Spatial Computing for Building Performance and Design

by

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Abstract

Accommodating urban population growth while reducing emissions from the built environment poses an unprecedented challenge to the architectural discipline. To enable more sustainable construction, the dissertation proposes a new computational design framework to investigate how building performance from an environmental and user perspective relates to spatial design. The dissertation surveys existing computational methodologies for design automation and identifies new opportunities and value propositions for architectural computing in design guidance, feedback, and optimization. Exploring methods that can be used to generate and optimize structural systems of buildings and interior layouts, a specific focus lies in the design of residential buildings. By applying generative design methods to building analytics, new ways for estimating the embodied carbon of a building and the environmental impact of system-level design choices can be explored.

First, the research demonstrates how generative geometric algorithms can be coupled with structural simulations to accurately predict the structural material quantity and, through that, the embodied carbon of a building in early stages of design. Second, a new method for representing, analyzing, and generating spatial layouts – the hypergraph – is proposed, that captures the characteristics of any given floor plan. Unveiling new architectural opportunities through automatic geometry creation, the hypergraph shows potential to improve the quality of residential spaces in terms of environmental performance and access to daylight. Enabling new design tools for architects, it offers creative applications and new collaborative workflows for incorporating new spatial metrics in the design process. Allowing for new quantitative insights in building performance, the research demonstrates that spatial efficiency can outperform envelope upgrades in terms of carbon emission savings.

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1. Introduction

1.1 Problem Statement

1.1.1 The Built Environment and the Planet

The architectural discipline faces an enormous challenge in the next decades. Buildings account for over 39% of annual global carbon emissions through their construction and operation (IEA, 2019a). Simultaneously, they are one of the main drivers of the global economy, provide critical infrastructure and shelter, and are integral to the functioning of society. It is this dual challenge, of having to build more, while emitting less, that requires us to rethink and redraw the frameworks of the architectural discipline. This thesis explores how design automation can be used to conceive and evaluate different spatial and technical systems at architectural scale, from internal layouts to whole buildings. The architectural challenge of the future will be the recalibration of the built environment into an integrated system that can respond to available resources and environmental conditions. This requires a rethinking of the building as a singular entity, and towards the built environment as a highly complex system that spans across scales and as a series of interdependent mechanisms, while featuring and responding to local climate demands, material availability, indoor comfort needs, and cultural and architectural expression. This dissertation proposes new forms of spatial computing to merge architectural, environmental, and structural constraints in the design of buildings as a new framework for architectural design. The research shows how spatial computation can be applied to rethink both the design of new buildings in early design stages and the analysis and retrofit of existing structures. For this, the dissertation proposes new modes of computational representation, analysis, and creation of architectural space.

The international community aims to limit our planet's warming to 1.5 degrees Celsius, which requires a substantial reduction in emissions (IPCC, 2018). The Shared Socioeconomic Pathways (SSP) are a set of climate scenarios proposed by the Intergovernmental Panel on Climate Change (IPCC) that aims to model different emission pathways (Bauer et al., 2017). If the world moves according to the best-case and most sustainable scenario (SSP-1) and drastically reduces emissions, the global carbon budget stands at around 930 GtCO2e, with around 350 GtCO2e remaining for the global building stock. Meanwhile, the International Energy Agency (IEA) and the United Nations (UN) predict a doubling of the floor area of global buildings (IEA, 2019b). Further, over 250 billion square meters of buildings will have to be constructed by 2050 to meet population increases and economic demands (IEA, 2019c, 2021). However, as visualized in Figure 1.1, the ratio between existing and new built area varies greatly between regions. For example, in North America, a higher proportion of existing floor area indicates that the main climate priority is the retrofit of existing buildings. In countries and regions with larger proportions of new floor area, such as India, novel sustainable construction methods for new buildings will be required. How can solutions that offer a long-term pathway to improved standards of living incorporate both sustainable and materially efficient construction methods?

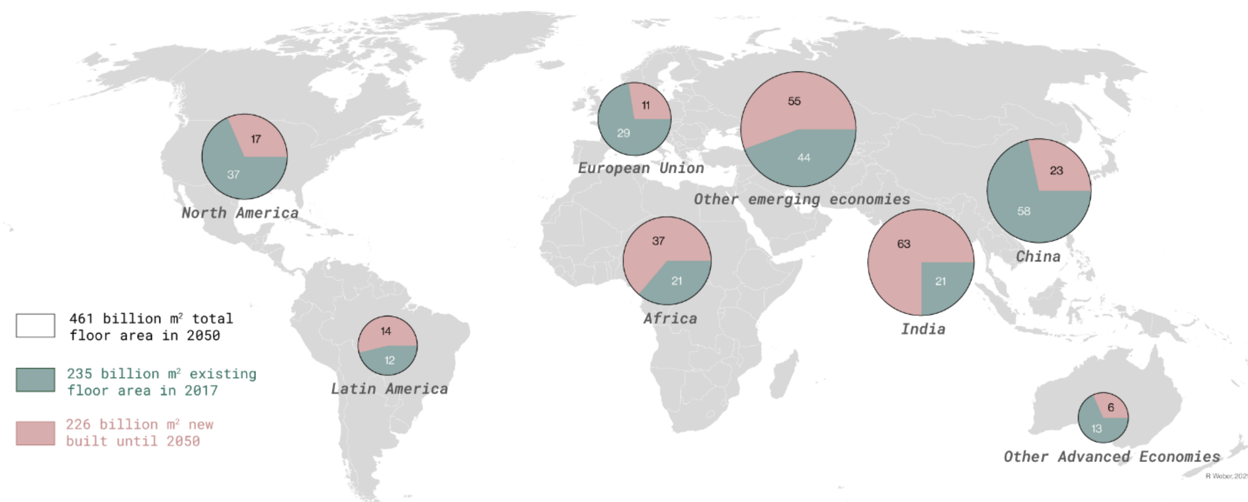

Figure 1.1: Global building stock in 2050

In order to meet carbon reduction targets and adapt to a warming climate (Staffell et al., 2023), proposed strategies have included: increasing energy efficiency (Reyna & Chester, 2017), electrification (Buonocore et al., 2022), lowering material resources (De Wolf et al., 2018; Zhong et al., 2021) and creating data-driven support frameworks (Ang et al., 2023; Heisel et al., 2022; Li et al., 2023; Mardaljevic, 2021). Building more sustainably and the resulting spatial patterns of urbanization will positively impact human health (Allen et al., 2015; Altomonte et al., 2019; Zhu et al., 2022), embodied (Fang et al., 2023b; Röck et al., 2020b; Simonen et al., 2017) and operational energy use (Güneralp et al., 2017), and will have co-benefits for building inhabitants (Baniassadi, Heusinger, Meili, et al., 2022; Bettencourt et al., 2007), the economy

(Hsieh & Moretti, 2019) and the environment at large (Churkina et al., 2020; Mishra et al., 2022).

Disciplinary insulation and continued specialization of both the architectural and the engineering domains make holistic decarbonization of buildings increasingly harder. At the same time, greater specialization has led to increasingly better performing structures, with the engineering discipline focusing on improving safety, following rigid code requirements, protecting people from natural disasters, and allowing for denser, taller, and more materially efficient buildings. Furthermore, increasingly complex heating, ventilation, and air conditioning systems (HVAC) can provide comfortable indoor environments in any climate. However, the depth of technical knowledge needed to design and conceive the technical building systems has multiplied the number of collaborators needed to create a building, led to a silo of knowledge, and increased the difficulty of optimizing these systems as a whole. Linear design processes separate the tasks of spatial design, structural design, energy, daylight, and construction detailing of a building. This gives a false sense that optimizing single building elements could lead to the most sustainable and livable buildings. New processes are needed to inform decision processes in the early stages of design, when building typology, material choices, and massing are decided; it is these design decisions that have the largest impacts on building performance (Paulson, 1976).

To assess and evaluate buildings holistically and automatically, we need new methods of spatial representation and algorithmic generation that go beyond traditional parametric geometry and can cross disciplinary boundaries: from architectural geometry to energy analysis or structural analysis. Typology, material, space, and performance need to be interconnected to influence material choices and promote more holistic design (Figure 1.2). Furthermore, how can the design of a single building be understood in its local context – in terms of materials, structure, building systems, and design? Together, the research creates a new framework for architectural computing, enabling architects and engineers to leverage digital design as a more collaborative and holistic tool for designing more sustainable buildings and cities. It provides insights into building performance and prompts us to reevaluate the existing metrics we use to assess performance in the built environment.

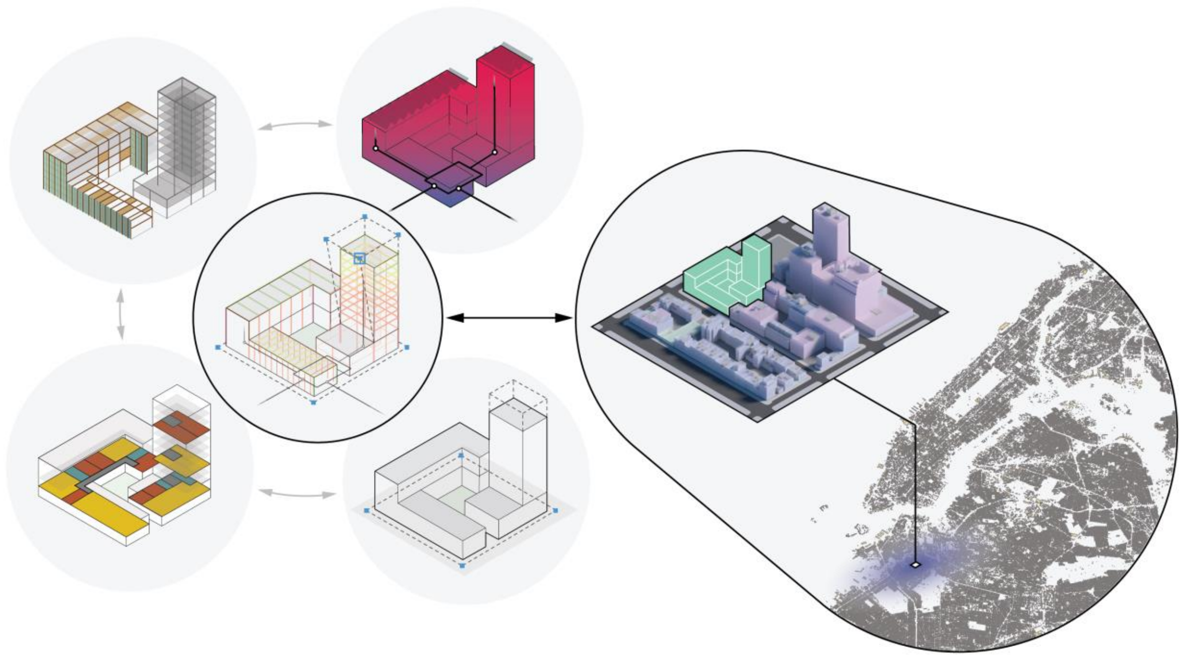

Figure 1.2: Integrated design framework guiding the development from local to urban context, integrating space to form and structure.

1.1.2 New Challenges for Architectural Design

As outlined in Figure 1.1, two very different challenges confront the architectural discipline: building quickly while using less resources and carbon to house growing populations in addition to retrofitting and adapting the extant building stock in metropolitan areas to address the needs of future generations. This challenge is exacerbated by the fact that global emissions from buildings, both in terms of operational and embodied carbon, should be reduced.

The new construction of buildings – and the material and design choices it entails – not only have an impact on how future inhabitants experience a building, but also can create lock-in effects in terms of urban development that could hinder the growth of a community and create dependence on carbon intensive energy sources in the future (Seto et al., 2016). It is well understood how different urban typologies enable higher densities of inhabitants (Firley & Deupi, 2023) and how building form, such as the height of a building, affects structural material quantities unproportionally (Khan, 2004) decoupling occupant density from tallness (Pomponi et al., 2021). Furthermore, it has been established how different urban typologies, particularly, suburban sprawl, are problematic from a carbon perspective (Ribeiro et al., 2019). However, this is often opposite of how the built environment is shaped and actively developed (Jones & Kammen, 2014).

Currently, research in low-carbon construction focuses primarily on decarbonization of individual materials, such as creating low carbon replacements for existing structural material systems. Meanwhile, there is a dearth of research on materials from a system perspective. However, different architectural typologies and construction methods have vastly disparate material uses. More comparisons are needed to quantify the impact of construction methods on total carbon emissions. Especially when creating low-carbon or lightweight building systems, the sustainability of a material is not only a result of its carbon impact, normalized by weight, but also how it benefits the whole building. Shorter spans might be buildable in timber, but if due to acoustic requirements or building code, a heavy concrete slab must be used as a decking, all the benefits of low carbon construction could be offset. This can be avoided by measuring building performance holistically and including the effects of construction techniques on both embodied, and operational performance, as well as occupant comfort.

The built environment has long adapted to different uses and habitation patterns. Modern cities will have to adapt their existing infrastructure and housing stock many times over. Being aware of the opportunities for creating buildings that can adapt to different uses during their lifetime is a design challenge that has yet to be solved. Brand offered a theoretical framework for a multi-layered approach through which different parts of buildings could be exchanged at different rates (Brand, 1995), depending on their life expectancy. In the current context, both the adaptation of existing buildings, as well as the creation of adaptable new buildings, is a key design challenge. In the US, adapting and converting building stock in urban centers from empty office buildings to much-needed residential buildings is urgently requested by lawmakers (BPDA, 2023). Conversions are notoriously difficult to design and construct and typically very expensive. Here, computational design tools can help to spatially adapt and reconfigure existing building stock, making renovations more predictable, feasible, and scalable.

1.1.3 Design in the Digital Age

Human imagination is closely linked to the tools and methods used in artistic practice. The architectural drawing and model, with their underlying physical or digital design processes, are both products that represent a building at scale, as well as modes of thinking and themselves artistic artefacts (Evans, 1986). Digital processes, offering unprecedented freedom for imagining new forms, have enabled the architectural discipline to explore new types of designs from a formal perspective. Furthermore, they have allowed the integration of environmental and structural analysis tools into the design process. This digital toolset not only allows for design evaluation and post rationalization but can be an integral component of the design itself.

Currently, digital design is understood as a fundamentally new concept and is only used by experimental design practices or in later stages of the architectural design process for project documentation. Although workflows seem digitized, design software mostly emulates analogue 2D drafting methods in a digital environment. While some architecture practices make use of more three-dimensional ways of working, enabled by tools from the naval, film, gaming, or aerospace industries, no truly unique architectural digital environments are currently used in the design stage at scale. Architecture-specific digital software is used for documentation of a building, after the design is (almost) complete; for example, building information modeling (BIM) is used to help coordinate different disciplines working on projects and as a documentation device. Compared to traditional geometric modeling, BIM associates geometry with supplementary data, such as product specifications or material properties. However, this method of working can only be used in design if no new geometry or construction systems are developed and buildings consist of parts that have previously been used, thus stifling innovation. There is a need for developing digital design environments, in which architects can take advantage of modern technological innovations, and that allow for inventing new geometries and structures. For this, new processes must be developed that can leverage human and machine intelligence, not only in documentation but also in the design of buildings.

Digital environments allow for direct visualizations of evaluation heuristics of a design such as area, material quantities, or daylight access. Coupled with physics-based simulation, form finding processes allow direct manipulation or creation of complex engineered shapes with high level inputs. It has been shown that coupling design methods with quantitative simulation feedback in an early design stage has the potential to significantly improve design outcomes (Burnell et al., 2017). This dissertation will show how engineering tools from different disciplines can be integrated into digital design environments, allowing for real-time interaction and quantitative feedback in the design of full buildings. Further, the thesis explores how such digital workflows could be created to help the design of regular buildings and analysis of existing urban conditions.

Architectural design has always worked with the idea of precedents – referencing and copying parts of existing structures both in terms of construction methods – and spatial configurations. Though not digitized, architectural monographs, featuring the work of critically acclaimed design offices, as well as design guides, are used in architectural education and by practitioners. However, this referential way of working has not yet been translated to digital environments. One of the main challenges in digitizing and comparing buildings is their inherent complexity. Spatial organization, structural systems, circulation typology, or wall construction cannot typically be measured in single numbers or even drawn or represented geometrically at the same scale. While the spatial organization could be expressed in a simple graph, akin to a bubble diagram, trying to embed wall construction details in the same method of representation will not lead to a better understanding of a building but instead make it virtually impossible to parse visual information. On the other hand, a 3D model with detailed geometry and material makeup of a wall section might make material quantities visible but makes typological or organizational workings of a building hard to compare and understand. To address this, new digital design methodologies and modes of representation are needed that can work across scales and translate between different design tasks and levels of detail.

Buildings are extremely complex assemblies and must balance often conflicting requirements that can be both quantitative and qualitative. Moving beyond simple rules of thumb, the dissertation proposes digital workflows that imagine a possible reality of designing a building based on high level information. From a building massing and very few descriptive parameters, it is possible to create a dimensioned structural frame, possible internal layouts, and simulations predicting energy use and indoor comfort. As a new framework for architectural design, the thesis proposes to merge spatial, environmental, and structural constraints in the design of buildings into integrative computational design workflows. The research shows how the framework can be applied to rethink the design of new buildings, in early stages of design, and the analysis of existing structures. This allows for optimization and evaluation of design choices, both in terms of how technical systems would affect the spatial aspects of a building, as well as how spatial requirements or design choices necessitate or influence the environmental performance of a building. The thesis explores how this integrative approach can be used for co-designing with computational means, automatically generating new, more efficient structures, and allow for the analysis and benchmarking of existing systems and environments.

1.1.4 Spatial design and quantitative analytics

Scientific and quantitative inquiries in architectural design have been relegated to the sidelines of architectural history. The scientific method and with it, quantitative analysis, are often conflated with a certain design aesthetic or style in architectural discourse. While structural engineering or building physics, with clear applications and measurable outputs, have been established as autonomous disciplines outside of architecture, measuring or computing space has largely remained a niche in design research, without any consensus within the discipline. As Steadman writes, computational methods have been largely misunderstood by architects whereas he found that the “purpose was to support design with scientific understanding and tools, not to mechanize the design process or to make it ‘scientific’, whatever that might mean” (Steadman, 2016).

Especially on the design generation side, because of the limitations of computational geometry, computer-generated floor plans or building designs often inherit a computerized aesthetic. This can result in both over simplified and over complex designs that sometimes time lack the nuance of manually generated geometry. On a building level, the artificial generation of a synthetic building floor plan with exact specifications has so far been an unsolved problem, because of its complexity. Floor plans are typically topologically varied geometric structures that cannot be captured with traditional parametric means. Attempts to create exhaustive manual representation of all possible configurations fall short because of the sheer number of possible solutions and are only able to enumerate designs in a very small design space (Steadman, 1973). Until now, simplifications, working in modular units, or within a set of design constraints, have been the only ways to create and explore a design space.

From an analysis perspective, there is no unified method of representation that can be used to capture and compare different designs. Quantitative measurement and benchmarking of buildings has been largely done via easy to measure attributes, such as the number of bedrooms or the floor area. The relationship of these metrics with actual spatial quality is limited, and more nuanced metrics should be explored. There are currently no metrics or an objective disciplinary consensus to evaluate what a "good" floor plan is. Compared to quantifiable metrics such as carbon, material use or energy consumption, the evaluation of interior layouts must combine different non-material and hard to measure aspects. This also has to do with how methods for representation are either explicitly display geometric features, such as a typical scale drawing of a floor plan or a 3D model, or showing only abstracted information, such as a bubble diagram of adjacencies in a floor plan. Different layers of information or spatial relationships are typically not preserved during the design process when using traditional means of representation. This dissertation explores new ways to represent building layouts, emphasizes measures that capture flexibility and adaptivity of spaces, and probes how to create a unique digital footprint of a spatial design.

1.2 Research Question and Scope

The decarbonization of the built environment is a challenge that encompasses many disciplines and, due to its complexity, touches many facets of society, with political, economic, and cultural implications. The dissertation focuses on technology as a lever to promote more sustainable building design, through performance prediction of spatial and technical systems in buildings. What technologies could help to provide higher quality housing for more people – using less materials, less energy, and less space?

The research hopes to expand the current research focus on optimizing single technical systems and higher efficiency to include exploring opportunities for investigating the architectural, typological, and spatial implications of how we can build buildings and cities more sustainably. The research addresses shortcomings of currently used computational modes of representation and proposes new data structures and algorithms that allow quantitative analysis and design generation of spatial configurations. By merging structural, energetic and spatial systems, integrative workflows for building performance evaluation are proposed to answer the following questions:

- Is it possible to use computation to link architectural space, structure, and physics?
- Can we learn from existing buildings to propose new design solutions?
- How can we create new metrics for quantifying how space is used?

1.3 Organization of Dissertation

The research explores how generative geometry can be used to represent a wide variety of buildings spatially, structurally, and energetically. Chapter 2 gives an overview of the current state of the art of environmental and computational design frameworks and their technical applications to frame the research challenges and opportunities of the dissertation.

In Chapter 3, design automation methods and applications for building floor plans are explored. Different approaches are compared with an emphasis on outlining how technical procedures and methods influence their use. Different types of value propositions of automating building layouts that go beyond design automation are identified. These different methods lay the foundation for algorithms and data structures that are further developed in the dissertation.

To represent a building floor plan geometrically, the hypergraph is presented in Chapter 4 as a new data structure. The hypergraph allows for the capture of complex spatial building features. Focusing on residential buildings, existing designs are mapped and evaluated. The hypergraph permits the geometric classification of floor plans from different cities around the globe and gives new insights into building performance. The thesis proposes new workflows that enable the automatic creation of topologically diverse building geometry. This creates opportunities for new types of analysis tools for early-stage architectural design. Utilizing established principles from parametric geometry and combinatorial and referential methods, a wide variety of structural geometries can be explored. The geometric methods are applied in collaborative design tools that augment existing design processes, by helping designers explore a much broader design space, co-create new designs, or reference existing designs.

In Chapter 5, the dissertation explores geometric methods that are needed to represent a building's structure. New geometric workflows are proposed for predicting embodied carbon of structural frames and lateral systems. Validations with real world buildings show practical applicability of the computational processes. They allow for more efficient predictions of how design changes affect the embodied carbon of a building as a whole. The interdependence of a building's structural and spatial parts is investigated to show how components must be considered together to achieve optimal performance gains. Furthermore, the thesis explores how operational and embodied carbon are connected and how different solutions are beneficial depending on a building’s context, available resources during construction, or design requirements.

In Chapter 6, the dissertation shows how integrative design models can capture the relationships of interdisciplinary systems, combining energetic, structural, and spatial concerns. The thesis introduces applications of such integrated design processes for both new and existing buildings in a series of case studies. The digital models created using design automation offer almost infinite possibilities. The thesis shows how methods of data visualization and analysis can be used in the building context to assess building performance, evaluate, and select designs. Furthermore, the framework allows for the evaluation of buildings to across scales from a local to an urban scale, offering insights for occupancy, large scale building retrofit of existing building stock, and embodied carbon analysis.

The contributions of the dissertation are discussed in Chapter 7. The different methods, algorithms, and frameworks developed in the dissertation are discussed with a focus on their impacts on computational design, structural design and building energy modeling. The limitations of the work are disseminated, and future research is outlined for developing new software tools for architectural design, interdisciplinary performance analysis, design generation workflows, and ideas for how the findings can impact sustainable construction and building policy.

2. Literature Review

2.1 Environmental Frameworks for Architectural Design

In the architectural discipline, different design frameworks have sought to combine systems-thinking rooted in scientific discourse from the field of ecology with architectural design. The challenge to drastically reduce emissions in the built environment, coupled with a global need for new and affordable housing and infrastructure, has reignited interest in framing design within its ecological context. Historically, environmental design frameworks sought to examine relationships between resources and structures and establish means of production and building as interconnected systems. This way of thinking does not directly imply architectural form and often struggles to directly connect with physical building processes. The term "environmental design" traces its roots to architects from the Bauhaus, who argued for "comprehensive design strategies that took care of both humans and nature," writes Anker (Anker, 2019). Computers were introduced to capture and map environmental data at an urban scale, such as density or income (de Monchaux, 2016) and proposed to help architects and planners in decision-making processes.

Similar to the contemporary notion of a carbon budget that serves as a top-down limit for guiding the development of buildings and environmental policy, computational design pioneers such as Alexander approached environmental design from a quantitative perspective, using computers as a way to parse complex information into design decisions (Alexander, 1965b). This way of thinking is also reminiscent of Fuller's principles from 'operational manual for spaceship earth' where he called for the creation of infrastructure that would account for the available resources on the planet (Fuller, 1969). Van der Ryn proposed the idea of Whole System Design, where architecture would function by utilizing existing materials and resources (Van der Ryn & Cowan, 1996).

Drawing from studies on complexity and natural systems, Simon's science of the artificial (Simon, 1970), introduced new ways of thinking about human made systems and how they can attain goals and adapt to their environments. Odum's systems language approach, which is typically used to describe self-organization of ecosystems, is used to describe environmental principles at architectural scale (Odum, 1983). Developing the systems approach further, Braham describes how complex and interconnected thermodynamic principles can be used to describe design across nested scales – shelter, setting, and site (Braham, 2016). However, design frameworks have been descriptive and theoretical, and have, for the most part, not found direct application in the design of new buildings.

On a smaller scale, design frameworks offering a connection between intent, geometry, and material properties, have led to the development of more integrative, performative structures. The resulting experimental structures, created using digital or robotic fabrication methods, are the direct result of integrated digital design processes. These frameworks of thinking were brought into built architectural practice as emergence (Hensel et al., 2013) and material-based-design computation (Oxman, 2010), taking inspiration from biology, and creating digital pipelines that apply structural principles from nature to an architectural material scale.

The interrelation between architectural form and technical building systems was driven to a satirical peak by Dallegret and his ‘environment bubble’ that reduces architecture to a transparent membrane that is inflated by air conditioning output (Banham, 1965). Translated to housing, Moe explored the concept of convergence, rethinking buildings as a whole, investigating how materials, energy systems, and ecological amortization can play together to maximize a buildings performance and minimize environmental impact (Moe, 2013). From the opposite direction, De Monchaux explored how simulations could be used to capture and predict environmental phenomena and tailor architectural interventions at an urban scale (de Monchaux, 2016).

2.2 Computational Frameworks for Architectural Design

Digital technologies have fully infiltrated the architectural design field. They have resulted in technological and cultural shifts that manifest both in the production and exploration of formal ideas, as well as technical processes in production (Carpo, 2012). The first architectural computer software (Sutherland, 2003) copied classical architectural drafting methods and worked as a digital canvas. Akin to a digitized typewriter, erasing and redrawing became possible. As a first use case, drawings could be automatically translated into structural models and analyzed as 2D trusses. Simple analytics of well-known mathematical formulations of Euclidian geometry and linear algebra allowed for easy measurement, area calculations, and dimensioning of drawings. It became clear that new modes of abstraction were needed to fully leverage computational environments for architectural production.

The geometric and computational methods explored in this dissertation draw heavily on decades of research in both the architectural and computer graphics disciplines. In architectural research, rule-based design strategies have been applied to both the generation and analysis of buildings. Specifically, shape grammars (Stiny & Gips, 1971) created a new way of understanding and transforming geometry in a procedural way across scales. Applied to unveil hidden patterns of decision-making in spatial design processes, shape grammars showed how to manually reproduce specific design languages and building layouts (Stiny, 1980). These grammar-based approaches have been applied to making (Knight & Stiny, 2015), architectural design in specific styles from Alvaro Siza (Duarte, 2005) to Frank Lloyd Wright (Koning & Eizenberg, 1981) as well as structural systems (Shea, 2000). The computational algorithms described later in the dissertation draw from a shape grammar context, digitizing rule-based subdivisions approaches that have been applied to study the underlying structure of abstract geometric art (Knight, 1989). Spatial relationships in traditional architectural floor plans could be embedded via relational graphs and tree structures (Alexander, 1965a). In graphic design, these linear transformations and rule-based, repetitive geometric operations gave rise to a new computerized aesthetic. In the 1960s, artists such as Mohr and Molnar started to develop a visual language from algorithmically generated drawings (Taylor, 2014). The first true infiltration of a digital aesthetic in architecture came with architects, such as Gehry, using methods to scan and translate physical models crafted by hand, into a digital world, to be manufactured at building scale (Carpo, 2017). These methods and frameworks are still in use by a number of contemporary artistic architectural practices (Ngo, 2016; Puente, 2021).

Fully digital design approaches leveraged software from the film industry and computer graphics to explore a new formal repertoire. Special effects tools, originally conceived to create animated movies, were appropriated by architects and used as digital canvases. Practices such as Zaha Hadid Architects, known for creating highly expressive buildings, inspired by abstract and graphical drawings, embraced these new technologies for form making. By forgoing physical model making and design processes for digital methods, new types of architectural form could be explored. The designs themselves are heavily influenced by their underlying digital representations such as non-uniform rational basis splines (NURBS) or meshes.

The development of digital design methods in the architectural discipline has been frequently coupled with digital fabrication capabilities. Computer numerical control (CNC) machines made mass customization attainable and architectural design tools allow for the direct control of material manufacturing processes. The ability to directly control fabrication machines through design software influenced contemporary research agendas, enabling the coupling of structural simulations with material design and fabrication processes, to create efficient shell structures, floor slabs or experimental structural systems. A digitalized aesthetic, enabled by this digital to physical fabrication pipeline has not manifested in the broader architectural discipline, rather the new ways of working are used to automate or digitize established design workflows.

In the wider architectural community, digital tools still resemble analogue architectural drafting methods. Highly detailed 3D models are well established, but only at the end of the design process. BIM is widely used (Schlueter & Thesseling, 2009) and allows for detailed accounting of all materials and spaces of a building. BIM models attach secondary information to a geometric representation, allowing identification and specification of building elements in a 3D model. They are created to avoid clashes between different building elements and coordinate all aspects of a building design with specialists and builders during the final design stages and construction. BIM models have been used in the design of full buildings, however, by design they limit designers to use prescribed material catalogues and have not been adopted in artistic practice during earlier design stages.

One of the main contributions of parametric design methodologies is the non-destructive editing of geometry. While architects design through traditional methods both physically with pencil and pen or cardboard, as well as digitally with 2D and 3D computer aided design (CAD) tools, drawn geometry is unaware of its previous states. Although undo functions allow designers to revert to previous versions of a design, they do not allow editing of previous decisions. The parametric paradigm, often enabled through node-based interfaces, simultaneously creates a tree of embedded geometric manipulations that are editable at all stages of design. This allows for relative creative freedom inside a given geometric representation paradigm. However, information is lost when data formats have to be bridged, for example, going from NURBS surfaces to Meshes, or subdivision surfaces to volumetric voxel representations. Furthermore, these translations into different formats are only possible within surface or volumetric based shape representations and which do not capture the information needed to fully represent architectural space. Architectural software has so far stayed within the parameters set by the computer graphics world for representing objects in known data structures: data structures where volumes, surfaces, edges or points are represented by coordinates in space. Architectural questions of area, topological configuration, environmental performance, energy use, or spatial relationships are always assessed a posteriori or achieved by running optimization algorithms that slowly converge to a desired result.

2.3 Digital Translations and Artificial Intelligence

New capabilities of AI-enabled workflows for image and text creation have been applied to the production of "high-quality artistic media for visual arts, concept art, music, and literature, as well as video and animation," as Epstein writes (Epstein et al., 2023). They have not currently proliferated architectural production workflows beyond the creation of conceptual visuals. Technical progress is especially rapid in imaging, where machine learning models are able to detect virtually any object in an image (Kirillov et al., 2023) or synthesize artificially generated cohesive images from simple text prompts (Ramesh et al., 2021). However, purely statistical models, especially for artificially generating images, lack an understanding of the content they produce. This is emblematic in research showing how pixel-based manipulations of images not visible to the human eye can render images unusable for image-based generation models (Shan et al., 2023). Currently, images can be created that are valid visually but spatially or topologically nonsensical. Just like the famous Escher paintings, they work on a small scale but create an optical illusion at the scale of an apartment with rooms within rooms, or hallways that lead into nowhere. With the technical speed of improvement in image-based models, these mistakes will become increasingly less frequent and might disappear altogether.

Image-based AI models often work with the notion of one-shot generation: Detailed text prompts are created that describe the desired output as close as possible. The generated image is not an abstraction but tries to represent the input as close as possible. However, levels of abstraction are crucial in the design context of a building where different geometric features and spatial and engineering constraints come together. Capturing these rich layers of information requires two-dimensional thinking and modeling in different plans, sections, and elevations, and in three dimensions. In architectural design, design decisions are often hard to capture in words, especially when conventions are not followed, and new spatial or structural innovation takes place. Drawing or sketching becomes an intuitive part of the design process where spaces are explored through drawing, rather than textual descriptions. It is challenging to create designer centered, intuitive workflows for describing geometric transformations with words through text prompts or code.

2.4 Automated Floor Plan Generation

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The first automated floor plan generation methods were introduced close to half a century ago. The underlying motivation has changed over time and still varies significantly between different projects and tools today. Automatic space layout creation methods were introduced as artistic speculations on the future role of computers and artificial intelligence (AI) in architecture in the 1970s. Friedman proposed the “Flatwriter” (Friedman, 1971) to generate apartment layouts that would accommodate usage preferences of all neighbors in cooperative housing projects. Automating the layout creation process was seen as an enabler for participatory design. Price proposed the “Generator”: A reconfigurable voxel based spatial unit that could be reconfigured by visitors into different layouts (Riley, 2002). Both pre-computational proposals envisioned floor plans designed by a modular kit of parts in a bottom-up process.

As an analogue process, Stiny proposed parametric shape grammars for the analysis and reproduction of building layouts (Stiny, 1980). By understanding the design and spatial qualities of existing buildings such as Palladian villas (Stiny & Mitchell, 1978) or Wright’s prairie houses (Koning & Eizenberg, 1981), the underlying patterns could be deployed to recreate buildings of the same type. Similarly, Alexander represented spatial relationships in traditional architectural floor plans via relational graphs and tree structures (Alexander, 1965a). These abstractions were essential first steps necessary for automating the generation of floor plans and continue to play a foundational role in contemporary computational approaches.

Grammar based design methods have been successfully implemented into computational workflows to procedurally compute building volumes with detailed facades. Notably Esri's City Engine (ESRI, 2024) which integrates the CGA++ shape grammar language (Schwarz & Müller, 2015) that enables the generation of differentiated building envelopes for visualization purposes of urban design proposals.

As of today, automated building-level layout tools have not made much headway into mainstream architectural practice where, their use is mainly reserved for speculative design exercises or specific niche applications such as office furnishing and electric lighting layouts in interior design (Heuman, 2020) or complex programming exercised for hospitals, airports or large scale residential and commercial developments (Das et al., 2016; Derix, 2010; Finucane et al., 2006). For such applications, automatically generated design options can augment or replace conventional manual design processes by offering not a single optimal solution but a family of directions for further design exploration (Wilson et al., 2019).

Current approaches for design automation of floor plans have a wide range of limitations that hinder their adoption in industry: Being only able to represent rectangular or orthogonal boundary conditions (Bisht et al., 2022), or responding to only either topological or spatial or boundary constraints (Hu et al., 2020b; Nauata et al., 2020b; Para et al., 2021; Sun et al., 2022; Wu et al., 2018a). Learning implicit geometric relationships, they are difficult to train and untransparent datasets cannot guarantee architectural quality or environmental performance (Weber et al., 2022b). Different methods were developed in tandem with different methods of representing floor plans geometrically, from unstructured CAD data to meshes, adjacencies, images or rectangles (Figure 2.1). Searchable database for floor plans, where room connectivity and wall geometry are represented as graphs (Dillenburger, 2016a) exist, however they only have been used for design analysis. New types of structured data, such as graph based data structures that are procedural in nature or parametrized command sequences (Wu et al., 2021), will enable new types of machine learning and design automation (Ritchie et al., 2023).

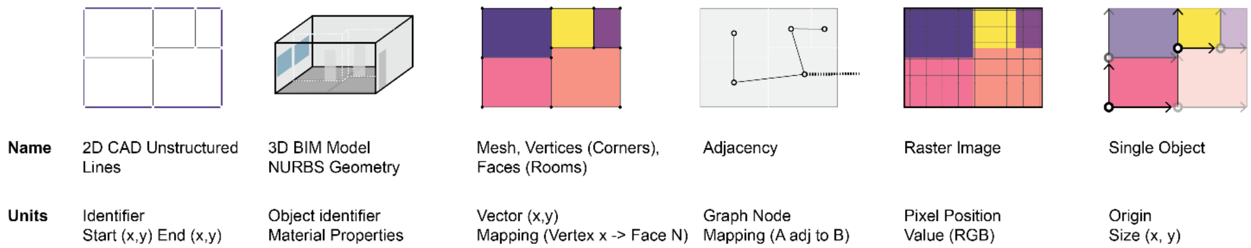

Figure 2.1: Overview of typical geometric data structures used in architectural workflows and for generative design of buildings.

In contrast to architectural design, the real estate sector has enthusiastically embraced and supported the creation of a plethora of floor plan and building automation software and practice. Several companies of varying size now focus on the creation of automatic layout tools to assist property developers and decision makers. They promise to maximize the potential buildable area and perform automatic analysis of a site, creating semi-automatic feasibility studies that can inform investment opportunities for land acquisition and maximize rentable area. Whether geared towards the real estate industry or conceived as in-house software tools in architecture and engineering firms, most current approaches tackle layout automation on the scale of a single building massing. They include different apartment (or in the case of hospitality, hotel room) mixes and simplified core placements with single or double loaded corridors. Drawing inspiration from the electronics industry, where design automation launched a revolution in efficiency is one possible avenue for exploration (Lin, Tang, Sangiovanni-Vincentelli, et al., 2023). However, further research needs to address the feasibility of platform-based design in a building context (Lin, Tang, Schiavon, et al., 2023).

2.5 Daylight Analysis

Lighting is at the core of architectural design and, conversely, architectural design is often shaped fundamentally by access and availability of daylight. Daylight is crucial for building performance, but even more so shaping the human experience inside a building. It is both a product of design, but also influenced by local weather, cultural norms, and practices (DeKay & Brager, 2023). Shading structures that maximize or minimize daylighting have been observed in historical buildings across the globe and are a key feature in the design of many new buildings (Lechner, 2014). Analogue simulation techniques utilize geometry to create artificial lighting scenarios with the real sun using a heliodon: for example, a sun dial that can be rotated in multiple axis to model any point on earth (Osser, 2007). Sun ray angles are used in the design process both to ensure ample daylighting inside of a space, and their effects on overheating of a space have been studied (Olgyay, 1963). Creating louver systems that enable light penetration while allowing glare and thermal control has been a common thread in architectural design around the world and is significantly shaping the architectural expression of buildings (Barber, 2020).

The development of raytracing rendering systems (Larson & Shakespeare, 1998) enabled accurate simulation of daylight and artificial lighting in virtual environments. Going beyond simple angular models for sun paths, diagrams, or physical models, the virtual simulation environments of today have enabled accurate evaluation and prediction of daylighting in architectural spaces (Ayoub, 2019). Being able to measure the influence of local weather, annual sun paths, the materials, shading systems, building and façade geometry in detail, allows for new insights for creating performative buildings (Weber et al., 2022a). Furthermore, as one of the main drivers of indoor comfort, daylight simulations are an integral part of energy simulation workflows (Kota & Haberl, 2009).

Accurate simulations allow for integration of building performance metrics into building certifications (USGBC, 2023), where they can promote sustainability of indoor environments (Reinhart et al., 2006). However, simulations themselves will not replace design intuition, as ubiquitous simulations without a goal in mind are, as Tregenza and Mardaljevic write “just as likely to overwhelm as empower the user” (Tregenza & Mardaljevic, 2018). Furthermore, from the author’s own experience in the classroom teaching introductory environmental simulation to architecture students, user interfaces and visual cues, or feedback given by simulation software can be highly influential, but also sometimes detrimental to design decisions and outcomes. A prime example of this is visual glare from direct sun light; while something to typically avoid in a commercial office environment, direct sunlight might actually be desired in a residential building, even if flagged by a simulation environment. This reaffirms the necessity of reflecting critically on simulation outcomes in order to design architectural spaces.

Daylight access is crucial for healthy buildings and cities. Therefore, it is vital to tailor metrics that can react and guide building designs to both enable daylight access to inhabitants as well as promoting sensible urban design (Mardaljevic, 2021). For new buildings, especially in urban environments, the impact of shading on outdoor thermal comfort and neighboring buildings must be addressed. Different regulations exist around the world. For instance, in Zurich, Switzerland, there is a limit on the number of hours a building is allowed to cast a shadow on a neighboring building, which the municipality controls via 3D models and sun path simulations (Canton of Zurich, 2021).

As simulation tools become faster, enabled by GPU ray-tracing engines or AI workflows and with surrogate models, creative architectural design and geometric workflows will become more important. If physically accurate daylight simulation enables us to quantify how performative a design is, what should we ultimately design? What kind of design space exploration methods do we deploy, and how do we set up geometric search spaces to have an increased chance of including more optimal designs? The dissertation investigates new ways to represent architectural geometry that can integrate with daylight simulation, both for better assessing the performance of existing buildings, as well as future buildings. Cutting down the simulation time of an annual raytracing simulation from hours to milliseconds enables architects to assess not one, but thousands or millions of design solutions, ultimately and hopefully increasing the quality of the spaces in which we live and work.

2.6 Building Energy Simulation

Building energy simulations are crucial in deepening our understanding of how to reduce energy consumption of buildings and cities, while influencing design and policy decisions across scales. They are useful in different design stages of buildings: from early-stage massing to detailed design decisions. Only through understanding and predicting energy use of a building can building systems such as HVAC or PV systems be dimensioned precisely.

Building energy models are physics-based heat-transfer and mass flow simulations that are industry standard for energy use predictions of buildings (Polly et al., 2011). For this, different, both commercially available and open-source software environments exist (Crawley et al., 2001; Dassault Systemes, 2023; Trynsis, 2023). Building energy models have been applied at different resolutions, and for different purposes. Fast single node transient analytical models can capture effects of natural ventilation in real time (Arsano et al., 2019). Highly complex models can represent different building typologies in detail (such as hospitals) and are used to size HVAC equipment or tailor building energy codes (Deru et al., 2011). Building energy models have been used to show co-benefits of energy efficient buildings on inhabitants (Samuelson et al., 2020) as well as urban environments(Baniassadi, Heusinger, Meili, et al., 2022).

On an urban scale, two main strategies are used to model and understand building energy use. First, top-down workflows are used to predict urban energy with data driven models based on measured data (Godoy-Shimizu et al., 2024) or making use of regression or machine learning models (Nutkiewicz et al., 2018). Second, bottom-up models aggregate single physics-based building energy models of individual buildings and apply them to whole neighborhoods or cities as urban building energy models (UBEM) have been proposed to predict operational energy use. Different applications for UBEMs have been identified, ranging from urban planning and neighborhood design, stock-level carbon reduction strategies, building level recommendations and buildings-to-grid integrations (Ang et al., 2020).

2.7 Structural Analysis

Designing a building's structural system is strongly intertwined with material choices, internal configuration, external requirements, construction methods and architectural requirements. Computational processes have allowed engineers to enable increasingly complex formal architectural expressions, from long-spanning roofs, cantilevers to high-rise buildings. Traditional structural or environmental analysis of buildings is conducted by specialists, using dedicated simulation software tools and workflows that are disconnected from the architectural design process. Dedicated software platforms allow for static and dynamic structural analysis for different loading conditions via finite element analysis (FEA) (Altair Engineering, 2023; CSI, 2023; Sofistik, 2023).

However, there is significant research in exploring how geometry and typology of structural systems can enable more efficient designs. Inspired by using physical models to enable efficient structural forms, form-finding explores the digital or physical process of optimizing or adjusting a set topology to create a structurally valid solution. Examples include hanging chain models with weights (emulating forces acting on a structure) to simulate funicular structures, soap-films to emulate minimal membrane surfaces, or sand models to determine tributary areas of columns (Bach et al., 1988). Connecting forces acting inside structures to graphical notation systems, as proposed by graphic statics (Culmann, 1866), has enabled analysis and creation of statically complex systems Figure 2.2. The direct relationship between (architectural) form and (structural) forces were first discovered by Maxwell (Maxwell, 1864) have since been explored computationally as thrust network analysis (Block & Ochsendorf, 2007), algebraic graphic statics (Van Mele & Block, 2014), and in three dimensions (Akbarzadeh et al., 2015). Further digital form finding models include particle spring systems (Kilian & Ochsendorf, 2005) or the force density method (Schek, 1974), rigid body systems (Kilian, 2007), Such form finding methods have mainly been applied to creating large-scale funicular systems with specialized architectural applications, such as shells or large-scale roofs (Adriaenssens et al., 2014). For this, Rippmann has shown how "digital processes that enable interactive formal exploration can enrich the known formal vocabulary" (Rippmann, 2016). The notation of graphic statics has proven useful as an idea to create a graph-based method for representing not forces, but space, as explored in the hypergraph notation in this thesis.

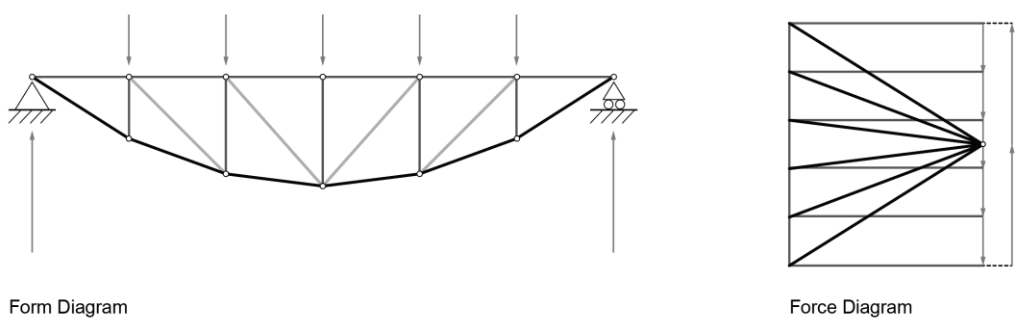

Figure 2.2: Graphic statics representation of a bridge truss in its architectural form (as the form diagram) and the internal forces (as the force diagram).

The direct relationships between geometry of a structure and the forces acting on it is a fundamental topic in architectural teaching and practice today (Allen & Zalewski, 2009; Lee et al., 2020). Furthermore, it has enabled the exploration of new architectural form through manipulation of strut and tie models in equilibrium (Warmuth et al., 2023), as well as procedural grammar based approaches (Mirtsopoulos, 2022) – creating new architectural geometry from through structural workflows.

Feedback loops that enable changes in structural geometry, were previously unintuitive, as they cannot be performed inside an analysis package and rely on often highly manual, cross-disciplinary workflows. To bridge the gap between different software platforms and environments, a series of integrated pipeline frameworks enables easier geometric transfer between external building performance simulation tools, as well as various visualization or web based environments (Buro Happold, 2023; Mele et al., 2017; Stefanescu & Cominetti, 2023; Wassail et al., 2023).

2.8 Embodied Energy and Carbon Analysis

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Embodied energy and with it the embodied carbon emissions of buildings are an important factor when assessing sustainability of a structure. With operational energy for heating and cooling being electrified and supplied through renewable sources, harder to decarbonize processes in manufacturing and raw material supply have to be targeted for carbon saving measures – making embodied carbon reduction critical in decarbonization of building materials (Röck et al., 2020a). Different strategies exist for reducing material quantities used in buildings, as well decarbonizing materials themselves (Fang et al., 2023a; Minunno et al., 2021; Pomponi & Moncaster, 2016). In the last years this has been incorporated in various building regulations in Europe, limiting the emissions that a building is allowed to emit in its projected lifetime (Rasmussen et al., 2023; SIA, 2017). However, embodied carbon analysis is typically done after the fact, even though its impacts would be much greater in early stages of design (Roberts et al., 2020).

While methods for estimation of operational energy on both building and urban scales are relatively well established (Reinhart & Cerezo Davila, 2016), there can be a high degree of uncertainty in prediction of the embodied carbon of a building. We can differentiate between benchmark datasets and material quantification methods.

Material quantification methods rely on an accurate tally of building materials used in a building that is then then multiplied by their specific carbon content. This is typically done via spread sheet-based tools, which are standalone and generic databases that serve as lookup tables for embodied carbon. As public or privately maintained databases, they include building materials, sometimes with associated suppliers and reference projects that encourage savings (Architecture

2030, 2024). A database such as EC3 (*EC3*, 2024) shows that it is not only crucial to choose material with inherently low carbon emissions, but also a manufacturer itself with a low carbon supply chain. The more thoughtful choice of manufacturer for building materials can cut emissions significantly. A number of CAD-integrated tools plug directly into architectural design workflows and connect architectural 3D modelling software to spread-sheet based databases (*Beacon*, 2024; *Impact*, 2024; *Lesosai*, 2024; *Tally*, 2024). This allows for an automated tally and highly accurate estimation of the embodied carbon. However, since exact material quantities must be known, such estimates are only possible at end of the design stage for a building when fundamental changes in structure and global design are hard and costly.

For estimation of embodied carbon of buildings where exact material specifications are unknown, we must rely on benchmark datasets. The estimated benchmark value is a normalized area value of kgCO2/m2 as a best guess. Additional information on location, building type, size and height, and structural system material increases the accuracy of the prediction (Wolf, 2017). However, building typology and use type alone do not give an accurate estimate for the embodied carbon per square meter and come with significant uncertainty (Simonen et al., 2017). Datasets with small number of projects cannot take local construction methods and material supply into account and are not yet available and applicable on a global scale. The high ranges and uncertainties stress the importance of more detailed information on a building's construction material or a full BIM model of a building. This dissertation proposes a hybrid approach that combines generative design with structural analysis to create detailed approximations of a building's structural geometry, and with it the embodied carbon, in the earliest stages of design.

2.9 Integrated Building Performance Simulation

Optimizing the design of a building as a whole is very challenging, as design decisions and performance metrics can be difficult to formulate mathematically and might be in direct conflict with one another. To negotiate between competing metrics, design intent or performance, different strategies have been deployed. On the one hand, performance scores can be generated to combine structural and environmental concerns (Bernett et al., 2021; Buelow, 2014; Turrin et al., 2012) daylighting and energy (Mcglashan et al., 2021), solar gains and view (Oswald, 2021), geometry and embodied carbon (Hens et al., 2021) or daylighting and building shape (Jayaweera et al., 2021; Konis et al., 2016; Peters et al., 2019; Shi et al., 2021). On the other hand, sampling methods can be deployed to explore a wide design space and inform decisions that pair qualitative architectural constraints, that cannot be captured numerically, with performance metrics (Mueller & Ochsendorf, 2015). Using evaluation strategies that link structural, architectural, and energetic design considerations, to inform the design process of a building allows for freedom of design while suggesting solutions that are significantly more performative (Weber et al., 2022a).

The most important design decisions that affect the performance of a building are made in early-stage design. However, accurate computational holistic performance analysis requires fully detailed BIM models with material specifications that are only available at the very end of the design process. Furthermore, rules of thumb and simple parametric models are only representative of prototypical and idealized buildings (Gauch et al., 2022) and cannot be used directly to evaluate a specific design (Kiss & Szalay, 2020).

Most recently, more accessible software environments, as well as faster simulation (e.g. novel algorithms for path-tracing or automatic differentiation, more performative computer hardware), have allowed for the integration of both structural (Preisinger & Heimrath, 2014a) and environmental analysis tools (Solemma, 2021) into architectural design workflows. Where real-time computation is not possible, machine learning tools such as surrogate modeling techniques allow for approximating computationally expensive metrics (Mueller, 2014; Reynolds et al., 2015). Most importantly, this allows for the connection of geometry creation with analysis.

2.10 Challenges and Opportunities

This chapter outlines how computation is used in a variety of ways in the architectural design process and how physics-informed simulation methods allow for the quantification and optimization of a building’s performance. Well established processes exist across disciplines for energy modeling, structural simulation, or design exploration of different formal geometries. However, buildings present an enormously challenging and complex design problem with many constraints, unknowns, and both qualitative and quantitative attributes, where there is no single optimal solution. This thesis outlines how siloed analysis workflows do not fully take advantage of currently available computational capabilities and new types of interdisciplinary workflows can enable and enhance the design of performative buildings. The thesis proposes new hybrid ways for representing and generating diverse geometries that allow for the automatic generation of distinct design solutions. Furthermore, the research proposes to create collaborative workflows that combine human design intelligence with generative design algorithms to create, search through, and evaluate more design options.

The sustainability of a building is not dependent on a single performance criterion. Buildings must be evaluated holistically, requiring a combination and integration of different disciplinary analysis processes. Evaluation must integrate embodied carbon, building operation, and spatial metrics with architectural design constraints. How spatial, structural, and energetic systems can work together is currently understudied. Different programmatic arrangements, as well as adjacencies, circulation, room sizes, or interior configurations are in a direct relationship with a building's structure and envelope. How can a change in spatial layout or typology allow for the utilization of a more efficient material system for a structural frame? How could requirements for natural ventilation influence the spatial aggregation of different programs or circulation?

Current building simulations are primarily limited to the buildings themselves. For cities, neighborhoods, or districts to become more sustainable, we must interrelate design on a local scale with its context. A circular economy where materials and construction systems are constantly reused needs better ways to quantify existing urban environments and predict future requirements. Structural and embodied carbon simulation on a building scale could enable cross-typological use of building materials and connect locally available resources with the design choices and guidance for the creation of new buildings.

The dissertation offers a design framework that views buildings not as a single entity but interconnected with their built environment. The thesis contributes computational workflows that are needed to implement these requirements and offers novel solutions for the spatial representation of geometry. This enables cross-disciplinary analysis workflows that can help buildings to be assessed and designed more holistically across scales. New types of design tools and geometric algorithms that support automated building design are needed for spatial characteristics to influence material choices and building systems and vice-versa.

The dissertation critically examines the focus of sustainable design on technological solutions. Energy modeling and building upgrades understood from a technological perspective, where

Urban Building Energy Models (UBEM) (Ang et al., 2020) can be used to create scenarios for specific energy systems and building envelope upgrades (Ang et al., 2023). Existing studies highlight the importance of urban morphology (Sun & Dogan, 2023), for instance on accessibility (Eggimann, 2022) or the urban heat island effect (Giridharan et al., 2007). However, little attention on a quantitative scale has been given to architectural typologies and spatial layouts and how they relate to urban occupant density and sustainability or carbon emissions.

2.10.1 Specific Research Goals

Based on the work analyzed in the literature review, this dissertation proposes the following research goals:

- Explore the value proposition of design automation techniques and propose a new classification for spatial design workflows in Chapter 3.
- Develop a new hybrid approach for representing, generating, and analyzing architectural floor plans and use it to gain new insights in the relationship of operational building energy performance and spatial characteristics of buildings in Chapter 4.
- Develop a new computational bottom-up approach for measuring structural material quantities and through that embodied carbon of buildings in Chapter 5.
- Address key issues in creating integrated design and analysis workflows for material quantification, energy use, and spatial design in Chapter 6, with design space exploration of new buildings and a case study for building retrofit.

3. Applications and Use Cases of Automated Floor Plan Generation

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3.1 Introduction

A floor plan layout creation method creates an architectural layout from a series of geometric constraints and/or programmatic requirements. So far only experimental artistic architectural design practices (Campo et al., 2019; Rehm, 2019) and the real-estate sector have been eager to embrace novel generative and AI-based layout automation tools, whereas the architectural profession at large has expressed some reservation against algorithms whose perceived ultimate goal might be to replace the profession. The purpose of this chapter is to clarify the capabilities and limitations of existing methods and envision how they could contribute towards the design of more elegant, effective, and flexible spaces on a scale ranging from individual floors and buildings to whole cities.

The construction sector – and especially the high-performance design community – have long embraced computer-based performance analysis methods for embodied and operational energy use associated with construction materials and building use. However, space efficiency evaluations are far less common. Usually, there is a design brief provided to the architect that stipulates a certain amount of program including a set percentage for circulation and space conditioning equipment. The sum of these space uses adds up to an overall building volume that can then be explored via massing studies. The spatial relationship between a massing volume or a floor plan and the distribution of program is, of course, quite complex, ranging from desired adjacencies to minimal width or depth requirements. In terms of future reuse opportunity, the design team would ideally also like to know how amenable a given floor plan is to adaptive reuse or which walls could be load bearing while supporting good daylighting etc.

A number of reviews on computational layout automation have been conducted that included industrial facility layouts (Liggett, 2000), focused on specific computational methods, such as evolutionary algorithms (Calixto & Celani, 2015; Dutta & Sarthak, 2011) or agent based methods (Rhee et al., 2019). Furthermore methods have been surveyed with a focus on methods optimizing for energy usage (Du, Jansen, et al., 2020; Du, Turrin, et al., 2020). In this chapter, purposes and use cases of automated space layout methods will be discussed. This serves as the technical and methodological foundation to introduce new approaches that productively combine these methods in further chapters of the dissertation. There, the focus lays specifically on early-stage architectural massing studies and existing building stock characterization.

3.2 Value Proposition

3.2.1 Use Case I – Design Feedback

Building massing decisions can have a significant and hard to predict impact on resulting interior space layouts, which in turn have cascading effects on building occupancy, structural efficiency, and even operational energy use. Fast simulations and generative design tools can help designers develop their own intuition for such relationships. In structural engineering education for architects and engineers, real-time simulations have become a useful tool to visualize problems and help designers build a geometric intuition to create more efficient structures (Black & Duff, 1994; Van Mele et al., 2012). Real-time visualization of the impact of design decisions can be useful to convey information to decision makers. When combined with novel interfaces, non-expert stakeholders or the local community can be engaged and learn about the design process more easily (Ben-Joseph et al., 2001).

Plugging in to existing design workflows, automatic layout generation could help to visualize how changes in a building's massing relates to constraints for circulation, program, or structural requirements, as illustrated in Figure 3.1. Showcasing how building cores must be dimensioned for a given floorplate and the influence of floor-plan typologies on the energy usage of a building (Dogan et al., 2015b) can give architects a more intuitive understanding in early design processes. Programmatic changes based on different lighting and thermal requirements can have a direct influence on a building's energy budget: Interactive approaches can give a more intuitive understanding of these requirements, leading to solutions that can negotiate between requirements of different stakeholders. Furthermore, materially integrated design processes can visualize how different construction methods and material systems have different constraints during the design process. A direct comparison and calculation of embodied carbon and achievable spans could help users find new more sustainable design solutions (Weber et al., 2021a).

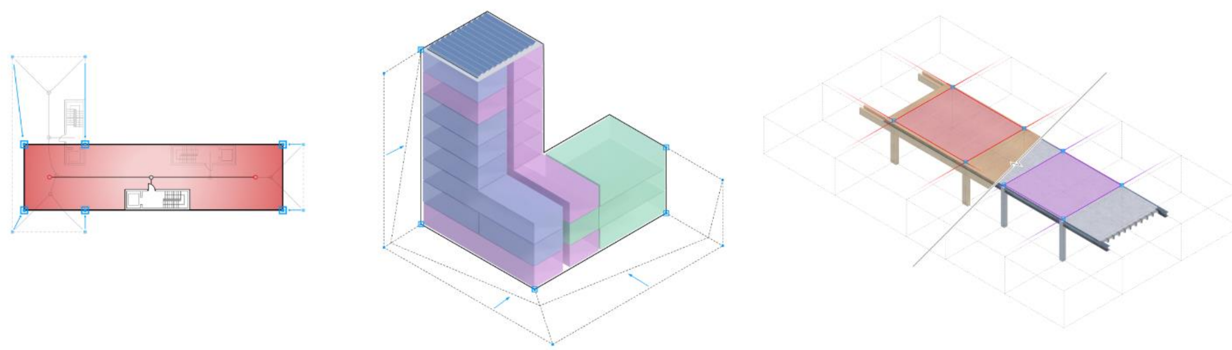

Figure 3.1: Pedagogical use of generative design tools to help build design intuition for circulation (left), program and energy (middle) and material-based constraints (right).

3.2.2 Use Case II – Design Exploration and Optimization

Generative layout tools can be used to augment different stages of existing digital design workflows. Parametric design spaces can be explored for optimization within predefined constraints (Brown et al., 2020b), and grammar- and aggregation-based automated methods have been used to create new types of modular structures (Tessmann & Rossi, 2019). As speculative and early-stage design tools, automated approaches offer the opportunity to test ideas at scale and generate design options iteratively that would be difficult to achieve with manual workflows (Figure 3.2).

With highly specific programmatic requirements in specialty typologies, such as hospitals or airports, automated layout methods can help designers to optimize floor plans with adjacency, pathfinding, energetic or daylight heuristics (Das et al., 2016; Du, Turrin, et al., 2020), or structural system efficiency (Zhang & Mueller, 2017). Multi-objective optimization and objective functions that are highly specific to the specified architectural problem can be used to negotiate between different (competing or diverging) goals. A series of experimental hybrid semi-automated methods have been deployed in such design processes where physics-based simulations can be steered by a user to inform programmatic distribution of layouts (Helme & Derix, 2014).

Referential automated methods can be deployed in later stages of building design. Leveraging architectural catalogues and previously generated designs, methods of automation can reuse and adapt established design solutions for new problems. This has been successfully demonstrated on a material scale where algorithmic workflows can identify closest fit solutions in existing material catalogues (Amtsberg et al., 2020) as well as for adaption of existing floor plan layouts into new building massing (Green, 2020).

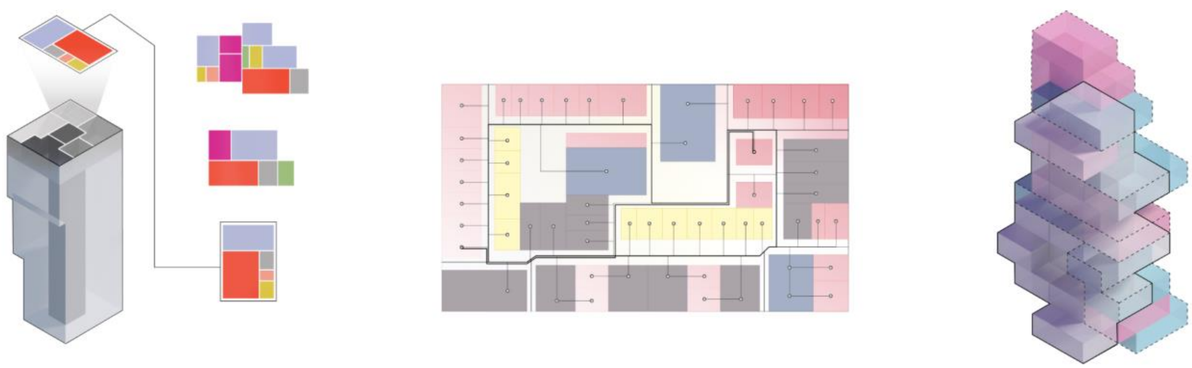

Figure 3.2: Use of automatic methods as design tool for automatically populating building massing (left), optimizing existing building layouts (middle) and the creation of novel design options (right)

3.2.3 Use Case III – Inventory Characterization

Automatic layout design tools not only offer opportunities for new buildings, but could be used to characterize and redevelop existing urban environments. Making use of widely available geometric massing GIS datasets, existing building stock could be modeled on a building level when combined with automatic floor plan layouts. This could lead better and more detailed understanding of existing housing stock and its embodied material quantities (Weber et al., 2021a).

A better and more visual understanding of future developments enabled by current zoning could lead to more informed decisions for housing policies and building laws and allow for non-experts from the broader public to engage with planning processes. A clear understanding of desired goals could lead to outcome or performance based zoning that can take metrics such as urban comfort, mobility, and daylighting in to account (Wilson et al., 2018). Identifying possibilities of reuse or densification on a large scale could empower lawmakers to better guide their cities development as depicted in Figure 3.3.

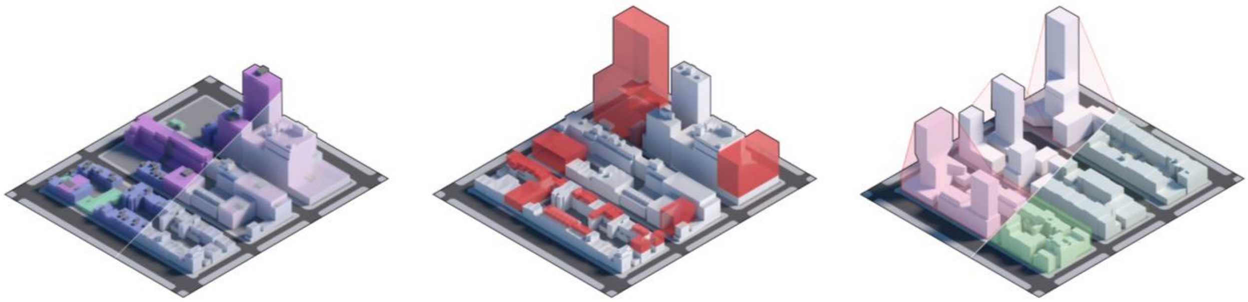

Figure 3.3: Opportunities of automatic space layout tools to be utilized for the survey of existing housing stock (left), to explore opportunities of densification (middle) and to identify implications of changes in zoning and building codes (right).

3.3 Methods

Following a description of possible use cases, this section reviews the computational methods underlying previously suggested approaches for automatic space layout generators. With origins in various engineering and computer science disciplines, many of the methods have been developed for different use cases and have been adapted for building design workflows. This opens the field to new ideas and approaches for spatial design, but can also lead to a mismatch, where methodologies have inherent shortcomings that are difficult to adapt to the requirements of the architecture and planning disciplines. Existing approaches can be divided into three categories: *bottom-up methods*, *top-down methods* and *referential methods*. This section outlines the strengths and weaknesses of these categories vis-à-vis previously mentioned use cases.

3.3.1 Indexing and Search

Four main databases were used to retrieve research articles for this review chapter: Web of Science (Clarivate, 2022), Google Scholar (Google, 2022), Journals indexed in the Architecture and Civil Engineering disciplines from Scopus (Elsevier, 2022), as well as CumInCAD (Martens et al., 2016), a database of conferences and journals in the architectural computational design disciplines. In a second step the references mentioned in the review and methods articles was analyzed and supplemented with new novel work that cited the relevant articles. A fully automated search and bibliometric analysis was not possible as floor plan and layout automation keywords are used in different disciplines for applications in electric circuit and factory layout planning and design. 49 different methods with geometric architectural outputs were identified of which 14 are bottom-up, 27 are top-down, and 8 are referential. Methods with architectural intent that did not result in a floorplan layout (e.g. only studied adjacency graphs in floor plans, or building massings) were excluded.

3.3.2 Bottom-up Methods

Architectural design briefs often have highly prescriptive spatial requirements. Because of heavily specified room sizes or adjacency constraints, layout designs often lend themselves well to be generated via bottom-up design processes. Bottom-up generator methods are therefore conceptually related to traditional design methods such as mind mapping of spatial relationships, bubble diagrams, and physical modelmaking strategies. When using modular construction logics that make use of prefabricated systems in concrete or timber (Staib et al., 2008) bottom-up aggregation logics enable the exploration of different design variations and part-whole relationships.

In a final structure, a series of predefined building blocks are aggregated into a larger assembly. As computational methods for the design of floorplans and building layouts, these aggregations can either be static (with predetermined architectural spaces) or adaptive (changing during computation) and can be coupled with heuristics to achieve a desired global outcome. Transformations during the aggregation process occur on the individual parts themselves.

During the bottom-up aggregation process, additional layers of information can be superimposed on the digital model to either change, swap out existing units or guide further aggregations. These heuristic methods can include analytic metrics such as spatial relationships (proximity requirements), environmental performance (daylight access, energy usage), structural efficiency metrics, or geometric details (proportions). A schematic of a bottom-up automatic design process for a series of rooms is described in Figure 4. Table 2 compares different approaches and implementations of bottom-up methods.

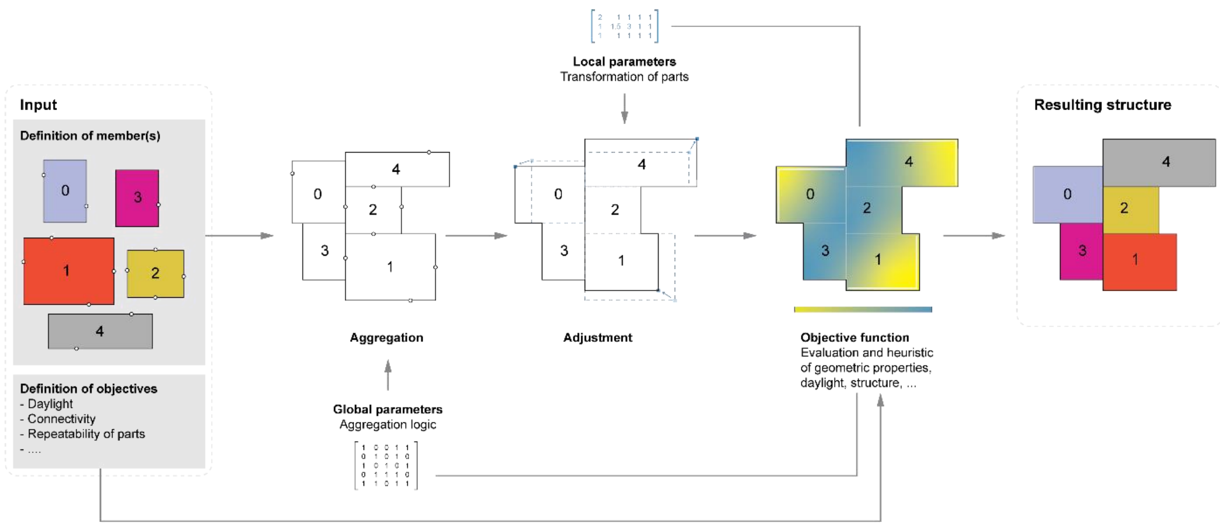

Figure 3.4: Schematic of bottom-up automatic space layout design methods. Starting with a definition of members and objectives, an initial aggregation and adjustment transforms the individual parts themselves. An objective function evaluates the outcome and drives local and global parameters to adjust the outcome.

Bottom-up processes for exploratory and speculative design have been embraced by the design community to create discrete building systems that reintegrate design thinking with computational methods of design and means of production (Sanchez, 2020). Applied to a building scale, they are particularly useful when designing for specific typologies that allow for modular construction and design logics in their realization. Members of a structure, the so-called discrete parts, can be aggregated to respond to specific architectural and spatial constraints or construction requirements, creating opportunities for robotic fabrication and reconfigurable structures (Retsin, 2019).

As a response to the large search spaces of bottom up design processes, the Model Synthesis algorithm creates a set of custom constraints that guide the aggregation of user defined modules into complex 3D shapes (Merrell & Manocha, 2010). Taking the adjacencies of parts of an existing 3D shape as an input, the method can generate new variations of larger dimensions that satisfy the original constraints. The method, also referred to as Wave Function Collapse (WFC), has since gained traction for creating 2D textures (using two dimensional pixel adjacencies) and 3D models for procedural level creation in computer games (Gumin, 2022; Newgas, 2021) as well as for modular design in the architectural domain (Pernecky & Tholt, 2022). To further guide the search towards solutions with controlled spatial qualities, machine learning (ML) guided heuristics have been proposed (Hosmer et al., 2020).

Table 3.1: Comparison of bottom-up automatic space layout creation methods in literature. Abbreviations are used for genetic algorithms (GA), mathematical programming (MP), typology (T), residential typology (R), office typology (O), public (P), and scales of application with single floor (S), multiple floors (M).

T	Scale	Objective Function	Optimizer	Inputs	Output	Speed	Architectural Quality	Citation
N/A	S	Minimal wall length	GA	Number and areas of rooms	Floorplan, based on grid	N/A	Low	(Rosenman & Gero, 1999)
R	S	Maximize cross ventilation, (perimeter to area ratio) and minimize weighted sum of distances (closeness of rooms)	GA	Tree representation of program	Floorplan, differentiated rooms connected	N/A	Low	(ROSENMAN, 2000)
P	S	Alignment, adjacency, orientation, proportion (of single rooms)	Physically Based	Area, adjacency	Modeling architectural design objectives in physically based space planning	N/A	Low	(Arvin & House, 2002)
R	S	Minimize gap space.	Evolutio-nary algorithm	Area, location preference	Assigned program on existing layout, differentiated boundaries	N/A	Low	(Inoue & Takagi, 2008)
R	M	Connectivity, adjacency, envelope containment, convexity	1.Baysian network for Program generation, 2. Metropolis algorithm	Area, fooootprint, aspect ratio, adjacency, adjacency type	Program layout	~ s to 7 min	High	(Merrell et al., 2010)
R, O	M	Shading of neighboring building, occupied area, courtyard size	Quadratic program-ming, simulated annealing	Boundary, total floor area, # courtyards	Massing with specified floor area	~16 min	Medium	(Bao et al., 2013)
O	M	Spatial configuration: semi-automatic methods for layout generation in practice	Physically based	Area, adjacency	Program layout	N/A	Med	(Helme & Derix, 2014)
R	M	Daylight, predicted	Simulated annealing	Programmatic units	Aggregation of	4 min	Low	(Yi & Yi, 2014)

		mean vote, shading			modular programmatic units			
R	M	Maximize area in boundary, proximity and connectivity of program	Rectangular Voronoi Subdivision, Genetic Algorithm	Area, weighted adjacency matrix	Volumetric Arrangement of layout	12 min	Low	(Chatzikonstantinou, 2014)
R	S	Adjacency, size	MP	600x400pixel raster image or vector graphic, area, adjacency	Layout on input image or vector graphic.	1.3-45.6 s	Medium	(Hua, 2016)
R	S	Connecting different room graphs to whole buildings	N/A	Programm graphs, layouts	Aggregation of multiple layouts	N/A	Medium	(Dillenburger, 2016b)
R	M	topology, room dimension and aspect ratio, building shape	Agent based	Program graph, area of rooms	Generated layout assigned to Grid voxel	~ Seconds	Low	(Guo & Li, 2017)
R	S	Compactness, site boundaries, topology, user rating, circulation, privacy	GA	Areas, adjacency, window door or entrance requirement.	Program layout	6s – 7.3 h	Medium	(Bahrehm and et al., 2017)
R	S	None - Exploratory	Graph theory	Dimensional constraints, adjacency	Program layout	~ 1.5-2min	Medium	(Bisht, 2022)

Methods of aggregation with large geometric freedom often create large search spaces that need clever heuristics to guide the exploration and output of good results. Additionally, stochastic methods do not necessarily find a solution, based on the problem settings. Furthermore, the bottom-up methods make it difficult to embed and control layers of hierarchy that are prevalent in architectural design such as different levels of circulation or structural load transfer that require differentiated building components or adjustments.

3.3.3 Top-Down Methods

Real-world architectural design is often highly constrained by predefined building massing that stems from urban scale considerations, building code, or regulations. This can result in highly prescriptive volumes that define the boundaries of a building that architects want to be fully occupied. When designing a building with such strong constraints on the envelope, defined through contextual requirements, site boundaries, or the reorganization of an existing structure, top-down design methods can be of interest. Methods for subdivision, fitting, shape packing, and iterative agent based methods have been applied across architectural scales to automate design problems (Figure 3.5), ranging from the material scale with optimal placements and dimensioning of shell components (Schwinn & Menges, 2015) to the layout and partitioning of geographical district scale (DeFord et al., 2021).

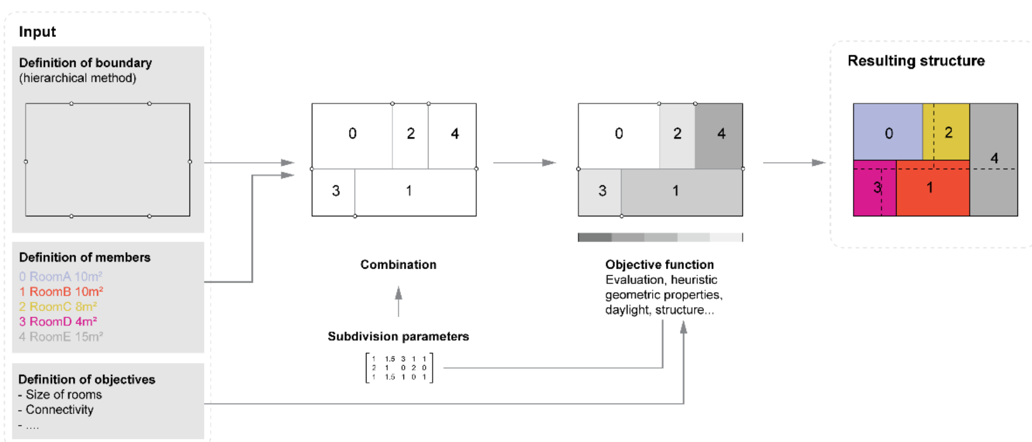

Figure 3.5: Schematic of top-down automatic space layout creation methods. Starting with a definition of boundary conditions, members and objective functions, an initial subdivision is evaluated by the objective function. Adjustment of the subdivision parameters results in a final structure.

Two promising technological inspirations and very active areas of research originate from the VSLI layout design and the Facility Layout Problem (FLP). Working with hierarchical systems that have interconnected rectangular modules, while integrating material constraints (Sherwani, 1993), the automation of VSLI circuits design has parallels to spatial layouts. As an optimization problem from the engineering community for arranging program in a given floor space, FLP is applied when machines in a factory hall for have to be laid out for a production line (Pérez-Gosende et al., 2021). There has been significant interest in trying to transfer FLP methods to the architectural domain to optimize the placement of room layouts. However, current methods for solving FLP problems make use of highly abstracted mathematical models that are difficult to be transferred to real-world architectural environments and their implementation in available software tools on the market has been limited (Drira et al., 2007).

Top-down methods take a massing or boundary as an input, as well as a series of entities as fillers or targets for insertion. The input design is subdivided based on geometric constraints to assign spaces. Compared to the bottom-up method, the transformations are done on the global boundary conditions directly, resulting in a solution that will always conform to the initial boundary condition. An overview of different top-down methods is given in Table 3.2.

Heuristics can be used to assess the current state of subdivision and can inform next steps in the case of iterative optimization processes. This can be computed using mathematical programming, such as Mixed Integer Linear Programming (Wu et al., 2018b), Squarified Treemap algorithms (Marson & Musse, 2010) or more geometry based approaches (Nagy et al., 2018; Wilson et al., 2019).

The top-down methods work best when used with fixed boundary constraints. Applied to building design in urban environments, the massing of a building is often predetermined (or highly constrained) by local building codes. In a first step, top-down approaches can be used to evaluate whether a certain boundary condition or building massing can be filled with a desired program or functional unit. To implement hierarchies, recursive subdivision methods that iterate over the resulting subspaces or programmatic clusters. Working on the end of a hierarchical system, the top-down methods are only able to cover a small, previously defined design space; in architectural practice that would mean that stand alone they are less useful for exploratory design stages where the boundary conditions (e.g. building massing) are not yet defined.

Table 3.2: Comparison of top-down automatic design methods in literature. Abbreviations are used for genetic algorithms (GA), mathematical programming (MP), typology (T), residential typology (R), office typology (O), public (P), generic (G), hospital (H), trade fair (TF), and scales of application with single floor (S), multiple floors (M).

T	**Scale**	**Objective Function**	**Optimizer**	**Inputs**	**Output**	**Speed**	**Architec-tural Quality**	**Citation**
O	S	Adjacency minimize travel distance	Quadratic assignment	Areas, adjacency	Assigned program on existing layout	High	Very Low	(Liggett & Mitchell, 1981)
O	M	Adjacency	GA	Areas, adjacency	Assigned program on existing layout	High	Very Low	(Jo & Gero, 1998)
O	M	Adjacency	GA	Areas, adjacency	Assigned program on existing layout	High	Very Low	(Gero & Kazakov, 1998)
O	M	Adjacency	GA	Areas, adjacency	Assigned program on existing layout	High	Very Low	(Jagielski & Gero, 1997)
H	M	Adjacency	GA	Areas, adjacency	Assigned program on existing layout	N/A	Low	(Bentley, 1999)
R	S	Adjacency room size	MP	Adjacency, area, min width/depth,	Assigned program on existing layout	N/A	Medium	(Medjdoub & Yannou, 2000)
R	S	Adjacency room size	GA, MP	Areas, adjacency	Design topology (with adjacencies) (tree) and assigned program on existing layout	N/A	Medium	(Michalek et al., 2002)
R	S	Adjacency , heating cost, lighting cost, spatial efficiency	GA	Program description (with min and max size), bounding box	Layout in bounding box	188 s	Medium	(Baušys & Pankrašovaité, 2005)
R	S	Custom fitness	GA	Areas, adjacency, proportions, building perimeter	Assigned program on existing layout (multiples of square foot units)	600s	Low	(Homayouni , 2007)
R	M	Adjacency	Stochastic Search	Adjacency, perimeter	Assigned program on existing layout	N/A	Low	(Terzidis, 2007)
R	M	Adjacency	GA	Connectivity , area, ratio	Assigned program on existing layout	N/A	Low	(Doulgerakis, 2007)

R	S	Practicality, originality, user input	GA, NSGA-II	Areas	Assigned program on existing layout	N/A	Low	(Banerjee et al., 2008)
R	S	Aspect Ratio, area	GA	Area	Assigned program on existing layout	N/A	Low	(Thakur et al., 2010)
R	S	Areas	Squarified Treemap KD Tree	Areas, connectivity	Assigned program on existing layout	N/A	High	(Marson & Musse, 2010)
R	S	Areas, connectivity	GA	Connectivity	Assigned program on existing layout	N/A	Low	(Knecht & Koenig, 2011)
R	S	Areas, connectivity	GA	Connectivity, hierarchy	Assigned program on existing layout	N/A	Low	(Koenig & Schneider, 2012)
R	M	Areas, Connectivity, Material constraints	Non-linear least squares	Connectivity, Areas, Wall fabrication specification	Rooms inside boundary, precast concrete walls	2-3.5 s Seconds	Med	(Liu et al., 2013)
R	S	Areas, connectivity	GA	Connectivity, hierarchy	Assigned program on existing layout	N/A	Low	(Koenig & Knecht, 2014)
R	M	Adjacency, thermal performance	MP	Areas, connectivity	Assigned program on existing layout	N/A	High	(Rodrigues et al., 2014)
O	M	Gap spaces	MP	Room templates	Rooms tiles in existing grid	Minutes ~80s	Med	(Peng et al., 2014)
T F	S	Mobility, accessibility and coziness of agent-based crowd simulation	Stochastic, Simulated annealing	Agent behavior	Rooms inside boundary	2 - 7 Minutes	High	(Feng et al., 2016)
O	S	Compactness	GA	Program description, ~47 geometric properties	Room tiles in existing grid	~520s Minutes	Low	(Dino, 2016)
H	S	Fitted program, view, travel distance, proportion	K-D Tree, Human evaluation	Program description,	Rooms inside boundary	N/A	Med	(Das et al., 2016)

T F	S	Congestion, exposure	GA, NSGA-II	Boundary, program description	Program distributed in boundary	5 days 20s per iteration	Med	(Villaggi et al., 2017)
R	S	Gap area	MIQP	Site boundary, program description,	Rooms inside boundary	~15 s Seconds	High	(Wu et al., 2018b)
G	S	Orientation, adjacency, user selected subdivision grammar	Optimizer (N/A) + Reinforce-ment learning	Site boundary, program description	Rooms inside boundary	N/A	High	(Saha et al., 2020)
G	S	Visibility, Tree Depth, Entropy	Covariance Matrix Adaptation	Parametrized geometric model	Optimized wall layout	2.25 - 7.41 s Seconds	Med	(Berseth et al., 2021)

3.3.4 Referential Methods

Learning from precedent has a rich tradition in architectural education and practice. Distributing design culture through "peer reviewed" publications of magazines and monographs (a publication describing the body of work of a single architect or architecture office) or through historical or topic specific anthologies and catalogues has analogies to the scientific community. Standardized reference works outlining basic architectural design strategies (Bielefeld, 2019; Heckmann et al., 2018; Jocher & Loch, 2012; Neufert, 1936) are used for teaching the design of building layouts. In both professional and educational settings, they are used as reference books for dimensioning of standardized building elements, such as stairwells, circulation, escalators, or bathroom layouts.

With technological advances in computation and ML, there has been a renewed interest in referential automatic layout methods. A high-level overview of the referential method is given in Figure 3.6 and a comparison of different methods in literature in Table 3.3.

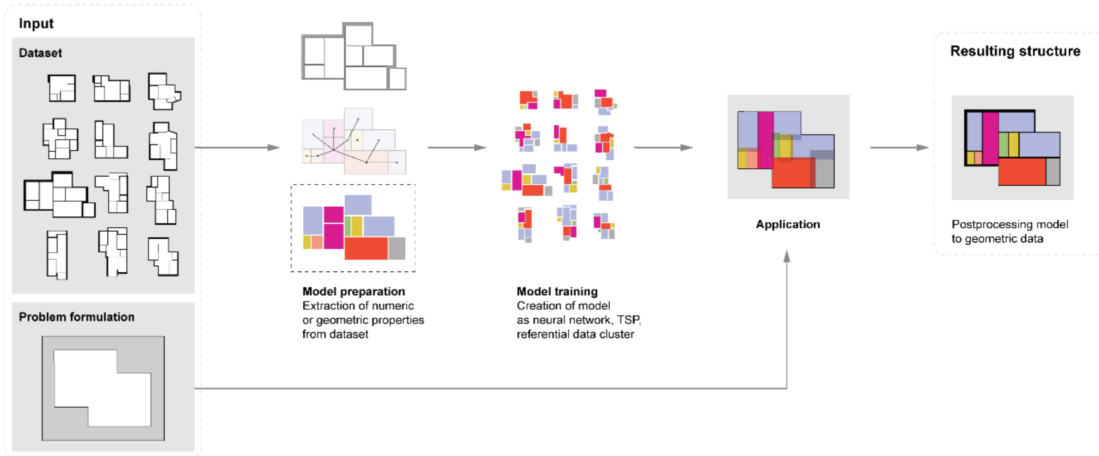

Figure 3.6: Schematic of referential automatic space layout creation methods. Starting with a dataset (catalogue) of existing structures. A desired property is extracted from the dataset and a model prepared and trained as Neural Net, analysis of shortest paths (TSP), or referential data cluster. The model is applied to a user specified problem formulation and postprocessed into geometric data resulting in a final structure.

A series of databases have been ported to be used for generative or transfer purposes and converted to annotated images or graph structures. For the creation of functional relationships between programs (Merrell et al., 2010) 120 commercial real estate plans for single family houses were encoded as graphs (Wood, 2007). A Japanese real-estate image databases from the with 5.3 Million images (Lifull, 2015) was ported for the use with ML algorithms (Nauata et al., 2020a). To more effectively train neural networks, a series of residential floorplan datasets were manually collected and annotated by researchers resulting in RPLAN with 80,000 floorplans (Wu et al., 2019), Rent 3D with 215 floorplans (Liu et al., 2015) and CubiCasa5K with 5,000 floorplans from Finnish real-estate marketing material (Kalervo et al., 2019). In industry, floorplan databases enable algorithmic lookup and reuse of floorplan drawings from previous work in the development of new layouts (Green, 2020; Lith, 2022). Several algorithmic methods for referential design have been used, the most prominent are ML-algorithms with deep neural networks such as generative adversarial networks (GANs), as well as mathematical programming methods to find closest matches.

Table 3.3: Comparison of referential automatic layout design method. Abbreviations are used for typology (T), residential typology (R), office typology (O), industry (I), commercial (C), public (P), generic (G), hospital (H), trade fair (TF), and scales of application with single floor (S), multiple floors (M), apartment boundary (AB).

T	**Scale**	**Database**	**Reference Source**	**Matching**	**Input**	**Output** (D) Direct (P) Post Processed	**Speed**	**Architectural Quality**	**Citation**
R	S	101 single story houses (Zonda, 2021)	256 × 256 pixel image, Color Coded	pix2pix NN via Runway ML	AB	Rooms color coded in boundary, manual tracing for vectors	N/A	Low	(Peters, 2018)
R	S	RPLAN (Wu et al., 2019)	256 × 256 pixel image, Color Coded	CNN for program location and walls	Entrance, AB	Wall map, vector of layout	4 s (Generation) 7 Days Training	Medium	(Wu et al., 2019)
C, R, I	S	700 plans (Boston, USA, collected by author)	? x ? px Image, color coded	pix2pix NN	Boundary of building	Rooms color coded in boundary, manual tracing for vectors	N/A	Low	(Chaillou, 2019)
R	S	500 plans, undisclosed	Program graph	Bayesian model, scored adjacency graph	Apartment type	Program graph	N/A	(None)	(Landes et al., 2020)
R	S	RPLAN (Wu et al., 2019)	128 x 128 pixel image, color coded	1. GNN, CNN program distribution, 2. CNN floorplan image	Entrance, AB, Number/ Type of rooms	128 × 128 floorplan image, vectorized floorplan	0.4s (Seconds) (Generation)	Medium	(Hu et al., 2020a)
R	S	117,587 Layouts (Lifull, 2015)	256 x 256 pixel image, program graph	Conv-MPN	Bubble diagram, (Program graph)	Room masks, fitted rectangles as rooms	N/A	Medium	(Nauata et al., 2020a)
O	M	120,000 volumetric designs (by authors)	Voxel graph, program graph	1. GNNs for the pro-gram graph 2. GNN voxel graph,	Program Graph, User input during generation.	Volumetric pixel grid representation of program	N/A (Generation) 20 minutes (with user interaction)	Low	(Chang et al., 2021)
R	S	RPLAN (Wu et al., 2019)	RPlan images parsed as program graph	1. Relational GAN, 2. Conv-MPN	Program graph	Vector representation of layout	<0.4s ~Realtime (Generation)	High	(Nauata et al., 2021)

The combination of large image libraries of floorplans with GANs enabled the creation of programmatic infills into arbitrary floorplan shapes for apartment layouts (Peters, 2018) and allowed for the transfer of different historical architectural styles to apartment floorplans (Chaillou, 2019). Recognizing the importance of hierarchies, strategies such as sequential infills (starting with the living room as high importance) (Wu et al., 2018b) or additional graph networks that inform the generation (Hu et al., 2020a) or training data (Nauata et al., 2020a, 2021) highly improve the plausibility of generated floorplans. Featuring online web interfaces, users can manipulate programmatic graphs while seeing a corresponding architectural layout in real time (Chang et al., 2021; Hu et al., 2020a; Nauata et al., 2021). However, an emphasis is laid on connectivity of rooms and their sizes or boundary conditions could not be influenced.

The image-based machine learning methods, however, only work on very constrained boundaries and small scales, as all information has to be encoded in a 256x256 pixel image. Even though they can be very accurate inside of a specific domain and create diverse solutions, because of scale limitations, they have only been applied to single story residential apartment layouts so far. Furthermore, the fuzzy outputs of image-based ML algorithms require significant postprocessing to recreate usable geometries, while using significant computational power and greatly varying in speed.

The strong dependence of the qualities of the outputs on good datasets, makes the lack of involvement of a diverse representation of the design community highly problematic. The large-scale datasets used so far in research are based on availability and have not been peer-reviewed or curated appropriately for architectural, spatial, or cultural qualities or environmental impact, creating unpredictable outputs.

3.4 Discussion

The previous sections summarize the substantial effort that has already gone into automated space layout generation with existing methods borrowing heavily from advanced computational design and machine learning approaches. It seems obvious that the real estate sector would embrace methods that can provide vital statistics on the marketability of a given massing, such as the number of housing units that can fit or the ratio of rentable to circulation areas. Given that an automated floorplan algorithm combined with a structural sizing tool can deliver a set of drawings that can, in principle, go through permitting and be constructed, it seems equally intuitive that many architects eye such methods with suspicion. The level of detail that such methods provide can create an impression of finality that one traditionally only encounters during later design stages. There is perceived real risk that architects further lose control of the design process at a time when only 2% of US homes are designed by licensed architects. Will that number fall even lower?

Such thinking seems somewhat defensive. Rather than hanging on to the *last* 2%, should the profession not focus on the *lost* 98% by creating the best possible design in the most efficient manner? How can the disciplinary knowledge inform design automation to provide better quality and more resource efficient spaces and housing?

As generative methods can produce an infinite range of different solutions a variety of heuristics are used to classify promising solutions or guide optimization processes. This creates an opportunity to include building performance as a driver for design generation, extending the purely geometric objectives such as adjacencies, position, or aspect ratio. Validated methods for building energy simulation and natural ventilation with EnergyPlus (Crawley et al., 2000), and daylight simulation using Radiance (Ward, G. and Shakespeare, 1998) have been integrated into layout automation workflows (Du, Turrin, et al., 2020; Rodrigues et al., 2014, 2019). Metrics further expanded to include views (Berseth et al., 2021) and agent based simulated of human behavior for both characterization and generation of new floorplans (Azizi et al., 2021; Feng et al., 2016; Nagy et al., 2017; Schaumann et al., 2020).

A big challenge in the creation of coherent layouts is the problem of scale. As programmatic requirements get more complex it becomes more difficult to coherent layouts that can integrate layers of hierarchy. This requires either a multi-step approach where programmatic units are clustered together and subdivided individually (Wu et al., 2018b) or smaller units (such as a single apartment) are created on their own and then assembled as units into a larger buildings (Rodrigues et al., 2019). Hierarchical approaches have also been successfully implemented to inform ML models, where placing the living room first in the creation of apartment floorplans increased the quality of solutions (Wu et al., 2019).

To support the creation of new hybrid methods, it is important that spatial, environmental, and structural considerations can work in parallel and inform one another. We propose to expand the list of existing metrics to create workflows that can enable floorplan layouts supporting the creation of sustainable and high performing buildings. In addition to combining traditional floorplan generators with the above-mentioned performance workflows, we see three specific use cases where automated floorplan methods can enrich the current design process.

First, for typical urban infills, arguably the most sustainable and urgently needed building typology to accommodate a growing population, top-down methods provide a natural starting point since many massing parameters have already been set through zoning and setback requirements as well as clients' desire to maximize buildable area. There, a hybrid approach seems very promising, combining both top-down and bottom-up methods to negotiate between programmatic requirements and the urban context (Rodrigues et al., 2015a, 2019). Referential methods can be used to augment currently prevalent metrics to evaluate layout designs, such as daylight access, aspect ratios, or material quantities, verifying the design quality or offer alternative spatial layouts (Table 3.4). These metrics can be tested at various scales from individual rooms to apartments, floors, or whole buildings for performance testing and optimization. In addition to combining traditional floorplan generators with the above-mentioned performance workflows, there are see three specific use cases where automated floorplan methods can enrich the current design process.

Table 3.4: A new set of holistic metrics to guide automated building layouts.

Spatial	**Environmental**	**Structural**
Modularity *Minimal change of the floorplan necessary to create different configurations while retaining same overall layout.*	**Daylight** *Provide access to daylight throughout the building, while minimizing direct solar radiation and glare.*	**Spans** Building layouts that work with minimal spans to reduce amounts of structural materials needed.
Compactness *Reduction of circulation to fit more in a building, while minimizing unused space.*	**Ventilation** *Layouts that promote natural ventilation (cross ventilation).*	**Continuity** *Layouts that stack loadbearing walls and enable optimal placement of shear walls to enable continuous carrying of loads.*
Adaptability *Creating layouts that enable flexibility of use by the inhabitants, creating rooms that can be used for different functions or layouts that enable different uses at the same time e.g. through shielding of noise.*	**Energy** *Minimization of building energy use by positioning and layering of less conditioned zones such as circulation to act as buffers to the conditioned spaces.*	**Material Integration** *Enable layouts that promote structural material systems with low embodied carbon and integrate fabrication constraints such as prefabricated timber modules.*

In the case of greenfield developments, bottom-up methods can be useful for quick design exploration by creating topologically different iterations. Material and construction constraints such as bay sizes, desired spans or prefabricated small-scale units can be integrated into the members to ensure solutions are feasible. Varying in resolution, the members of a bottom-up method do not have to be defined as single rooms but could be larger units or building parts, that can be refined or filled using top-down or referential approaches.

A third use case relates to building stock analysis. By applying floorplan generator to whole neighborhood massing models, existing urban analysis methods from daylighting to operational and embodied energy can be significantly refined since a floorplan help quantify the amount of material in a building, the likely number of occupants, and the location of internal walls that block daylight.

3.5 Conclusions

In this chapter, existing automatic floorplan layout creation methods in architectural design have been surveyed and a categorization into three methodologies has been introduced. The bottom-up method proposes to work with a set of parts, such as rooms or preassembled units, and to aggregate them into a larger structure. As an exploratory tool, it allows for the fast generation of different design options. Aggregation strategies can be further coupled with heuristics to guide the assembly. However, navigating often complex constraints or boundary conditions can be very challenging in the very large design space. There, top-down methods can offer an alternative, starting directly from geometric constraints, such as a building or site boundaries that get subdivided into smaller units. For this, different subdivision or packing strategies can be deployed. Third, referential methods are being investigated to make use of existing buildings and datasets. Geometric properties of existing or premade layouts can be fit or adapted to a new context. Fueled by recent advances in machine learning algorithms, spatial relationships have been captured as graphs or bitmap images and encoded into neural networks, enabling lookup and synthesis.

The further accessibility of machine learning algorithms and advancements of computational tools integrated into traditional geometric modeling environments used in architectural design could help bridge the interdisciplinary gap for architects to apply more domain specific knowledge. In our survey, we can show how floorplan layout automation is a dynamic field, both in terms of industry developing new tools, and business cases, as well as in academic research. We can see different disciplines engaging with the topic, ranging from architectural design research, civil engineering, building physics and technology, as well as computer graphics. Showing the opportunities of hybrid approaches that go beyond purely spatial properties (e.g. proportions, areas or connectivity) to create believable floorplans, there is potential to further evaluate layouts based on environmental, and structural constraints that can serve the occupants. We propose the hybridization of the three methods, coupled with a new set of interdisciplinary metrics and performance indicators to guide future building layout automation. Working together in an iterative loop, the strengths of the different strategies can be applied at different points in the design process.

This chapter shows how automating building layouts can have a wide range of value propositions. Current use cases in the real estate industry can be expanded to create design tools that utilize automated floorplan layouts to give feedback about program, occupancy, or embodied carbon in the early stages of design. Using algorithmic and data driven solutions, they can optimize building layouts during the design process or explore creative solutions for new construction. Furthermore, they could lead to developing a better understanding of existing building stock or changes in building policy: empowering architects, urban designers, law makers and the public to make more informed decisions towards creating sustainable cities of the future.

4. Hypergraphs for Design and Analysis of Floor Plans

A version of this chapter has been published as:

A hypergraph analysis framework shows carbon reduction potential of effective space use in housing. Ramon Elias Weber, Caitlin Mueller, Christoph Reinhart. 2024. https://arxiv.org/abs/2405.01290

4.1 Introduction

Current estimates predict that the global built area may grow by 250 billion square to house a growing population (IEA, 2019c, 2021). Such estimates are necessarily extrapolations from current building practices. While many decades of building science research and practice have enabled design teams across the world to precisely predict carbon reduction savings that can be attained through any number of upgrades for building operation (Ang et al., 2023; Baniassadi, Heusinger, Gonzalez, et al., 2022; Reyna & Chester, 2017; Zhong et al., 2021) and materials (Röck et al., 2020b; Simonen et al., 2017), surprisingly little attention has been paid to space evaluation methods. The ubiquitous energy use intensity (EUI) metric, defined as energy use per conditioned floor area, has become the de facto benchmark for high-performance buildings, leading to sometimes absurd situations where over-sized single-family homes with rooftop photovoltaics are hailed as beacons of sustainability despite of their significant material and space use per occupant.

Given that energy use roughly scales with building size, reducing the floor area per apartment unit, while maintaining good indoor environmental conditions, offers a complementary path towards a net zero building stock. Traditional architectural design workflows are unsuitable for this type of exploration since they rely on a human manually drawing interior walls while considering a plethora of architectural, safety, and Americans with Disabilities Act (ADA) requirements (Civil Rights Division, Disability Rights Section, 2010). In residential construction, the position of these interior partitions obviously impacts access to daylight, thermal comfort, and views to the outside. Many design decisions are intuitively made by architects based on prior experience or reference projects (Heckmann et al., 2018; Jocher & Loch, 2012) but without assessing their impact on building performance (Çavuşoğlu & Çağdaş, 2017) due to the time, effort, and technical sophistication required to conduct this type of analysis. However, coupling methods of design with quantitative simulation feedback in an early design stage has the potential to significantly improve design outcomes (Burnell et al., 2017).

While the construction industry has long shied away from quantitatively evaluating space use, the urgency of the climate crisis along with a shortage of architects to meet the global housing demand has led to some, mostly developer-driven and proprietary attempts to automatically generate floor plans (Weber et al., 2022b). Most current implementations are linked to financial cost models, evaluating multiple ways to divide a building footprint into a desired number of apartment units (Archistar, 2024; Sidewalk Labs & Google, 2024; Test Fit, 2024). Current approaches for within-unit room divisions are an active area of computer graphics research but are not presently used in the architecture field due to various limitations; including only being able to represent rectangular (Ślusarczyk et al., 2023) or orthogonal boundary conditions (Bisht et al., 2022), or solely responding to either topological or spatial or boundary constraints (Hu et al., 2020b; Nauata et al., 2020b; Para et al., 2021; Sun et al., 2022; Wu et al., 2018a). On a technical level, machine learning (ML) based models create neural networks that relate the geometric graph structures from room walls to an adjacency graph (vector (Shabani et al., 2023; Tang et al., 2023) or pixel-based (Carrera et al., 2024)) or use reinforcement learning to subdivide a space (Kakooee & Dillenburger, 2024). This results in a linear, one-sided generation process, where a room adjacency graph is converted into a visually real and geometrically valid floor plan. Inherently these statistical processes do not allow for exact specifications of room sizes, boundary conditions, or further geometric manipulation of parts of the final output, as are needed in architectural design. Furthermore, implicit geometric relationships are difficult to train and floor plan training data is sparse, scarce, and unvetted; thus, such approaches can neither guarantee architectural quality nor environmental performance (Weber et al., 2022b).

In this work, we present the hypergraph, a generalizable shape generator and descriptor for floor plans. The hypergraph represents key characteristics of the shape divisions of any given floor plan layout, enabling both the mapping and benchmarking of suitable, high-performing floor plans, as well as their automatic generation. A hypergraph is created from existing building floor plans and can be applied to new conditions. This allows for translating cultural conventions and practices into new designs, and a fully transparent source attribution. We introduce a spatial analysis workflow to minimize “excess space” while retaining the same spatial functionality of a given floor plan. The concept of excess space is based on the notion that a room with a certain program, for example, a bedroom, has minimum functional requirements in terms of furniture (bed, dresser, cabinet) and space around that furniture that supports its proper use. Areas beyond those functional requirements are then defined as excess. Furthermore, an automatic integration of environmental analysis methods, assessing energy use and daylight, allows us to benchmark high-performance designs and maximize occupant comfort conditions.

4.2 Methods

4.2.1 Residential Building Floor Plan Repository

We assembled a reference library of ~1,444 real world floor plans, combining award winning residential floor plans from North American and European contexts from the literature (Stamm-Teske et al., 2010; Zapel, 2017) and online databases (De Gruyter, 2023) with residential developer plans (Badger & Buchanan, 2023). The library contains unique real-world floor plans (and their mirrored geometry). Using publicly available data from real-estate brokers and public housing providers, the dataset represents a small subset of a city's actual apartments. However, we curated the library to encompass a variety of different designs and to represent the prevalent apartment layouts of each city, from studio apartments to large multi-room apartment units and across price ranges from public housing to high-end apartments. From the reference library, dataset floorplans are sampled to map the distribution of number of bedrooms of the real-world data surveyed in Singapore (Wee Kim, 2021), New York (Gaumer, 2022) and Zurich (City of Zurich, Mayor's Office, 2023). As almost 80% of residents in Singapore live in government-provided housing (Department of Statistics Singapore, 2021) that is built in a standardized fashion, there is less variety in the building stock. This is reflected in a smaller dataset than from Zurich or New York. We compare the real-world data with our dataset in Figure 4.1.

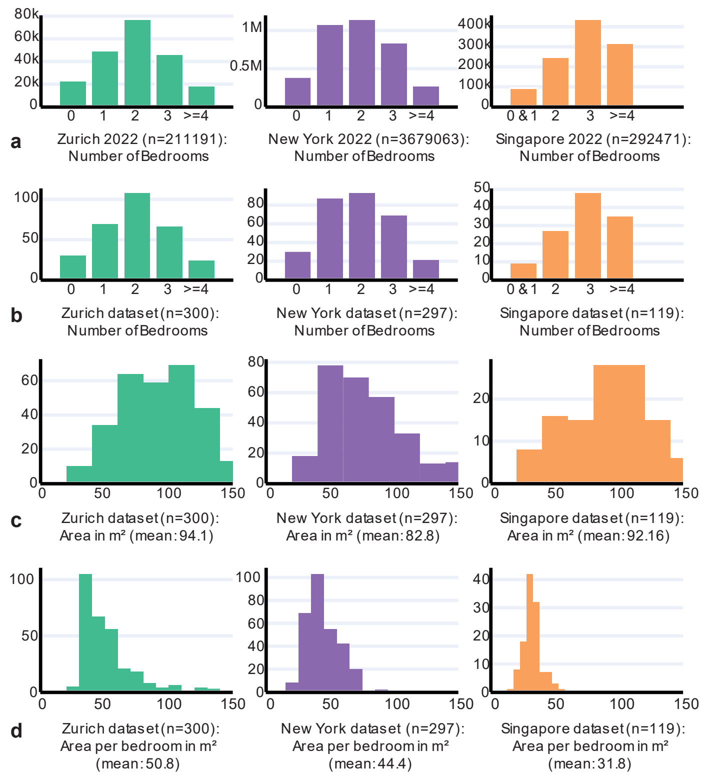

Figure 4.1 Floor plan dataset. Distribution of the number of rooms of the cities of Zurich, New York and Singapore in 2022 by number of bedroom (a), compared with our reference dataset of analyzed floorplans (b). Histogram plot of apartment area in each city (c) and the area per bedroom (d).

4.2.2 Reference Apartment Buildings for Artificial Floor Plan Insertion

To test the artificial generation of floor plans and application of reference floor plans into new boundary conditions, we gathered reference buildings from three different cities. Four buildings from Singapore, Zurich, and New York were chosen to qualitatively reflect the contemporary residential housing architecture of their city. For reasons of data protection for the residents, as well as the architects, we have anonymized the buildings and refer to them as Building A, B, C, D from their respective city. The building boundaries, as well as the floor plans from Zurich, New York, and Singapore, that we used to benchmark the artificially generated floor plans are illustrated in Figure 4.2, Figure 4.3 and Figure 4.4.

Figure 4.2: Zurich building A-D

Figure 4.3: New York building A-D

Figure 4.4: Singapore building A-D

4.2.3 *Creation of hypergraphs*

We introduce the hypergraph as a shape descriptor for building floor plans. Graph based data structures have been applied successfully to represent and generate structured data in biology (Guo et al., 2022), chemistry (Krenn et al., 2020), robotics (Zhao et al., 2020), building structures (Whalen & Mueller, 2022), computer games (Merrell, 2023), and urban planning (Fiser et al., 2016). For the design of building floor plans, graph-based data structures have been deployed to represent wall lines and adjacency graphs (Weber et al., 2022b). The presented hypergraphs are a combination between an access graph and a subdivision graph. While previous work used the explicit geometric structure of, for example, a molecule, wall segment, or street intersection, as a part of a graph, the hypergraph here is a combination of explicit geometry through adjacency of specific rooms and implicit geometric representation through the subdivision graph. Both graphs can be accessed and analyzed independently via edge and node type specification in our custom data-format.

The BSP (De Berg et al., 2008) tree of the subdivision graph simultaneously represents the final geometry, as well as its step-by-step construction. Each node corresponds to an area (or ratio) and a subdivision angle α, with (directed) edges connecting the child nodes to the parent node that was subdivided (Figure 6). Our BSP implementation allows for subdivision of polygons with 3 or more boundary vertices and includes convex and (most) concave polygons. In the BSP tree, the root node specifies the overall area of the subdivision graph. Subsequent children (of type “subdivision”) always have degree 2 and assigned areas, as well as a subdivision angle alpha. Leaf nodes of the subdivision graph have a degree 0 on the subdivision graph and area assigned a programmatic type of either (living, bedroom, kitchen, bath, extra, foyer) and a unique id. The access graph is defined by lists of unique ids in the leaf nodes. Different hypergraphs are illustrated with annotated edges in Figure 4.5 and Figure 4.6. Compared to existing methods, the purely geometric nature of the hypergraph creates a direct relationship between graph and spatial form. It is an explicit and not an iterative or optimization-based process that can be computed in real-time.

The outer most child nodes therefore represent the rooms in the final floor plan, while inner nodes correspond to the intermediate parent areas in the subdivision process. Even though the room adjacencies are defined geometrically through the subdivision, the access graph represents the spatial adjacency by (undirected) edges that connect the room nodes (e.g. through a door or an open wall). This dual representation of the internal organization can be captured from any given floor plan boundary. Furthermore, a mapping of both graph nodes of the subdivision and adjacency graphs to the resulting rooms allows for the recording of secondary information, such as room type. The procedure is fully reversible, meaning that a spatial floor plan layout can be encoded in a graph and the same floor plan layout will emerge given a graph and the original boundary polygon.

4.2.4 Preprocessing and Data Preparation of Floor Plans

The apartment floor plans were sourced as raster images. They were input into the CAD software Rhino where the images were traced and rooms annotated with their respective program, circulation access, façade with lists of lines and room access (doors). We deploy the inverse of the subdivision algorithm to find the corresponding subdivision graph, and the points in the door locations to determine access via the access graph. Both graphs are combined into a hypergraph and stored together with façade, circulation, and boundary lines in a json database.

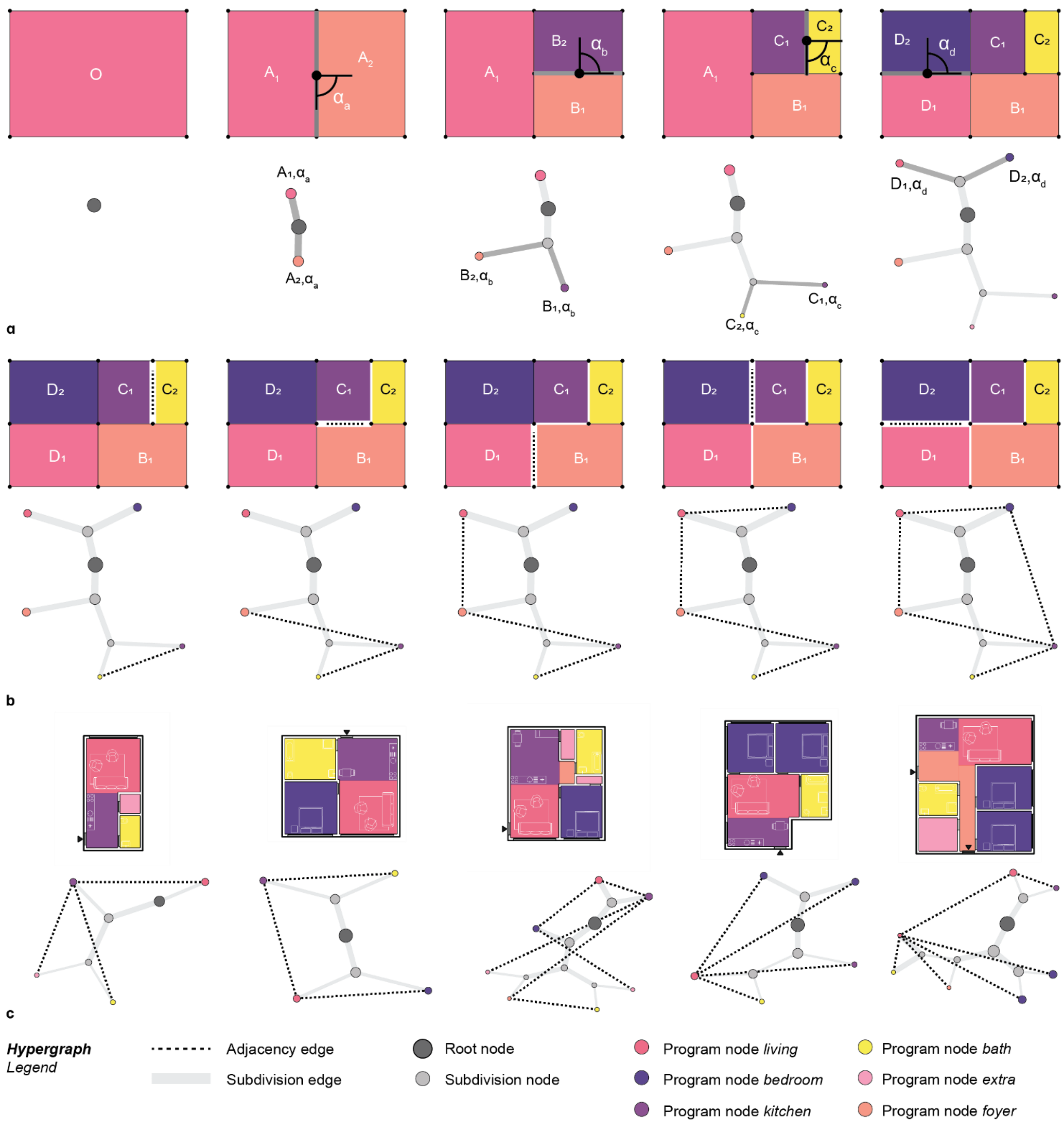

Figure 4.5: Step by step generation of the subdivision graph (a) from area O, represented by the grey point (graph root). It is subsequently divided into area A_1 and A_2 with the angle α_a, A2 is divided into B_1 and B_2 with angle α, B2 is divided into C1 and C2 with angle angle α_c and A1 divided into D1 and D2 with angle α_d. The access between rooms is converted into a graph (b) where edges connect the room nodes of the subdivision graph that connect (e.g. the rooms that are accessible between one another). Different subdivisions therefore result in different hypergraphs (c).

Figure 4.6: Input boundaries (a,c) with applied generative infill (b,d), where from left to right the resulting floor plan, the source floorplan and its corresponding hypergraph are shown.

4.2.5 *Implementation and Visualization*

The geometric floor plan creation process has been implemented in the commercial architectural CAD software Rhino via a custom geometry library in C# through the scripting platform Grasshopper (Robert McNeel & Associates, 2022). For the functionalities of the the open source linear algebra library Math.NET (Ruegg et al., 2023) and the 2D polygon clipping and offsetting library Clipper2 (Johnson, 2023) are utilized and extended. For the visualization and representation of the hypergraphs, the graph data structure are converted in NetworkX (Hagberg et al., 2023) and visualized with the force based Kamada-Kawai algorithm (Kamada & Kawai, 1989) that is applied to the nodes of the subdivision graph.

4.2.6 *Limitations of the BSP subdivision graph representation*

In the current BSP tree implementation, we can represent almost any geometric polygon and subdivision. Even though we were able to represent the studied buildings, there are certain limitations for apartment geometry and configuration that currently cannot be captured in the data format. Failure cases of the subdivision algorithm include highly complex non-convex boundary geometries, as well as polygonal boundaries with holes. While convex boundary geometries are guaranteed to produce a feasible result, highly concave boundary conditions do not. Typical apartment layouts, and those that we observed in our database, fall into the former category, however, this is not guaranteed, especially for synthetic datasets. On an architectural level, we limited the scope of the current implementation to single story floor plans of multi-unit residential buildings while excluding duplex apartments and single-family homes.

4.2.7 *Apartment Validity Heuristic.*

Even though the subdivision algorithm produces a geometrically feasible floor plan, the resulting geometry might not be spatially valid. Different failure cases exist where apartment boundaries are subdivided and produce architecturally infeasible rooms that are inaccessible or don’t have access to daylight (Figure 4.7). For creating artificial floor plans that would be further used in a design context, a visual inspection of the results together with placed furniture items that visualize the scale of rooms, proved to be useful.

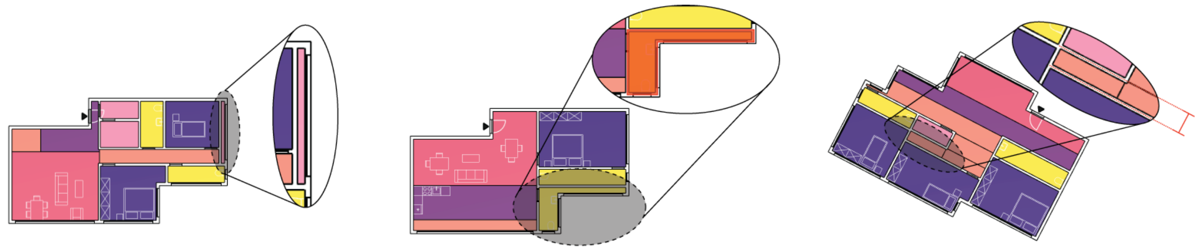

Figure 4.7: Different failure cases where the subdivision algorithm creates a geometrically valid but spatially infeasible floor plan: An infeasible room blocking a bedroom façade access (a), subdivision resulting in infeasible room geometry (b), and subdivision resulting in foyer spaces that are too thin to be passable (c).

However, for analysis of large-scale datasets automatic procedures are needed to identify feasible results. Since all hypergraphs are created from a geometrically feasible reference floor plan, we can compare the room geometry of the artificially created floor plan with the original reference floor plan. For this comparison to be computationally efficient, we utilize a scoring method that is computed from the perimeter of the room polygons. The perimeter difference score (Equation 1) can be applied to single room polygons (Figure 4.8), as well as whole apartment floor plans (Figure 4.9) to determine geometric changes between target and reference. It is a computationally efficient indicator of fit. For more accurate control, more computationally intensive pathway and geometry analysis could be envisioned [48]. Furthermore, we can use the furniture placement algorithm to verify if an apartment is feasible by comparing the minimum required furniture to the placed furniture (Figure 4.8).

$$\delta_p = \left| 1 - \frac{L_{SA}\, L_B}{L_A L_{SB}} \right|$$

Equation 1: Perimeter difference score δ_p, where L_A is the perimeter of polygon A, L_{SA} the perimeter of the square polygon with the same area as A, L_B the perimeter of polygon B, and L_{SB} the perimeter of the square polygon with the same area as B.

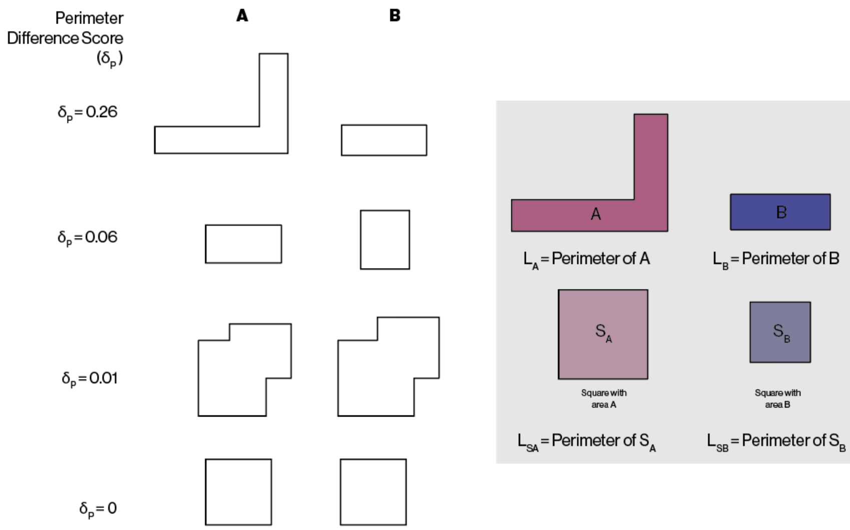

Figure 4.8: Example reference (a) and target (b) boundary room polygons with corresponding perimeter difference scores.

4.2.8 Environmental Evaluation Workflow

The automated workflow was implemented in the commercial architectural CAD software Rhino and its integrated scripting platform Grasshopper (Robert McNeel & Associates, 2022) where the generated floor plan geometry can be automatically converted to be used by the energy simulation software EnergyPlus (Crawley et al., 2001) and the lighting simulation tool Radiance through the Climate Studio package (Solemma, 2023). The simulations were conducted on a Windows computer with the following specifications: 64 GB Ram, Nvidia GeForce GTX 1080 Graphics card, Intel(R) Core (TM) i7-6700 K @ 4.0 GHz Processor. The full daylight and energy simulation required >10s of calculation time per apartment. Settings for the energy simulation of each city and settings for high and standard performing building envelopes are listed in Table 4.1. For each apartment we calculated the EUI in kWh/m^2/yr for both a standard and high-performance building envelope. To only compare building geometry related factors, we kept the HVAC system the same, even though in a standard building energy retrofit a more efficient HVAC system could be installed. To calculate the sDA (indicating the fraction of space with more than 300 lux of daylight on average) we only looked at specific rooms in an apartment that require daylight, excluding bathrooms and extra (storage) space. Furthermore, we created a sDA score of each apartment by weighing the area of each room (Equation 2).

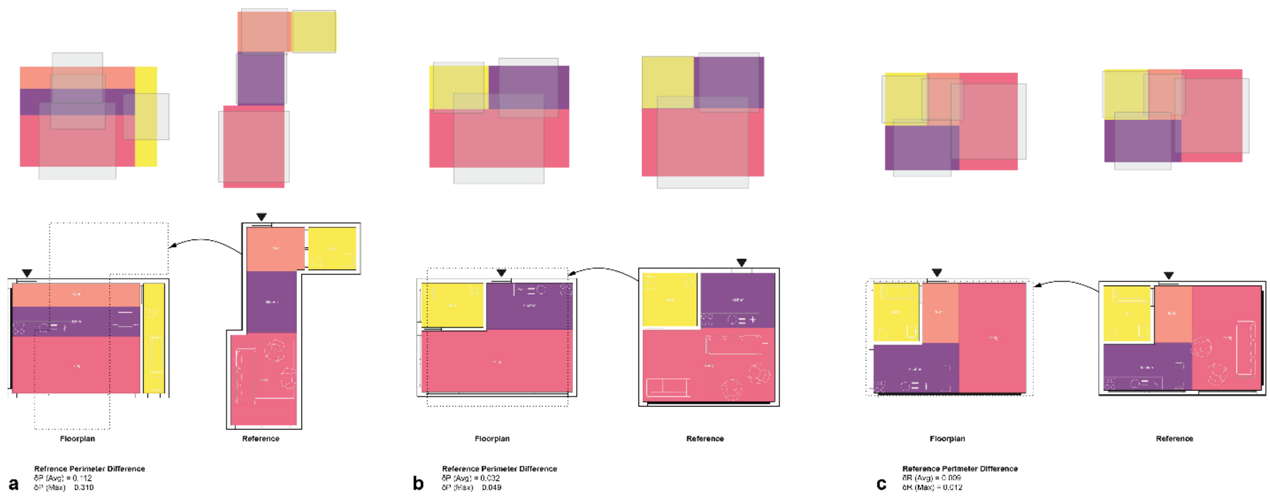

Figure 4.9: Example fitted floor plans, their reference floor plans and the corresponding perimeter difference δ_R. A low fit with a value of $\delta_R\ (average) = 0.112$ (a), a medium fit with a value of $\delta_R\ (average) = 0.08$ and a very close fit with a value of $\delta_R\ (average) = 0.009$.

$$d_{tot} = \frac{\sum_{i=1}^{n}(d_i * A_i)}{\sum_{i=1}^{n}(A_i)}$$

Equation 2: To get the apartments overall daylight score d_{tot} we multiply the area of each daylit space with its sDA value from our radiance simulation and divide it by the sum of the area of all daylit spaces.

Table 4.1: Energy simulation settings for climate studio and energy plus

City	**New York**	**Singapore**	**Zurich**
Energy Zone Template	Ashrae 90.1 – Climate Zone 4	Ashrae 90.1 – Climate Zone 1	SIA 2024
Weather File	USA_NY_New.York-LaGuardia.AP.725030_TMYx.2004-2018.epw	SGP_SG_Changi.Intl.AP.486980_TMYx.2004-2018.epw	CHE_ZH_Zurich.Fluntern.066600_TMYx.2004-2018.epw
Grid Carbon Intensity (kg/kWh)	0.55 [51]	0.4057 [52]	0.128 [53]
Energy Template	Ashrae 90.1 – Climate Zone 4	Ashrae 90.1 – Climate Zone 1	SIA 2024
Standard Envelope			
U value (W/m²K)	0.3		
Window to Wall Ratio (WWR)	0.6		
Window	DoublePaneClr		
HVAC	Standard Electric HP COP [3,3]		
High-Performance Envelope			
U value (W/m²K)	0.1		
Window to Wall Ratio (WWR)	0.6		
Window	Triple Pane LoE		
HVAC	Standard Electric HP COP [3,3]		

4.2.9 Furniture Placement

To spatially evaluate a floor plan, we test fit the layout with furniture. In the computer graphics discipline Furniture placement algorithms have been widely explored using machine learning and procedural techniques (Deitke et al., 2022; Fisher et al., 2012; Para et al., 2021; Yu et al., 2011). The use of furniture blocks to test spatial feasibility has been used in the architectural discipline and building codes in defining minimum planning standards in different countries, especially when it comes to affordable housing (Jacoby et al., 2022). A room is deemed feasible if it fits a certain number of predefined furniture blocks. However, the planning standards are only visual guides meant for manual placement of furniture blocks by architecture professionals and are not automated digital procedures. Inspired by the spatial scoring system developed by the City of Berlin's public housing provider (Howoge, 2023) and the City of London's planning standard (Design for London & Mayor of London, 2010) we translate the manual workflow to an automated digital approach and procedurally place furniture blocks (Figure 4.10a) into a floor plan, where furniture blocks are placed recursively along the boundary geometry of each room (Figure 4.10b). By grouping furniture items inside a program together we can provide different simple configurations using a faster, less computationally intensive, procedural method.

Each apartment has a minimal number of furniture items that need to fit, to be a valid floor plan (Figure *4.11*). In the case of bedrooms and bathrooms we distinguish between a primary room, such as a bathroom with a bathtub and secondary bathroom, with toilet and sink only, in the larger apartments. We used the same minimal furniture to assess floor plans of Zurich, Singapore, and New York. The workflow is very flexible and could be adjusted to include more nuanced cultural requirements. An example floor plan subdivision is valid if all required furniture can be placed (Figure 4.10h). If the furniture placement is infeasible (Figure 4.10i) that is an indication that the hypergraph subdivision did not create a feasible layout.

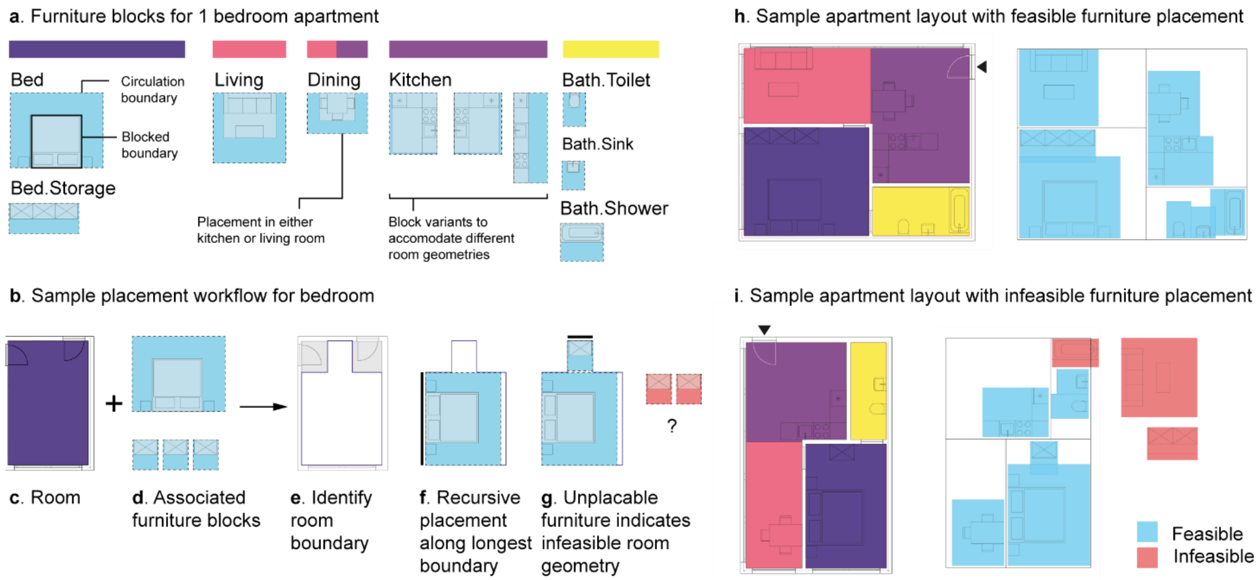

Figure 4.10: Example floor plans for a one-bedroom apartment, where all required furniture can be placed (a), creating a valid apartment layout. If furniture is not placeable inside the room geometry an invalid apartment layout was created (b) and a different hypergraph should be chosen to subdivide the floor plan boundary.

4.2.10 Excess Area and Emissions

To show the carbon impact of excess area, and to compare it to the potential energy savings of building envelope upgrades, we compute an emission delta for each floor plan. To calculate the excess carbon from excess area, we use a floor plan furnished with a minimum furniture area. After placement of the furniture, we sum up the total furniture area and compare it to the minimum furniture area of the corresponding apartment size Figure *4.11*. We derive the total excess area from a subdivision of the furniture area with the total apartment area and the carbon emissions from excess space by multiplying the excess area with the local grid carbon content and EUI (Equation 3-6). This value indicates how much carbon could have been saved if the apartment was built in a more compact size with the same number of bedrooms. The emission difference of excess area and envelope upgrade Δ_e is derived from Equation 7, using the EUI results of the environmental simulation. If the emission delta $\Delta_e$is positive, the emissions from excess space exceed the emissions that could have been saved through a high-performance building envelope.

Figure 4.11: Minimum furniture by apartment size.

$$F_{tot} = \sum_{n=1}^{n} (F_n)$$

Equation 3: F_{tot} is the total furniture area (in m^2) sum of all furniture areas F_n of all furniture objects inside the apartment (extra rooms count as furniture, foyer rooms do not). If the F_{tot} is smaller than the minimum furniture area (Extended Data Figure 4). If the furnishing was unsuccessful and F_{tot} is clamped at the minimum furniture area.

$$A_e = A_{apt} - (F_{tot} * M)$$

Equation 4: A_e is the excess area (in m^2) derived from subtracting the sum of all furniture areas F_{tot} from the total apartment area A_{apt} with a multiplier buffer. A positive A_e indicates excess area (an apartment exceeding sufficiency), a value close to 0 indicates a good fit and a value of less than 0 indicates no excess area and a compact apartment. The multiplier (M) can be adjusted to cultural contexts. We use M=1.6 to create apartments with target areas according to the German public housing standard *(Howoge, 2023)*: Studio 34m^2, 1 Bed 53.6 m^2, 2 Bed 72.6 m^2, 3 Bed 93.1 m^2 , 4 Bed 105.9 m^2, 5 Bed 118.7 m^2.

$$C_e = A_e * EUI_s * g_{cc}$$

Equation 5: C_e is the excess carbon emitted from an apartment per annum (kgCO2e$/a$), where A_e is the excess area (m^2) (*Equation 4*), EUI the Energy Use Intensity (kWh$/$m$^2/a$) derived from the energy simulation of the apartment with standard building envelope, and $g_{cc}$the local grid carbon content (kgCO2e/kWh).

$$\Delta_e = C_e - (A * EUI_s * g_{cc} - A * EUI_{hp} * g_{cc})$$

Equation 6: Δ_e is the difference between the carbon emitted from an apartment from excess space C_e $(Equation\ 5)$, and the excess carbon emitted from not having an envelope upgrade, where A is the apartment area (m^2), EUI_s the Energy Use Intensity (kWh/m^2/a) of the apartment with standard envelope and EUI_{hp} the Energy Use Intensity (kWh/m2/a) of the apartment with high performance building envelope, and g_{cc} the local grid carbon content (kgCO2e/kWh).

4.3 Results

4.3.1 The Hypergraph Framework is a Graph-based Representation of an Architectural Floor Plan.

The architectural design of residential buildings, the fitting of apartment units, as well as the internal subdivision within units to create a floor plan, remain processes that are typically performed manually by an architect. The hypergraph aims to computationally execute this two-dimensional design process by providing a unique mapping that either divides a building outline into apartments or an apartment into rooms. This mapping can be applied to any building outline and stored as a graph-based representation. In this paper, we will apply the hypergraphs to subdivide residential apartment units into rooms. To generate a hypergraph, key components of a typical architectural representation of a floor plan (Figure 4.12a) are analyzed to extract the floor plan boundary (Figure 1b) and the different rooms with their specified program (Figure 4.121c). A binary space partition (BSP) tree (De Berg et al., 2008), is constructed to represent the geometric subdivision of the boundary into different rooms, where the outer most nodes are the actual rooms of the apartment, color coded by program (Figure 4.12d). An undirected access graph represents the connectivity between rooms and through that defines the spatial organization of the floor plan (Figure 4.12e). The resulting hypergraph (Figure 4.12f) is a combination of the two subgraphs, the BSP tree, and the access graph, with nodes representing rooms and edges representing spatial subdivision or access. The BSP tree subdivision can be applied to all convex and simple concave polygonal boundaries, which allowed the encoding of all real-world floor plans we encountered. Given the same boundary condition, the hypergraph constitutes a bijective mapping that results in the same floor plan and vice versa. The same hypergraph can be applied to a variety of boundary polygons that will result in a unique floor plan for each boundary condition (Figure 4.12g), while different hypergraphs applied to the same boundary condition result in different internal subdivisions (Figure 4.12h).

4.3.2 Spatial and Environmental Assessment of Floor Plans

To describe a whole building, we can apply the hypergraphs to an apartment boundary, generating detailed floor plans for each apartment unit. A fitting procedure is shown in detail in Figure 2, in which an apartment boundary polygon (Figure 4.13a) is subdivided by a library of different hypergraphs (Figure 4.13b) to create different internal apartment configurations (Figure 4.13c). We then use the apartment boundary polygon and its orientation towards the building circulation to filter floor plans with similar orientations and façade to adiabatic wall ratios. The hypergraph method removes the need for manual drawing of floor plans and preparation of geometry for different environmental simulation procedures. It allows the complex structure of a floor plan to be described as a graph, a quantifiable and searchable data structure that encodes key parameters of a design. To filter geometrically valid but spatially inadequate outputs, a series of heuristics filter and rank feasible results. With this, we can generate architecturally feasible floor plans where rooms have an aspect ratio and size that makes them usable for their specified use, have access to a façade, and are configured in a way that allows access within the apartment and to the building's circulation. For assessing the spatial validity of a floor plan, we propose an automatic version of the spatial scoring system developed by the City of Berlin’s public housing provider (Howoge, 2023). Using automatic placement of furniture blocks we can assess if rooms are large enough to result in livable spaces and compare the overall area to reference floor plans with the same occupancy (Figure 4.13d).

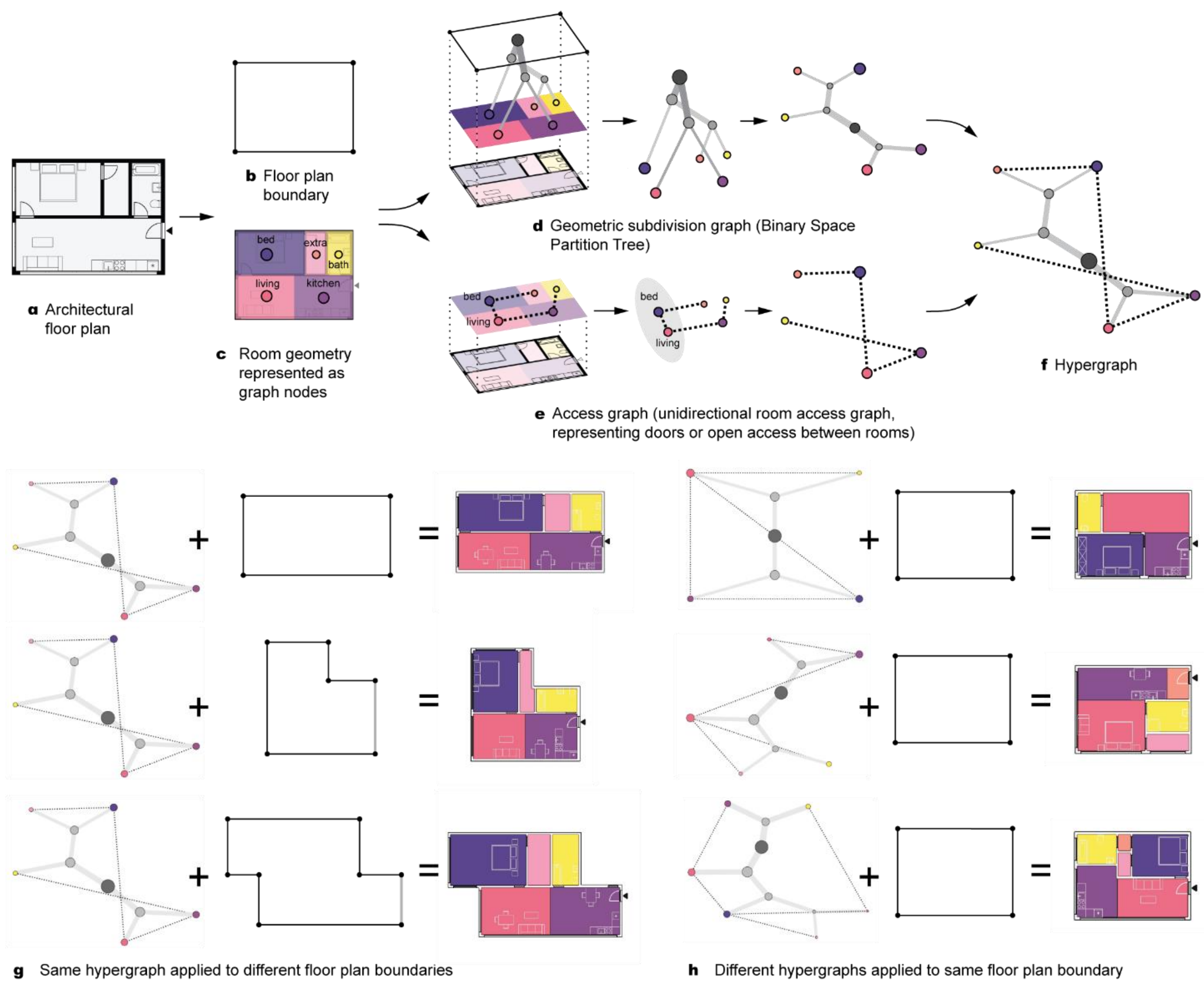

Figure 4.12: The hypergraph is generated from an architectural floorplan (a) that is converted into a boundary (b) and programmatic zones (c) that are translated into the graph nodes. Geometric subdivision of boundary into the rooms is computed with a binary space partition tree (d). The access between rooms is represented as a unidirectional room access graph (e). Combined they result in a hypergraph (f). A hypergraph can be applied to different floor plan boundary (g) to create floor plans with a similar typology. Different hypergraphs can be applied to the same floor plan boundary to create floor plans with different internal configuration (h).

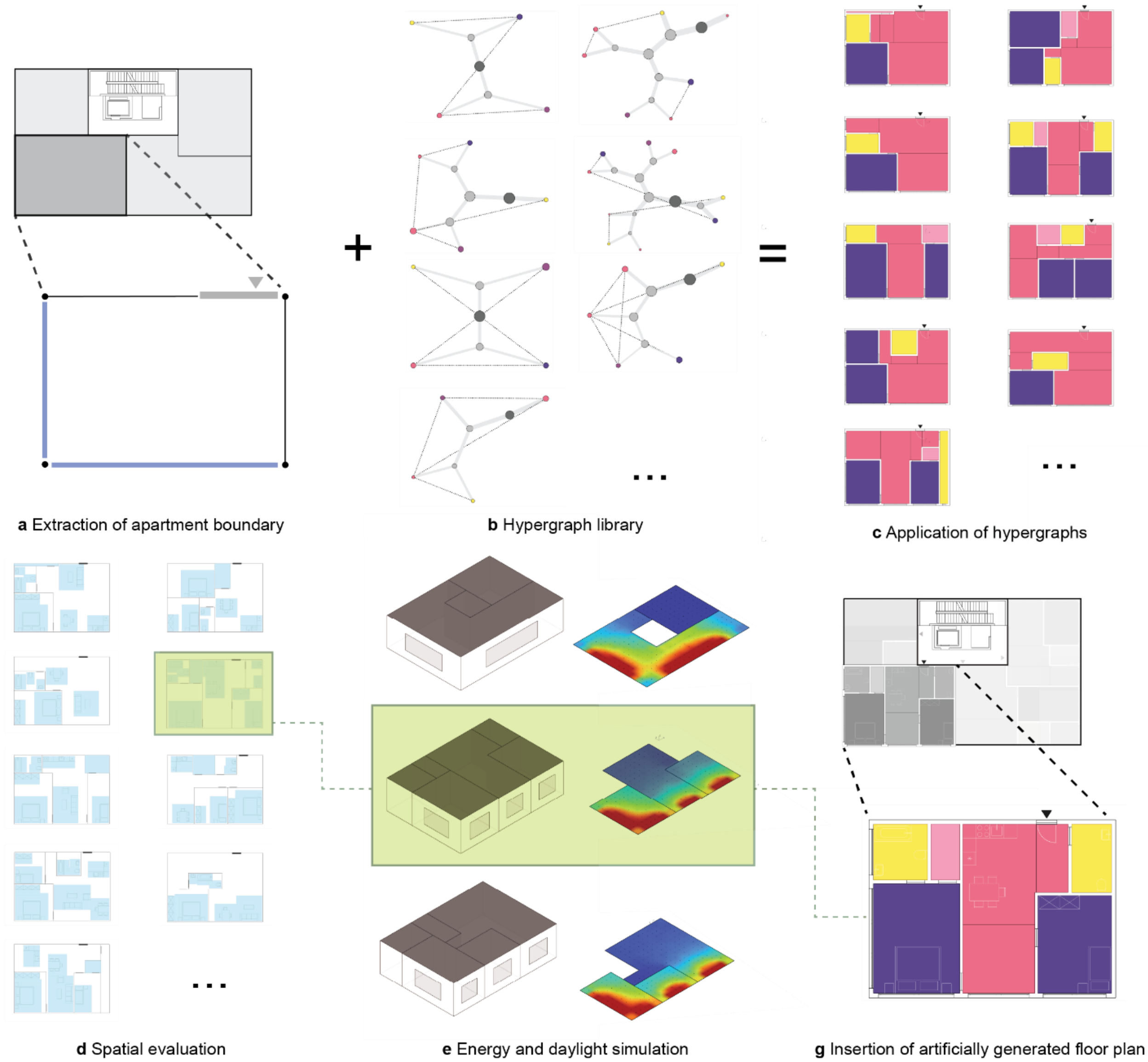

Figure 4.13: Steps for fitting an apartment using the hypergraph method. An apartment boundary is extracted from a building (a) and combined with a library of hypergraphs (b). The applied hypergraphs generate different internal subdivisions for the apartment boundary (c). A spatial evaluation using placement of furniture, accessibility and room geometry is performed to filter feasible solutions (d). An energy (e) and daylight analysis (f) is performed to evaluate the resulting floor plan and a chosen plan is inserted into the building (g).

To estimate daylight and energy performance, the selected floor plans are automatically converted into a simple 3D model, with walls and windows, that creates a building energy model of the apartment. Building energy models are heat-transfer and mass-flow simulations that are industry standard for energy use predictions (Polly et al., 2011). Furthermore, we calculate daylight access in the apartments through assessing the spatial daylight autonomy (sDA), a metric for interior spaces that, through a yearly illuminance simulation with physics-based raytracing and local weather data (Illuminating Engineering Society of North America, n.d.), predicts the percentage of hours per year when a minimum light level of 300 lux can be achieved with daylight (Figure 4.13e). While whole building energy models typically do not have the geometric resolution of single rooms, the models generated with the hypergraph method will allow more detailed energy performance analysis that can capture effects of airflow and natural ventilation for more accurate predictions. Detailed room geometry further allows for more accurate daylight predictions than simple shoebox models or whole building massings, as the internal configuration of a floor plan will determine how light is obstructed inside an apartment.

4.3.3 Characterization and Comparison of Floor Plans

To show the spatial analysis potential of the hypergraph framework we created a dataset of residential floor plans from around the globe (see Methods, Residential building floor plan repository). In order to characterize differences between cities, we compared a representative subset of floor plans from three different cities: Zurich, New York, and Singapore. Contrary to explicit representations with Euclidian geometry or pixel-based representations, the hypergraph encodes relative spatial relationships in addition to geometric properties. This allows the mapping of spatial and typological similarities between floor plans that have different boundary conditions. Based on the number of rooms, subdivision graphs have a variety of sizes which requires comparison functions to work with matrices of different dimensions. For comparison of different hypergraphs, we compare the subdivision matrix (derived from the spatial subdivision graph) separately from the access matrix (derived from the room access graph).

We can describe the overall configuration and complexity of a hypergraph through the number and degree of access and subdivision edges, normalized by the number of rooms. Using a principal component analysis (PCA) of key attributes (Figure 4.14), we can demonstrate that the hypergraph method can be used to distinguish and group similar floor plans according to size and occupancy, as well as compactness (Figure 4.15a). Hypergraphs with lower graph complexity, corresponding to smaller size and occupancy, are grouped in the left around the x-axis, while more complex configurations are grouped towards the right. This creates opportunities to quantify spatial differences of apartments across cities, such as simpler spatial properties of apartments in New York, when compared to small-scale, more complex floor plans with higher hypergraph subdivisions in Singapore. The hypergraph allows us to show and encapsulate architectural differences and investigate spatial configurations that are encoded in local architectural practices, prevalent construction techniques, building codes, and climate.

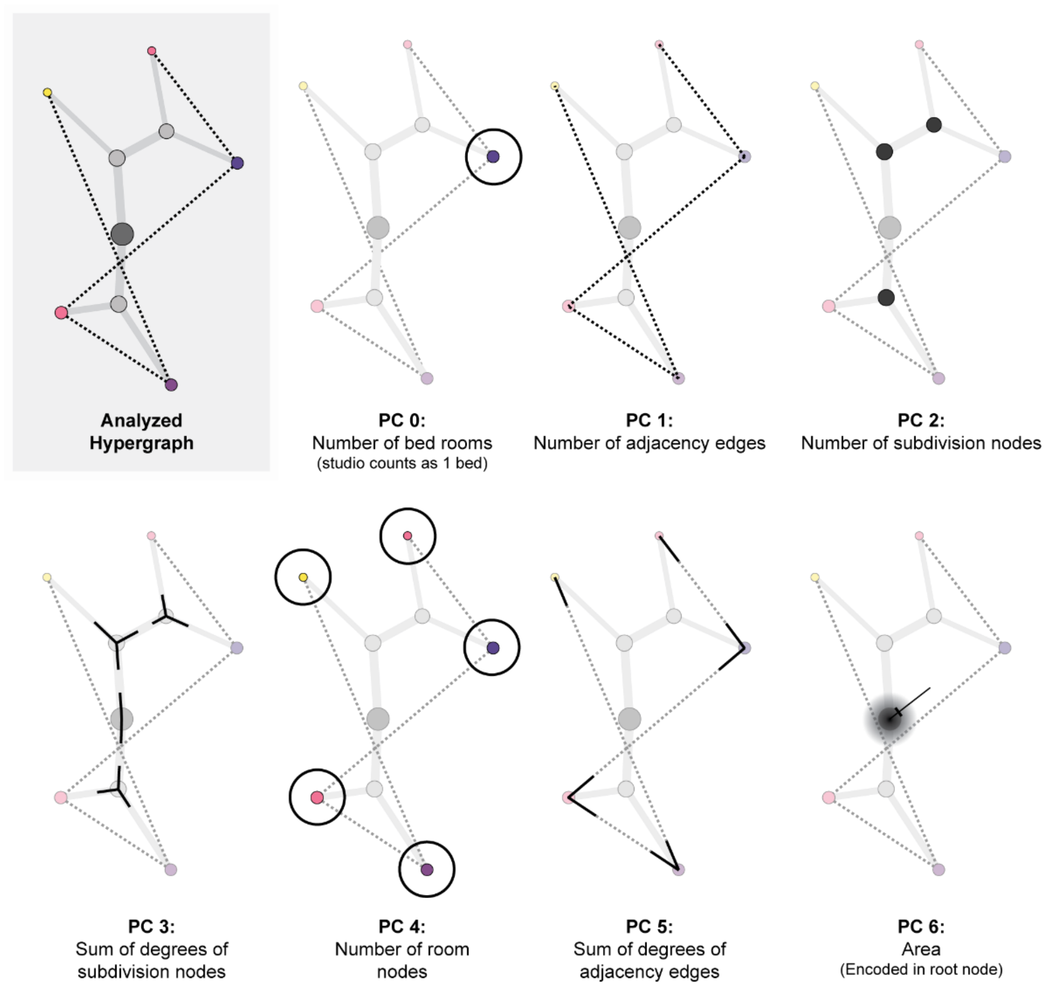

Figure 4.14: Visualization of graph properties that were used for inputs into PCA.

4.3.4 *Building Performance Analysis of Floor Plan Database*

An automated spatial and environmental analysis allows us to capture differences in daylighting across apartments in the three cities. The results of our simulations support qualitative architectural observations, including that residential apartments in Zurich and Singapore have more access to daylight and are mostly daylit from different sides, while apartments in New York in larger buildings have less daylight access (Figure 4.15b). To study the energy efficiency of different apartment geometries, we derive two building energy models for each apartment, with a standard and a high-performance building. The difference in energy use of the two models shows the energy savings from upgrading the building envelope. We conduct an automated spatial analysis to assess if a floor plan is usable and how its area compares to the minimum size requirements for its occupancy. With this, we can quantify the unused space of a floor plan, and with it, the excess emissions associated with heating or cooling. Floor plans that are too large in area or have large ‘unusable’ circulation areas are penalized. A comparison shows how excess emissions from unused space can be significantly higher than savings from building energy upgrades, assuming that the size of the apartment could be reduced until no excess space remains. We find unused space to be more impactful than envelope upgrades, especially in the more temperate climate in Zurich (71.6%), while the opposite is found in hot and humid Singapore (33.0%) where floor plans are already compact and envelope performance is crucial due to the climate. In New York, a balance from both measures yields best results (61.0%) (Figure 4.15c). This means that in the case of new construction, apartments that are closer to the minimal spatial requirements with less excess space will have significantly lower energy use, even when constructed with less performative envelope standards.

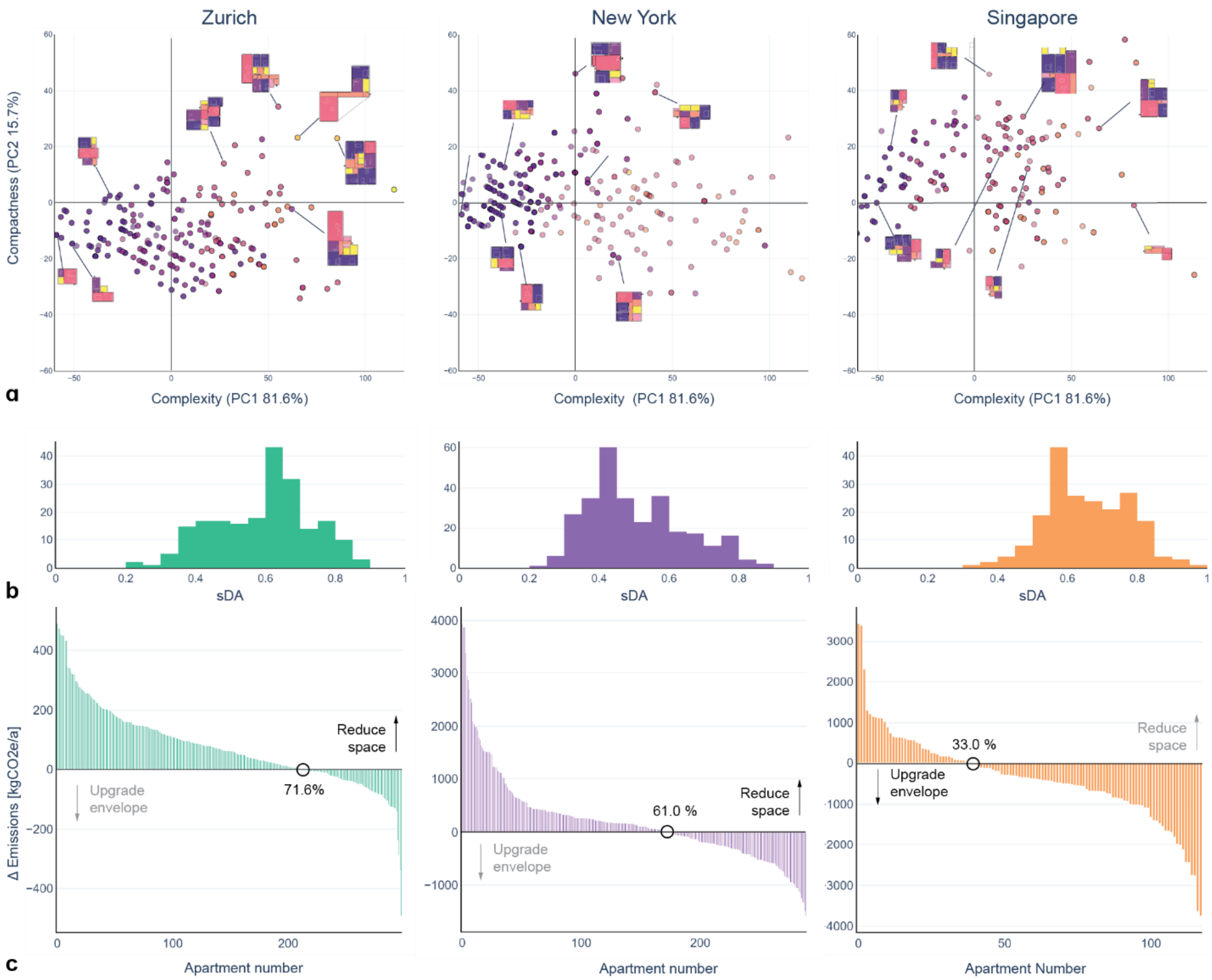

Figure 4.15: Mapping of all floor plans of Zurich, New York and Singapore with their graph structure (a) and sDA performance (b). Comparison of emission from excess space compared with envelope upgrades (c) from the calibrated dataset.

4.3.5 Artificial Generation of Alternative Floor Plans

Apart from analyzing existing floorplans, hypergraphs can also be used to generate new floorplans. We used the hypergraphs of all collected floor plans and test fit them automatically into real-world boundary geometries of residential buildings from Zurich, New York, and Singapore. A sample building for each city that was fitted is shown in Figure 4.16a (for all reference buildings see Figures 4.2-4). Depending on the apartment boundary, there are different numbers of valid apartment subdivisions possible, and the hypergraph fitting method was able to propose alternative apartment layouts inside the real-world buildings. The apartments created through the hypergraph fitting method were then assessed for daylight to compare their sDA. Even though not all of the artificially generated floorplans would be spatially desirable, the aggregated results of the simulation could be used to predict the daylight performance of a building (Figure 4.16b). When comparing the sDA performance of the artificially created apartments, the third quartile of results is within a 20% range or better than the real-world floor plans for sDA and in 5% of cases (Zurich) outperformed the reference floor plan by up to 24% (5.8% of cases in New York by up to 16%, and 0.4% of cases in Singapore by up to 10%). Furthermore, a more detailed qualitative analysis of example floor plans that performed in the upper percentiles of the performance ranges reveals significant opportunities for the design of new buildings: different spatial configurations that substantially increase daylight, alternative spatial configurations that retain daylight performance, opportunities for adding additional rooms (which indicates that the chosen number of rooms might be too small), or reducing the number of rooms (which indicates that a floor plan might be too tightly fitted) (Figure 4c).

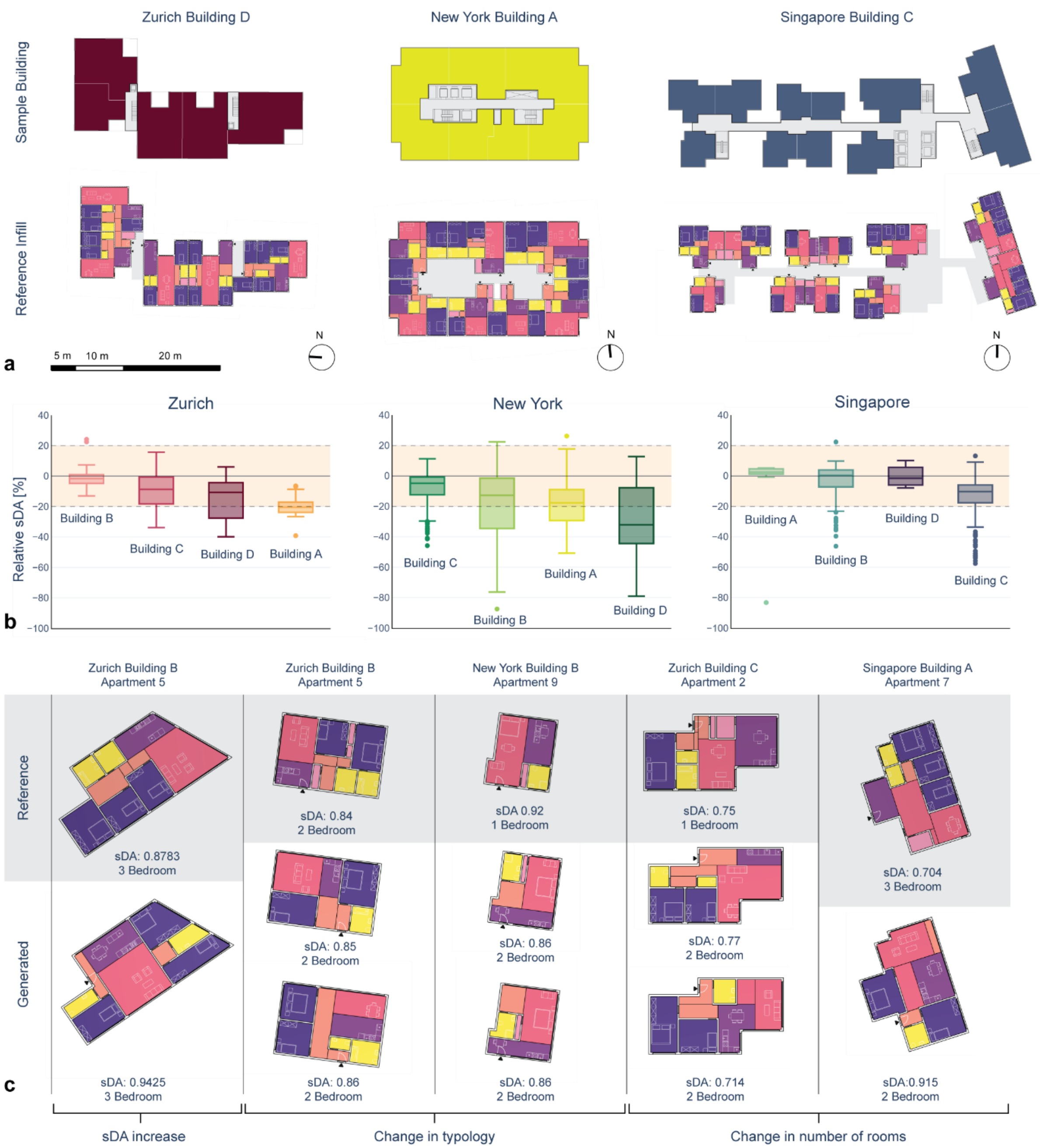

Figure 4.16: Three sample buildings with reference floor plans (a) that are being replaced by hypergraph generated floorplans (all buildings are defined in Extended Data Figures 1-3). The relative sDA performance of all successful floor plans with equal or more rooms (b) and single artificially generated floor plan examples (c) highlighting different opportunities.

4.4 Discussion

In summary, we have demonstrated how the hypergraph framework, as a bijective mapping procedure for creating and representing apartment floor plans, can be used to describe spaces across the world. To our knowledge, the hypergraph is the first method that can generally describe apartment geometries and can translate architectural geometry into graph-based representations and vice versa. We show how the method can be used for mapping and comparing different apartments and propose alternative solutions for existing buildings. These assessments will impact retrofit decisions and regulations on a policy and city planning level, allowing us to better understand and shape dense urban environments. Secondly, the automated testing and generation of multiple design options will create opportunities for better design of new buildings, from providing design ideas to creating quality controls that can predict achievable daylight levels and energy performance for a given context. It could allow for new types of software that would allow self-building and design for communities that cannot afford professional architects, while ensuring that the automatically generated buildings have architectural precedents that promote healthy and sustainable spaces.

Currently, emissions from buildings vary greatly (Goldstein et al., 2020) and our method shows new pathways for helping architects align the energy performance and spatial requirements on an urban level with the comfort and needs of a building's inhabitants. The automated nature of the procedure lowers the barrier for environmental simulations of all buildings, which is key in enabling sustainable building design across the globe. We can show how, in the design of a building, the spatial configuration is more important than building envelope specifications when it comes to building energy usage. Both in the surveyed reference floor plans, as well as in our artificially generated ones, it would have been more favorable in terms of total carbon emissions to build with less space instead of higher performance envelopes. With this we demonstrate that space sufficiency can become a highly impactful carbon mitigation strategy, informing future building energy policy, and should guide the standards and building codes of cities in the future. To address the climate crisis, an overhaul (Asensio & Delmas, 2017) of current environmental certifications – such as the cost balance method in ASHRAE 90.1 (*ASHRAE 90.1-2022 (I-P)*, 2022) or LEED (USGBC, 2023) standards that currently do not award spatial efficiency and compactness – is needed. Given the prevalence of EUI in such certifications, smaller spaces are penalized due to higher “equipment” per floor area ratios. Contrary to current energy codes that specify performance requirements, our results show great potential in savings through spatial efficiency measures and thoughtful planning and design of buildings – and with it the possibility to include spatial metrics for designing buildings with greater energy sufficiency (Hu et al., 2023).

While the paper shows substantial promise for using automated floor plans to lower building energy use, the authors acknowledge that there are important questions of ownership when using an automated procedure that is based on precedent designs. If clearly vetted floorplans are in the public domain, or are generated in-house by an architecture firm, reproducing geometric configurations will be highly beneficial to increase the speed of design workflows. Questions of intellectual ownership will arise that will have to be addressed by legislators, which ties into the existing debate around large language models (Grynbaum & Mac, 2023) and generative AI (Epstein et al., 2023). However, a key difference with the hypergraph approach is a clear source attribution of each graph and the possibility to explicitly map differences and similarities to existing designs. When deployed responsibly, this could enable validated, quality-controlled design databases.

The hypergraph method specifically targets spatial generation of residential building layouts. Currently the scope of the research focuses on single apartments and excludes overall building layout, structural systems, and interfacing with building level mechanical, electrical, and plumbing (MEP) systems. Future research should address the influence of overall building form on interior layouts, both in terms of spatial efficiency, as well as building performance. Automated spatial evaluation of interior layouts, by predicting use and occupancy, will allow architects to calibrate the overall design of a building to its intended use – by choosing appropriate low-carbon spanning systems that work with the interior configuration, tailoring the building form to allow for more daylight, and enabling building layouts where the rearrangement of interior walls can enable different use scenarios for residents (Schneider & Till, 2005). Furthermore, the detailed building energy models that can be created through the hypergraph representation allow for automatic generation of air flow zoning models that can be used to simulate natural ventilation, replacing current practices of manual modeling or simplified assumptions (Tarkhan et al., 2022).

The fully automated method can be used to create architecturally valid apartments that can be combined with environmental performance analysis to evaluate and automatically generate culturally relevant and high-performing buildings. By utilizing architecturally vetted reference designs and heuristic procedures that respond to local requirements, the hypergraph method can produce high quality spaces from virtually any boundary condition. While the method yields geometrically valid options, these designs may not always be of sufficient architectural quality as it depends on the quality of the underlying floorplans in the reference database. However, using only a minimal dataset, we managed to generate artificial solutions that are on par – and up to 24% better in daylight performance – than the real-world built references. This reveals that our method has great potential to lastingly improve the performance of new construction worldwide. We further see opportunities to apply the method to automated benchmarking of building retrofits including the conversions (Poleg, 2023) of some of the currently 20% empty office buildings (Rowden, 2023) in the United States to residential units (Hadden Loh et al., 2023).

5. Automated Structural Modeling for Embodied Carbon Estimation

A version of this chapter has been published in:

Generative Structural Design for Embodied Carbon Estimation. Ramon Elias Weber, Caitlin Mueller, Christoph Reinhart. Proceedings of the IASS Annual Symposium 2020/21 and the 7th International Conference on Spatial Structures, 2021

5.1 Introduction

In the coming three decades, over 226 billion square meters of buildings are projected to be built worldwide – a doubling of the global building stock (IEA, 2019c). With construction and energy use of buildings already accounting for almost 40% of current carbon emissions (IEA, 2019a), there is an immediate need for new strategies that combine net zero energy building operation with net zero carbon construction practices. Combined, these two approaches have the potential to save over 150 GTCO2 emissions over the coming 30 years (Figure 5.1) – up to a third of the current carbon budget (Rogelj et al., 2019). While the bulk of previous efforts focused on reducing operational energy use, the figure underlines that we must start at decarbonizing the very foundations of buildings before they are built.

In places such as Europe and the United States – where over two thirds of the anticipated building stock by 2050 is already built – the fight against emissions in the built environment will largely be focused on renovation of existing buildings and cities (IEA, 2019c). Detailed case studies for the redevelopment of a landmark building have revealed the enormous CO2 savings that can be achieved by renovation instead of building from scratch (Adlerstein, 2016). In certain cases, a retrofit can save more carbon than a newbuild in its entire lifetime. This emphasizes the importance of assessing embodied carbon in the existing building stock to better inform development decisions on both the building and urban scales, in addition to estimating carbon impacts of early-stage design decisions for new construction.

Better strategies are needed for both estimation and reduction of embodied carbon in current and future buildings. Existing benchmarks are inconclusive, using embodied carbon values with a wide range of carbon content, ranging from 300-1650 kgCO2e/m2, depending on the source

(Clark, 2019). This significant uncertainty and variance originates from highly diverse databases and statistical averages of general housing stock or varying building archetypes (Davila, 2017). More accurate surveys can inform new strategies for minimizing embodied carbon in early design stages and can inform decision making on building retrofits and material choices.

A net zero carbon production of building materials comes with significant technical challenges in availability and scalability of sustainable materials (such as timber) and production methods, that in many cases are not yet economically feasible, such as renewable steel or concrete production. This increases the importance of design strategies that can have a massive impact on embodied carbon: increased structural efficiency, optimization strategies for utilization of less material, reusability of materials (Brütting et al., 2019), more economic and adaptive usage of space and longer lifespans of structures – building more with less (Reinhart & Cerezo Davila, 2016).

Different computational strategies have been proposed to calculate and best estimate the embodied carbon impact of buildings. They have largely focused on surveys of recently constructed buildings, where building specifications and material quantities are already known. Where available, building information models (BIM) can be combined with a suite of specialist computational tools and material databases to assess their embodied carbon. Such an analysis can inform different material choices and design decisions in the later planning stages to reduce the embodied carbon (Architecture 2030, 2024). When deployed on a larger scale, for city redevelopment or masterplans, accurate modelling of existing buildings is often not feasible, as it would require the manual creation of 3D BIM models and on-site surveys by specialists.

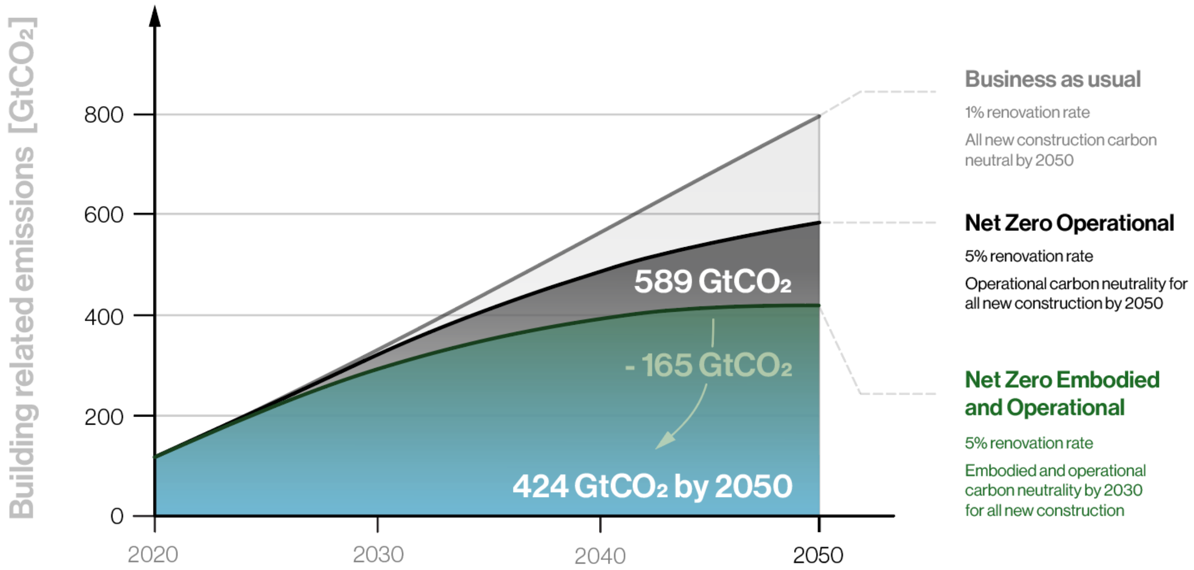

Figure 5.1: Excel model of building related emissions from buildings in the years 2020-2050. Embodied carbon emissions of 410 kgCO2/m2 for existing and new built and 100 kgCO2/m2 for retrofits are assumed. The Net Zero Operational assumes a fully decarbonized grid by 2050 and Net Zero Embodied and Operational assumes an additional linear decrease of embodied carbon from 2030 to 2040 to 0. Global floor areas and operational emissions are based on projections by the International Energy Agency (IEA) (IEA, 2019c)

To estimate the embodied carbon of un-built or un-surveyed buildings, area calculations from massing models can be multiplied with area normalized benchmarks. More detailed data on building elements such as façades can be included when specified in a building's massing. However, area normalized estimation of a building's structure can be highly problematic. An analysis of multi-story concrete residential buildings in India showed more than 60% of the embodied carbon to be from the structure (Bardhan, 2011). In the case of steel framed buildings the embodied carbon database EC3 reveals for their "Commercial Core & Shell - Steel Example" building, that 49% of total embodied carbon emissions are from the steel structure alone and over 66% when including structural concrete elements (*EC3*, 2024). These structural material quantities do not scale linearly with size and are dependent on myriad factors including construction method, loads and building size.

We identify a gap between fuzzy benchmark numbers and high-resolution BIM models for embodied carbon estimation and thus introduce in this paper a hybrid approach to measure embodied carbon, specifically of steel-framed buildings, using generative structural design and sizing optimization. As outlined in Figure 2, our algorithm takes building massing and automatically dimensioned structural elements for the embodied carbon calculation, while relying on proven methods for the building envelope, creating a proxy parametric building model that serves as a simplified BIM model. A comparative study with real-world building data shows how our workflow can estimate structural material quantities comparable to real-world building data. The fully automated nature of the model further allows for its implementation with existing carbon estimation tools in urban modelling software and its use with surrogate modelling and machine learning algorithms in the future.

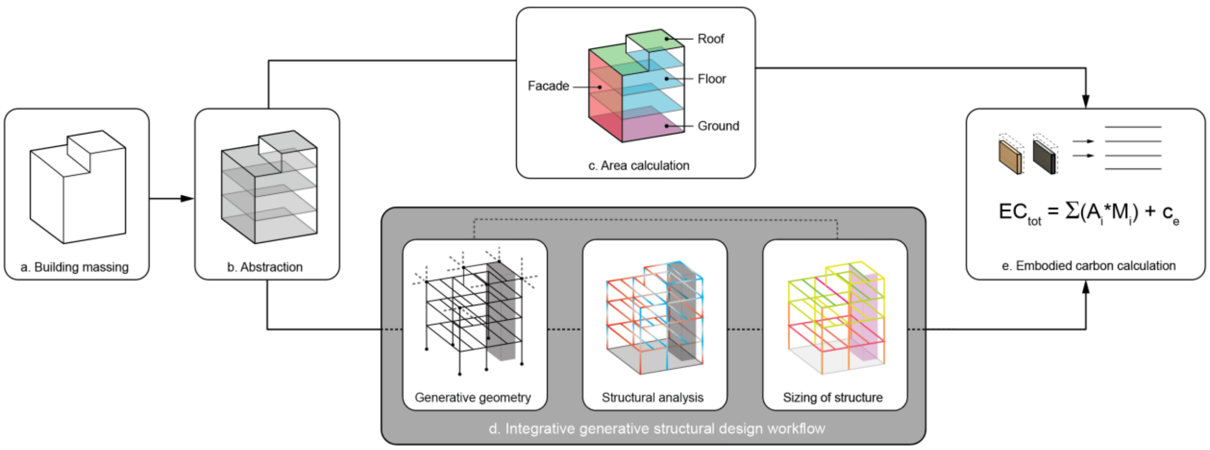

Figure 5.2: Proposed workflow for embodied carbon calculation: Building massing (a.), geometric abstraction (b.), area calculation of linearly scalable building elements (c.), integrative generative design geometry generation analysis and sizing of structural members (d.) and final embodied carbon calculation (e.).

5.2 Methods

The proposed physics-based estimation of embodied carbon creates a generative model of a building's structure for material quantification – a quasi-BIM model of a building's structural elements. In steel framed buildings optimal relationships between structural primary girders and secondary beams have been widely explored (Ruddy, 1983), resulting in rules of thumbs that have commonly used today. To further investigate the inherent relationship between primary and secondary structural members the relationship between spans and structural material quantity are analytically computed and converted to embodied carbon in Figure 3. Derived from an analytical equation a simple beam model with prismatic members of rectangular (concrete, timber) or I-shaped (steel) cross sections optimally sized for typical loading shows the inherent relationship between geometric subdivision and spacing of members.

The relationship across steel, concrete and timber systems show the different behaviour of the materials and the cost of primary span, most significantly affecting steel structures. In a more detailed analysis for real world buildings, this chapter focuses on buildings constructed with steel framing, a construction system that is widely used for standard commercial developments of large-scale office and residential buildings. In this chapter we specifically investigate estimating structural material quantities of the main structural floor framing of such buildings, which is a major component of total structural material and varies widely based on geometry and material decisions. We create a geometric layout of the steel framing system, which we dimension using an assumed load derived from building codes. Without knowing the actual geometry of a building's structure, through optimizing the generative geometry model towards low weight while incorporating constraints of clear span and loads, we create a fully dimensioned structural system for any building massing.

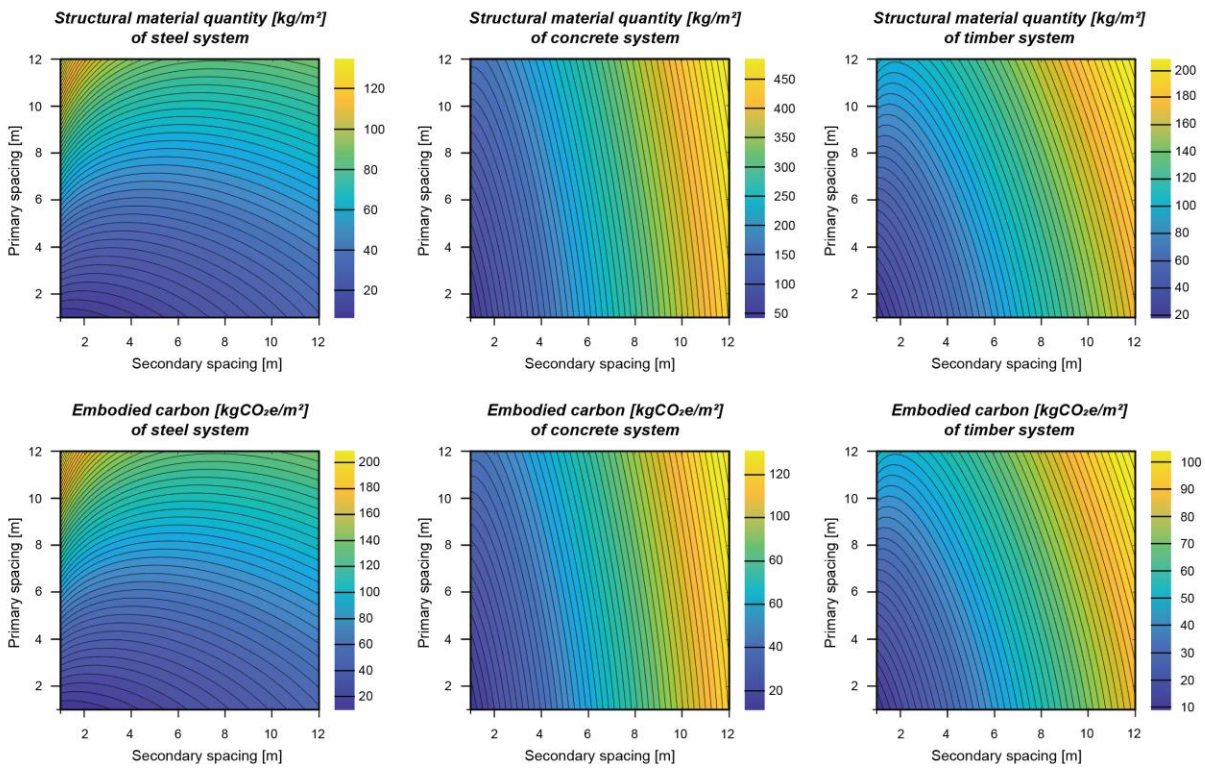

Figure 5.3: Structural material quantity and embodied carbon of steel, concrete and timber system with differentiated primary and secondary member spacing. Embodied carbon values are computed by multiplying the structural material quantities by embodied carbon coefficients: 0.50 for timber (glulam beams and CLT panels), 1.55 for steel (I-shaped structural sections), and 2.00 for concrete (beams with one-way flat slabs, 2% reinforcement ratio), selected from the 2019 ICE Database v3.0 (Hammond & Jones, 2011).

To test and calibrate the generative models, we relied on a data set of four steel frame buildings, as adapted from Tan (Tan, 2016). A single floor of the steel framing plans with dimensioned cross sections and loading serve as the benchmark for our simulation. As our testing framework, we used the 3D modelling package Rhinoceros 3D with its parametric node based visual scripting environment Grasshopper (*Rhino and Grasshopper 3D*, 2024). Custom scripts were combined with optimization framework DSE (Brown et al., 2020a) and the structural solver Karamba3D (Preisinger & Heimrath, 2014b).

The four buildings feature different architectural typologies as shown in Figure 3; Building #1 is an office tower, building #2 a school, building #3 a warehouse, and building #4 a university. Through this typological diversity, the clear spans range from 2 to 16.5 meters. Cores and walls were abstracted as supports while steel columns were included in the model.

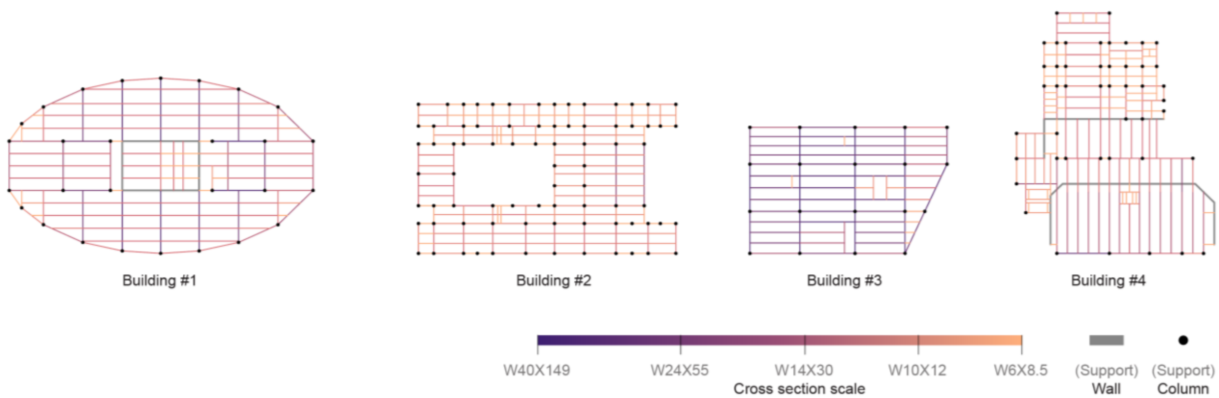

Figure 5.4: Steel framing plans of initial case study dataset Building# 1-4.

Based on the benchmark data sets, a façade load of 500 plf (0.68 kN/m) was applied to the perimeter beams as well as a dead load for the concrete deck of 45psf (2.2 kN/m2) and an additional superimposed dead load for finishes and equipment of 20 psf (1kN/m2). Live loads vary based on programmatic requirements referenced from ASCE 7-10 Table 4-1 (Engineers, 2010) and sum up to to a total of 125 psf (6 kN/m2) for building #1, 115 psf (5.5 kN/m2) for building #2, 315 psf or (15.1 kN/m2) for building #3 and 145 psf or (6.9 kN/m2) for building #4.

The reference steel framing data set relies on a series of detailed structural design assumptions, such as cambering of the steel beams and concrete slab on steel deck that works compositely with the beams; both of these inclusions increase the steel beams' structural capacity. We simplified these features, as they are not implemented in the structural solver. We therefore adjusted our benchmark model to differ slightly from the real-world dataset by using the real-world geometry with optimized cross sections as the comparison benchmark for the generative system. A maximum displacement of maximum beam length divided by 120 (instead of 240) was chosen to account for these differences. Resulting in a maximum displacement of 6.2 cm (#1 with 14.7m max. span), 5.4 cm (#3 with 12.8m max. span), 6.9 cm (#4 with 16.5m max span) and 3.2 cm (#2 with 7.6m max. span).

For the geometric generation of a beam layout, we propose two generative methods; the Voronoi method and the cut out method. As visualized in Figure 5.5 both methods produce quasi optimal solution averages that predict the weight of the structure. The Voronoi method subdivides the floor into equal areas, and the number of divisions, which defines the bay size, and the beam spacing can be input parametrically. The cut out method creates a rectangular grid with variable bay sizes in x and y direction and adjustable column cadence that is cut out from the boundary curve of the original floor plate. After generating the geometry, the structural members are split up into a hierarchy of girders and beams which is reflected in their structural simulation. After generating the geometry, we apply the loading of the original building, including area and façade load, to the structure and automatically size cross sections based on Eurocode. The final volume of the beam geometry is measured and returned as total mass per m2. Each of these methods can be optimized or sampled over the input parameters, which generate a range of results.

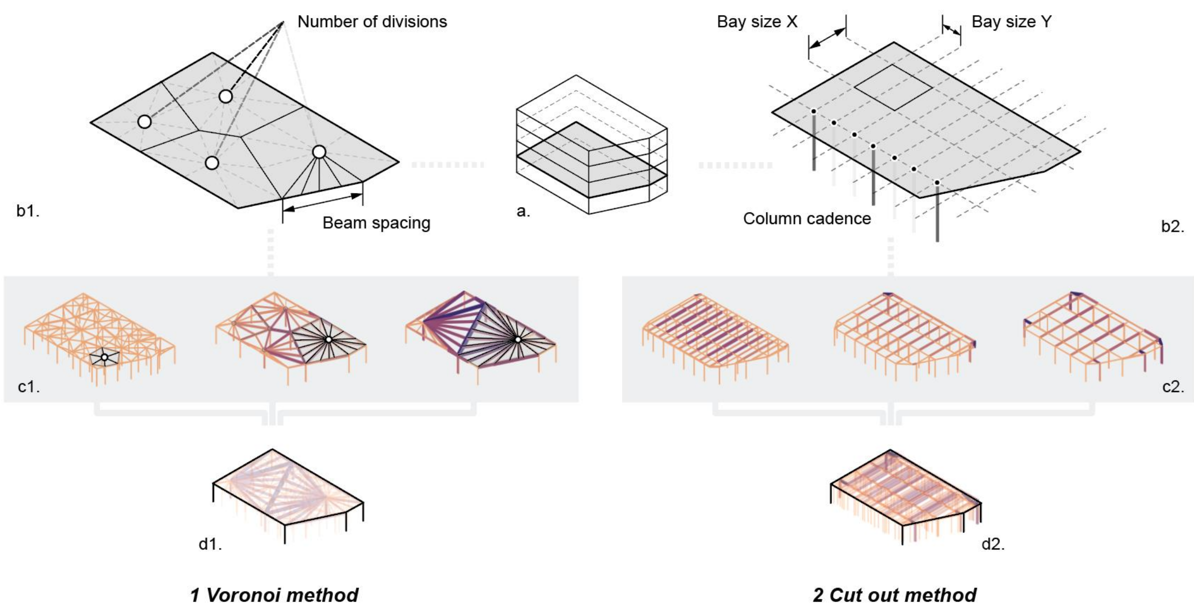

Figure 5.5: Voronoi (1) and Cut Out (2) method take a floor slab of an existing massing as an input (a.). Both methods adaptively subdivide the floor area (b1., b2.) to create a variety of layouts with differentiated bay sizes and beam spacings (c1., c2.). An average of quasi optimal solutions leads to the predicted weight and sizing of the structure (d1., d2.)

5.3 Results

The following section describes the results of the Voronoi and Cut out method applied to our building dataset, as well as sampling larger design spaces with parametric variation of the input variables.

When applied to our reference buildings (#1-4) the results of both the Voronoi and the Cut out method are described in Figure 5.6. To study the structures more consistently, the former US cross sections were adapted their closest fitting European counterpart and converted to HEA/HEB/HEM /HEAA as our structural solver works with European sizing code. This differs from the original weights due to differences in sizing from US to Eurocode. The conversion is described as observed building (a.) with total mass ranging from 40 to 76 kg/m^2. To benchmark and compare the geometric creation methods and the sizing algorithm we additionally calculate the optimal sizing based on the original geometry (b.).

The optimal sizing should return results as close to the original as possible to best reflect the built structure, resulting in error ranges from 1.6% to 12.7%, reflecting the simplification of cambering and composite action from the original dimensions. For the Voronoi method (c.) the average girder span of the original building and a bay size of 3m was chosen as input parameters. This resulted in bay sizes of 10.68m (#1), 5.7m (#2), 10.16m (#3) and 8.2m (#4).

Using the girder average length as the input variable proved to be appropriate for the more regular structures #1-3 while the large variety of spans of the lecture hall of the university building #4 with 16.5m building #4 caused a slight distortion. Error ranges fall under 10% in buildings #1-3 and 12.7% in building #4.

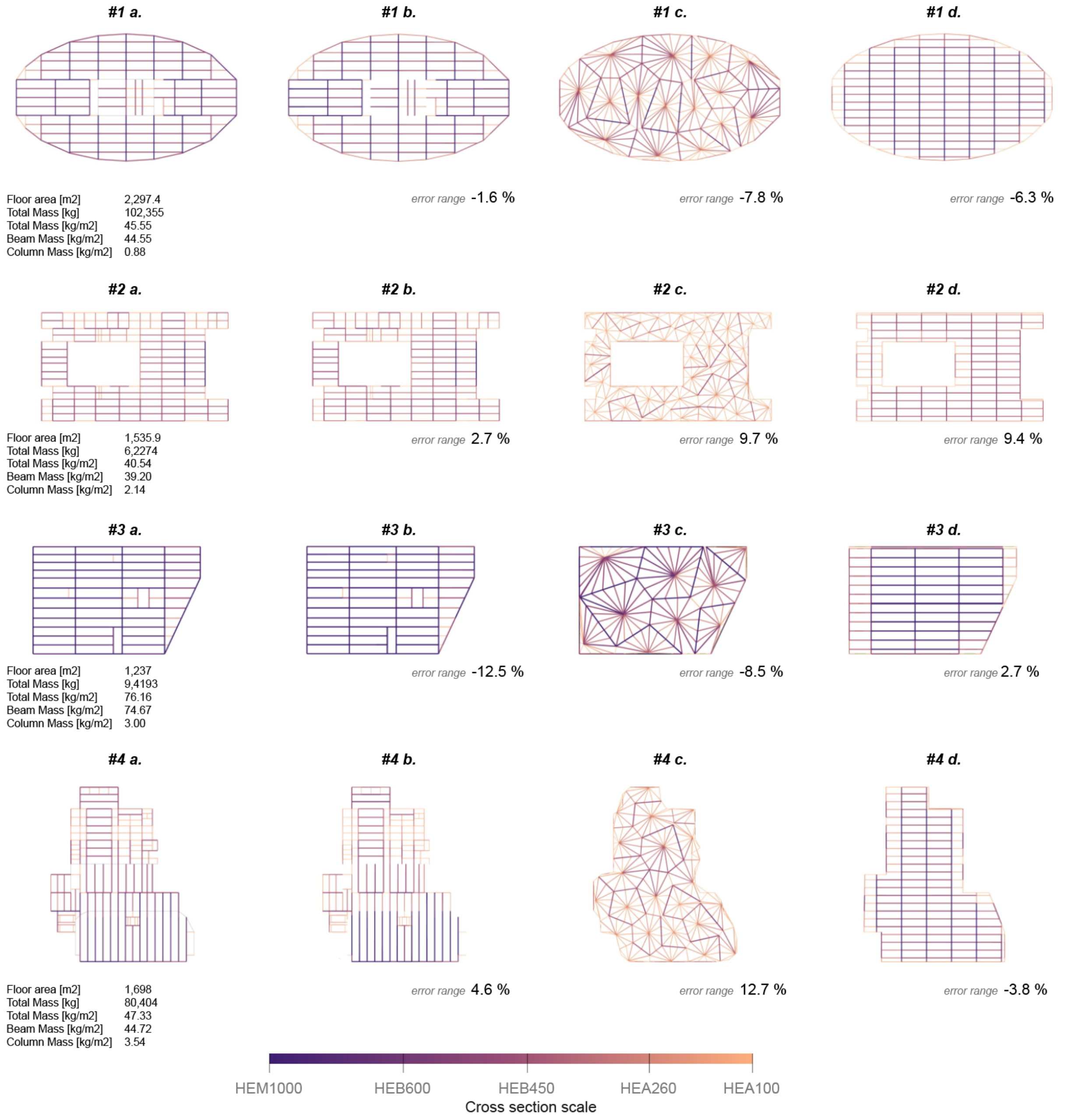

Figure 5.6: Buildings #1-4 with the observed building (a.), an optimal sizing of members based on real geometry (b.), optimal sizing of members based on Voronoi method (c.) and Cut out method (d.).

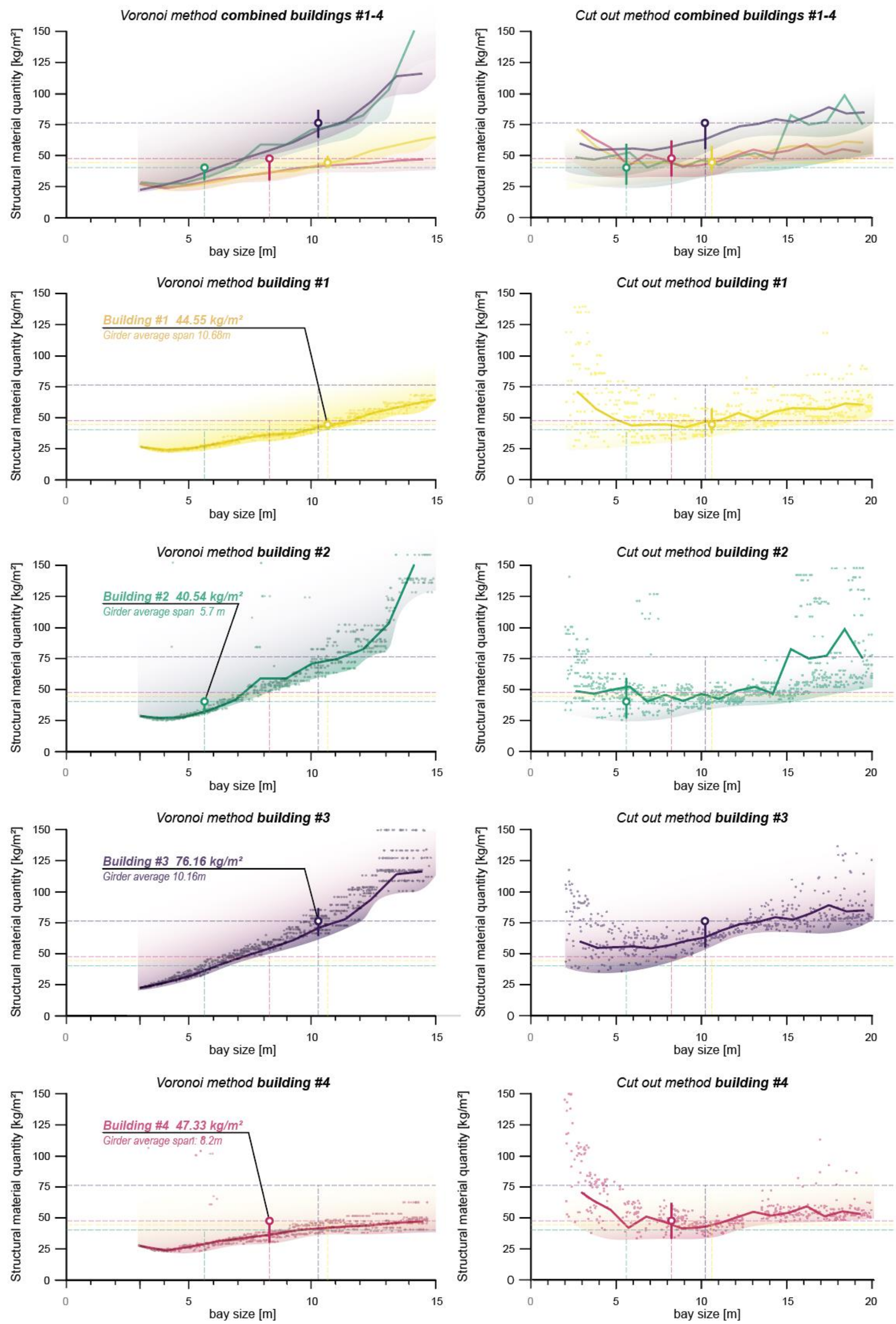

Figure 5.7: Comparison of 1000 samples of Voronoi and Cut out method on the #1-4 Building Dataset.

The *Cut out* method (d.) was used with input parameters most closely representing the original building. For buildings #1,2 and #4 the grid size was set at 8x2.5m with columns every corner in x direction and every 5^{th} beam in y direction. For #3 longer spans of 12x2.5m and columns, every corner in x and every 2^{nd} in y direction were chosen. The warehouse building, with it is high load, stressed the maximum standardized cross section and artificially larger cross sections had to be provided for the sizing algorithm to find a solution.

To further study the parameter space of the two methods, a series of 1000 samples was calculated with random input samples, applying both Voronoi and Cut out method to each building geometry, as shown in Figure 5.7. The models were calculated with varying seed values for subdivision point placement, bay sizing (3-15m), beam spacing (3m) in the Voronoi method and varying x and y grid length (2-20m) and fixed column cadence (2) in the Cut out method. The scatter plots display the Pareto front and the median axis of the real buildings and the original structural quantity in kg per m^2 of the reference structure.

The structural material quantities fall in a 10% range of generated values from our real building values when the bay size of the original building is known. Averaged over +- 0.5m bay size, the results stay within a 25% margin of the average samples generated with the Voronoi method (#1, 1.1%, #2 17%, #3 3.6%, #4 24.5%) and within a 17% margin with the Cut out method (#1 5.8%, #2 15.6%, #3 16.5%, #4 9.2%).

5.4 Discussion and Conclusion

The regular office building (#1) and school building (#2) with short spans show prediction errors Structural systems are one of the most carbon intensive parts of a building and therefore a crucial component in assessing a building’s embodied carbon. Given the difficulties posed by the reduction of carbon emissions to the building industry’s efforts to combat climate change, better modes of analysis and prediction can help us to gain a better understanding of existing housing stock. Furthermore, the relationships between broad structural material quantity loading, architectural programs and geometry can inform future construction systems and design decisions. The method presents a first step towards analysing a housing stock based on external geometry and can take advantage of large geometric GIS datasets with building massings available for cities and buildings worldwide.

Currently, a building's embodied carbon can be assessed either via a benchmark database or a full material survey. Current databases are sparse and limited in their architectural program, location, typology, and construction system and therefore come with significant uncertainty. There are no big public repositories, and the existing databases are small. As De Wolf writes; "Industry lacks the appropriate benchmarks to know how much materials are needed for various structures." (Wolf, 2017). Proprietary and with a wide range of low carbon to commercial buildings, making them difficult for benchmarking. A full life cycle analysis (LCA) is always done after the fact; a full material survey requires a full 3D BIM model that is only available at the end of the design process, after the most important design decisions are difficult to adjust or require a laborious accounting of an existing structure by specialists.

One of the main sources of uncertainty is a building's structure. Compared to material quantities of building envelopes, it is hard to estimate based on a building massing. We propose a physics-based method for estimating embodied structural material quantities of steel frame structures. A generative geometry workflow creates a mock-up structure from a given building outline that is fully dimensioned using realistic loading conditions and cross sections. This creates a simplified structural model of a steel framing system we can further use to analyse a building's embodied carbon.

Generative design algorithms that are typically used for the creation of novel buildings are proposed to reverse engineer structural components of existing structures. Our unique approach offers two methods for generating geometry and structural material quantities. Due to the limited dataset, it is unclear if one method can perform significantly better. Our results show that all structures are highly sensitive and rely on a correct input of loading and span.

The regular office building (#1) and school building (#2) with short spans show prediction errors of under 10%. Special cases can pose a challenge for the algorithmic prediction, such as the warehouse building (#3) with large spans that go to loading limits for conventional steel cross sections. Furthermore, the university building (#4) with a large lecture hall shows how long spans can have a high impact and distort averages.

The method is currently limited by its inputs – bay size, materiality, and loads – that needs to be assessed beforehand. GIS information such as zoning, the year the structure was built, and requirements of loading per building code can help define these inputs on a broader scale.

The results of both our cross-material analysis and the building dataset show how we do not need precise geometry for minimal embodied carbon, as scale and spans are the decisive factors. While a number of geometric configurations are not efficient, there is still a lot of architectural freedom for the design of low-embodied carbon structures. The flat design space suggests that various complex load paths can create an efficient structure. Our findings are supported by statistical analysis of the deQo Database that suggested a correlation between span and embodied carbon is crucial in determining a building's embodied carbon and is far more important than floor area or building exterior massing (Wolf, 2017). This trade-off between large spans and structural material quantities is clearly visible and suggests that "open floor plans" with inherently more material should be carefully evaluated for their architectural trade-offs. Competing motivations of future spatial flexibility and low embodied carbon must be further assessed and studied more in depth.

The results and analysis of the structural framing plans show a large variety of structural material quantity over the four sample buildings, almost doubling the embodied structural material quantities, and thus embodied carbon, based on different spans and loads. The analysis of our parameter space shows that a correct estimation of the bay size of the real structure allows for an estimation of the buildings structural material quantity using our two methods.

In this paper we present a first proof of concept for a novel generative design workflow for embodied carbon analysis. Future work utilizing larger calibrated building datasets will be required to make embodied carbon predictions with high accuracy. Further assessing the performance and refining our geometric methods. An integration with secondary geometric details for building envelopes floors and cores will allow for a comprehensive study of embodied carbon. Additional material systems widely used in construction such as concrete, brick and timber systems would have to be investigated to make predictions about larger urban building stock. For example, the inclusion of lateral systems in the simulation would enable predictions of tall buildings. As scaling effects have a great effect on skyscrapers exposed to wind loads, which is reflected in non-linear increase of their structural mass with greater height (Khan, 2004).

A more precise estimation of a building's internal geometry could further enable more comprehensive operational energy simulations, incorporating previously unknown variables such as thermal mass or internal layout. Engineers and architects make key LCA design decisions during schematic design development. The implementation of fast analytical and predictive tools in design environments could enable more informed early-stage design decisions. Accurate prediction of embodied carbon is crucial for decisions regarding existing housing stock. From the small scale – informing stakeholders towards retrofit decisions and better estimate impact of new real estate developments – and on a larger scale – guiding city scale building code and policy implementations for embodied carbon building standards and large-scale masterplans.

6. Layout Automation Algorithms for Building Retrofit and Adaptive Reuse

6.1 Introduction

With an estimated 3.8 million housing units missing (Khater, Sam et al., 2021), cities across the US face a housing crisis. The spatial misallocation prevents large parts of the population from accessing affordable housing, increases societal inequality (Weinstock, 2023), and impedes economic growth substantially (Hsieh & Moretti, 2019). Meanwhile, the largest metropolitan areas have office building vacancy rates of almost up to 30% (Khater, Sam et al., 2021), begging the question of rezoning and redeveloping commercial districts to provide the much-needed housing supply. Policymakers have started to develop initiatives and incentive structures to convert office buildings to residential units in cities such as Boston (BPDA, 2023), DC (DC Office of Planning, 2020), New York (City of New York, 2023) and San Francisco (Breed, 2023). However, compared to new construction, there are distinct challenges in planning and construction. Programmatic conversions come with a change of circulation requirements, building services, and HVAC systems. Furthermore, some office buildings in the US feature building dimensions that are typologically different from residential units, creating problems for access to daylight within subdivided units (Badger & Buchanan, 2023). This research outlines strategies of how computational design methods could be used to help in the design stage of building reuse and how existing commercial buildings can be assessed for potential building occupancy and daylight availability when converted into a residential building. For this, this chapter features case studies with real-world reference buildings that have been converted into residential units.

This chapter presents computational design methods and algorithms that help in designing building retrofits, with a particular focus on commercial-to-residential conversions. Algorithmic methods can help predict the spatial potential of a building retrofit through detailed geometric analysis. Creating spatial scenarios and different fitted floor plans allows the assessment of occupancy and future livability of a building after a retrofit. Utilizing design automation to create apartment subdivisions and floor plans allows for the exploration of thousands of options. To evaluate a myriad of possible floor plan designs, daylight analysis is used as a proxy for livability and is combined with the internal spatial assessment through automated furniture placement.

Economic constraints on housing and the environmental challenges associated with creating more low-carbon housing make building conversion an ideal candidate for sustainable construction in urban centers. There is no consensus on what methods are best to assess what buildings are good candidates for conversion. Large architecture practices have proposed black box scoring systems (that are not open source) or geometric assessments based on rules of thumb (Dundon & Krieger, 2023). The current state of the art of manually assessing a building, as a trained architect, does not seem scalable to systematically guide building policy or evaluate and conceive design proposals for thousands of buildings. This research establishes a new methodology for systematic assessment of a building, that could be used for both evaluation of an entire building stock, as well as during design ideation of a full floor plan of a single building or floor plate.

6.2 Background

6.2.1 Environmental simulation and building retrofits

Building retrofits themselves, without programmatic conversions, are key in lowering carbon emissions in cities across the globe. Different strategies have been deployed for achieving carbon emission reduction targets through building retrofits, including building envelope and HVAC upgrades and electrification. These strategies must be deployed in a location-specific manner to achieve the largest impact (Ang et al., 2023). Benefits of building retrofit, when compared with new construction, can include significant reduction in embodied carbon (Rinke & Pacquée, 2022). Different studies have addressed how automatic simulation of urban scale datasets can create digital models to inform decision-making processes (Chen et al., 2017; Deb & Schlueter, 2021; Rodrigues et al., 2015b). Machine learning models have been used to speed up simulation workflows and augment bottom up energy simulation Building Energy Models (BEM) (Ali et al., 2024; Nagpal et al., 2019). Various challenges in multi-building scale retrofits have been identified, including a lack of documented case study projects that are publicly available, an underrepresentation of non-residential projects, and shallow retrofits that do not meet high energy standards and substantially increase building performance (Bjelland et al., 2024).

Different studies have addressed decision-making frameworks for building adaptation and conversion during retrofits (Baker et al., 2017; Nedeljkovic et al., 2023). The Netherlands and Belgium stand out as countries where office to residential conversions have been widely implemented (Rinke & Pacquée, 2022) with Brussels having 20% of its new housing demand met by converting office buildings to residential units in 2018 and 2019 (Stiernon et al., 2023). While methods for evaluating the feasibility of building retrofits typically rely on high-level parameters related to economic feasibility, there is no consensus on what makes a building adaptable (Rockow et al., 2019). Economic frameworks have been developed that take market characteristics and location into account (Geraedts, 2017). Theoretical architectural frameworks approach building retrofits from a conceptual material level with the idea of layers of different permanence (Brand, 1995) or porosity (Rinke & Pacquée, 2022).

Integrated computational design frameworks have been proposed to estimate embodied carbon or building energy performance with a bottom-up approach. Instead of relying on high-level data, normalized from reference projects, a high-resolution digital model of a building is created to approximate operational or embodied carbon emissions. This has been successfully validated for the estimation of material quantities of steel structures (Weber et al., 2021b) or the influence of programmatic layouts on building energy use (Dogan et al., 2015a). Furthermore, as a benchmarking tool for different structural systems, simplified digital models can help in early-stage design to optimize between carbon emissions and cost (Gauch, 2023). Daylight is a crucial metric for building performance and is shaped both by the building and its environment (DeKay & Brager, 2023). Access to daylight is key for healthy human experience inside a building (Ko et al., 2022). Daylight access often doubles as a proxy for access to natural ventilation, which can also play an important role in low carbon building design.

6.2.2 Floor Plan Automation

Recent developments in computational geometry and machine learning have accelerated the possibilities of design automation and artificial generation in an architectural context. Developer driven design automation tools have been created to automate building massing design (Archistar, 2024; Autodesk, 2024; Sidewalk Labs & Google, 2024; Test Fit, 2024). At the scale of a building layout, however, different approaches are still developed at a theoretical research level (Weber et al., 2022b). Graph-based machine learning methods have been applied to learn from residential building layouts and generate artificial layouts from desired adjacencies (Bisht et al., 2022) while responding to various constraints (Nauata et al., 2020b; Shabani et al., 2023; Sun et al., 2022; Tang et al., 2023). However, the research stemming mostly from the computer graphics field has so far been only applied to the generation of visually correct floor plans from high-level inputs and based on architecturally unvetted floor plan datasets (Weber et al., 2022b). A different approach has been proposed with the hypergraph, a bijective graph mapping of floor plan geometry that allows for the creation of artificial floor plans inside a boundary geometry in real-time (Weber et al., 2024). Currently, the automated layout generation methods have not been applied to building retrofits, where so far only very limited and specific cases have been studied with automated workflows. Specific software has been proposed for reconstructing and evaluating structurally load-bearing walls in apartment retrofits in Korea (Kim et al., 2021). Furthermore, shape grammars have been applied to repurpose existing masonry buildings where load bearing walls cannot be adjusted (Paulino et al., 2023).

6.2.3 *Research Scope*

With policies in many cities geared to address building retrofits, new quantitative tools for better assessment of the existing building stock are needed. This will be important to shape legislation around building retrofits, assess proposals from developers, and give cities a better idea of the spatial potential of their underutilized building stock. This research addresses building retrofits at the scale of a single, representative building. Furthermore, we focus on internal spatial subdivisions and reconfiguration and keep building geometry constrained. The research introduces new types of geometric algorithms that can be used to create simplified circulation layouts for residential buildings and integrate spatial subdivision with environmental assessment of the floor plans. They can be dimensioned and adjusted to match local requirements and building codes and can be used to align structural and spatial constraints. In the scope of this research an algorithmic workflow for cross-disciplinary representation of a building model in early stages of design is developed. It should only be used to comparatively evaluate building systems, since the models are simplifications of real buildings and are not able to fully represent a building in all of its details. Occupant behavior has an especially large influence on the energetic performance of a building and is currently not modeled in detail. Furthermore, the geometric layouts include simplified assumptions of different circulation typologies and do not consider, for example, requirements from the Americans with Disabilities Act (ADA).

6.3 Methods

This chapter introduces a holistic architectural geometry generation and analysis workflow for building retrofits, with a specific focus on programmatic conversions. As illustrated in Figure 6.1, and based on a building massing, a full digital building model is produced that can be evaluated for spatial performance. A series of variables are presumed fixed at the outset, such as the overall building geometry, material assemblies or the number of desired apartment units. Procedural geometric methods are developed for creating programmatic layout subdivisions of whole building floor plates. These layouts can be filled with detailed architectural floor plans via the hypergraph representation, as introduced in Chapter 4. The hypergraph-created floor plans, as well as the initial layouts, can be optimized to better fit into the existing structural layout of the building via a snapping routine. The synthesis workflow allows the programmatic layout, internal floor plans or structural grids to respond to each other to create more feasible layouts.

For evaluation of the full building floor plans, a spatial analysis is combined with Radiance based daylight simulations via Climate Studio (Solemma, 2023). The workflows are not designed to capture every custom-building geometry, but can be used to represent placeholders, and simplified volumetric representations of actual buildings.

6.3.1 Data Structures and Implementation

A mesh data structure is introduced to represent building program, structural grids, and high-level layout subdivisions. The meshes consist of N-dimensional faces, where a single face boundary is represented by a series of vertices, encoded as points in xy coordinates. Custom simplification routines identify vertices in a straight line and delete them to simplify faces. N-dimensional mesh faces are not typically used in computational modeling packages used in industry and quadrilateral and triangular meshes are the standard in rendering, for example. Because of this, for the purposes of this research, a custom mesh data structure was implemented in .NET for use within the Rhinoceros and Grasshopper 3D modeling environments (Robert McNeel & Associates, 2022). Native workflows were extended with geometric algorithms, described in further detail in this section. All simulations were conducted on a Windows desktop computer with the following specifications: 64 GB Ram, Nvidia GeForce GTX 1080 Graphics card, Intel(R) Core(TM) i7-6700K @ 4.0 GHz Processor. The fitting of a full floor plate with layouts via the hypergraph method took around ~1 min with an addition ~30 seconds for the daylight simulation.

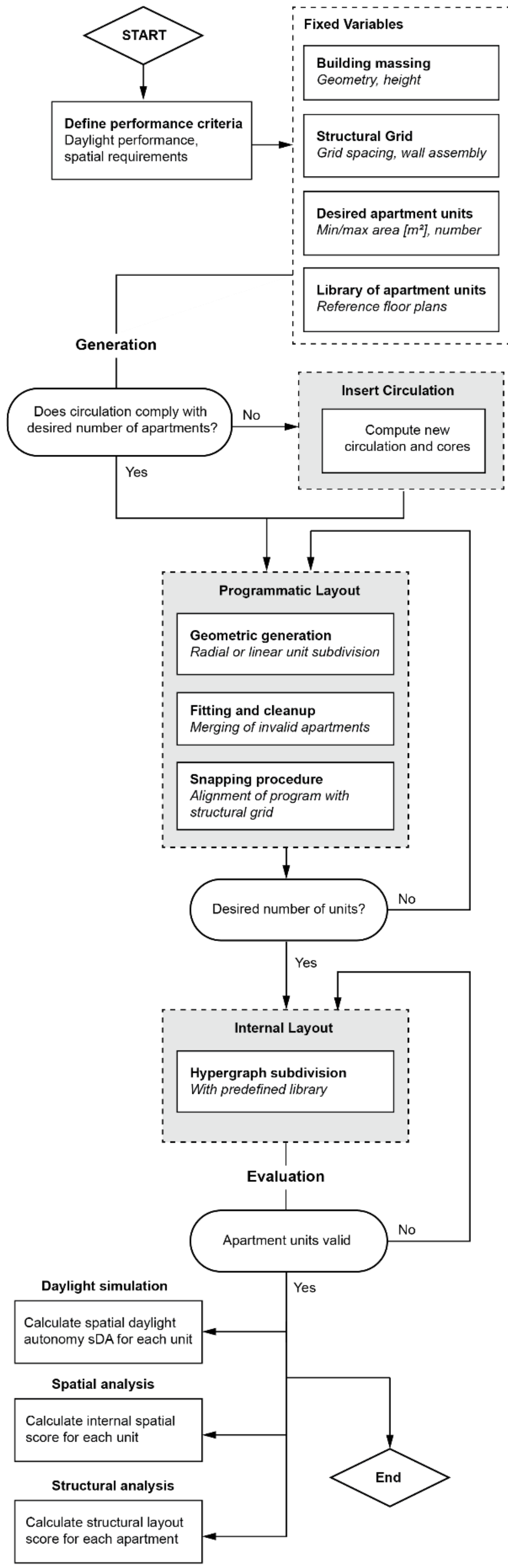

Figure 6.1: Workflow for creating an integrated building model.

6.3.2 Geometric Algorithms

In order to create the programmatic layout of a building, different existing geometric algorithms are combined and a series of algorithmic workflows are developed. In the scope of this research, buildings are abstracted as two-dimensional outlines and their volumetric massing interpreted as simple extrusions thereof. To simplify, and to speed up computation, only closed two-dimensional polylines without holes are considered. Meanwhile, more complex building shapes can be subdivided into smaller shapes that can be analyzed individually. To convert a two-dimensional closed polyline (defined as a series of points in a xy-coordinate system) into a building outline, a series of geometric properties are captured that help determine automated placements of a building's core and structural layout. The median axis– a geometric property of a closed polygon – creates a series of curves along the center of a shape. There are a variety of existing geometric algorithms to create a median axis. A version based on the Voronoi subdivision algorithm (De Berg et al., 2008) is proposed in this research. The Voronoi based median axis algorithm has proven to be working fast (in real-time) and robust with different polygonal geometries.

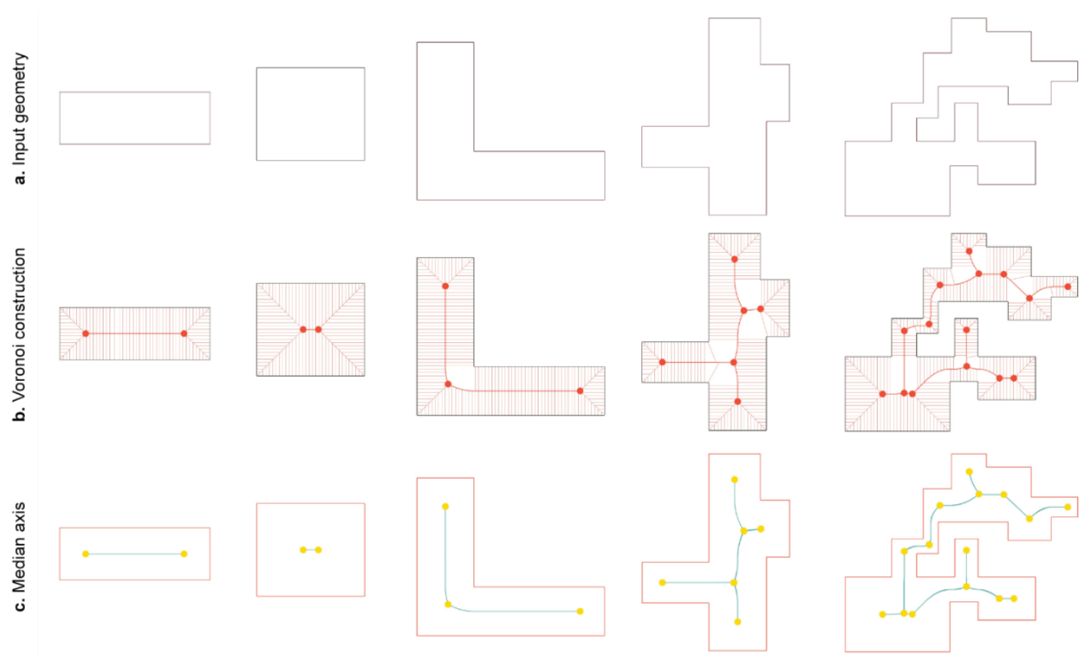

Figure 6.2: Median axis construction workflow where from an input geometry (a) a voronoi subdivision from points along the edges is created (b). From this subdivision, interior edges and nodes are extracted, by discarding all edges that touch the polygonal outline, resulting in the median axis (c Blue). Median axis nodes (c Yellow) are placed where more than two edges meet.

A snapping procedure is used to convert any face edge into an axis, where an axis is defined as a direction (xy) and a starting point (xy) on either a world x-axis or y-axis. Such axes can be used to simplify mesh bounds, as shown in Figure 6.3. An existing implementation of the density-based spatial clustering of applications with noise (DBSCAN) algorithm (Ester et al., 1996) is used to align axes within a specified distance. Furthermore, the axes can be transferred from one mesh to another to align mesh edges to a specified grid (Figure 6.4). Applying custom snapping to a building context, this allows the alignment of a programmatic layout to the structural grid or vice-versa.

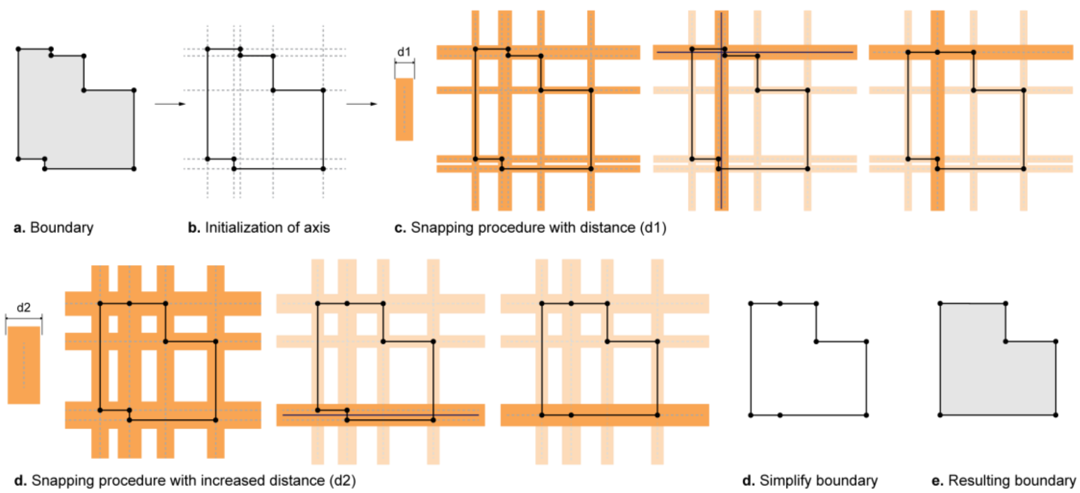

Figure 6.3: Snapping algorithm, where the edges of a boundary (a) are used to create snapping axis (b) that are used to simplify the boundary. Different snapping distances can be used to further simplify the boundary polygon.

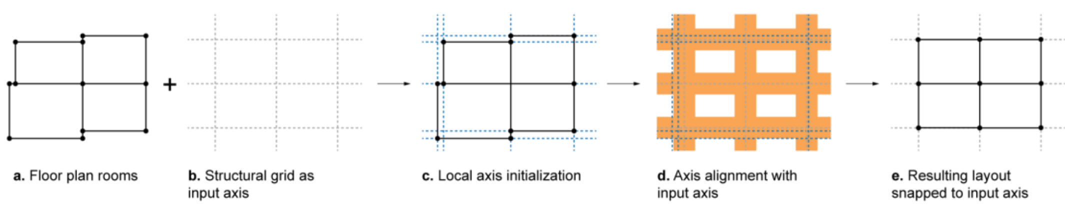

Figure 6.4: Snapping algorithm, where a secondary geometry, for example a structural grid, can be used as input axis to align an input geometry (a) to a desired grid (b-e).

6.3.3 Circulation

A geometric procedural workflow can be used to create different building circulation typologies from a building outline. Through programmatic change in a building, there could be a need for alternative circulation cores inside a building. Alternatively, the method could be applied to the creation of design proposals during the design of new buildings. This process is further illustrated in Figure 6.5, where the median axis algorithm is applied to a boundary geometry to place core and circulation. By simplifying and straightening the median axis, the polygonal boundary can be split into two parts along the central spine. This allows for further splitting the input boundary geometry into head-edges (the edge of the boundary face touching the straightened spine) and side-edges (the boundary edges that do not touch the spine), which can guide different core placement options. For the placement of the cores, different geometric variables such as the section depth, the distance between the cores, tributary area of each core, as well as an additional linear circulation can be defined.

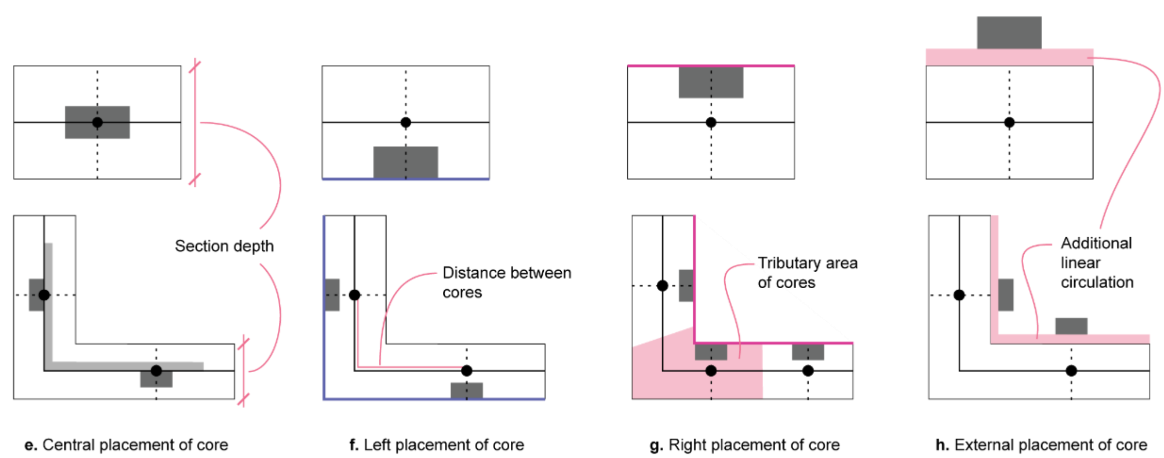

Figure 6.5: Sample subdivision of a rectangular and L-shaped building outline for placement of circulation and core. The outline is subdivided via its median axis (a-d) and creates different placement possibilities for core and circulation (e-h).

6.3.4 Programmatic Layout

To create a programmatic layout of a building floor plate with dedicated zones for each residential unit, as well as core and circulation area, a linear procedural process is deployed, as described in Figure 6.6. Input zones are either defined from an artificial core and circulation layout or in the case of a building retrofit with an existing circulation, defined by existing constraints. Linear or radial subdivisions of each of the programmatic zones create different units that are then output into a final layout. For the subdivisions, randomized areas with a fixed minimum and maximum apartment size can be used to explore various configurations. Alternatively, a specified unit mix can be translated into area requirements and used to fit a program more exactly. A cleanup routine of the resulting mesh surfaces can be deployed to merge units that have no access to a façade or circulation or do not fit the minimum area requirements.

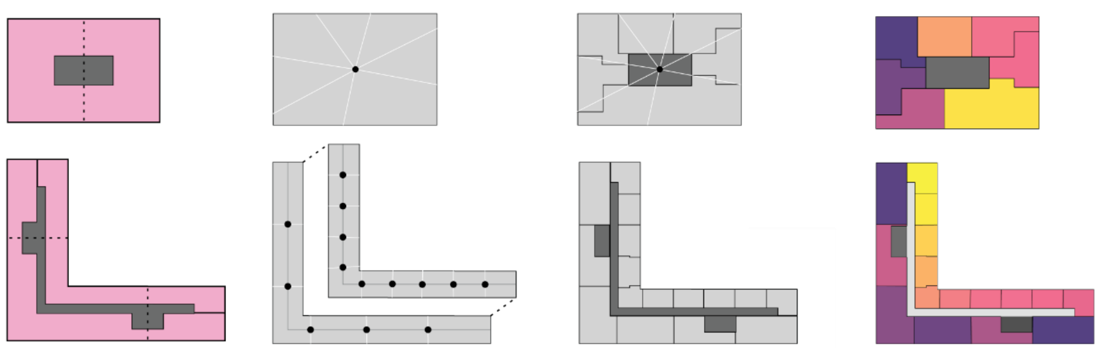

Figure 6.6: Geometric subdivision of an input geometry to represent a building layout with circulation and apartment units (a-h).

6.3.5 Internal Layout

To create the internal layout and full floor plan of the building, the programmatic layout is subdivided into rooms via the hypergraph representation (Weber et al., 2024). As shown in Figure 6.7, a hypergraph can be applied to a unit boundary to subdivide it into an apartment floor plan. The hypergraph is an encoding of a binary space partition tree and an adjacency graph that can be applied to any given boundary polygon. For this, reference floor plans, with hypergraphs generated from existing apartments, are used. The reference library with ~1,444 floor plans consists of vetted architectural floor plans from literature (Stamm-Teske et al., 2010; Zapel, 2017), as well as residential developer plans (Badger & Buchanan, 2023).

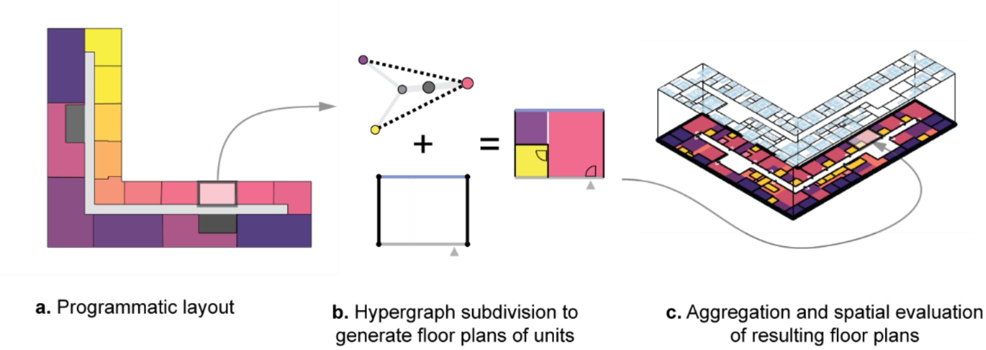

Figure 6.7: Creation of floor plans from programmatic layout (a-c)

6.3.6 Alignment Procedures

To increase the alignment of the structural grid and internal layout, an alignment procedure utilizing the snapping algorithm (Figure 6.4) can be deployed, where the structural can be adapted to the programmatic layout or the resulting subdivided floor plans adapted to the structural grid. In building retrofits, the structural grid is often a fixed constraint where changes would be very costly, and often times the program must adapt to it. The success of the alignment is determined by the structural layout intersection score as outlined in Equation 6.1.

$$L(D) = \frac{C_{inside}}{C_{All}}$$

Equation 6.1: To get the structural layout intersection score L of a floorplan subdivision D, the number of columns inside a space C_{inside} are divided by the total number of columns C_{All}. Inputs for the subdivision can be either fully subdivided floor plans or unit circulation layouts.

The alignment workflow with resulting layout intersection score is further illustrated in Figure 6.8, where an initial programmatic layout is first adjusted to a structural grid, the structural grid adjusted to the layout, and the final floor plan subdivision adjusted to the structural grid – resulting in a final building layout that minimizes column intersections with interior spaces. As shown, the snapping procedure can increase the structural layout alignment score substantially while only minimally affecting the spatial layout.

6.3.7 Furniture Ratio

To create a linear scale that would compare different unit floor plans based on their interior layout, the furniture ratio is described in Equation *6.2*. The ratio is dependent on the number of rooms in the apartment as it prompts a different furniture area. The furniture ratio could be adapted to use more nuanced furniture layout algorithms, but for the scope of this research, it was restricted to the standardized apartments described in section 4.2.9 of the dissertation.

$$F = \frac{A_{furniture}}{A_{standard}}$$

Equation 6.2*:* To get the furniture ratio F the sum of the furniture area in the given unit is divided by the area of the furniture in the standard unit (as described in section 4.2.9).

6.3.8 Building Layout Tested for Retrofit

As a real-world case study building for a retrofit, the office to residential retrofit of 1616 Walnut Street in Philadelphia is used. The retrofit process of the office building, constructed in 1929, was clearly documented (Badger & Buchanan, 2023) and serves as a comparison for artificially generated programmatic layouts and floor plans. Its relatively narrow floor plate of 17x40m makes it an ideal candidate for conversion into residential units, with ample daylight available Figure 6.9. The real floor plan can be further compared to artificial ones created using the generative geometric algorithms.

6.3.9 Evaluation

The procedural geometric workflow allows the testing of different spatial proposals. To rank different floor plans and test them for feasibility, a variety of spatial and environmental metrics can be deployed. The hypergraph floor plan evaluation techniques outlined in chapter 4, such as the perimeter difference score with the original reference floorplan, can be utilized (Weber et al., 2024). Furthermore, placing furniture inside each apartment results in a resulting furniture area that we can compare to the required minimal furniture area of the number of the apartment according to its number of bedrooms (Studio 21.4m^2, 1 BR 33.4m^2, 2 BR 45.4m^2, 3 BR 58.2m^2, 4 BR - 66.2m^2, 5 BR 74.2m^2). The ratio of actual to required minimal furniture area can then be benchmarked against the real-world floorplan. Furthermore, the spatial daylight autonomy (sDA) is computed for each apartment, measuring the percentage of space with more than 300 lux for rooms with daylight need (bedroom, kitchen, living, foyer). In the last step, the structural layout alignment is computed for the final floorplan to measure intersections with the load-bearing columns.

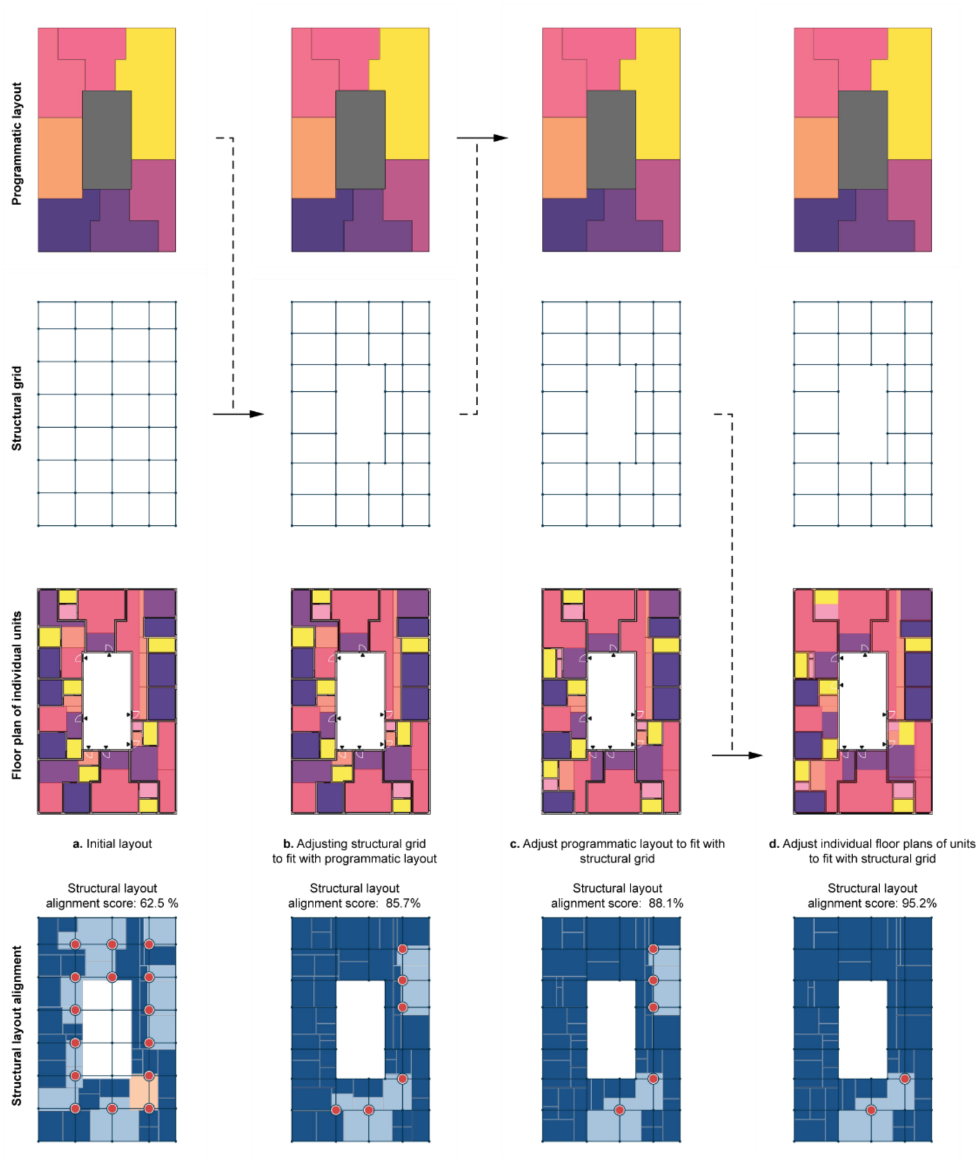

Figure 6.8: Snapping algorithm for bidirectional alignment, where a secondary geometry, for example a structural grid, can be used as input axis to align an input geometry (a) to a desired grid (b-e). The layout intersection score is given as a percentage of columns not intersecting with rooms in the building, with red dots marking the columns that intersect a room in an apartment floor plan.

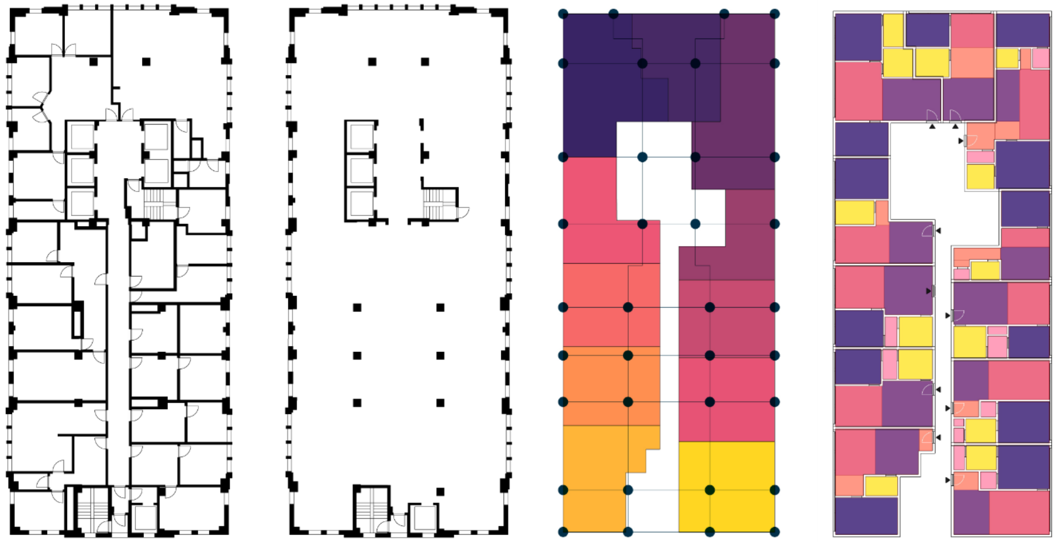

Figure 6.9: Real world office building converted into residential units. Seventh floor shown for evaluation of developer designed residential floor plans (Badger & Buchanan, 2023).

6.4 Results

For the existing office building, 100 different apartment subdivisions were generated and evaluated for performance. For each apartment unit in the programmatic subdivision, a floor plan with the lowest perimeter score difference (see Chapter 4) was evaluated for daylight using the sDA metric. Furthermore, occupancy of the floor plate with the proxy of the total number of bedrooms is measured for each of the iterations. The result, as illustrated in Figure 6.10, shows the large potential for generating design options with better daylight than the reference floor plate.

Of all layouts, only one possible floor plan layout of the units was chosen for daylight and spatial analysis, there, different unit geometries had a few possible subdivisions while others had hundreds of possible infill options. Not all layouts resulted in a feasible or complete layout, the random linear subdivision resulted in ~60 % of unit circulation layouts that did not have access to the interior building circulation. In those layouts the inaccessible units were not placed, resulting in a single apartment with 0 sDA in Figure 6.10d.

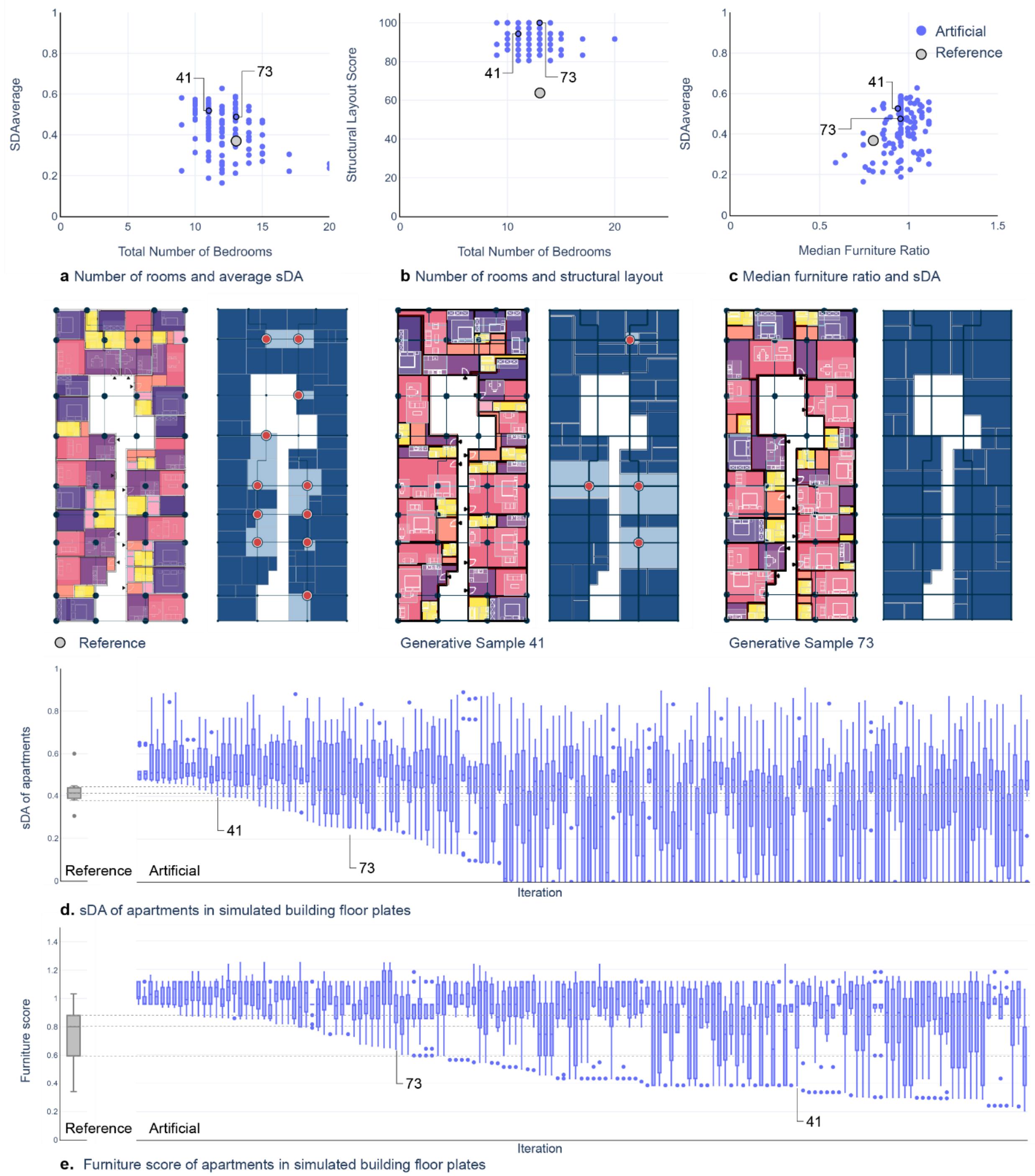

Figure 6.10: Design space exploration of artificially generated floor plates of a converted residential building. The different iterations are compared in terms of number of rooms and daylight in (a), structural layout (b). Furniture ratio and daylight are shown in (c). (d) shows the distribution of daylight from all generated floor plates and (e) the distribution of the furniture score.

6.5 Discussion

This chapter demonstrated applications for synthesizing spatial and environmental analysis workflows for the design of building retrofits. The case studies build on the previous chapters that introduced the hypergraph for automated floor plan generation, as well as procedural geometric workflows. Computational workflows offer pathways for integrating machine intelligence into architectural design workflows. Computational design methods can create thousands of possible building geometries and with it, large design spaces for exploration. This highlights the need for developing holistic building performance metrics that could be used to evaluate digital building models in future research. The speed of generation makes the methods feasible for generating diverse synthetic data for machine learning, speeding up future design workflows with surrogate models. The automated nature of the process creates the possibility to test different structural and material systems and their impact on whole buildings and overall performance. While currently only a simplified steel frame structure with a concrete core is shown, alternative material systems can be explored using the same processes.

In the evaluation of building retrofits, the workflow showed potential by creating significantly more performative design solutions as compared to the built designs. The results showed how typical fitting concerns for building retrofits could be avoided altogether through iterating through a large geometric design space. Furthermore, the generative design method enabled comparing between different buildings to evaluate retrofit opportunities at an urban scale, as well as testing of various alternative circulation strategies.

The investigation prompts more research into procedural mapping and comparison of circulation typologies and program configurations. It enables the potential for analyzing building stock in fine detail and evaluate future urban configurations, or the impact of zoning regulations from an occupant and carbon perspective. Typically, economic or political forces determine the unit mix and programming of buildings.

The research shows the potential of thinking about the building program from a performance perspective, evaluating how programmatic changes could mean less conflict with an existing structure for building retrofits, or enable greater daylight access in certain building geometries. New types of flexibility metrics could show the tradeoffs between keeping an existing structure and potential adaptability or infill potential, investigating if and how embodied carbon and spatial configurations are related.

Currently, the geometric workflows are experimental in nature and not ready for wide distribution in architectural practice. Furthermore, building codes (fire, egress) and ADA requirements are currently not included in the geometric computation, limiting the analysis to simplified geometry. Further investigations could include evaluating layouts for their flexibility to accommodate different layout configurations.

6.6 Outlook

Building retrofits are a defining challenge of urban centers and the built environment in the next decades. Investigations into new computational processes that can help us better understand the potential of the existing building stock have the potential to prompt more adaptive reuse. Future research could address how design automation methods of single buildings can inform zoning policy or urban design on a neighborhood or city scale. Spatial scenarios that allow insights of design decisions on daylight and occupancy of a building could improve decision-making processes at scale. Layout automation could be used to identify possible candidates for retrofitting and adaptation, depending on the desired unit mixes or scale of the retrofitting intervention. Furthermore, augmenting the full digital models with detailed material quantities of the fit out would allow for accurate prediction of the embodied carbon impact of a building retrofit. This could allow for studying trade-offs between embodied carbon and spatial intervention.

7. Conclusions

This dissertation has argued for the automated creation of detailed geometric models in early-stage design of buildings to help inform design decisions towards lowering carbon emissions and increasing user comfort. It presented opportunities for design automation and gave an overview of different technical methods for the automated design of building floor plans. With the hypergraph, it showed a new algorithmic workflow that can be used to generate, evaluate and represent existing floor plans. Furthermore, it outlined how structural simulations can help identify and lower the embodied carbon of a building and can be combined with energetic and spatial models. This final chapter presents concluding remarks, applications of the proposed strategies, as well as their limitations, and lays out future work.

7.1 Contributions

7.1.1 Contributions to Computational Design

The dissertation contributes to computational design in a methodological sense, by creating new frameworks and approaches for architectural design that can leverage machine intelligence, challenging prevalent design practices. Different theoretical frameworks that support, replace or rethink traditional digital design methodologies are discussed. The thesis contributes to expanding the scope of building design automation from a purely computational pursuit that aims to create believable floor plans or explores building geometries formally, to an architectural framework that can leverage spatial and environmental simulations for exploring new, performative designs.

Furthermore, the dissertation contributes new computational models that can be used to represent building geometries. Especially for early design stages, the new algorithmic processes can help to predict spatial implications of design choices. Expanding on traditional modes of digital representation borrowed from different disciplines, the hypergraph, as a spatial method of representation, was developed with the representation of building floor plans in mind. Drawing on the design tradition of referencing existing building geometries in architectural design, the hypergraph allows a translation of the referential way of working into the digital. This enables unprecedented quantitative assessment of architectural designs. It shows the potential of utilizing generative algorithms not only for the development of new designs, but for the analysis and comparative assessment of existing buildings.

Automated geometric procedures allow for the rapid exploration of different designs, while adhering to high-level constraints. The geometric algorithms expand existing workflows, allowing the creation of more diverse and differentiated design spaces for building designs. Contributing new methods for design discovery, this further expands the ability of architects to test different and more design ideas in the creation of buildings. Applicable to not only new, but also existing buildings, through geometric constraints, these methods contribute new workflows for the design of building retrofits. The methods can contribute to different steps in the design process: from early stages where the building massing is chosen, to later design phases where different interior configurations are assessed or explored.

7.1.2 Contributions to Structural Design

In engineering, decarbonization efforts often focus on specific materials or construction systems. This emphasizes carbon reduction strategies such as low-carbon concrete mixtures, reuse of steel elements, or shape optimization to lower material use in existing material systems. However, the impact of architectural and spatial programming on the structural material requirements, as well as construction system design choices are typically hard to compare and understudied. This dissertation contributes to further the understanding of carbon implications of different structural typologies, material systems, as well as spatial design choices.

Generative modeling is introduced as a new analysis methodology to help estimate material quantities and predict the impact of structural system design choices. The dissertation showed how fast FEA methods, typically deployed for dimensioning and analysis of structural elements inside a building, can be used for estimating structural material quantities. This was demonstrated with a high degree of accuracy and high-level inputs, using real world reference buildings. While geometric models are usually deployed at the end of the building design process to measure carbon impacts with detailed LCA analysis, deploying material quantity estimation methods at the outset of the building design process, allows guiding of design decisions in the earliest stages of design. While digital twins are typically created as a virtual copy of an existing design after construction, the work showed the potential for creating detailed geometric models in the beginning of the design process. As a new paradigm for estimating building performance, this gives architectural designers and engineers a tool for more accurate benchmarking of the influence of structural and architectural design choices on their building.

By utilizing a bottom-up approach for material estimation, the dissertation contributes to structural design of low carbon buildings. This research emphasizes the importance of understanding how the internal configuration of a building is in a dialogue with its structural system. This vertically integrated building model creates the opportunity for comparative evaluation and the possibility to utilize quantitative metrics during all stages of the design process. The dissertation introduces methods that can contribute to building retrofits within existing structural systems. By creating new geometric procedures that allow for aligning structural grids with spatial constraints and vice versa, existing buildings can be assessed quantitatively, weighing carbon with spatial benefits.

7.1.3 Contributions to Building Energy Modeling and Sustainable Design

The dissertation introduced the hypergraph as a new representation for interior architectural floor plans of buildings, as well as different geometric methods for creating simplified programmatic subdivisions of circulation zones and units within a building. Typically, simplified geometry with a shell and a core is input as zones into a building energy model. Using a more accurate representation of zones that reflect actual building geometry and internal configuration can factor into more accurate building energy models and energy use predictions across scales. Furthermore, more accurate geometric representation of individual rooms allows for more accurate daylight modeling, revealing opportunities in the design of new buildings, as well as more accurate assessment of existing building stock. Building energy models are key for creating sustainable buildings and their automatic generation via the hypergraph lowers the barrier to entry and allows for faster and more accessible use.

7.1.4 Linking architectural space, structure, and physics

The dissertation contributes to enabling new types of workflows that link space with structure and performance analysis, in turn facilitating new forms of spatial computation. On a technical level, these interdisciplinary modes of design and analysis are enabled by geometric algorithms, data structures, and design space optimization methods introduced in the dissertation. On a methodological level, the dissertation showed the importance of considering buildings as a whole when aiming to reduce carbon emissions. Importantly, the performance optimization of building envelopes or structural systems must be considered in tandem with the architectural space and building layouts. Using a digital, full building model that includes structural material quantities, operational energy requirements, as well as spatial metrics, allows for a better understanding on how design decisions impact carbon emissions and indoor comfort to enable sustainable building design. The hypergraph, introduced in Chapter 4, enables the automatic generation of building energy and daylight models for design. On an analysis side, the new modes of representation allow quantitative analysis of building layouts at scale, showing how architectural space can be the driving factor for sustainable performance and outperform savings from building envelopes. On a design side, the automatic creation of environmental analysis models enables lowers the barrier to obtain feedback on daylight or energy use, allowing for quicker design iterations and considerations of energy use or daylight in the earliest stages of design. Chapter 5 showed how interior organization and layout through spans inside buildings are key for lowering embodied emissions from structural materials. This contributes to the ongoing discussion of how we want to benchmark and certify the sustainability of buildings and how building policies must reflect spatial use as a significant driver of sustainable construction.

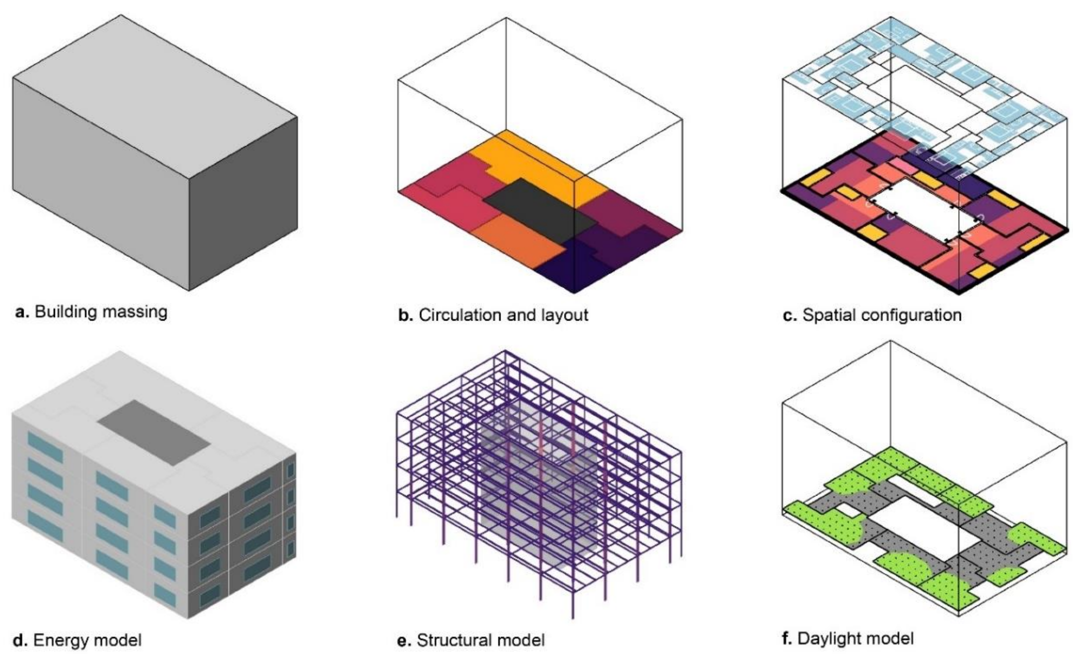

Figure 7.1: From a building massing, (a) detailed geometric models are automatically generated, including; circulation and layout (b), spatial configuration (c) energy model (d), structural model(e) and daylight model (f).

7.1.5 Learn from existing buildings to propose new design solutions

The hypergraph as a new descriptive and generative representation mode allows for new types of digital workflows that make use of a referential way of working. As shown in Chapter 4, the hypergraph enables the creation of scalable databases that can be searched and sorted by key parameters and evaluated for building performance. The capturing of existing spatial configurations and their transfer into new boundary conditions creates opportunities for a fully digitized way of working with architectural precedents. As a data structure, the hypergraph allows for source attribution of designs and for new types of hybrid workflows, where existing layouts can be modified to fit new boundary conditions, creating new hypergraphs, while building up on existing design intelligence. The dissertation proposed new ways how we can learn from existing urban environments, capturing and benchmarking different prevalent apartment typologies and configurations, to gain new insights into their spatial performance.

7.1.6 New metrics for quantifying how space is used

The dissertation proposed new metrics and design evaluation workflows that can analyze buildings from a spatial perspective. By automating manual methods of spatial assessment through interior fit outs and furniture blocks, Chapter 4 presented automated ways to quantify performance beyond square footage. The research showed how this could be used to benchmark different surveyed designs and for assessing artificially generated layouts. The furniture blocks can be adjusted to fit different cultural requirements. This interior assessment, coupled with the hypergraph representation, makes it possible to compare floor plans that are geometrically and topologically different from a spatial perspective (Figure 7.2). The work highlights the importance of spatial utilization, being connected both to building energy use and operational emissions through area that is heated or cooled, as well building materials and embodied emissions through a building’s structure.

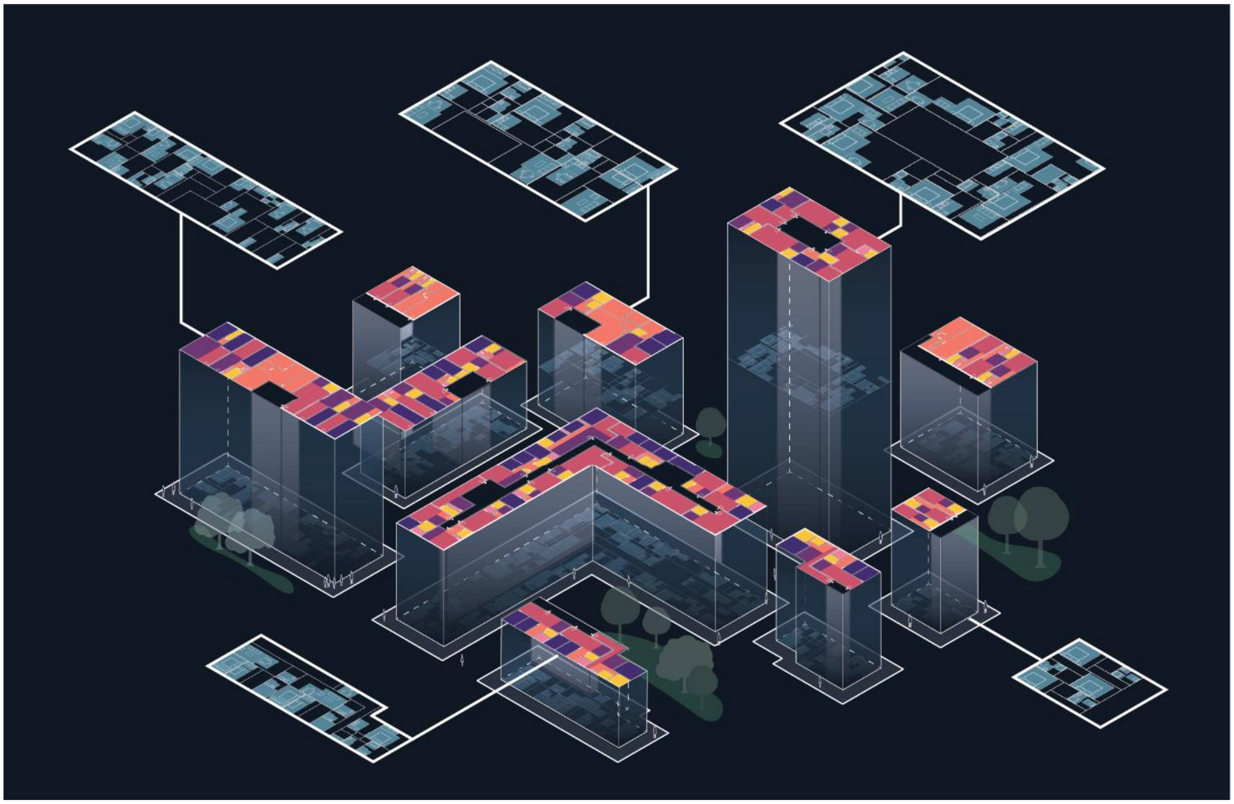

Figure 7.2: An illustration showing different buildings with their artificially generated residential floor plans that are analysed spatially.

7.2 Limitations and Future Work

In this dissertation, different methods for digital spatial and structural representation of building geometry have been developed. Even though the presented digital studies were created through automated workflows, in the scope of this research the algorithms remain technical experiments that will require significant developments for stable implementations that could be deployed in industry. On a computational side, cloud-based workflows with parallelized processes can be used to create faster user feedback and speed up simulation workflows. As the computational concepts are platform independent, future web and local software tools could be used to interact with the generative workflows that were developed in this dissertation, from structural material quantifications to the hypergraph floor plan layouts.

From a software perspective, the shift from a drawing tool to a design environment, where simple geometric forms can be assessed for feasibility or carbon impact, is significant and will necessitate future development and research. New design environments in which designers not only interact with geometry, but also with data, are needed. Current environmental and structural simulation tools that are paired with design environments, such as Karamba (Preisinger & Heimrath, 2014b) or Climate Studio (Solemma, 2023) in this dissertation, are third party software packages that take geometry as an input and deliver numbers as output, be it the energy use intensity (EUI) in kWh/m2 of a building or structural material quantity in kg. In architectural design, however, a single quantifiable unit is not sufficient to assess designs. Different metrics are not comparable or quantifiable in carbon, such as daylight, or quantifiable at all, such as architectural expression, yet are as important for the ultimate quality of a building and the life of its inhabitants. Research showed that there is typically no silver bullet for a sustainable design and many different design solutions lead to comparable results that use less embodied and operational carbon, presenting a huge opportunity for architectural design and expression (Weber et al., 2022a). This highlights the importance of visual comparison, opening up new research avenues for tailoring and teaching preference in hard to quantifiable variables to machine learning models. Furthermore, it highlights the importance of specifying and creating new metrics that can navigate large design spaces.

Digital parametric workflows, such as the programmatic subdivision for residential buildings, as introduced in Chapter 6, are highly prescriptive, specific, and unable to represent all possible design solutions. Randomized sampling of possible designs might lead to a highly differentiated design space, however without the guarantee that a good solution is present. Furthermore, the automatic and fast creation of different iterations or design options creates very large design spaces with massive amounts of data, as well as different, and often conflicting parameters. New procedures must be developed to sort, categorize, evaluate, and filter successful design solutions and create geometric computation that ensures novelty and diversity in design output.

The present implementation of the hypergraph method has some geometric limitations. The current method could be extended and generalized to enable the application on larger floor plans that encompass multiple apartments or a whole building in a single hypergraph. Furthermore, since all hypergraphs in the dissertation have been extracted from existing apartment floor plans, there is an opportunity to optimize and create hypergraphs themselves artificially to explore new typologies or adapt a graph to a new boundary condition. Future work should address how such graph-based procedural design workflows can be augmented and automated through machine learning algorithms.

The computational workflows presented in the dissertation enable the automatic creation of detailed building energy models with zones that reflect actual building geometry and floor plans. This will enable new opportunities and future research for naturally ventilated buildings. In natural ventilation, the configuration of rooms is decisive and more detailed zoning could include different levels of simulation into the floor plan assessments, from rules of thumb to detailed airflow networks inside of a whole building. Automated floor plan creation was primarily used as a building performance analysis and benchmarking tool in this dissertation. When designing new buildings, future work should address in more detail how construction systems and spatial configurations of buildings relate and how they can be used to design more affordable and low-carbon housing.

Currently, architectural designs are mostly disseminated through analogue publications of project drawings in different levels of details, with architectural publishers ultimately responsible for professional peer review and critique of designs. In the digital age, new questions regarding ownership, dissemination, and biases emerge in architecture that are already heavily debated in other disciplines. Currently there are no accessible, curated, digital databases of designs, a significant hurdle for deploying automation methods such as machine learning algorithms. Meanwhile, the databases that do exist have been collected without regard for architectural quality or location, which is highly problematic as they are used in active research. Future work further needs to address the problems with authorship of digital designs that emerge from machine learning algorithms. While the hypergraph method presented in this dissertation allows for a clear source attribution, other machine learning methods do not. Research and debate within the discipline need to address what it means for architecture discipline if design ideas can be copied easily. With the wealth of data and new quantitative comparisons and opportunities, the discipline must rethink what good design is and how to judge it and furthermore learn from existing buildings and cities what makes them performative.

The dissertation established bottom-up models as an important tool for architectural design. Future work should address the spatial impacts of low-carbon building design in terms of material efficiency, operational energy expenses, and user comfort. The digital and physical world are converging with better models and better predictions, that make the impact of design decisions visible. There, fast and accessible analysis tools are critical in making information that requires specialized engineers, such as natural ventilation or indoor comfort to everyone, and helps designers build an intuition to spatially respond to it. However, with models getting more and more accurate there is the risk of an increased confidence in computational simulations where designers become unaware of its limitations, such as structural simulations that use idealized material properties and do not take construction details into account or building energy models where user behavior and schedules are critical for accurately predicting energy usage.

The dissertation has evaluated building performance on the level of a single building. However, to address carbon emissions globally, grid level emissions, as well as locally available materials can be crucial for design, system, and material choices on a building level. It is important to understand a building as part of a region, city or neighborhood. More research needs to address the impact of urban morphologies and interactions between buildings in terms of material flows on carbon emissions. The urban fabric of a city with its density and program dictates lifestyle choices such as transportation modes that can have significant secondary level effects, integral to urban life and development.

7.3 Concluding Remarks

The dissertation presented a new framework for architectural design that enables the consideration of spatial, structural, and energetic constraints in the early stages of the design process. Introducing generative modeling not only as a design but analysis tool, allowed for new insights into building performance and pathways for low carbon buildings. The quantitative analysis of residential buildings in cities around the world showed the importance of space and architectural design for sustainable construction. Spatial efficiency and programmatic layouts are inherently linked with a building's structure, the embodied emissions, and its energy consumption – sustainable design of buildings is inherently architectural and cannot be achieved as a technological after thought.

Computational design has enabled architects to imagine every possible formal idea. In fact, many of the tools, workflows, and geometric concepts utilized in this dissertation were originally developed for exploring and fabricating highly complex geometry and experimental construction systems. There is nothing we cannot build. However, the better questions are: how and what should we build? How can we best leverage our digital technologies and human design intelligence towards shaping our world for the better? By creating a spatial computation framework that integrates environmental, and structural analysis into design workflows, this dissertation hopes to inspire architects of the future to create buildings that can respond to the global challenge of building more, with less.

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