cqd.io/e/ec3cwkf19z
Structure	Mass Timber	226.2	-	563	cqd.io/e/ec3yh6a1t4
Envelope	Normal weight Concrete Floor	237.5	0.1	2400	cqd.io/e/ec3t7c51b6
Envelope	CONCRETE HW RefBldg	376.9	19.6	2400	cqd.io/e/ec3yx2kaf9

Table 3- List of materials and emissions per m2

Building Element	Material Name	A1-A3 Carbon [KgCo2/m2]	Thickness [m]	Density [kg/m3]	Reference
Envelope	⅝” Gypsum Board	2.94	0.0158	640	cqd.io/e/ec3923010c

Envelope	½" Gypsum Board	1.83	0.0127	640	cqd.io/e/ec3nka35n3
Envelope	Metal Siding	2.71	0.025	7870	cqd.io/e/ec382nu1ux
Envelope	Roof Membrane	4.2	0.032	500	cqd.io/e/ec3b9xcfmp
Envelope	Typical Carpet Pad	3.87	0.03	400	cqd.io/e/ec3ape53st
Envelope	Typical Insulation-fiberglass	1.40	Per ISI	12	cqd.io/e/ec3tk883t4
Envelope	2PaneWin-Al	101	-	-	cqd.io/e/ec3ku1dd70
Envelope	3PaneWin-Al	116.7	-	-	cqd.io/e/ec3m65sdy5

Table 4- List of HVAC scenarios and emissions [32]

Building Element	Material Name	A-C Carbon [KgCo2/m2 floor area]	Efficiency [32]
HVAC	VAV chiller with central air source heat pump reheat	57.3	Standard
HVAC	PVAV_PFP	127.8	Standard
HVAC	DOAS_WSHP_FluidCooler_Boiler	39.8	High efficiency
HVAC	DOAS_FCU_Chiller_ASHP	82.3	High efficiency

Appendix 2- Grid Carbon intensity

Table 1- GCI and climatic region of studied cities

	City	Province	Carbon Intensity of Grid [g Co2/KWh] [37]	ASHRAE Climatic Region [37]
1	Montreal	Quebec	1.7	6A
2	Winnipeg	Manitoba	2	7
3	Vancouver	British Columbia	15	4C
4	Toronto	Ontario	30	5A
5	Calgary	Alberta	540	7
6	Halifax	Nova-Scotia	690	6A
7	Saskatoon	Saskatchewan	730	7

Appendix 3- Modeling details

Table 1- Details of studied geometries

	Shape	Footprint Area [m2]	Footprint Perimeter [m]
1	Sqr	1025	128
2	Sqr +	1025	144.2
3	Sqr H	1025	158.5
4	Rec	1025	133.3
5	Rec +	1025	142.9

6	Rec H	1025	172.6

Appendix 4- Results Summary

Table 1- Average TC per structural material across cities

City	Structural Material	TC [tonCo2/m2]
Calgary	Concrete	4.80
	Steel	5.29
	Wood	4.69
Halifax	Concrete	5.59
	Steel	6.05
	Wood	5.45
Montreal	Concrete	0.35
	Steel	0.85
	Wood	0.28
Saskatoon	Concrete	7.46
	Steel	7.935
	Wood	7.30
Toronto	Concrete	0.59
	Steel	1.09
	Wood	0.52
Vancouver	Concrete	0.43
	Steel	0.93
	Wood	0.36
Winnipeg	Concrete	0.36
	Steel	0.86
	Wood	0.29

Table 2- TC per geometries across cities

CityCode	Geometry	TC [kgCo2/m2]			
		Min	Max	Mean	Median
Calgary	Rec	3.31	10.24	5.46	4.83
	Rec+	3.36	10.25	5.54	4.93
	RecH	3.46	10.51	5.73	5.07
	Sqr	3.28	10.17	5.42	4.825
	Sqr+	3.37	10.28	5.55	4.95
	SqrH	3.42	10.45	5.66	5.03
Halifax	Rec	3.84	11.22	6.24	5.61
	Rec+	3.92	11.66	6.33	5.72
	RecH	4.09	12.09	6.55	5.965
	Sqr	3.84	11.26	6.21	5.53
	Sqr+	3.97	11.53	6.35	5.71
	SqrH	4.07	11.78	6.47	5.845
Saskatoon	Rec	5.17	14.96	8.36	7.39
	Rec+	5.26	15.09	8.49	7.55
	RecH	5.45	15.8	8.8	7.86
	Sqr	5.12	14.95	8.31	7.34
	Sqr+	5.27	15.07	8.5	7.57
	SqrH	5.38	15.35	8.68	7.78
Toronto	Rec	0.39	1.29	0.73	0.66

	Rec+	0.4	1.35	0.76	0.66
	RecH	0.4	1.32	0.75	0.67
	Sqr	0.37	1.34	0.73	0.62
	Sqr+	0.39	1.39	0.77	0.65
	SqrH	0.39	1.41	0.77	0.66
Vancouver	Rec	0.28	1	0.56	0.46
	Rec+	0.28	1.06	0.59	0.46
	RecH	0.28	1.01	0.57	0.47
	Sqr	0.25	1.05	0.56	0.43
	Sqr+	0.28	1.1	0.6	0.46
	SqrH	0.27	1.1	0.6	0.46
Winnipeg	Rec	0.23	0.89	0.49	0.37
	Rec+	0.23	0.95	0.51	0.37
	RecH	0.23	0.89	0.49	0.37
	Sqr	0.2	0.94	0.49	0.34
	Sqr+	0.23	0.99	0.52	0.365
	SqrH	0.22	0.99	0.52	0.36
Montreal	Rec	0.23	0.88	0.48	0.36
	Rec+	0.23	0.94	0.51	0.36
	RecH	0.22	0.88	0.48	0.36
	Sqr	0.2	0.93	0.48	0.33

	Sqr+	0.23	0.98	0.52	0.36
	SqrH	0.22	0.98	0.51	0.35

Chapter 5- LCA Surrogate Model

A Machine Learning-Based Surrogate Model to Approximate Building Carbon Footprint in Early-Stage Design

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Abstract

Buildings account for more than 40% of global carbon emissions per year. Carbon emissions from buildings come from two sources: embodied carbon (EC) and operational carbon (OC). Building professionals conduct life cycle assessments (LCA) to measure and understand the trade-offs between EC and OC. Simulation-based techniques are used for design space exploration to identify potential building designs. However, these approaches can be time-consuming and computationally expensive, and they cannot provide real-time design feedback to the user which is very useful for decision-making. Moreover, EC and OC assessment tools are disjointed and lack interoperability issues which impede holistic LCA. These limitations restrict design space exploration and hinder the design decision-making process.

Recent advancements have made ’surrogate models’ an emerging option for building performance assessments; these are machine-learning models fitted to a sample of results from a parametric simulation, such that they act as a fast but approximate replacement for the original detailed simulation. Many articles have developed surrogate models to assess or optimize energy performance, however examples of surrogate models to predict embodied carbon and environmental impacts are rare. This gap is mainly due to the poor availability of LCA databases.

In this paper, we generate simulation results from a parametric model for whole building LCA and propose a methodology to use this synthetically generated database to develop an ML-based prediction model to of OC and EC. We test the model using two case studies. The results show that the model achieves high prediction performance using the minimal inputs available during early design phases. The results indicate that ML techniques can be used by building designers with no or limited LCA expertise to instantly estimate building sustainability performance and help them select design options with reduced OC and EC.

1. Introduction

Every year, buildings make up 42% of greenhouse gas emissions (U.S. Energy Information Agency, 2020). Governments all over the world have announced several regulations and policies to reduce carbon emissions produced by the built environment (Thilakarathna, et al., 2020; Lewis, 2021; COP26 Goals, 2021). To measure carbon emissions within the built environment, building professionals use whole building life cycle assessments (LCA), which captures both embodied carbon (EC) and operational carbon (OC) (Seyrfar, Ataei and Movahedi, 2021). Utilizing low-carbon strategies to reduce total carbon may have diverse impacts on EC and OC, increasing one with the aim to achieve savings in the other (Ramesh, Prakash and Shukla, 2010; Hernandez and Kenny, 2011). Therefore, evaluating both EC and OC is crucial for overall environmental impact reduction (Stephan and Stephan, 2016). Sustainability policies along with social awareness requires cutting carbon emissions and decarbonizing the built environment. This has resulted in a growing number of tools and models in evaluating carbon footprint (Kiss and Szala, 2020). Existing simulation-based modeling methodologies to conduct LCA are time-consuming and data intensive. Lack of interoperability between design and LCA tools has imposed challenges in conducting LCA especially during early stages when uncertainty about the building is high (Venkatraj, et al., 2020). As a result, LCA experts are motivated to develop novel tools that would assist individuals with LCA-based design decisions in a fast, iterative manner to support the design process better.

In this context, machine learning (ML) based methodologies are attracting growing attention and have established a good surrogate to physics-based engineering methodologies (Ngo, 2019; Han, et al., 2022). Research showcasing the application of building energy consumption prediction models have been published recently. While this work is promising, studies utilizing prediction models for building sustainability and LCA evaluations are lacking, mainly due to the unavailability of a large-scale LCA dataset (Mohandes, Zhang and Mahdiyar, 2019).

The application of ML-based surrogate models, specifically for evaluating EC and OC, is still an open research problem. In this study, we developed a simulation-based parametric framework to automatically generate a building LCA dataset. This dataset was then used to train and test two ML-based surrogate models that would predict building energy from a life cycle perspective.

2. Literature Review

2.1 LCA tools

Various building LCA tools and technologies exist to evaluate the OC and EC of a building. Some commonly used tools to evaluate building carbon emissions are Athena Impact Estimator, Tally, OneClick LCA, OpenLCA (Aygenç M. Life Cycle Assessment (LCA), 2019; Attia, et al., 2012) . Despite the availability of these tools, building professionals still hesitate to incorporate LCA-based design decisions due to the lack of expertise or data (Asl et al., 2017). However there are several challenges in incorporating these tools.

For example, a simple physical model generates large volumes of information, making it difficult for a novice designer to compare and correlate different combinations of factors (Amasyali and El-Gohary, 2018). Similarly, tools that run LCA models require information such as bill-of- material (BOM), material and processes carbon intensity, grid intensity, etc. If the model includes OC, it needs an embedded dataset on building energy consumption to estimate from. Another approach to OC is calculating the emissions based on building an analytical model that needs various inputs such as thermal properties, HVAC specifications, occupancy schedules, etc., whereas EE tools require material quantities, construction specifications, and systems/equipment information. Another issue is incompatibility of building LCA tools with the design process. As the current tools are incapable of handling uncertainties existing in the early stage, they are applicable in later stages when the information is available. That unfortunately limits the influence of LCA analysis as the later stage changes are not showing a high impact on building performance (Ngo, 2019). The other issue is that LCA tools are not well integrated into the design platforms which requires data transfer between different software which may cause inaccuracy in modeling due to loss of data (Shadram and Mukkavaara, 2018). Lastly, the tools are not compatible with fast and live result reporting which is important for designers to see the impact of design changes and compare scenarios (Venkatraj, et al., 2020; Attia, et al., 2012; Asl et al., 2017; Feng, Lu and Wang, 2019). Overall, This workflow is not very user-friendly; ultimately, designers are reluctant to utilize these tools (Attia, et al., 2012; Harkouss, Fardoun and Biwole, 2018; Abbasi and Noorzai, 2021; Santos, Schleicher and Caldas, 2017; Elbeltagi and Wefki, 2021; Chari and Christodoulou, 2017) .

In addition to design compatibility, building performance assessment tools including LCA tools need to be integrated with other optimization algorithms using other parametric modeling tools or custom scripting, which enhance the efficiency of design space exploration and provide fast evaluation of the pertaining section of design space (Seyedzadeh, Pour Rahimian and Rastogi, 2019; Touloupaki and Theodosiou, 2017; Muthumanickam, Duarte and Simpson, 2023). This workflow is computationally expensive, and time-consuming, and it requires significant experiential knowledge (Touloupaki and Theodosiou, 2017; Muthumanickam, Duarte and Simpson, 2023). All these reasons result in limitations in evaluating design options before selecting the optimal design.

2.2 Surrogate modelling

In a study by Westermann and Evins (2019), conducted the first comprehensive review of using surrogate models in building performance simulation (Westermann & Evins, 2019). They examined around 57 studies where surrogate models were applied across various building-related tasks, such as early-stage design, sensitivity analysis, uncertainty quantification, and optimization, among others.

Several studies have explored the combination of surrogate modeling and BPS to predict energy consumption. For example, Singh, Singaravel, Klein, and Geyer (2020) developed a deep learning neural network model using data from EnergyPlus simulations of a building in Munich, Germany. The aim was to mitigate both computational time and prediction discrepancies by utilizing surrogate models as an alternative to traditional simulation tools (Singh et al., 2020). Another study introduced five surrogate regression models to predict the annual energy consumption of office buildings in five cities, each representing distinct climates: Harbin (severe cold), Beijing (cold), Shanghai (hot summers and cold winters), Kunming (mild), and Hong Kong (hot summers and warm winters) (Lam et al., 2010). The researchers generated 1001 data samples using DOE2.1E simulation software, with 12 design parameters serving as input for the models. Similarly, Yi, Srinivasan, and Braham (2015) applied a surrogate regression model to a mid-sized office building in the U.S., using data derived from EnergyPlus simulations (Yi et al., 2015). In another study, Singh, Deb, and Geyer (2022) developed a web-based tool by integrating a surrogate ML model with a building information modeling (BIM) system to predict energy consumption during the early design phase (Singh et al., 2022). This surrogate ML model was built using a Convolutional Neural Network (CNN).

With the goal of comparing different ML algorithms for developing surrogate models several studies, have selected different algorithms and assess the accuracy of results mainly for energy consumption. For example In an study by Birdsell and Evins the performance of four types of surrogate models for building energy performance simulations were explored, finding that gradient-boosted decision trees excel in predicting energy use. Similarly, in order to select the most suitable algorithm, a review by Ghoroghi et. al. (Ghoroghi, 2022) can be helpful. In their study they address the challenge of leveraging ML methods to deliver LCA in order to draw more accurate LCA while supporting life cycle decision making. In their study they reviewed applications of (Artificial Neural Network (ANN), Supported Vector Machine (SVM), Random Forest (RF) and other algorithms used in the scope of ML and LCA. This study was undertaken for selecting algorithms of this study. However, it is important to note that the performance of an algorithm depends on several factors such as the size of the dataset, quality of data, model parameters, etc. Therefore, the results of these studies are not comparable, and we cannot conclude that one algorithm is better than the other (Olu-Ajay, 2022; Runge and Zmeureanu, 2019).

2.3 Combining LCA and surrogates

In recent years, researchers have increasingly recognized the benefits of surrogate models for sustainability assessments in design optimization and prediction. While the use of ML-based surrogate models is more prevalent in energy assessments, their application in LCA remains less common. For instance, Sharif and Hammad (2019) developed an ANN-based surrogate model to predict energy consumption, LCC, and LCA for building renovation scenarios. Their findings indicated that the ANN model significantly reduces computational time compared to traditional BEMs, while still maintaining acceptable accuracy (Sharif & Hammad, 2019). Similarly, Monshet et al. (2021) applied surrogate modeling techniques to optimize building envelopes—such as window-to-wall ratios and insulation thickness—and identify optimal design solutions for LCC and sustainability assessments (Monshet et al., 2021). Toosi et al. (2021) further advanced this approach by developing an integrated LCSA model that combines LCA, LCC, and SLCA, incorporating ML to enhance the design-assessment process and applying the model to optimize energy storage systems in a case study (Toosi et al., 2021). Azari et al. (2016) used a multi-objective optimization algorithm, integrating ANN and Genetic Algorithm, to explore optimal building envelope designs by analyzing energy use and LCA in office buildings (Azari et al., 2016). Additionally, Płoszaj-Mazurek et al. (2020) employed CNN to optimize the carbon footprint of buildings in regenerative architectural design. They tested four different algorithms to extract knowledge about the relationships between construction planning and project performance, demonstrating that ML methods can serve as valuable tools for exploring vast design spaces in sustainable architectural design (Płoszaj-Mazurek et al., 2020).

3. Research design and methods

To develop a surrogate-based method to quickly estimate total carbon in different types of buildings a three step methodology was defined. In the following sections, these parts are explained in detail.

1. LCA Dataset synthesis
2. Surrogate model development
3. Surrogate model evaluation

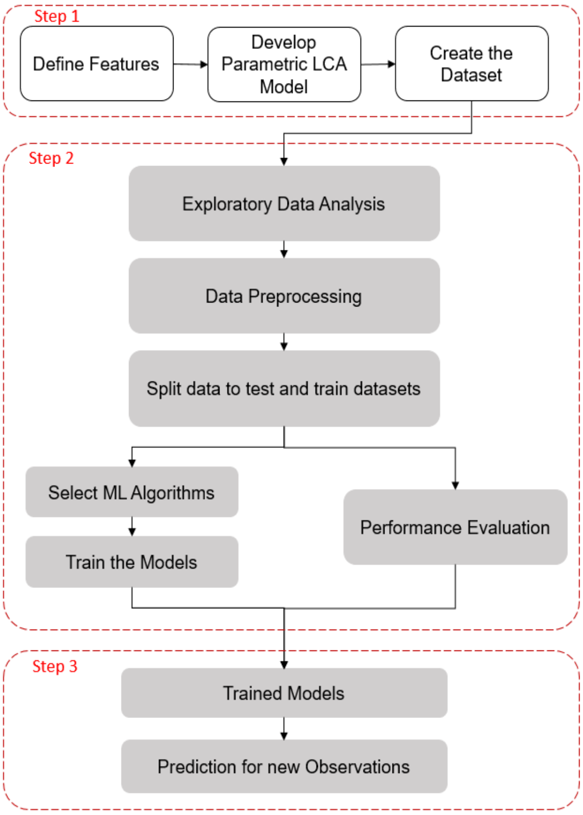

Fig. 1 -Research Methodology of developing surrogate models

3.1 LCA Dataset synthesis

The study uses synthetic dataset of over 20 thousands buildings, which includes thermal and architectural features along with their embodied carbon, operational and total life carbon emissions evaluated over 60 years. To do so, a parametric model was generated which automatically generated the design scenarios within the design space and calculated LCA results. This data included A-C stages of building lifecycle and covers emissions of building enclosure, structure and mechanical systems. Also to incorporate the energy consumption and resulting operational emissions, an energy model for each scenario was made in the generative parametric model and pertaining energy consumption was calculated. To calculate the OC, grid carbon intensity of the city was taken into account.

3.2 Surrogate model development

3.2.1 Exploratory Data Analysis (EDA)

In this part, some trends were extracted from the dataset that can provide an overview of the relationship between the target variable(total life carbon) and design parameters. This dataset has over 20,000 observations for 7 cities across Canada and includes 8 design parameters and 4 variables. The variables include OC ($kgCO_2/m^2$), EC ($kgCO_2/m^2$), EUI (kWh/m^2) and TC ($kgCO_2/m^2$) and the design parameters are as tabulated in Table 1.

Table 1-Overview of Design Parameters in the dataset

	Design Parameter	Secondary Parameter	Range	Number of values
1	Geometry		Sq, Sq+, SqH, Rec, Rec +, RecH	6
2	Envelope	Level of Insulation	Code minimum High Insulation	2
		IGU	Double glaze-Aluminum Triple glaze-Aluminum	2
		WWR	0.25 0.5	2
3	Structure		Concrete, Steel, and wood	3
4	HVAC system		Dedicated Outdoor-Air System Packaged rooftop heat pump VAV AHU w/ PFP Terminals DOAS + VRF DOAS ERV + Packaged Rooftop Heat Pump	4
5	Orientation	Azimuth	-60, -30, 0, 30, 60	5
6	Cities		Vancouver, Edmonton, Winnipeg, Saskatoon, Toronto, Montreal, Halifax	7
	Total Observations			**20,160**

Based on exploratory data analysis (EDA), main trends of the dataset have been identified to provide an overview of data. This highlights the different range of carbon emissions across different cities as illustrated in Fig 2. This plot depicts the distribution of total carbon emissions for various cities. As the plot shows cities such as Toronto, Winnipeg, Vancouver, and Montreal show significantly lower range of total carbon emissions while, another group of cities including Calgary, Halifax, and particularly Saskatoon exhibit higher emissions, with Saskatoon showing the greatest range.

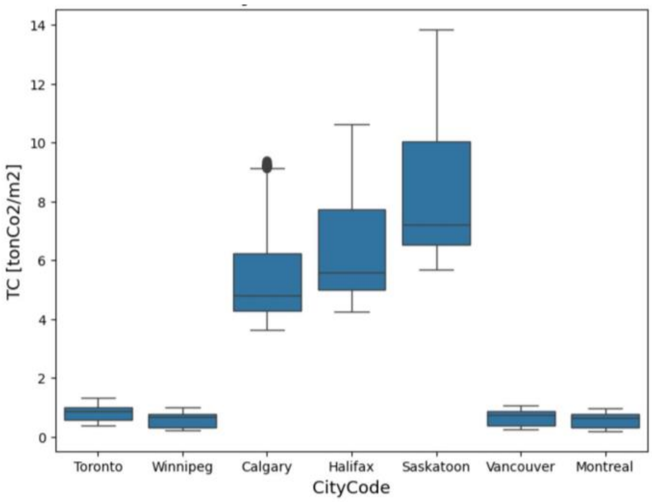

Fig 2. Distribution of total carbon emissions for various cities

In addition to the analysis of carbon emissions across different cities, further insights were extracted on construction materials and total carbon emissions. Fig.3 illustrates the distribution of total carbon emissions for buildings per three structural materials: steel, concrete, and wood. Steel and concrete construction materials are associated with higher median total carbon emissions, indicating that these materials contribute more to the total carbon footprint of buildings. Wood, on the other hand, results in lower median emissions, which could point towards its potential as a low-carbon construction material. EDA also shows the strong impact of HVAC scenarios on TC.

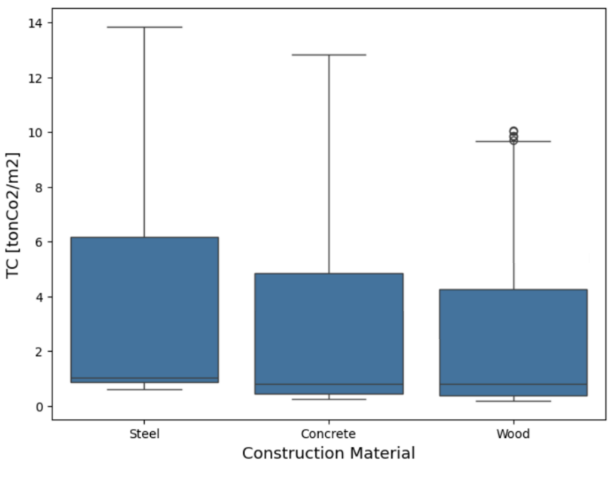

Fig 3. Construction Material vs Total Carbon

3.2.2 Preprocessing

In this step, various preprocessing techniques were applied on the dataset in order to make a clean dataset in an appropriate format to conduct surrogate modelling. Initially, the features were categorized based on their nature into numerical and categorical types. For numerical features, we applied the StandardScaler method to standardize them by adjusting the mean to zero and scaling to unit variance. This standardization is crucial to ensure that the numerical features can contribute equally to the model.

For categorical features, we employed the OneHotEncoder method to convert them into a binary matrix. This encoding method is crucial for interpreting categorical data by creating separate binary columns for each category. Additionally, we dropped three features at this stage: Total EC (tCO2/m2), OC (tCO2/m2), and EUI (kWh/m2) and focused on building TC. At the end of this step, a clean, standardized, and unbiased dataset is ready for training the model.

3.2.3 Developing Surrogate Models

For developing the total carbon prediction models, the dataset was divided into two partitions: 80% for training and the other 20% for testing, as is also often used in machine learning (Veiga, et al., 2021, Zhang, et al., 2015, Zheng, et al., 2024). Two different machine learning algorithms were used in this paper, Ridge Regression (RR) and RF. The method of developing both models are explained in the subsections below.

3.2.3.1 Ridge regression (RR)

RR is straightforward and commonly-used for developing predictive algorithms. It also showed high accuracy and performance in prediction of wide range of variables in the literature (Javanmard et. al, 2021). In RR, a new function is generated by combining the sum of the squared estimate of the error function and the penalty value with the number of parameters, which is used to estimate the parameters of the regression model (Zheng, et al., 2024).

3.2.3.2 Random Forest (RF)

RF is an ensemble machine learning algorithm that combines multiple Decision Trees to efficiently classify or predict outcomes. It is widely-used for its flexibility, practicality, and effectiveness in handling high- dimensional data (Xika, et al., 2019, Kalilia, Chakraborty and

Popescu, 2011). RF builds numerous decision trees in parallel, to reduce the bias and variance of the model effectively (Breiman, 2001).

After generating a large number of trees, they collectively vote for the most popular class. These procedures are commonly referred to as RFs. RF uses random sampling of training observations and random subsets of candidate variables for splitting nodes (Zheng, et al., 2024).

In the modeling we utilized Cross-validation, as the most common approach to ensuring the robustness of the model, in order to conduct the uncertainty analysis of models. In the basic approach, called k-fold cross- validation, the training set is split into k smaller partitions. The following procedure is repeated for each of the k “folds”. In cross-validation a model is trained using the folds as training data, and the trained model is validated on the remaining part of the data. The performance measure reported by k-fold cross-validation is the average of the values computed during the loop, and commonly, k is set to 5 or 10 (Fushiki , 2011). In this study we used 10 folds for cross validation.

3.3 Performance evaluation of models

Both prediction models were assessed to evaluate their performance. The elapsed time to train the algorithms was used as a measure to compare their efficiency. We employed three widely accepted evaluation metrics to assess the performance of the predictive models: R2, MAE (Mean Absolute Error), MSE (Mean Squared Error), and RMSE (Root Mean Squared Error). R2 is a metric used to quantify the goodness-of-fit measure for a regression model. It measures the proportion of the variance in the dependent variable that can be explained by the independent variables (features used for prediction) and shows predictive power of the models. The R2 score can range from 0 to 1, where a score of 1 indicates a perfect fit, meaning that the model's predictions match the observed values perfectly. On the other hand, a score of 0 suggests that the model provides no better prediction than simply using the mean of the observed values. MAE, as the name suggests, calculates the mean absolute differences between the predicted and observed values and provides a measure of the average prediction error where a lower MAE indicates better predictive accuracy. MSE quantifies the average squared differences between predictions and actual values, giving higher weight to large errors. RMSE represents the square root of MSE and is useful for providing an interpretable measure of accuracy in the original units of the data (Zhang, et al., 2024). The RMSE, which is the square root of the MSE. This metric, is helpful because it provides a measure of prediction accuracy in the original units of the data. It is particularly useful when an interpretable measure is needed for assessing how well the model fits the observed data.

4. Results and Discussion

4.1 Accuracy

The performance of the RR and RF model are compared in Fig.4. As the graphs depict the actual values on the x-axis and compare them against the predicted values on the y-axis. In this graphs, the black dashed line represents the ideal scenario where the predicted values equal the actual values. Therefore, closer dots to the dash line shows more accurate prediction and less discrepancy between actual value and predicted values.

The RR model was evaluated using a 10-fold cross-validation approach. The performance metrics, reported in Table 2, show that the model achieved a mean test R2 of 0.924 with a standard deviation of 0.001, indicating high predictive power and consistency across different folds.

Table 2- Performance Metrics for RRModel

Metric (For Test Set)	Mean	Std
R2	0.924	0.001
MAE	0.743	0.005
MSE	0.857	0.011
RMSE	0.926	0.006

The RF model was also evaluated using a 10-fold cross-validation. As reported in Table 3, the model exhibited good performance with a mean test RMSE of 0.063. These metrics suggest that the model is highly accurate, capturing nearly all the variance in the data.

Table 3- Performance Metrics for RF Model

Metric (For Test Set)	Mean	Std
R2	1.00	0.00
MAE	0.04	0.001
MSE	0.004	0.001
RMSE	0.063	0.002

The comparative analysis of the RR and RF models reveals that both models show good performance in making TC predictions. Fig. 4 also shows actual and predicted values in test data for the both models. As it can be inferred from the graph, the predicted values closely match the actual values in both models. Therefore, it is concluded that the models have captured the variability in the data well, as there is no obvious systematic deviation between the predicted and actual values across the sample index. The consistent overlap across the different levels of total carbon suggests that the RF model is performing well across the entire range of data.

However, the RF model shows significantly better accuracy compared to RR model across all evaluation metrics. For Example, the RF has much lower RMSE (0.063) and MAE (0.040) values compared to the RR (0.926 and 0.743, respectively). This highlights its superior performance and robustness. Overall, the RF is the preferred model for this dataset due to its higher accuracy and better performance.

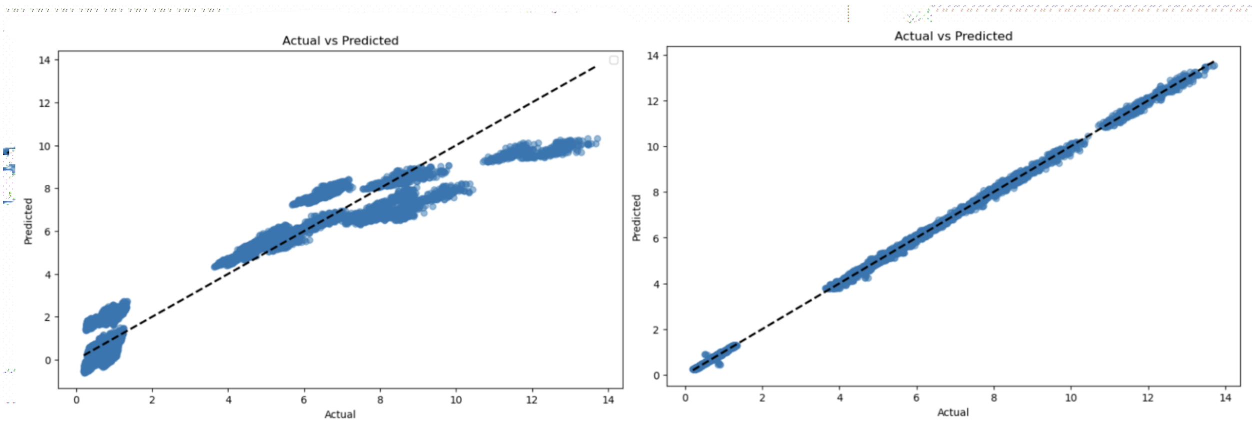

Fig 4- Actual vs. Predicted Values for RR (Left) and for RF (Right)

The plot shows that while the RR model generally aligns with the actual data, there are deviations, particularly for higher values of the target variable. This indicates that the model captures the overall trend well but may struggle with accurately predicting extreme values. The graph also suggests that the RF model predictions are highly accurate and unbiased. The points are accumulated around the line, which shows accuracy in prediction compared to RF and no significant bias in predictions at different value ranges.

In comparing the two models, the RR model, exhibits higher prediction error and may not perform as well on more complex relationships within the data. So, for tasks involving more complex, non-linear relationships, the RF model is likely to provide more accurate predictions compared to the RR model. However, the RR model still performs adequately, especially in scenarios where linearity is a primary assumption.

4.2 Feature Importance

The feature importance values provided by the RF model give an indication of how sensitive the prediction is sensitive to each feature. Higher values indicate more sensitivity to the feature. The features like CityCode_Saskatoon, CityCode_Calgary, CityCode_Halifax represent the city codes and have high importance, suggesting that the location (or the city) has a significant influence on the predictions made by the model. Also, different HVAC scenarios play a crucial role, indicating that the type of HVAC system used influences the target variable. WWR is less influential factor, still contributes to the model. It represents the proportion of windows to walls in the buildings, which can affect energy efficiency. The features like Construction Material are also among the most important factors.

4.3 SHAP Values Analysis

To gain a deeper assessment of feature contributions, SHAP (SHapley Additive exPlanations) values analysis was used. SHAP values provide a unified measure of feature importance and help explain individual predictions. The SHAP analysis allows us to see both the magnitude and direction of the impact associated with each feature on the model's output. By calculating the mean absolute SHAP values for each feature, the average impact of each feature across all predictions can be quantified (Shap Values, 2024).

Similar to the feature importance results, city codes have a significant impact on the model predictions. The plot shows that variations in these features lead to substantial changes in the model output. Also, HVAC related features are critical in determining the energy efficiency and performance of buildings. The SHAP values highlight their importance in the predictions.

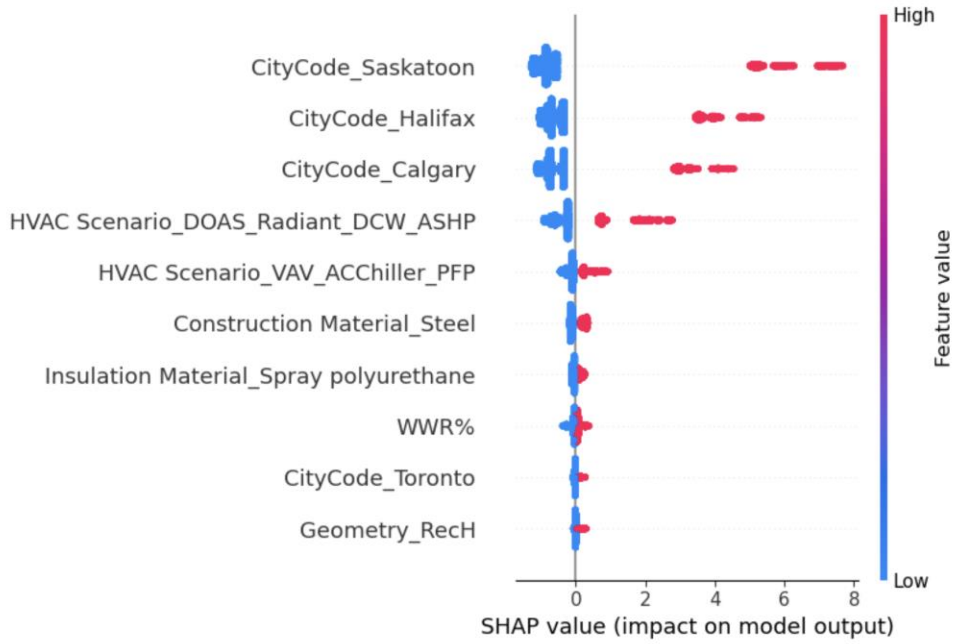

Fig. 5-SHAP Summary Plot for Top 10 Features

4.4 Predicting some observation by using the model

To further understand the model's predictions for individual observations, SHAP waterfall plots were utilized. These plots provide a detailed breakdown of how each feature contributes to the final prediction for a specific data point. Below is the SHAP waterfall plot for two observations, illustrating how the features influence the model's output.

Table 4: New Observations for Predicting via Model

Features	First Observation	Second Observation
CityCode	Winnipeg	Calgary
Geometry	RecH	Sqr+

Construction Material	Wood	Wood
Window Scenario	2PaneWin-Al	2PaneWin-Al
HVAC Scenario	VAV_ACChiller_PFP	DOAS_Radiant_DCW_ASHP
WWR%	0.25	0.25
Orientation	30	0
Level of Insulation	High-Ins	High-Ins

For the first observation, the model predicts a value of approximately 0.335 for building total carbon. The waterfall plot shows the contributions of each feature to this prediction, with blue bars indicating features that decrease the prediction and red bars indicating features that increase it.

The prediction for the second observation is approximately 7.235. The SHAP values for each feature show how they collectively lead to the final prediction. Similar to the previous observation, certain features like city codes and HVAC scenarios have a notable impact, either positively or negatively.

The SHAP waterfall plots provide a detailed view of the contributions of individual features to specific predictions. This enhances the interpretability of the model by showing how different factors influence the output. Features like city codes, HVAC scenarios, construction materials, and insulation materials play significant roles in determining the model predictions.

5. Conclusions

This study investigated the feasibility of developing a surrogate for whole-building LCA models using ML to predict building's total carbon, to address building sustainability performance from a life cycle perspective. The study generated a synthetic building LCA dataset to train and test two surrogate models as surrogate models for the detailed LCA model. The two ML models were compared in order to select the most accurate prediction tool. The analytical results indicate the most accurate model had a MAE value of 0.04 and R2 of 1 and a RMSE value of 0.063. Also, the new observation predictions demonstrate that the predicted and simulated values of total carbon have an error margin ranging from 3% to 4%. These results highlight the benefits of using Surrogate models for building LCA in terms of time, and accuracy.

To conclude, our study makes notable contributions to the field of life cycle assessment. We establish that surrogate models offer an effective and efficient means of predicting total carbon. By comparing different algorithms, we showed that the RF model outperformed RR. This finding opens the door to using surrogate models for decision-making in early building design to incorporate LCA.

In particular, the machine learning algorithms can predict the total carbon accurately using features related to the building design. Compared to existing LCA modeling methods, the machine learning models can process and analyze large amounts of data quickly and generate fast and reliable results, which indicate their potential as surrogate models to LCA calculation models. Moreover, the machine learning algorithms can automatically learn from and improve upon data and be adapted to suit a variety of different datasets, allowing more potential studies on different predictors related to buildings, occupants, and the environment (e.g., climate conditions). By identifying the factors that have the greatest impact on building carbon, the machine learning prediction models could support data-driven decision-making in applying life cycle thinking at the early design stage, helping architects and engineers improve the environmental performance of the building designs. The prediction models can also assist researchers in obtaining quick approximations of the carbon footprint of buildings, thereby enhancing the efficiency of time-consuming building research. Future studies can test exploring the use of more complex methods such as neural networks and methods such as Transfer Learning to more reliably predict performance.

6. References

Abbasi, S., & Noorzai, E. (2021). The BIM-Based multi-optimization approach in order to determine the trade-off between embodied and operation energy focused on renewable energy use. *Journal of Cleaner Production*, *281*, 125359. https://doi.org/10.1016/j.jclepro.2020.125359

Ahmad, A. S., Hassan, M. Y., Abdullah, M. P., Rahman, H. A., Hussin, F., Abdullah, H., & Saidur, R. (2014). A review on applications of ANN and SVM for building electrical energy consumption forecasting. *Renewable and Sustainable Energy Reviews*, *33*, 102–109.

Amasyali, K., & El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. *Renewable and Sustainable Energy Reviews*, *81*, 1192–1205. https://doi.org/10.1016/j.rser.2017.04.095

Amber, K. P., Ahmad, R., Aslam, M. W., Kousar, A., Usman, M., & Khan, M. S. (2018). Intelligent techniques for forecasting electricity consumption of buildings. *Energy*, *157*, 886–893. https://doi.org/10.1016/j.energy.2018.05.155

Amini Toosi, H., Lavagna, M., Leonforte, F., Del Pero, C., & Aste, N. (2022). A novel LCSA-Machine learning based optimization model for sustainable building design: A case study of energy storage systems. *Building and Environment, 209*, 108656. https://doi.org/10.1016/j.buildenv.2021.108656

Aygenç, M. (2019). *Life Cycle Assessment (LCA) of a LEED-certified green building using two different LCA tools* (Master's thesis, Middle East Technical University).

Azari R, Garshasbi S, Amini P, Rashed-Ali H, Mohammadi Y (2016). Multi-objective optimization of building envelope design for life cycle environmental performance. Energy Build 126:524– 534. https:// doi. org/ 10. 1016/j. enbui ld. 2016. 05. 054. https:// www.scien cedir ect. com/ scien ce/ artic le/ pii/ S0378 77881 63042 36

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Chari, A., & Christodoulou, S. (2017). Building energy performance prediction using neural networks. *Energy Efficiency*, *10*(5), 1315–1327.

Ciulla, G., & D'Amico, A. (2019). Building energy performance forecasting: A multiple linear regression approach. *Applied Energy*, *253*, 113500. https://doi.org/10.1016/j.apenergy.2019.113500

COP26 Goals - UN Climate Change Conference (COP26) at the SEC – Glasgow 2021. (n.d.). Retrieved December 8, 2021, from https://ukcop26.org/cop26-goals/

Deb, C., Zhang, F., Yang, J., Lee, S. E., & Shah, K. W. (2017). A review on time series forecasting techniques for building energy consumption. *Renewable and Sustainable Energy Reviews*, *74*, 902–924. https://doi.org/10.1016/j.rser.2017.02.085

Deng, H., Fannon, D., & Eckelman, M. J. (2018). Predictive modeling for US commercial building energy use: A comparison of existing statistical and machine learning algorithms using CBECS microdata. *Energy and Buildings*, *163*, 34–43. https://doi.org/10.1016/j.enbuild.2017.12.031

Dong, B., Cao, C., & Lee, S. E. (2005). Applying support vector machines to predict building energy consumption in tropical region. *Energy and Buildings*, *37*, 545–553. https://doi.org/10.1016/j.enbuild.2004.09.009

Elbeltagi, E., & Wefki, H. (2021). Predicting energy consumption for residential buildings using ANN through parametric modeling. *Energy Reports*, *7*, 2534–2545. https://doi.org/10.1016/j.egyr.2021.04.053

Emami Javanmard, M., Ghaderi, S. F., & Hoseinzadeh, M. (2021). Data mining with 12 machine learning algorithms for predicting costs and carbon dioxide emission in integrated energy-water optimization model in buildings. *Energy Conversion and Management*, *238*, 114153. https://doi.org/10.1016/j.enconman.2021.114153

Fan, C., Xiao, F., Yan, C., Liu, C., Li, Z., & Wang, J. (2019). A novel methodology to explain and evaluate data-driven building energy performance models based on interpretable machine learning. *Applied Energy*, *235*, 1551–1560. https://doi.org/10.1016/j.apenergy.2018.11.081

Feng, K., Lu, W., & Wang, Y. (2019). Assessing environmental performance in the early building design stage: An integrated parametric design and machine learning method. *Sustainable Cities and Society*, *50*, 101596. https://doi.org/10.1016/j.scs.2019.101596

Fushiki, T. (2011). Estimation of prediction error by using K-fold cross-validation. *Statistics and Computing*, *21*(2), 137–146. https://doi.org/10.1007/s11222-009-9153-8

Ghoroghi, A., Rezgui, Y., Petri, I. *et al.* Advances in application of machine learning to life cycle assessment: a literature review. *Int J Life Cycle Assess* 27, 433–456 (2022). https://doi.org/10.1007/s11367-022-02030-3

Harkouss, F., Fardoun, F., & Biwole, P. H. (2018). Multi-objective optimization methodology for net zero energy buildings. *Journal of Building Engineering*, *16*, 57–71. https://doi.org/10.1016/j.jobe.2017.12.003

Hou, P. (2019). *Data-driven environmental system analysis: Addressing data gaps in life cycle assessment* (PhD thesis, University of Michigan). Retrieved from https://deepblue.lib.umich.edu/handle/2027.42/151638

Hou, P., Jolliet, O., Zhu, J., & Xu, M. (2020). Estimate ecotoxicity characterization factors for chemicals in life cycle assessment using machine learning models. *Environment International*, *135*, 105393. https://doi.org/10.1016/j.envint.2019.105393

Jain, R. K., Smith, K. M., Culligan, P. J., & Taylor, J. E. (2014). Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy. *Applied Energy*, *123*, 168–178. https://doi.org/10.1016/j.apenergy.2014.02.057

Kapp, S., Choi, J. K., & Hong, T. (2023). Predicting industrial building energy consumption with statistical and machine-learning models informed by physical system parameters. *Renewable and Sustainable Energy Reviews*, *172*, 113045. https://doi.org/10.1016/j.rser.2022.113045

Khalilia, M., Chakraborty, S., & Popescu, M. (2023). Predicting disease risks from highly imbalanced data using random forest. *BMC Medical Informatics and Decision Making*. https://doi.org/10.1186/1472-6947-11-51

Kiss, B., & Szalay, Z. (2020). Modular approach to multi-objective environmental optimization of buildings. *Automation in Construction*, *111*, 103044. https://doi.org/10.1016/j.autcon.2019.103044

Lai, F., Magoulès, F., & Lherminier, F. (2008). Vapnik's learning theory applied to energy consumption forecasts in residential buildings. *International Journal of Systems Science*, *39*(6), 673-685. https://doi.org/10.1080/00207160802033582

Lam, J. C., Wan, K. K. W., Liu, D., & Tsang, C. L. (2010). Multiple regression models for energy use in air-conditioned office buildings in different climates. *Energy Conversion and Management*, 51(12), 2692–2697. https://doi.org/10.1016/j.enconman.2010.06.004

Lei, L., Chen, W., Wu, B., Chen, C., & Liu, W. (2021). A building energy consumption prediction model based on rough set theory and deep learning algorithms. *Energy and Buildings*, *240*, 110886. https://doi.org/10.1016/j.enbuild.2021.110886

Lewis, M. (2021). States Act to Reduce Embodied Carbon in Public Procurement. *Engineering News-Record*.

Machine Learning in MATLAB - MATLAB & Simulink. (n.d.). Retrieved October 10, 2021, from https://www.mathworks.com/help/stats/machine-learning-in-matlab.html

Mohandes, S. R., Zhang, X., & Mahdiyar, A. (2019). A comprehensive review on the application of artificial neural networks in building energy analysis. *Neurocomputing*, *340*, 55–75. https://doi.org/10.1016/j.neucom.2019.02.040

Monshet, S., Froese, T. M., & Evins, R. (2022, May 25-28). *Implementing surrogate modeling techniques for designing optimal building envelopes: A case study.* Presented at the Canadian Society for Civil Engineering (CSCE) Annual Conference, Whistler, Canada. Available from University of Victoria. https://dspace.library.uvic.ca/handle/1828/14104

Ongsulee, P. (2018). Artificial intelligence, machine learning and deep learning. *International Conference on ICT and Knowledge Engineering*. https://doi.org/10.1109/ICTKE.2017.8259629

OneHotEncoder. (2024, July 2). scikit-learn. Retrieved from https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.OneHotEncoder.html

Płoszaj-Mazurek M, Rynska E, Grochulska-Salak M (2020) Methods to optimize carbon footprint of buildings in regenerative architectural design with the use of machine learning, convolutional neural network, and parametric design. Energies 13(20). https:// doi. org/ 10. 3390/ en132 05289

Renewable Heat Incentive Scheme – Everything You Need to Know. (n.d.). Retrieved December 8, 2021, from https://www.theecoexperts.co.uk/renewable-heat-incentive

Shams, I., Mostafaeipour, A., Hoseini, N., Hoseinzadeh, E., & Hossaini, S. (2021). Evaluation and analysis of energy consumption in agricultural crop production using the DEA model based on hybrid artificial intelligence methods. *Renewable Energy*, *168*, 699-715. https://doi.org/10.1016/j.renene.2020.12.120

Sharif, A, & Hammad, A. (2019). Developing surrogate ANN for selecting near-optimal building energy renovation methods considering energy consumption, LCC and LCA. *Journal of Building Engineering, 25*, 100790. https://doi.org/10.1016/j.jobe.2019.100790

Siano, P., & Sarno, D. (2016). Assessing the benefits of residential demand response in a real time distribution energy market. *Applied Energy*, *161*, 533–551. https://doi.org/10.1016/j.apenergy.2015.08.019

Singh, M. M., Deb, C., & Geyer, P. (2022). Early-stage design support combining machine learning and building information modelling. *Automation in Construction*, 136, 104147. https://doi.org/10.1016/j.autcon.2022.104147

Singh, M. M., Singaravel, S., Klein, R., & Geyer, P. (2020). Quick energy prediction and comparison of options at the early design stage. *Advanced Engineering Informatics*, 46, 101185. https://doi.org/10.1016/j.aei.2020.101185

U.S. Green Building Council. (n.d.). LEED rating system. Retrieved December 8, 2021, from https://www.usgbc.org/leed

Wang, S., & Srinivasan, R. S. (2017). A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models. *Renewable and Sustainable Energy Reviews*, *75*, 796–808. https://doi.org/10.1016/j.rser.2016.10.079

Xu, Y., & Guo, J. (2021). Building energy consumption prediction based on machine learning algorithm and Internet of Things technology. *Sustainable Cities and Society*, *65*, 102588. https://doi.org/10.1016/j.scs.2020.102588

Yıldız, D., & Saygın, D. (2016). Forecasting electricity consumption in Turkey using artificial neural networks and support vector regression. *Energy Sources, Part B: Economics, Planning, and Policy*, *11*(6), 545–555. https://doi.org/10.1080/15567249.2012.677827

Westermann, P., & Evins, R. (2019). Surrogate modelling for sustainable building design – A review. *Energy and Buildings*, 198, 170–186. https://doi.org/10.1016/j.enbuild.2019.05.057

Yi, H., Srinivasan, R. S., & Braham, W. W. (2015). An integrated energy–emergy approach to building form optimization: Use of EnergyPlus, emergy analysis and Taguchi-regression method. *Building and Environment*, 84, 89–104. https://doi.org/10.1016/j.buildenv.2014.10.013

Appendix

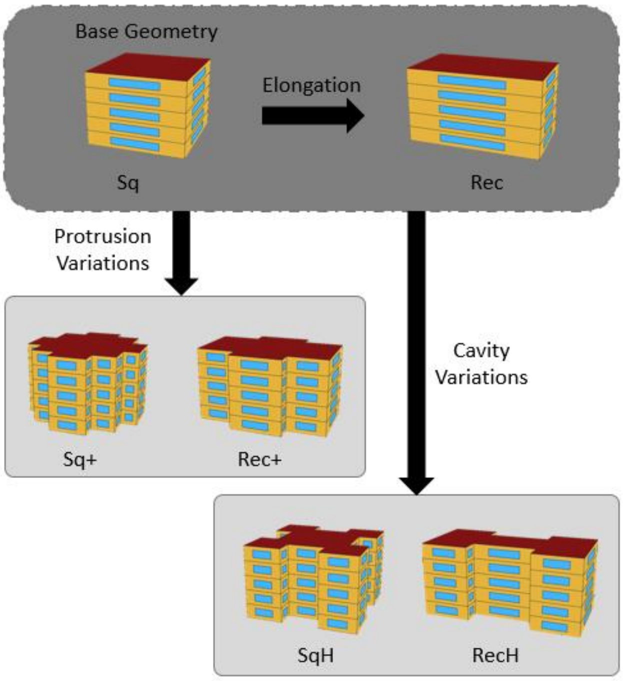

Fig. 1- Variation of geometry

Chapter 6 – Thesis Conclusion

This thesis was driven by the need for fast, interactive surrogate models that can help architects, engineers, and other stakeholders find sustainable building designs. The idea behind these surrogate models is that they can be trained on the results of detailed simulations and then used to quickly estimate a building's performance. This allows users to explore a wide range of design alternatives and refine their solutions in ways that would be difficult or time-consuming with traditional models.

The goal of this research was to establish the technical foundation for a broader application of surrogate models in design processes that integrate life cycle assessments (LCA). By building on the latest advances in machine learning and the rapidly evolving field of LCA, we aimed to address gaps in existing tools and enhance the capabilities of sustainability assessments.

As a result, we developed tools that train surrogate models, capable of handling a wide range of design parameters across different climates in Canada. These models can be integrated into the design process, enabling various stakeholders to assess, evaluate, and refine early-stage designs based on their carbon footprint. The parametric model developed here gives architects the ability to explore the full design space, while the surrogate model extends simulation limits to predict outcomes for a broader range of scenarios.

One major challenge we addressed is the difficulty professionals face in using LCA results to guide the design process. To tackle this, we designed the tool to communicate LCA data in a way that is clear and practical for designers. Instead of overwhelming users with numbers and tables, the tool provides visual representations of design scenarios through a web-based interface. Features like color coding were introduced to highlight carbon hotspots and compare scenarios, helping to show how different design elements impact a building's overall carbon footprint.

The tool was also designed to be user-friendly and flexible, catering to users with varying levels of LCA knowledge. Non-experts can use it to assess carbon ranges for different design scenarios, while technical users can dig deeper into the model and adjust it to meet specific needs.

The methodology is flexible enough to be applied to different regions by simply changing datasets—such as incorporating local Environmental Product Declarations (EPDs)—or adjusting variables like grid carbon intensity and weather data. The model can also be expanded to assess other environmental metrics, such as biogenic carbon and carbon capture, giving it the potential to compare various sustainability scenarios beyond just carbon emissions.

This research provides a foundation for further exploration. Two key areas for future work are:

Carbon-Positive Buildings: While this study focuses on reducing the carbon impact of buildings, there is a growing interest in designs that not only avoid carbon emissions but actively capture and sequester carbon. Future iterations of this tool could report on how much carbon a building sequesters and the trade-offs between embodied and operational carbon, pushing the envelope towards carbon-positive architecture.

Retrofit Scenarios: With additional development, surrogate models could be used to simulate the carbon impacts of retrofitting existing buildings. A more detailed LCA module could evaluate the embodied carbon of retrofits and the operational carbon savings, helping to select the most sustainable retrofit options. The tool could also compare the emissions of new construction with retrofitted buildings, providing deeper insights for owners, contractors, and policymakers looking to make environmentally sound decisions.

In summary, this tool was designed to meet the diverse needs of various stakeholders. Architects can use it to pinpoint low-carbon design options and predict the carbon impact of design changes. Policymakers can leverage the model to evaluate carbon benchmarks for different building types, materials, and regions. The tool can also assess the effectiveness of new technologies or materials, making it a valuable resource for those working on the cutting edge of sustainability. Additionally, it serves as an educational tool for students and researchers, helping them explore the link between design decisions and carbon outcomes. Project planners and owners can use the tool to assess sustainability features and ensure compliance with certification standards. Ultimately, this tool bridges the gap between LCA data and design decisions, making sustainability a more integral and accessible part of the building design process.

Appendix

Evaluating Building Carbon Footprint in Concept Design Stage

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Abstract

Early-stage design decisions are known to have the highest impact on building performance, but key sustainability measures are often postponed to later stages in the design process. This is partly due to the limitations of the current data-intensive methods of Life Cycle Assessment (LCA) which are incapable of handling the uncertainty that exists early in the design process.

This paper develops a method to evaluate the environmental impacts of a buildingin the early stages of design, to drive the design process towards sustainability targets. The main objective of this paper is to provide insights into the influence of early-stage form-finding on the total carbon footprint of a building. The scope of this study encompasses building geometry, structure, mechanical systems and envelope, and spans their impact on both embodied carbon as well as operational energy consumption and associated carbon emissions. A design exploration approach is deployed using a parametric model in which 162 design solutions for a midrise commercial building are modelled. The results show the dominance of embodied over operational carbon and the significant impact of structure on building carbon footprint. The results also indicate direct connection between building carbon footprint and building perimeter/VFAR that can be used for carbon estimations at concept design stage.

Highlights

- Building structure, envelope and mechanical systems has correspondingly highest impacts on building embodied carbon.
- Building emissions are a function of VFAR (Vertical surface area to Floor Area Ratio)
- Compact forms show remarkably low emission in all stages of life.

Positive protrusions are more carbon-intensive than cavity forms.

Introduction

The impact of buildings on the environment is well recognized, with the building sector being one of the major contributors to carbon emissions. As the world grapples with the urgent need to reduce greenhouse gas emissions and mitigate impacts of climate change, the building industry has come under pressure for its carbon footprint. The carbon footprint of a building encompasses the total greenhouse gas emissions associated with its manufacturing, construction, operation, and eventual demolition.

Building carbon footprints has become a prominent topic of discussion among architects, engineers, and policymakers alike. Various codes and topics have emerged to address the issue of building carbon footprint, with the aim of reducing emissions and promoting sustainable building practices. Many existing methods and tools for evaluating building carbon footprint focus on the construction stage, with an emphasis on selecting the lowest-carbon-intensive materials and technologies.

However, it is becoming increasingly clear that simply optimizing material choices during construction is not enough to achieve the ambitious carbon reduction targets set for the current decade. To truly make significant strides in cutting carbon emissions, a new level of carbon reduction must be deployed which is only achievable by considering building carbon footprint in the early stages of the design and planning process (1). This approach, however, presents significant challenges as the early stages of building design are characterized by uncertainty; making it difficult to accurately simulate and quantify the carbon footprint of a building (2–4)

To bridge this gap this paper aims to provide knowledge for early-stage carbon-sensitive decision-making. Therefore, a parametric model is developed to explore whole design space and evaluate environmental impacts of all design solutions. This includes both embodied and operational carbon and their balance on total carbon of the building. First, the method and modelling stage is explained. Then, the results are reported and the impact of building form, structure, opaque and transparent envelope and energy consumption on carbon footprint is investigated. Next, suggestions for low-carbon design for this project and similar design questions are presented and lastly general highlights for carbon footprint estimation in early stage are proposed.

Literature review

LCA has been the main assessment framework to analyse environmental impacts of the buildings, however, due to complexity and lack of data most of the research has been focused on one section of buildings, such as structure (5) mechanical systems (6), enclosure (7) or operational emissions (8,9). They also tried to tackle building carbon calculations feasible by simplifying scope. This part of the

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literature contains the research with the scope of a combination of components (10–12). However more holistic approach is needed to investigate trade-off and multi-aspect impact of building components on total carbon footprint of the buildings. also shows the necessity of holistic LCA. Therefore, in this study whole building considering structural, enclosure and mechanical systems of the building are taken into account. Another aspect of holism is quantifying trade-offs of operational end embodied carbo and close connection between these two on total carbon footprint of buildings. Much research manage to decrease one without considering the negative impact of carbon associated with the other, therefore in this study whole building carbon is measures and the correlation of design parameters on upfront carbon and operational carbon is investigated.

Despite the benefits of considering holistic LCA, this scope seems to be hard to implement in early stages of the design using current tools and software. This is mainly due to uncertainty and lack of available data in early stages of the project. In concept stage, little is known about the building because decisions about building system are not made yet, therefore LCA calculations are not possible in early stages of design using current methods.

For architects, there has been a vicious loop in sustainable design of making concept stage design decisions based on carbon footprint, which they cannot be measured in early stages because they don't know much about their buildings yet. Therefore, there is a need to shed light on early-stage design decisions for low-carbon buildings. This method will facilitate benefiting from carbon reduction measures achievable through early-stage design decision. In this research we have developed a method to make LCA feasible as early as concept development and help architect and engineers to develop their design aiming minimize carbon footprint.

some research try to incorporate carbon footprint in early-stage design. For instance, Gagnon et al. undertook a comparison between holistic and sequential design approaches for a residential building. They considered 39 design variables primarily related to the envelope system and evaluated the design alternatives based on three objectives: cost, thermal comfort, and greenhouse gas emissions (13).

Bernett et al. developed a decision-making framework for early design stages, aiming to generate schematic designs that are ranked according to energy use, embodied carbon, and construction cost. This framework facilitated the assessment of different design options, however the scope only covers structure and envelope and the studied geometries are case-specific which makes using the results difficult for other design projects (14).

Similarly, other researchers employed a multi-objective optimization approach to address various aspects of building design. One study focused on balancing HVAC energy cost and occupants' comfort (15) while another considered envelope design with respect to energy use, environmental impact, and financial cost (7) Additionally, there were studies that investigated envelope design variables based on operational and embodied energy (16) Or building form based on structure carbon capture (17)

Despite these efforts, the literature review highlights the absence of a comprehensive framework that incorporates holistic approach to early design stage and models whole building components in LCA calculation. It also should address major changes in building to reflect design changes and provide knowledge on changes in carbon footprint as a result of design.

Methods

This study has a holistic approach to building life cycle assessment. To define the scope of the study and quantify impact of design decisions of building carbon footprint, buildings main components and contributor to carbon emission were selected. A previous study by the authors identified main contributor to building carbon emission therefore, in this study building structure, heating and cooling systems and envelope are incorporated in this study (18).

The base model is a 5-story commercial building in the city of Vancouver with square footprint and total floor area of 5130 sqm. To investigate the impact of early-stage form finding six geometry types was considered. The base model is a building with square and rectangle (type compact). For each type, 2 other variations were also developed: protruded geometry with a protrusion in façade (type plus) and a cavity geometry with negative protrusion in surfaces (type X). All types have the same total floor area and footprint area. Building envelope are modeled according to ASHRAE construction detail.

The City of Vancouver is located in cool climate zone based on ASHRAE , however, to study the environmental impact of conventional enclosure details and evaluate the impact of different levels of insulation, construction sets of two other climate zones were also studied. Therefore, in addition to the recommended construction sets for Vancouver climate zone, building envelope was also modelled using construction sets for two colder climatic zones (i.e. cold and very cold) to investigate higher level of insulation in the building (19). The three construction scenarios for building envelope are referred to code minimum, high insulation and high-performance (refer to table 1). For windows, three high-performance insulated glass unit were studied. Also, to model different variations, three window-to-Wall ratio were investigated. To reflect emissions associated with HVAC system results of a previous study by Rodrigues were used and emission associated with equipment, distribution system and refrigerants was measured(20). Carbon intensity of materials are extracted from Inventory of Carbon and Energy (21).

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Table 1-Design Parameters

	Building Element	Parameter	Range	Number of values
1	Geometry	Type	Square, Rectangle	2
		Shape	Compact, Plus, X	3
2	Envelope	Insulation	Code-minimum High-insulated High-performance	3
		IGU	Double glaze-Aluminium Double glaze-PVC Triple glaze-Aluminium	3
		WWR	0.25 0.5 0.75	3
3	Structure	Concrete framing		
4	HVAC system	Dedicated Outdoor-Air System		

The modelling pipeline of this study is comprised of a chain of software and tools to investigate design, energy modelling and simulation as well as LCA calculations. Energy simulation and energy load is calculated using EnergyPlus, and LCA calculations are conducted in grasshopper, energy modelling is done using Ladybug tools (22) and geometrical model is developed in Rhinoceros and developed in grasshopper. Also structure is designed and analysed using Karamba 3D (23).

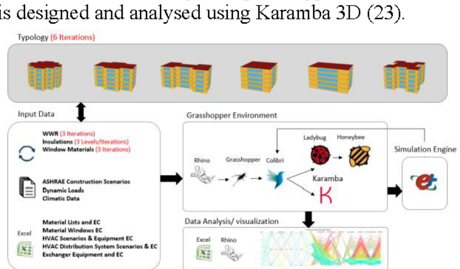

Figure 1-Modeling framework

Results

Embodied Vs. Operational carbon.

With a glance at average embodied and operational carbon, it is understood that total emissions has direct correlation with building perimeter. Compact forms show the lowest total carbon compared to articulated forms. In other words, square and rectangle show correspondingly the lowest total carbon compared to their plus or X variations. Among the two protruded forms, X types has higher total carbon emissions than Plus types due to higher perimeter of this variation.

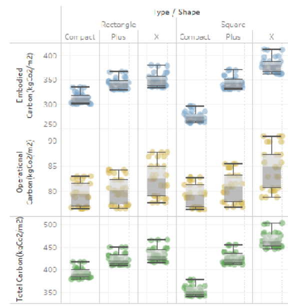

Figure 2:Average embodied carbon versus average operational carbon for each geometry

Embodied Carbon

The graph below demonstrates embodied carbon break down of studied cases. As the graph shows (Figure 3) the main contributor to building embodied carbon in all typologies is building structure with the average share of 64% of building total carbon. In the next step, building enclosure, makes up to 24% of building total carbon followed by HVAC emissions with average share of 12% in building total Carbon footprint. This is in line with previous study on sensitivity analysis of building carbon footprint (18).

As the Figure.3 shows forms with lowest VFAR and compact geometries has even load distribution in structural elements which reduces tension and increases the e efficiency of the structure. This leads to the lowest structure emission in compact forms among three variations. This is echoed by the lowest average envelope emission in compact variations that brings the embodied emissions of compact types by 14% and 19% percent lower than their plus and X version.

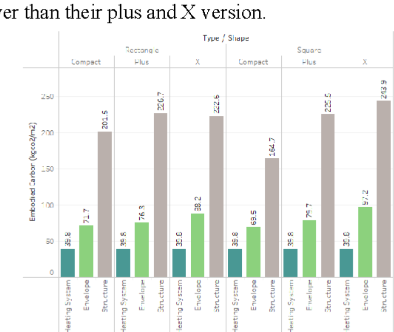

Figure 3: Breakdown of embodied carbon by building element.

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Envelope

In both shapes (square and rectangle) building X type has higher Emissions resulted from envelope followed by type plus and compact respectively. In other words, embodied emission of envelope is in line with building VFAR.

The figure below shows the embodied carbon break down of envelope among the scope of studied cases. As mentioned in method section windows in this study are selected from hight performance windows to reflect common trend of popular method for controlling energy consumption. It is inferred from the Figure 4 that use of high-performance windows has added to envelope embodied carbon more than other envelope components. Average share of window emission is roughly equal to average wall emission. As the average WWR is 0.5 in this study, it can be concluded that high performance windows have equal embodied emission as high insulated wall.

Following windows, wall, roof and floor has respectively contributed the most to the envelope EC. This demonstrates the impact of vertical surface design as the highest carbon-intensive part pf building envelope. This is more important in highrise buildings with larger façade area.

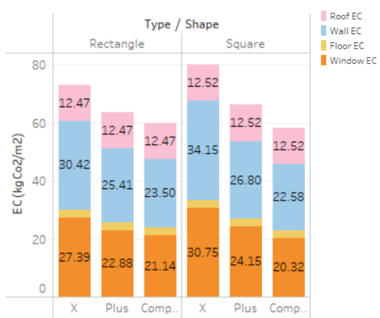

Figure 4- Breakdown of envelope carbon by element

WWR: Figure 4 reveals the high importance of envelope design with regards to high-performance windows. Low carbon design in colder climates requires special attention to openings and reducing thermal conductivity through transparent envelope. However, the impact of using this carbon-intensive material on total carbon is normally neglected. This graph compares the share of opaque and transparent envelope per geometry. As the Figure 5 shows, the envelope emission is highly influenced by building's vertical surface area to floor area ratio (VFAR) in all geometries. In geometries with more protrusions, wall and window area increases and consequently VFAR rises compared to compact forms. Therefore, articulated forms has higher emissions through envelope. More importantly the graphs show the spiral impact of increasing WWR on carbon emission. This can be crucial in designing based on view, and the optimum point of WWR should calculated through multi-object view-carbon simulation to provide proper view while controlling carbon emissions (see Table 2).

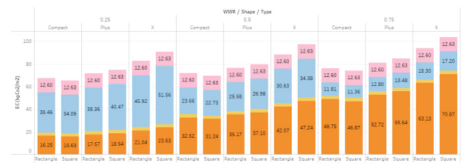

Figure 5- Breakdown of envelope embodied carbon by WWR

Window Material: By comparing average EPDs, it is simply understood that triple glazed window has highest emission due to complex manufacturing process and higher material quantity and using this window will add to building emissions. Conversely, the impact of using high-resistance window material on operational carbon and the balance on total carbon is hard to predict in early stages. The graph below summarizes the impact of using different window materials on total carbon and trade-offs between embodied and operational carbon. As the graph show, triple glazed windows tend to show less total carbon in building life span. Therefore, it is concluded that high embodied carbon of these windows can be balanced off by savings in operational carbon and led to lower total carbon compared to double glazed windows. This is very dependent to wall insulations and climate and should be investigated according to design project.

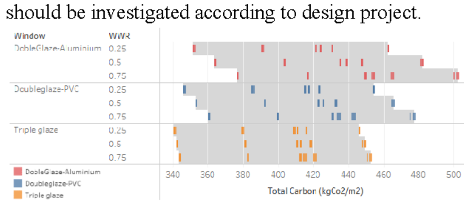

Figure 6- The impact of window material on total carbon per WWR

Wall Material: To investigate the impact of insulation level, three insulation scenarios are considered. All insulations are modeled using rockwool material with low carbon intensity. As Figure 6 illustrates, by increasing insulation level, building embodied carbon increases and operational emissions decreases. The results show that these two diverse impacts are balanced-out and total carbon remains constant. This graph suggests negligible impact of over-code insulation on reducing total carbon footprint of building in BC where the carbon intensity of grid is very low (24) however, this might not be a valid design suggestion for regions with high grid carbon intensity.

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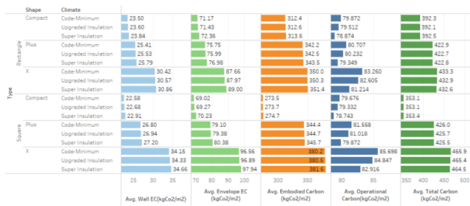

Figure 7-Embodied, operational and total emission by geometry per insulation level

The results propose necessity of calculating optimum point for the project insulation to benefit from proper thermal insulation to lower building carbon. Closer look at the results shows that in compact forms, upgrade level has the lowest total carbon while in X type super insulation has the lowest total carbon. This highlights the need for higher insulation thickness in forms with protrusions.

Structure

As mentioned earlier, structure has the highest impact on building total carbon footprint and no decision aiming low carbon design can be made without considering the structure system. The impact of structure per design iteration is calculated through an estimation model developed in Karamba. As the structure design is highly dependent on circumstantial factors and has high details in this study a simplified structural module was developed to design the structure of thousands of buildings variations. This is crucial for design-assistant calculations that explore the whole design space with acceptable accuracy. The results may vary from detailed structural design, but reliable for early-stage decision making in terms of scope, quantity of data and quality. The results have shown similarity with data of previous references (5).

The graph below illustrates the impact of geometry on building structure. It is observed that compact forms has high efficiency structures and consequently the lowest carbon emission compared to their articulated variations among studied cases. Carbon emitted from building structure increases significantly in expanded forms both in super and substructure.

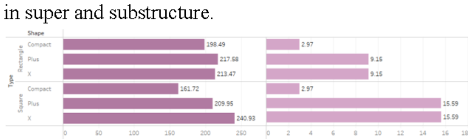

Figure 8-Structure carbon per geometry per material

Operational Emission

True assessments of the impact of design decisions on building carbon footprint is only genuine if the embodied and operational emissions are considered and their multi-aspect impact is analysed in design decision-making. To do so, the energy load in all subcategories was measured and illustrated in Figure 9. Equipment and lighting loads are constant as they are a function of occupied area, while heating, cooling, fan and pumps loads varies according to building type and thermos-physical features. As the graph shows types X has the highest average operational carbon emissions followed by plus and compact type respectively. Operational carbon shows the same trend of increase by increasing VFAR, like embodied carbon.

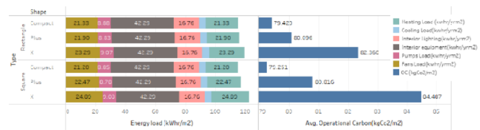

Figure 9- Breakdown of energy load and operational carbon by geometry

Discussion

The trade-off between embodied and operational emission has always been an interesting topic yet difficult to estimate for architects. Figure 10 shed light on the multi-aspect impact of design decisions on carbon captured or emitted from buildings. As the graph indicates compact types in both shapes have significantly lower toral carbon compared to articulated variations. This gap is larger among square variations due to wider range of VFAR changes for square. In rectangle variations, however, the buildings total carbon in fluctuates in a smaller range as a result of limited building VFAR (see Table 2).

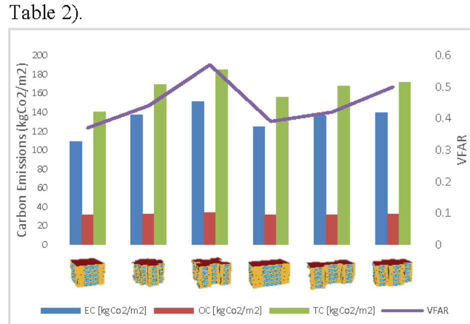

Figure 10- Embodied, operational, total carbon and VFAR per geometry

Graph 10 and 11 show the cumulative carbon through a buildings life span. As it is inferred, the graphs have the same slope which represents roughly equal annual operational carbon (compared to embodied carbon). This indicates the low impact of operational carbon compared to embodied carbon for areas with low grid carbon intensity. Similar exploration in areas with higher carbon intensity is suggested for future studies to investigate the impact of building detail design (material/components) on annual energy consumption.

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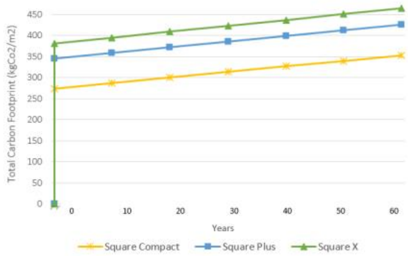

Figure 11- Cumulative carbon content of square buildings in 60 year lifespan

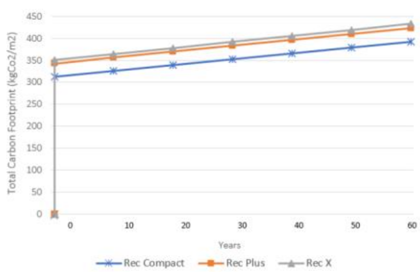

Figure 12- Cumulative carbon content of rectangle buildings in 60 year lifespan

The graph below compare building embodied carbon versus operational carbon per geometry. It is undrestood that for this design problem building square X by far has the highest emission. Compact square and rectangle has the lowest emissions respectively. The emission for rec_plus, rec_X and Sqr_plus are close and the differences can be neglected in favor of other design objectives such as view, day lighting , etc.

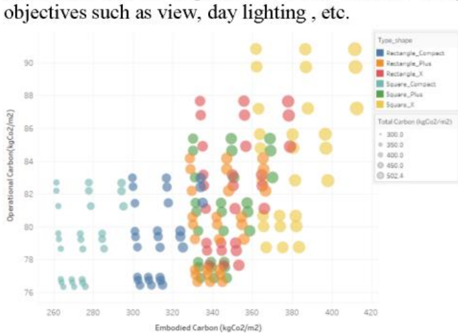

Figure 13-Embodied and operational carbon of all studied cases

Conclusions

In this study the embodied carbon, operational carbon and total carbon of 162 design variations were studied. The result of this study shows dominance of embodied carbon compared to operational carbon for midrise commercial building in BC, Canada. Therefore, in similar areas with low carbon intensity special attention should be driven to early-stage design to maintain low embodied carbon in order to establish building's low carbon intent. In designing low-carbon buildings, building's optimal structure design should be top priority to reduce building's lifetime emission. In the next step, architects should be mindful of impact of building form on carbon footprint of envelope, especially in windows and opening design decisions. Finally the results show that total carbon of building is highly dependent to VFAR, therefore, architects can estimate the final carbon footprint of their design in accordance to changes in shape and VFAR in concept design stage.

References

1. Hollberg A, Ruth J. LCA in architectural design—a parametric approach. International Journal of Life Cycle Assessment. 2016 Jul 1;21(7):943–60.
2. Schneider-Marin P, Harter H, Tkachuk K, Lang W. Uncertainty analysis of embedded energy and greenhouse gas emissions using BIM in early design stages. Sustainability (Switzerland). 2020;12(7).
3. Zolfaghari Z, Jones J. A multi-variable building energy optimization: assessing the role of energy efficient lighting technology in changing the optimal window-to-wall ratio in an office building. International Journal of Sustainable Energy. 2022;
4. Torabi M, Mahdavinejad M. Past and future trends on the effects of occupant behaviour on building energy consumption. Journal of Sustainable Architecture and Civil Engineering. 2021;29(2):83–101.
5. De Wolf C. Low Carbon Pathways for Structural Design : Signature redacted Signature redacted Signature redacted. 2017;(June):212.
6. Rodriguez B. Embodied Carbon of Heating, Ventilation, Air Conditioning and Refrigerants (HVAC+R) Systems. [Seattle]: University of Washington; 2019.
7. Pal SK, Takano A, Alanne K, Palonen M, Siren K. A multi-objective life cycle approach for optimal building design: A case study in Finnish context. J Clean Prod. 2017 Feb 1;143:1021–35.
8. Torabi M, Labbafan S, Farajnia B. Data for electricity consumption, thermo-physical characteristics of residential buildings in Tehran. Data Brief. 2022 Feb 1;40.
9. Mohammadsaleh Norouzi A, Labbafan S, Farajnia B, Torabi M, Norouzi M. Article

https://doi.org/10.26868/25222708.2023.1644

information Article title Dataset on environmental impacts and costs of energy consumption in educational buildings in Iran. Available from: https://ssrn.com/abstract=4439231

10. Fleischer G, Schmidt WP. Iterative screening LCA in an Eco-Design tool. International Journal of Life Cycle Assessment. 1997;2(1):20–4.
11. Hollberg A, Genova G, Habert G. Evaluation of BIM-based LCA results for building design. Autom Constr. 2020;109(October 2019).
12. Andersen CE, Rasmussen FN, Habert G, Birgisdóttir H. Embodied GHG Emissions of Wooden Buildings—Challenges of Biogenic Carbon Accounting in Current LCA Methods. Front Built Environ. 2021;7(August):1–15.
13. Gagnon R, Gosselin L, Armand Decker S. Performance of a sequential versus holistic building design approach using multi-objective optimization. Journal of Building Engineering. 2019 Nov 1;26.
14. Bernett A, Kral K, Dogan T. Sustainability evaluation for early design (SEED) framework for energy use, embodied carbon, cost, and daylighting assessment. J Build Perform Simul. 2021;14(2):95–115.
15. Wright JA, Loosemore HA, Farmani R. Optimization of building thermal design and control by multi-criterion genetic algorithm.
16. Pal SK, Takano A, Alanne K, Palonen M, Siren K. A multi-objective life cycle approach for optimal building design: A case study in Finnish context. J Clean Prod. 2017 Feb 1;143:1021–35.
17. Hens I, Solnosky R, Brown NC. Design space exploration for comparing embodied carbon in tall timber structural systems. Energy Build. 2021 Aug 1;244.
18. Torabi M, Evins R. An LCA Framework to Prioritize Carbon-Sensitive Measures in Residential Building Design Energy in Cities group , University of Victoria , Victoria , B . C , Canada . Abstract. In Ottawa: IBPSA; 2022.
19. American society of heating refrigerating and air conditioning engineers. ASHRAE Standard. New York: The Society; 2019.
20. Rodriguez B. Embodied Carbon of Heating, Ventilation, Air Conditioning and Refrigerants. 2019;(April):33–5.
21. Hammond PG, Jones C. INVENTORY OF CARBON & ENERGY (ICE). 2008;
22. Smith A, Gill G. LADYBUG : A PARAMETRIC ENVIRONMENTAL PLUGIN FOR GRASSHOPPER TO HELP DESIGNERS CREATE AN ENVIRONMENTALLY-CONSCIOUS DESIGN Mostapha Sadeghipour Roudsari , Michelle Pak.
23. Architekten W, Airport F. Linking Structure and Para- metric Geometry. 2011;110–3.
24. Government B. Electricity emission intensity factors for grid-connected entities [Internet]. [cited 2023 May 4]. Available from: https://www2.gov.bc.ca/gov/content/environment/climate-change/industry/reporting/quantify/electricity

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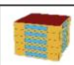
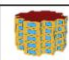
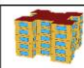
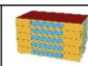
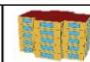
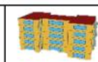
Table 2- Building typologies and summary of the results

Shapes						
Code	Square-compact	Square-Plus	Square-X	Rectangle	Rectangle-Plus	Rectangle-X
Embodied Carbon [kgCo2/m2]	108.79	136.97	151.21	124.24	136.09	139.22
Operational Carbon [kgCo2/m2]	31.46	32.09	33.54	31.53	31.80	32.70
Total Carbon [kgCo2/m2]	140.26	169.06	184.75	155.78	167.90	171.92
VFAR	0.37	0.44	0.57	0.39	0.42	0.5

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