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ARCHITECTURAL DESIGN, BIM, AND ARTIFICIAL INTELLIGENCE: A REVIEW OF RULE-BASED AND MACHINE LEARNING APPLICATIONS

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ARCHITECTURAL DESIGN, BIM, AND ARTIFICIAL INTELLIGENCE:

A REVIEW OF RULE-BASED AND MACHINE LEARNING APPLICATIONS

A THESIS APPROVED FOR THE

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Abstract

Architectural design projects can reach high complexity, long lists of requirements and intricate architectural programs, require effective ways to assess and predict building performance. Building Information Modeling (BIM) has proven to be a valuable tool in improving the design process by offering a range of resources for managing geometric data and building performance. However, BIM's current limitations, particularly in terms of geometry and function representation and its ability to predict performance, hinder its full potential. In this context, Artificial Intelligence (AI) is presented as an opportunity to enhance BIM workflows. AI's capabilities in prediction, automation, and analysis have the potential to improve design processes, offering more accurate simulations and predictions. This research explores how AI can be integrated into BIM-supported architectural design by conducting a case study using early-stage design AI tools, specifically Autodesk Forma. The study examines how AI-powered design tools can assist in the creation of building designs that meet specific performance criteria, such as energy efficiency, sustainability, and compliance with local regulations. Through this case study, the research aims to provide insights into how AI is helping to refine the BIM design process and to uncover the potential of AI in overcoming BIM's limitations. Ultimately, the findings will highlight the growing role of AI in architecture and offer perspectives on its future integration into design workflows.

Chapter 1. Introduction: Current scene of Architectural Design

1.01 Introduction

Architectural design is a longstanding discipline that has existed for centuries. As society has become more complex, the challenges faced by the building industry have also increased, leading to a demand for more advanced design tools and methods (Chad B., 2006). Complex design problems are common nowadays. The presence of multiple systems—structural, HVAC, electric, plumbing, and telecommunications—can, for instance, become difficult to manage in projects such as hospitals or hotels, especially considering the demand for increasingly shorter delivery times.

While projects of relative simplicity can still rely mostly on the designer's background expertise (Dorst, 2019), for instance, a small house can usually be designed based on the personal knowledge and experience of the architect. In this type of scenario, the systems used are simple and relatively straightforward, with a reduced program that is usually repeated with similar outcomes. However, for more complex projects such as hospitals, airports, large office projects, or educational facilities, the personal experience and background knowledge of a single architect—or even a group of architects—may not be sufficient to ensure how well a particular design would perform over time. The intricate interdependencies between systems, as well as the complex functional relationships within architectural programs, pose a design problem in which human cognition alone cannot process and predict the implications of so many factors.

An example of design complexity in the current design scenario is prefabricated/industrialized design. From the use of industrialized products in construction to the complete production of prefabricated buildings, prefabricated components need to be selected, combined, and configured based on a combination of requirements and inter-system compatibility (Smith et al., 2010). Prefabricated products are combined with other prefabricated products or on-site elements to shape a building. These different elements play different roles in the building—structural, enclosure, MEP, divisions, and finishes—while different product options and specifications increase the possible number of combinations as well as the number of possible interdependencies between systems. With an ever-growing number of building products, systems, and construction technologies available on the market, it could be argued that professional expertise alone might not be sufficient to address the complexity of the decision-making challenge posed. Therefore, new design tools are needed to better inform the selection, combination, and configuration of building systems and components to appropriately fulfill project requirements.

To overcome this problem, it is necessary to provide designers with the capabilities to improve collaboration among disciplines so that the selection and integration of different building systems can be made from multiple functional perspectives (Morin & Romero-Torres, 2024). To that end, the use of design tools that can reliably simulate and predict the performance of a proposed building design is paramount. Computational support has been developed over the last two decades to provide this type of support, allowing the development of simulation models that can predict , with a certain degree of accuracy, the implications of various design decisions from multiple perspectives. In this regard, computational tools may offer more consistent and collaborative design platforms by enabling different stakeholders to evaluate and compare building performance before committing to a particular choice.

Building Information Modeling (BIM) has been described as “a digital representation of physical and functional characteristics of a facility creating a shared knowledge resource for information about forming a reliable basis for decisions during its lifecycle, from earliest conception to demolition” (National BIM Standard US, 2023). BIM has been used in architectural design for almost two decades as a support technology for the design process. BIM allows design to represent project-relevant data in a computational and machine-readable model, which enables a better representation of the project in an intelligent and non-redundant way. This includes not only the representation of geometry but also non-geometric information, such as requirements, along with other functional and performance-specific data. Moreover, it provides a centralized platform for collaboration between professionals and disciplines, which improves communication and the sharing of project data.

Despite the valuable capabilities that BIM offers to design and its widespread adoption in the AEC industry, it still has important limitations. Two key shortcomings are worth mentioning here. First, BIM provides only limited capabilities for design automation beyond parametric, rule-based modeling, and custom scripting. Second, it offers insufficient interdisciplinary support for systems integration. In particular, BIM tools lack a consistent framework for predicting and explaining building performance from a multi-system and multi-scale perspective. This limitation affects the level of support BIM can effectively provide for interdisciplinary collaboration, process automation, and decision-making, as negative interactions among different systems cannot be readily understood.

Recent technological advancements have introduced Artificial Intelligence as a tool which can provide resourceful capabilities to overcome BIM lack of prediction, automation and decision-making support capabilities. Artificial Intelligence refers to the concept of 'a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments' as defined by the US AI act (*National Artificial Intelligence Initiative Act*, 2020). AI's predictive capabilities have already been established in other areas such as medicine, business, and finance. The positive impact AI has had on improving efficiency and effectiveness in predictive workflows—such as cancer detection in medicine—supports the idea that AI could be used in architectural design. The potential that AI offers in enhancing architectural design through performance prediction and automation is the focus of this thesis.

The subsequent sections of this chapter will provide an overview of concepts regarding architectural design that are considered important for achieving successful outcomes. These concepts will set the framework for how the design process is understood in this thesis and how design performance can be predicted and assessed. This is relevant to set the parameters for evaluating AI's potential benefits to the design process. First, the design process will be considered under the ontology of Structure, Behavior, and Function (SBF) (Goel et al., 1997) In this framework, design is characterized as a propositional process, where the proposed building is expected to fulfill a set of desired functions. Based on this framework, performance will be studied as the measurement of how well the proposed design fulfills the desired function. Performance is considered a key concept (Augenbroe, 2019); this thesis will focus on two main approaches that ensure performance requirements are met. On the one hand, structural constraints set parameter conditions that limit design possibilities to ensure functional goals are achieved. On the other hand, performance-based design uses simulation and prediction to assess how the proposed design meets the required project functions. Both approaches will be compared, with an argument favoring performance-based design as more effective in addressing complex design problems. Lastly, this thesis will highlight the importance of performance in guiding design-related decisions, such as suggesting appropriate strategies or validating decisions applied to the design.

1.02 The Structure-Behavior-Function (SBF) framework.

To understand how today's technological advancements may improve and support architectural design, it is important to define the goals that design supports and establish the parameters under which a successful design is evaluated. The Structure-Behavior-Function (SBF) Framework explains the elements that compose design from a high-level perspective. In the context of this thesis, it highlights the importance of function in design (Goel et al., 1997). The SBF framework is based on the SBF ontology, which characterizes design as being composed of three categories. In the case of architectural design, these can be defined as:

- Structure: The physical entity—in architecture, this would be a building.
- Behavior: The actions the structure enables, such as providing safety or shelter.
- Function: The set of desired behaviors for which the building is designed.

Considering these three concepts, it can be said that the goal of design is to fulfill a set of functions. Therefore, the role of designers is to propose a building that ensures these functions are met.

To further explain the SBF framework, a simple design object—a chair—can be used to illustrate additional concepts that ensure a building fulfills its intended functions. The structure of a chair consists of its physical form, which can vary in material, texture, size, and shape. The function it fulfills is seating. However, a chair may exhibit other behaviors, such as standing, being used as a table, blocking a door, making noise when dragged, or being easy to move.

These secondary behaviors may be positive or negative depending on the context of use (Gibson, 1986). For example:

- If a chair makes noise when dragged, this is generally undesirable.
- If a chair is easy to carry, this is usually beneficial.
- However, for outdoor chairs that should remain fixed, being easy to move would be undesirable.

This characterization allows design to be explained in terms of function and behavior, helping to determine how a chair should be designed to meet its intended function. For example, the primary function of a chair—seating—can be further refined to comfortable seating. Ensuring comfort requires considerations such as shape, material, and texture. A well-designed chair that optimizes these parameters would likely be comfortable.

However, other behaviors can also impact comfort. For instance:

- If a chair makes noise when dragged, it may be perceived as uncomfortable.
- If a chair is placed next to a bed but cannot be used to place objects, this could also be seen as inconvenient.

These relationships between different behaviors are called behavioral interactions (Cavieres, 2018). Even though a chair is a relatively simple design object, it still involves behaviors that can either interfere with or enhance its desired function.

To ensure a successful design, it is important to predict how well a proposed design will fulfill its intended functions. The concept used to evaluate the degree to which a design meets its intended function is known as performance (Augenbroe, 2019).

In architectural design, the object of design is typically a building, which varies in use, typology, size, and shape. The complexity of a design problem depends on these factors. Buildings fulfill multiple functions and are composed of various subsystems, each serving a specific role. For example:

- The HVAC system conditions air in terms of temperature, humidity, and ventilation.
- The electrical system supplies power for lighting, appliances, and HVAC.
- The building envelope separates the interior from the exterior, ensuring safety, privacy, and climate control.

As building complexity increases, the number of functions and behaviors also grows. Like the chair example, some behaviors may interfere with function fulfillment in buildings. Complex buildings introduce multiple behavioral interferences that must be carefully considered to ensure performance goals are met.

To clarify how behavioral interference can occur in a building, consider an office building equipped with an HVAC system designed to regulate temperature through a thermostat. The system is programmed to maintain 75°F by adjusting its power output accordingly.

However, occupants report that the HVAC system fails to maintain a comfortable temperature, and the air is too cold. Upon inspection, the HVAC units are functioning correctly, but the issue persists.

The root cause is a behavioral interference between systems:

- The thermostat is installed near a copier, which generates heat.
- As a result, the thermostat detects a higher-than-actual room temperature.
- The HVAC system responds by overcooling the space, leading to discomfort.

This example highlights how different systems interact within a building and how unintended behaviors can impact performance. Proper analysis and planning are crucial to ensure that design goals and performance requirements are met.

Given the complexity of modern buildings, computational tools can help designers assess and improve performance. The next section will compare two different approaches to ensuring performance goals are met:

1. Constraint-based design, which sets parameter conditions to limit design possibilities.
2. Performance-based simulation, which uses computational models to predict and assess design outcomes.

1.03 Constraint-based vs. performance-based design.

As defined in the previous section, performance is characterized by how well a building fulfills the functions and requirements it was designed for. However, different design approaches exist to ensure that a design meets its intended functions.

On one hand, there is the constraint-based approach, which uses predefined restrictions to ensure that all possible solutions inherently fulfill the desired functions (Gao et al., 2020). On the other hand, there is performance-based design, which relies on simulation and predictive tools to assess whether a proposed design meets its functional and regulatory requirements (Becker, 2008).

Both approaches can be found in architectural codes, which establish minimum standards for buildings to ensure accessibility, durability, safety, fire resistance, and other essential qualities. However, different codes use different methods to guarantee compliance:

- Constraint-based codes impose specific dimensional, material, or typological restrictions. For example, they may specify maximum egress path lengths for fire safety or minimum restroom dimensions for ADA accessibility.
- Performance-based codes define functional requirements without prescribing specific geometric, material, or typological solutions. Instead, they require designers to demonstrate that a proposed design meets the required performance levels through analysis or simulation(Kennon & Harmon, 2018).

A comparison between these two approaches can be seen in daylighting regulations. A constraint-based code might mandate that window openings must equal at least 10% of a room’s floor area to ensure adequate daylighting. A performance-based code, however, could instead require that a minimum illuminance level be met within the space, allowing designers flexibility in achieving this through larger windows, skylights, or reflective surfaces.

While constraint-based codes provide clear and enforceable guidelines, they have limitations. Their binary nature means a design either meets or fails the specified constraints, without indicating how well it fulfills a function. Because these constraints are based on generalized conditions, they may not account for complex interactions between design elements. Additionally, as more variations are introduced to address different case scenarios, the regulations become increasingly complex and restrictive.

For instance, egress path regulations typically define minimum widths and lengths to ensure safe evacuation. However, multiple contextual factors—such as occupancy type, number of turns, floor material, temperature, air quality, glare, lighting, and noise—can all influence egress effectiveness. While codes attempt to address these variations by adjusting path dimensions based on building type or occupancy, fully accounting for all possible conditions would make them overly rigid and difficult to apply.

In contrast, performance-based design allows for a more adaptable and precise approach. By measuring and analyzing multiple factors, it provides a deeper understanding of how different design alternatives perform, rather than simply determining compliance with rigid constraints. Instead of imposing fixed dimensional requirements, it enables designers to explore customized solutions that optimize performance for a given project. Furthermore, it allows for the comparative analysis of different alternatives, making it possible to identify the most efficient or cost-effective solution.

Consider the case of a large hospital. Standard egress path dimensions may not account for patients requiring wheelchairs, those connected to medical machines, or individuals unable to use stairs. In such a scenario, performance-based simulations can model real-life evacuation conditions, considering the specific needs of different users. This approach also makes it possible to compare design alternatives—such as adding ramps versus incorporating fire-safe rooms—to determine the safest and most practical solution.

Performance-based design relies heavily on computational tools, as it requires simulations and quantitative measurements of design performance. (Augenbroe, 2019) outlines a structured approach to evaluating performance, which consists of four key steps:

1. Agreement on performance criteria and quantification: Establishing the required functional goals and measurable indicators.

2. Identification of key elements and parameters: Defining which building components and environmental factors influence performance.

3. Virtual experiments and simulations: Running analyses to predict how the design behaves under different conditions.

4. Quantification and stakeholder feedback: Evaluating results and using them to refine design decisions.

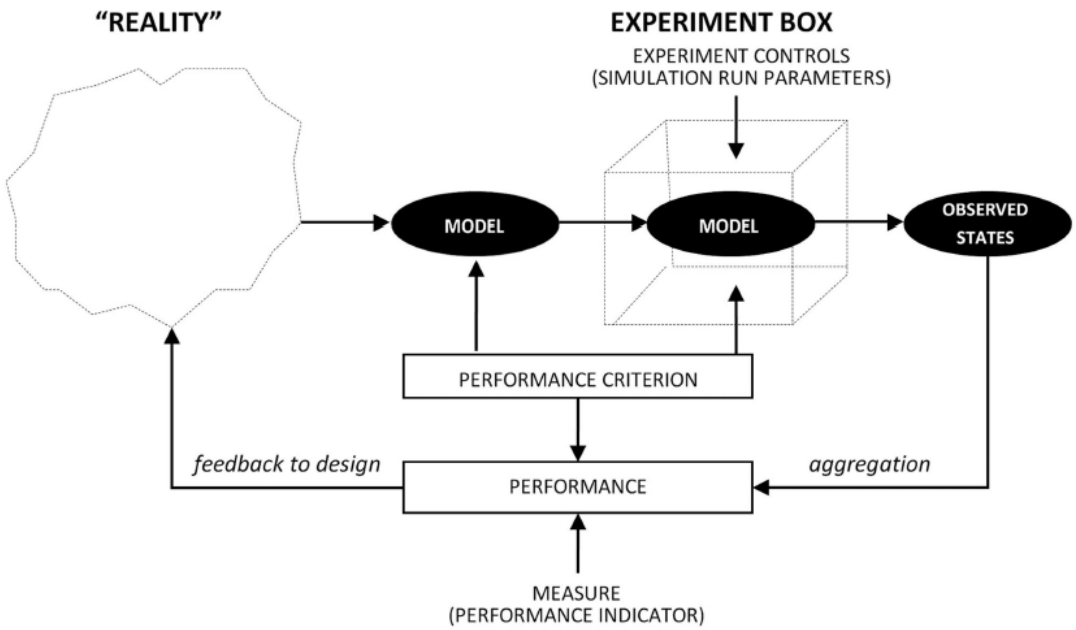


Figure 01.G. Augenbroe Performance experiment process diagram. (Augenbroe, 2019)

Figure 01 shows a diagram of the process of measuring performance. The main idea is that a model of reality is subjected to an experiment under a set of criteria parameters, and the observed values of these parameters are studied to analyze how well the model fulfills the desired functions. In the context of digital design tools, Building Information Modeling (BIM) models—a digital representation of a proposed building—allow for simulations to be digitally run and measurements of performance criteria parameters to be obtained.

It is relevant to point out that as important as simulation is, it is also crucial to establish an appropriate set of agreed-upon performance criteria. These criteria usually come in a set of parameters (performance indicators) and acceptable and optimal values or allowances. The criteria represent the desired state for the design, and the alignment of the design-measured parameter values with the criterion parameter values means that the design is fulfilling the desired goals.(Augenbroe, 2019).

Alternatives are compared and assessed by comparing the performance measurements and studying which one is closer to the performance goal. If we consider the previously mentioned case of prefabricated architecture, the multiple choices of industrialized products and their possible configurations can lead to a wide range of possibilities to decide from. Performing simulations can help decide which product or configuration is better considering multiple parameters. For example, if we consider a design alternative for a Structural Insulated Panels (SIPs) façade, a design team might want to study which configuration options performance based on different indicators, such as weight, price, or number of elements used in the combination. Considering that different elements have parameters values different configuration alternatives are produced trying to optimize the layout. Performance-based design would be capable of providing values of how much the different alternatives perform in the different established indicators. Once indicators measurement values are obtained, a process of benchmarking, can lead to an informed decision of which panel better fulfills the multiple desired goals.(Augenbroe, 2019) uses radar charts to compare design alternatives based on different performance parameters. Figure XX shows a performance comparison between a PV panel system and a green roof for a building considering five performance indicators: annual energy saving, acoustic comfort, lifecycle greenhouse gas emissions, extra structure load effect on cost, and maintenance costs.

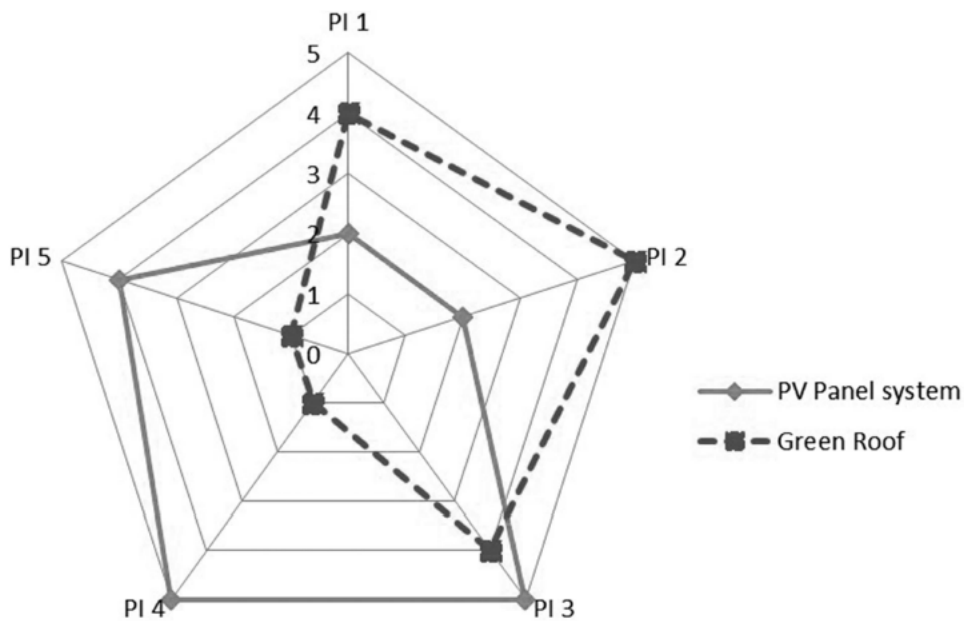


Figure 02. G. Augenbroe radial chart for multicriteria performance benchmarking. (Augenbroe, 2019)

1.04 Discussion: the importance of performance prediction in the design process.

Even though the design workflows can be iterative and may not follow a linear evolution, the overall design process has a linear structure, which potentially evolves from the early stages of design to a constructed building in use. This process is divided into different stages, where different milestones are reached as the projects advance. Complex architectural problems with numerous requirements and functions to fulfill require reliable and consistent performance predictions along the design process to make informed decisions.

The tools and methods used in the architectural design process are of great relevance, as their capabilities support a more or less effective and efficient process. The design process has changed and evolved based on the technologies that support it. Departing from hand-drawn plans, through CAD software, and nowadays BIM, computational technology developments have changed the workflows in architectural production. This evolution from non-computational design methods to computer-based tools could be associated with an evolution from descriptive design, through explicative design up to predictive design. Each of these steps in design represents a higher degree towards a more informed and performance-based design. Descriptive design refers to that level of design on to representing the geometric and material characteristics of the building; this level of design is not only representative of hand-drawn architectural projects but also CAD-drawn projects. Following the SBF framework, descriptive design limits the representation of the structure. Explicative design incorporates explanatory information about how a design behaves. Building Information Modeling (BIM) provides explanatory design capabilities to the design process. Even though explanatory design provides behavior explanation, it is predictive design that provides feedback on how a proposed design can potentially behave. This kind of design has the potential to support a more informed, performance-based design.

Predictive design is based on estimating in advance how a building will behave to increase certainty and obtain better results. These capabilities, as previously discussed, are supported by technical tools. BIM platforms represent a conceptual jump from CAD as they provide a centralized intelligent representation of a building, while CAD tools are based on computers representing two-dimensional documentation, or 3D geometry. BIM provides a parametric, centralized representation of a building, including its geometry but also characteristics, materials, and multiple other relevant non-geometric parameters and data.

Even though BIM platforms do not usually provide integrated predictive tools, the information modeled in BIM is usually exported to simulation models as an input to predict how the design will perform. Some examples of these simulative predictive tools include energy simulation tools, life cycle assessment tools, evacuation simulation tools, or solar analysis tools. Artificial Intelligence has one of its main potentials to provide predictions to support decision-making, in a more accessible and user-friendly way. The combination of AI with digital data models in BIM can potentially boost existing BIM capabilities to include predictive capabilities. By including predictive capabilities, performance-based design will be supported, and therefore, complex design problems will have more reliable outcomes.

Considering that BIM and AI can both support a more performance-based approach towards informed and reliable design, it is important to study both more in depth. The next chapter will focus on the role of BIM supporting the design process, both the capabilities that BIM contributes to and how the design process is structured when supported by its capabilities. This is relevant as AI will potentially not substitute BIM but complement it. An overview of Artificial Intelligence, including capabilities, benefits, current examples, and potential for architectural design, will be discussed in Chapter 3. Additionally, Chapter 4 will provide a case study on an existing design tool called Autodesk Forma to analyze and better understand how current AI tools are being introduced to architectural design, both by analyzing the tool itself and developing a design exercise using Forma as a design tool.

Chapter 2. Building Information Modeling (BIM)

BIM computational capabilities have introduced new benefits to the design process. Nowadays, complex design problems require intelligent and capable design tools to improve design representation and performance simulation in design. As buildings become complex, including multiple systems and elements, the tasks of selection, configuration, and performance simulation of elements and design alternatives become important and necessary. The surge of Building Information Modeling (BIM) in the last couple of decades has brought new digital representation capabilities for improving representation, selection, and integration of building systems and elements, along with simulation of certain performance aspects of a building. BIM provides modeling and decision-making support for all stages of design, including programming, conceptual design, construction, and building operation and maintenance (O&M).

BIM is both a computational modeling technology and process that allows the machine-readable, parametric-driven representation of building models. BIM also allows interoperability across different applications, including simulation applications to predict the performance of design alternatives during the design process. In this way, collaboration among different specialists can be supported in a way that improves project delivery. BIM platforms allow for centralized, non-redundant project representation in an intelligent way, allowing for improvement in project analysis, documentation, process automation, interoperability, and collaboration between stakeholders.

This chapter focuses on BIM as an enabling technology that improves the project delivery process, enhancing design, construction, and project O&M decision-making. The first section provides an overview of BIM capabilities and benefits. The second section describes the main characteristics of BIM platforms from a technical perspective. The third section focuses on BIM as a process, outlining different project delivery methods, main workflows and design stages, and the role of BIM in each of them. This chapter concludes with the limitations and potential of BIM, providing a basis for the next chapter, in which the potential of Artificial Intelligence will be discussed. To understand how BIM enhances project delivery, it's essential to examine its role as a platform. The previous section highlighted BIM benefits. The next section provides the technological foundation for implementing these advantages.

2.01 Benefits and capabilities of BIM

The National Building Information Model Standard Project Committee describes BIM as "a digital representation of physical and functional characteristics of a facility creating a shared knowledge resource for information about forming a reliable basis for decisions during its lifecycle, from earliest conception to demolition" (National BIM Standard US, 2023).

In literature, BIM has been presented in two complementary ways: as a process and as a technology. As a process, BIM enhances building delivery throughout its lifecycle (Abanda et al., 2017a). As a technology, it refers to the BIM platform, which serves as the vehicle for its implementation (Heidari et al., 2024). Computational capabilities have been present on the AEC industry already for several decades (Suzuki, 2021). Early Computer-Aided Design software (CAD) introduced basic forms of digital representation already in the 1970s, introducing tridimensional modeling, drafting automation along with overall project documentation. Soon after, interoperability between different applications along with centralized data management system became a relevant capability. However, Building Information Modeling (BIM) supposes a bigger conceptual and process change for design. Differently from CAD, BIM integrates data-driven workflows, allowing for improved collaboration, intelligent design representation, performance analysis, and lifecycle management. This shift transforms not only how designs are created but also how they are coordinated, analyzed, and maintained throughout a building's lifecycle.

There are three main benefits that BIM enables: parametric representation, simulation, and collaboration. BIM allows users to digitally create a model of a building where important parametric relationships can be established by means of algebraic or logical expressions. At the same time, BIM facilitates management of building data, including geometric and non-geometric data, allowing for more complete specification and processing of relevant information. Non-geometric data can include basic descriptions of requirements, function, material or process properties, among others. BIM interoperability allows for both synchronous and asynchronous exchange of information between different applications, supporting the use of advanced design analysis and simulation applications to evaluate building performance, which is necessary for collaborative decision-making.

One of the main characteristics of BIM is to provide a common project model (Abanda et al., 2017b), this digital model represents with different levels of detail thought a project the building itself A BIM digital model in centralized non-redundant, consistent thanks to automatic low-level correction. These corrections improve model coherence and consistency, all introduced modifications are automatically expanded in all model views.

Due to the general complexity of many projects nowadays, BIM-parametric representations have allowed for better processing and management of information with increasing levels of automation and consistency, helping to avoid many mistakes that were common when projects were completely developed using drawings and paper documentation.

A key technological aspect of BIM that has enabled such levels of automation and data consistency is the object-oriented structure of its models. According to the object-oriented modeling paradigm, a BIM model is described by a set of object types (i.e., called families in Revit). These high-level types describe basic categories of objects representing different parts of a building, which are then instantiated in a design file during a modeling session. A building model is a collection of different types of instances, and each instance can be further characterized by specific property values defined by either the user or procedurally by an algorithm (i.e., script). This object-oriented structure becomes relevant in the design of buildings, including some degree of prefabrication, as they are composed of instances of industrial construction products, which can be represented and configured using BIM object types and instances.

The second main benefit of BIM is the support it provides for analysis and simulation. BIM models can be used for analysis of multiple aspects of a project and to simulate its performance according to various types of requirements. Some examples of BIM analysis include structural assessment via frame analysis, quantity take-off and cost analysis, clash detection, and automated code-checking. Performance simulation applications include ventilation analysis via computational fluid dynamics (CFD), energy consumption, thermal comfort, daylighting, acoustic comfort, occupation, and circulation analysis via multi-agent simulations, to name a few. BIM simulations help to understand and analyze if buildings are fulfilling the desired requirements they were designed for. Simulation is related, therefore, to the measurements of performance; performance is characterized as how well a design fulfills a set of desired requirements. Simulation helps stakeholders to understand how a particular design alternative is going to perform, and how well it will meet different performance requirements. By knowing in advance how a design candidate will perform, and the implications of certain choices, decisions, and trade-offs can be made, improving the probability of desirable outcomes, and reducing uncertainty and risk. In the context of complex design problems, performance-driven trade-offs become especially relevant. When there is an intricate set of requirements that can potentially interfere with each other, performance analysis can help to better understand how design choices affect these requirements and make more informed decisions. This can help balance and consider multiple goals such as energy efficiency, functionality, comfort, cost, and aesthetics.

The third important benefit that has improved design is how BIM allows project stakeholders to collaborate. BIM provides a common digital space for representing, managing, and exchanging project data. By providing this common space, stakeholders can capture their project requirements from an early stage, while designers coordinate the integration of different building systems. A centralized representation not only of the project but also of its requirements, its goals, and objectives can help organize project workflows, the resources needed for each phase of the project, as well as the professionals required to provide technical support.

2.02 BIM as a platform

BIM is a modelling technology and associated set of processes to produce, communicate and analyze building models (Kumar, 2015). As mentioned in the previous section, BIM is a process which improves project delivery, and this process improvement is supported by the implementation of software, called BIM platforms. BIM platforms are computer programs that digitally represent the building geometry, characteristics, functions, requirements in a parametric way.

This section will study general characteristics and considerations of BIM platform's structure. It is relevant to study BIM platforms to better understand their role in the process of project delivery, which will be addressed in the next section. BIM platforms are computer programs that allow users to create a structured parametric model of a building composed of objects that represent building elements.

BIM models are characterized by being structured or divided into building elements represented by digital objects(Sacks et al., 2018), this means that each element is modeled as an instance of an object type. As such, building elements instantiate a set of properties inherited from the object type, with various property values defined by the user according to specific needs. Some of these properties' values can be established based on parametric relationships, which control the interaction with other building elements. An example of this can be a wall, where its height, width, and layer composition can be automatically established based on its location or connectivity with other elements. Parametric rules can also be defined regarding whether a wall can "host" other building elements such as a window or a door, a sink or a stair, or types of connections when it is intersecting with other walls. Parametric objects are crucial to BIM's structure. The BIM handbook provides some of the main characteristics of parametric objects; this can help to better understand how data is structured in BIM and therefore make better use of building data for processing it in performance analysis. The points provided by Sacks et al. are (Sacks et al., 2018):

- Parametric objects are geometric definitions with data and rules associated
- Parametric rules modify other adjacent objects
- There are different levels of association and hierarchy,
- Objects have the ability to receive broadcast, export sets of attributes.

BIM digital models represent a conceptual change compared to CAD models. CAD models represent geometry only, but without the specific building semantics. This means that the computer has no understanding of what the geometric element actually means, in terms of its function, spatial conditions or relationship to other building elements. In BIM, however, model elements carry building semantics, by being categorized by function and role inside the building.(Belsky et al., 2016).For example, a building element such as a single interior door is characterized in the model by its category 'door', which includes the rules that define where it can be placed (nested in a wall), its possible materials, role in the model, dimensions parameters, etc. These semantics are defined by an object-oriented schema at the core of BIM applications.

This conceptual difference between CAD and BIM digital modeling allows for more intelligent representation of buildings, in a centralized and consistent way, where elements have 'meaning' based on their inherited characteristics and role they play in the building. This semantic structure of a BIM model makes it machine readable (Sacks et al., 2018), providing the foundation for new forms of computational support and automation in the design process. However, meaning in BIM has also considerable limitations, as they are mainly limited to rule-based structural relationships. This lack of behavior modeling limits the capacity of BIM to assess behavior in a more consistent way, as it is limited to those structural relationships that are coded. Improving explicit behavioral representation in BIM would improve its performance assessment capabilities. The use of Artificial Intelligence in this behavior in BIM has been studied by several authors (Belsky et al., 2016; Cavieres, 2018) and is believed to have potential to improve its possibilities.

02.1 Simulation: performance assessment.

An important capability and use of BIM is the possibility of processing the model to simulate its behavior during its life and analyze how a design proposal may or may not fulfill the project performance requirements. Building simulation can provide stakeholders with insights about building behavior during early stages of design and benchmark the performance of different design candidates. Additionally, building performance simulation allows users to understand possible functional conflicts between competing objectives, enabling stakeholders to collaborate on trade-off analysis and decision-making (Augenbroe 2019).

Performance can be characterized as the measurement and study of how well a building fulfills the function it has been designed for. Measurement and analysis of performance become relevant to comparing and validating design options. The goal of a building is to serve a set of functions, therefore, to validate a design option as successful it is important to measure if the functions are being met and how well they are being met. To measure performance, a set of agreed-upon parameters are measured in a model (simulation).

These measurements of the parameters are then considered for making decisions about the object of study.(Augenbroe, 2019)

The main idea is that a model of reality is subjected to an experiment under a set of criteria parameters, and the observed values of these parameters are studied to analyze how well the model is fulfilling the desired functions. In the context of digital design tools and Building Information Modeling (BIM) models, a digital representation of a proposed building allows us to digitally run simulations and obtain measurements of performance criteria parameters.

However, current BIM simulation tools face limitations. On the one hand, simulations rely on simplified rule-based algorithms; oversimplification can sometimes lead to unreliable results. Moreover, these simulations are often time-consuming and require the input of several parameters. The need to define multiple parameters can potentially limit their use during early stages of design, as these parameters may not have yet been defined. On the other hand, as mentioned in previous sections, the limited representation of behavior in BIM limits its possibilities to account for behavioral interdependencies, which can become crucial for correctly assessing complex design problems. Therefore, if these behavioral interdependencies are not correctly addressed, the performance simulation results that may be achieved will potentially not be accurate. This limitation suggests that performance in BIM needs to be improved to be more reliable and accessible during early stages of design. Artificial Intelligence capabilities suggest that it could potentially improve BIM performance capabilities.

All in all, the BIM platform brings to the AEC industry numerous useful capabilities, which have the potential to improve the process of project delivery. BIM's parametric object-oriented structure, its centrality and interoperability as well as digital capability for integrated simulation, are some of the main characteristics of BIM. The next section will describe project delivery workflow and how BIM capabilities play a role in improving this process.

2.03 BIM as a process: Project delivery and building lifecycle workflow.

The project delivery process is based on a set of requirements for a proposed building. BIM works as a collaborative platform for project delivery, including a more complete and consistent representation of building elements, parametric automation, and interoperability to support advanced analysis and performance simulation. This section analyzes the structure of project delivery process to better understand how BIM digital capabilities affect each stage, and the limitations of current technologies. This will be the basis for later studying how Artificial Intelligence capabilities can improve BIM's role in project delivery workflow.

Project delivery encompasses the process from early predesign stages to the building handover. The design phase would include everything from conceptual design to construction documentation, and additionally to project delivery and design, we could also consider post completion stages, such as building operation and maintenance (O&M) and building repurpose and recycling, to cover the whole lifecycle of a building, where BIM capabilities are used. The outcome from each stage is transferred and used as input for another stage, with design, construction, operation and repurpose/recycling being approximately linear.

While the design process itself has a non-linear nature, a common workflow structure with different stages or phases is typically established, mostly for contractual reasons. These stages are often revisited, and it is common for designers to go back and forth. However, the stages represent milestones and greater levels of detail in the development of the project toward construction. The general phases during the project delivery process can be defined as pre-design, conceptual design, schematic design, design development, design documentation, and construction administration. Additionally, beyond these project delivery phases, we can consider building operation and building repurposing or building recycling as additional stages in the building lifecycle. It is relevant to consider all building lifecycle stages during design, as decisions taken during design can affect the correct functioning of the building in future stages of its lifecycle. Figure 03 depicts a diagram of the project delivery and post-completion stages.

BIM building digital models represent a common space for representation and simulation of the building being delivered, with an incremental addition of levels of development, in a collaborative and coordinated way between all the project stakeholders. Digital capabilities allow us to automate a great number of tasks, improving quality and efficiency. Moreover, simulation and analysis support decisions by increasing certainty and accuracy.

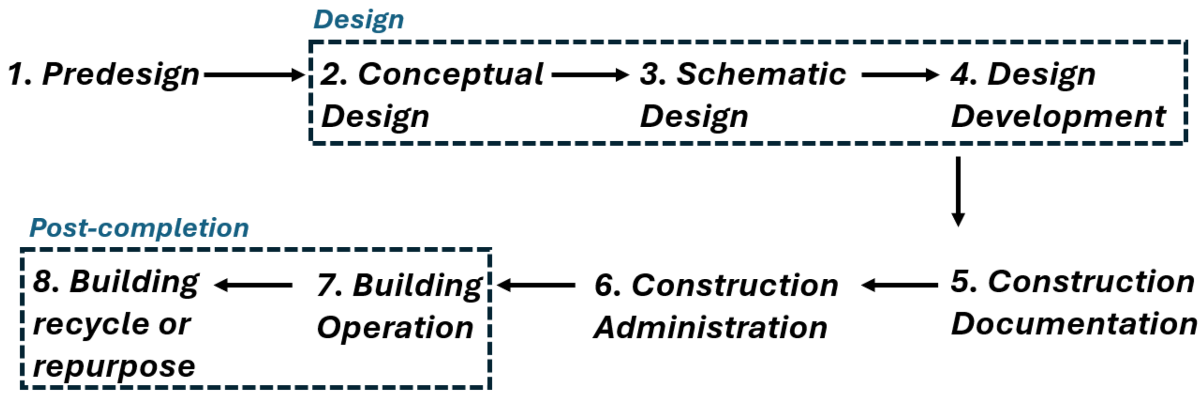


Figure 03. Project lifecycle stages.

A relevant Benefit that BIM bring to the design process is how the focus and effort of design can concentrate on early design stages, by providing automatizing to later stages of design when model development and documentation are more standardized. This automation frees design teams to better study and consider early stages of design when decision taken have the greater possibility to affect the building whole lifespan performance. The Mac Leamy curve (MacLeamy, 2010), is a good representation of how earlier in the design process the greater capability of affecting the building lifespan, likewise, it also explains how the later on the design process the higher the cost effort that modification causes.

As BIM platforms are used to generate a building model throughout a process, the digital model evolves as the project evolves, increasing the level of information added. The Level of Development Specification, originally proposed by the American Institute of Architects (AIA) in the E202-2008 document (The American Institute of Architects, 2008) and currently led by the BIM Forum, provides an industry guideline on best practices for the implementation of BIM in the Architecture, Engineering and Construction industry (AEC).

The goal of the LOD framework is to provide a common language to describe the development of BIM elements, improving coordination between architects, engineers, and contractors, by ensuring that BIM models are progressively refined as projects advance following certain conditions. Such conditions are specified by levels of granularity of information added to the models, which roughly correspond to stages of the delivery process, as follows (BIM Forum, 2024):

- LOD 100: Conceptual Stage: Conceptual model *(basic massing, no precise details)*.
- LOD 200: Schematic Stage – Building elements begin to take shape with general specifications and approximate sizes, but it still lacks precise details.
- LOD 300: Detailed Design Stage – Building elements are now fully defined, including exact dimensions, materials, and placement, but it may still lack some fabrication details.
- LOD 350: Coordination Stage: Includes connections and interfaces between components to facilitate trade coordination.
- LOD 400: Fabrication Stage – At this stage, the element includes all the details required for fabrication, installation, and construction, including accurate component sizes, materials, and connections.

- LOD 500: As-Built Stage – This is the most developed level, representing the final, built version of the design, including actual as-built conditions and complete data.

LOD Stages become relevant for the BIM based design process as its definition of incremental level of design is aligned with the incremental level acquired in different project delivery stages. LOD stages will be referenced throughout the upcoming project delivery stages description as it is commonly used as a framework for communication g what BIM models can relied on for and clearly understand the usability of and limitations of BIM models at different stages (BIM Forum, 2024).

2.04 Project delivery stages

The upcoming section will provide a description of each building-lifecycle stage from the perspective of the BIM-supported project process. For each stage an overview of how BIM platforms support workflows will be complemented with some highlights of how AI new predictive analysis and decision-influencing capabilities bring benefits.

04.1 Predesign

At the beginning of the project delivery process, predesign is typically the first step. Predesign involves gathering and defining project requirements, goals, and objectives, in relation to all project stakeholders. Ideally, it also considers the entire project lifecycle, from early design through building operation, and even to building recycling or repurposing.

During predesign, a set of requirements based on the building program, social and physical context, code regulations, and any special needs are established. These requirements represent the functions that the building must fulfill to ensure a successful project. It is also during this phase that performance standards and goals are set. The methods for measuring the fulfillment of these functions, as well as the specific values that represent success, should be determined before design begins. For example, if one of the goals is to achieve a low-carbon-footprint building, the predicted embodied carbon emissions (in tons) could be used as a method for measuring this goal, with an eCO_2t/sq ft value set as the maximum to indicate goal fulfillment.

BIM's capabilities for collaboration and interoperability provide a platform that allows project requirements to be integrated early in the project development process. This ensures they can be shared, discussed, and coordinated, helping to prevent conflicts and undesirable modifications later on. BIM technology enables the creation of schematic volumetric shapes that capture the requirements, objectives, and conditions of all building parts and stakeholders throughout the entire project lifecycle. This level of development could be represented by a hypothetical Level of Development (LOD) 000, which does not define the building's geometry but outlines the requirements it must meet.

04.2 Conceptual Design

Conceptual design represents the first stage of the design process. It is the initial proposition phase, where the requirements defined in the predesign stage are further studied and analyzed. These requirements are then matched with architectural strategies that can address them in a conceptual manner. During this phase, different design options are proposed and studied, using tools that help predict, at a high level, the implications of design strategies on the development and lifespan of the building.

Early in the design development process, decision-making is particularly influential. The ability to shape the development and success of the project is greatest during this stage, and therefore, careful attention must be paid. The outcome of this stage should be a set of conceptual alternatives—design strategies that have been thoroughly analyzed and benchmarked. This provides a solid foundation for making informed decisions and a reliable base for continuing the design process in later stages.

BIM tools offer parametric capabilities to model conceptual masses, capturing design strategies such as programmatic and spatial relationships, structural and material solutions, and interactions with the context or environmental conditions. These conceptual masses not only serve as a representation of the design but also allow for early performance simulations, which predict how different scenarios will impact building development. This level of model development would align with Level of Development (LOD) 100.

However, current BIM tools have limitations when it comes to providing fast, accessible, and reliable performance predictions during the early stages of design. Conceptual models lack detailed parametric definitions, as many building details have not yet been decided. In these cases, simulations that require a large number of parameters to be input are often irrelevant at this stage of design.

Artificial intelligence (AI) predictive capabilities have the potential to improve performance prediction during the early stages of design, increasing both accessibility and reliability, even when the project definition is still limited. Moreover, AI generative tools could be particularly useful for efficiently exploring alternatives during this phase.

04.3 Schematic design.

In this stage, the most promising conceptual design strategies are selected for further development. To achieve this, various analyses are conducted to compare alternatives and select the best option. BIM analysis and simulation capabilities can support this decision-making process. The selected strategies are then further developed, progressing from Level of Development (LOD) 100 to LOD 300. This provides documentation and data that can be interpreted by clients and other stakeholders, helping them decide the direction the project should take, based on the project requirements and goals.

The collaborative nature of BIM allows for the inclusion of multiple stakeholders in this process, ensuring that decisions made do not negatively impact the performance of different project aspects. Although not all stakeholders may be fully involved at this stage, a shared collaborative space can serve as a tool for all participants to study how decisions may affect their areas of responsibility.

04.4 Design development

The difference between schematic design and design development lies in the level of decision-making, certainty, and approval reached. During schematic design, alternative design decisions regarding architecture, structure, and MEP (mechanical, electrical, plumbing) systems are analyzed and discussed by the project stakeholders. A general building proposal is selected for further detailed development. In this stage, systems integration, constructability, and trade coordination must be analyzed and resolved. For prefabricated elements, considerations such as the prefabrication sector, supply chain capabilities, repeatability, site logistics, and constraints need to be studied.

During this design phase, BIM models are typically developed to Level of Development (LOD) 350 to LOD 400. Manufactured product models are introduced, requiring the import of product models from online catalogs and databases, often using IFC as an exchange format.

Schematic design and design development are the two stages where BIM projects demand the most effort. This is because the building model is defined and determined during these stages. With BIM, project documentation can be automated. In contrast, traditional projects that do not use BIM cannot automate this process, so project effort is concentrated during this phase. Automation increases the efficiency of the design workflow, reduces human errors, and ensures consistent, reliable outcomes. Since documentation is usually repetitive, the potential for automation is high. While BIM already represents a significant advancement in this area, AI capabilities could further improve this process.

As the level of development and design development increases, the complexity of BIM models reflecting the project's advancement also grows. This is especially relevant in intricate and complex projects. Collaboration and coordination become increasingly important, as large BIM models can pose challenges for effective collaboration. New AI capabilities could offer better coordination strategies or help predict potential conflicts. Additionally, project definition requires further analysis of the building's performance. As with earlier stages, schematic design and design development would benefit from more reliable and accessible performance prediction tools.

04.5 Construction documentation

This stage represents the continuation of the design process, aimed at producing all the necessary documentation and data for bidding and constructing the building. During this phase, a complete set of drawings and written documentation is produced by designers. This information will be used by contractors and subcontractors, first to propose a construction schedule and cost, and then to develop all necessary tasks to deliver the final building for use.

In traditional project delivery, this stage requires the greatest amount of effort; however, the use of BIM challenges this. The project definition from previous stages now serves as the foundation for producing all the drawings and documents in a more automated and efficient manner. Traditional methods of documenting a project often involve representing redundant information in multiple drawings. In contrast, with BIM, the central, non-redundant model automatically generates views, meaning that building data needs to be modeled only once. This not only reduces the time and effort required to produce documents but also minimizes mistakes, inconsistencies, and contradictions between them. BIM also improves coordination and collaboration among the disciplines involved in this stage, as well as enhances interoperability.

However, BIM platforms face some limitations in construction documentation workflows. For example, the automation offered by BIM in highly defined models is limited. If a change is made in an LOD 400 model, the propagation of those changes affects many other elements across the model. In this case, element interdependencies, represented in BIM as rule-based structural relationships, may not account for all required changes, making the model less flexible and changes more effort-consuming. Artificial Intelligence

(AI) could help by predicting how changes will affect the rest of the model, making modifications at this stage more flexible.

At this stage, interoperability becomes a critical issue. Sharing information with contractors and manufacturers is essential, and data must be transferred correctly and accurately to avoid mistakes and misinformation. BIM’s interoperability capabilities could be improved if the semantic definitions of what elements represent were more accurate and extensive. AI’s intelligent analysis and prediction capabilities could further improve how different tools communicate.

04.6 Construction administration

During this stage, the project is built, and the various contractors and subcontractors, after bidding and winning the contract, begin managing and executing the necessary actions to construct the building as outlined in the previous stage.

Using the BIM model, construction simulations can be performed to study best practices, including scheduling, supply chain management, and assembly order. These simulations help avoid mistakes, reduce time, and lower costs. Coordination and interoperability issues become especially critical during this phase. Although the level of development in the model typically doesn't need to increase, the sharing and visualization of information by different construction teams—along with the complexity and effort involved in making changes—benefit from improvements in management, data sharing, and visualization tools.

04.7 Building operation and maintenance (O&M)

Building O&M usually represents the longest and most costly stage in a building lifecycle, it involves multiple interaction between stakeholder and activities such as scheduling, space planning, repairing, and emergency managing.(Peng et al., 2017) Traditional manual building O&M takes high amount of time and cost, mistakes and data loss.(Zhao et al., 2022). The use of BIM offers multiple benefits that help overcome the limitations of manual O&M. By providing a digital model, all building elements and maintenance data are easily and efficiently handed to those in charge of building O&M. Furthermore, the digital model, which represents an as-built version of the actual building, can record, manage, process, and extract new data, making tasks in this stage easier (Sacks et al., 2018). Data processing capabilities that predict and understand the needs derived from the building's use can significantly improve its performance. BIM's limited capabilities in this regard offer only modest improvements. However, when combined with digital twins and artificial intelligence, BIM models can leverage both modeled data and actual performance recordings. This structured data not only benefits building O&M but could also provide valuable insights for improving future design performance predictions.

04.8 Building repurposing and recycling

If the entire lifecycle of a building's requirements is considered during its design, repurposing or recycling should also be accounted for as stages of the project when the building's original use is no longer intended. Considerations include how the building's spaces, dimensions, and structure may serve a different purpose, or if the building is dismantled, whether its elements can be reused in another building or easily recycled.

Repurposing and recycling requirements can also be measured in a BIM model by running simulations and analyzing its performance. Collaborative and simulative BIM capabilities can improve the understanding of how different design decisions impact later stages of the building's lifecycle. For instance, life cycle assessment (LCA) simulation tools help study how different decisions may affect the building's carbon footprint when it is recycled or demolished. AI's predictive capabilities can enhance this analysis by providing more accessible and reliable predictive tools, even in early-stage design.

2.05 Discussion on BIM General Limitations

BIM offers numerous benefits to architectural design, representing a significant improvement in digital design tools. Enhanced representation, collaboration, automation, and simulation are some of its key advantages. However, these capabilities also come with limitations, which have been discussed in previous sections. These limitations can be categorized as follows:

- Representation and building modeling, including customization and exploration of alternatives.
- Simulative and predictive accessibility and reliability.
- Flexibility and model modification in later design stages.
- Interoperability issues, such as data loss when sharing information between tools.
- Further automation of workflows and model detailing, particularly in later design stages.

These limitations stem from the structure and capabilities of BIM, which need further development and integration with other technologies to provide more effective tools for architectural design. One reason for these limitations is BIM's restricted ability to represent the behavior of the building model and its elements. If these behavioral characteristics, including interdependencies, were better represented, performance assessment, interoperability, and flexibility in model changes could potentially be improved.

Artificial intelligence (AI) predictive and analytical capabilities could help address some of BIM's limitations. It is important to note that AI is not intended to replace BIM, but rather to complement and enhance it by leveraging BIM's centralized data representation and parametric structure. AI could provide increased flexibility, reliability, and automation in BIM design workflows. Its analytical tools could enrich the semantics of BIM models, improving their behavioral definition. This improved representation of not just geometry but also behavior could lead to more intelligent interoperability, better performance predictions, as behavioral interdependencies are more effectively addressed, and further automation. Additionally, parametric generative AI could benefit BIM by automatically generating design alternatives from early design stages, thus increasing design exploration.

Given the benefits BIM provides to the architectural design workflow and the potential improvements AI could bring to its current limitations, it is important to further study AI—its capabilities, current uses, and potential applications to advance the design process. The next chapter will provide an overview of these topics.

Chapter 3. AI in architecture

3.01 Introduction

This thesis aims to study and analyze new technologies applied to the architectural design process. Architectural design is a complex, nonlinear process that encompasses everything from conceptual design to technical systems integration, as well as construction documentation and administration.(Castro Pena et al., 2021; Grobman et al., 2010). The previous chapter provided an overview of the general process of project delivery and architectural design, analyzing the current technological standard for project representation and management—Building Information Modeling (BIM). It outlined its main characteristics, capabilities, benefits, and limitations.

Artificial intelligence is emerging as a potentially disruptive technology in both research and professional practice across various fields, including healthcare, finance, business, engineering, and design, among others (Connolly et al., 2023; Livberber & Ayvaz, 2023; RIBA, 2024; Xu et al., 2021). Therefore, artificial intelligence has been selected in this thesis as the technology to be studied in relation to the field of architecture, given its potential to enhance current BIM capabilities and address its limitations in architectural design.

AI is already being used in architecture, there are multiple AI approaches which have been applied to the architectural design process. This section provides statistical data on the use of AI in architectural practice, based on a 2023 survey of over 500 RIBA-member architects, published on the RIBA AI report of 2024 (RIBA, 2024),. While 98% reported having at least basic to advanced knowledge of AI, only 6% claimed to use it in most or all projects, whereas 59% stated they do not use AI in any project. This suggests that, despite AI being widely known and discussed in the profession, it has yet to become common practice.

Regarding its applications, over 50% of surveyed architects have experimented with AI for generative purposes, with early concept visualization being the most common use. However, more than 50% have never used AI for simulation and predictive tasks, with the least utilized applications being standards and compliance checking, as well as construction product and material selection and analysis. This disparity in AI adoption may be due to the limited availability of tools for these applications or a lack of familiarity among users.

It could, therefore, be relevant to analyze the potential of AI's predictive capabilities in architecture, as they appear to be less commonly used today. Nevertheless, regardless of the most common types or applications of AI, it has yet to be established as a standard practice in the profession. However, given the significant benefits AI has provided in other fields, its integration into architecture could offer similar advantages. (Connolly et al., 2023; Livberber & Ayvaz, 2023; RIBA, 2024; Xu et al., 2021), it is plausible to think that it could improve its importance in architectural design in the future.

3.02 What is Artificial intelligence

Artificial intelligence is a wide term used and interpreted in different ways, which has raised a lot of interest in many professionals and academics from a great number of fields of fields (Xu et al., 2021). AI can sometimes seem to be a confusing and ambiguous term, however a common definition for AI is a computational model that imitates or resembles a capability of human intelligence. (Sheikh et al., 2023). The High-Level Expert Group on Artificial Intelligence (AI HLEG) of the European Commission (EC) defines AI as “Systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals.”(High-level expert group on Artificial Intelligence set up by the European Commission, 2019). The US National AI act claimed, “The term ‘artificial intelligence’ means a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments.” (*National Artificial Intelligence Initiative Act*, 2020). Howard Garner defined AI as a “biopsychological potential to process information, solve problems or create products that are of value in a culture” (Gardner, 1999). From the various definitions of AI, two general characteristics can be identified: AI is a computational model that simulates human intelligence, and its primary capabilities include acquiring and processing data, making predictions, decisions, and recommendations, and achieving a given objective with a certain degree of autonomy.

AI is widely discussed among academia and believed to have large potential, it is important then to look at what benefits does it contribute with, Author S. Sharma proposes 4 categories of general benefits of using AI, these are, growth and profits benefits (scalability, value co-creation, productivity, quality), performance/ease/comfort benefits (accuracy, speed, computation, time and cost saving, decision making), safety benefits (real time monitoring, robotic assistance), sustainability benefits (optimal resource usage, energy savings)(Sharma, 2024). These categories reflect the general benefits that Artificial intelligence capabilities bring, which in areas such as healthcare, business, finance or education have already been largely applied (Al Kuwaiti et al., 2023), for instance AI is used to help diagnosis cancer, machine learning models are used for predicting the result of strategic decision in business or Chat GPT is used as an educational tool (Ali et al., 2024; Pesheva, 2024; Tripathi et al., 2023). To better understand how these benefits are enabled by AI and how they are or can be applied to the field of architecture, it is important to review the evolution of AI from its origins to the present day, as well as the capabilities and applications of different types of AI.

Even though AI has raised in importance during last years, its development can be traced back to the 40’s and 50’s decade when Alan Turing published “computing machinery and intelligence” in 1950, where he discussed how to create and intelligent machine and how to test its intelligence (The Turing Test) or designed “the bomb” an electro-magnetic machine for decoding messages in the WWII in 1940 (Haenlein & Kaplan, 2019). However, the term Artificial intelligence was not used for the first time until 1956 John McCarthy did a conference called “The Dartmouth Summer Research Project on Artificial Intelligence”(Trappl, 1985). After the first development considered the origin of AI, around the decades of the 60’s and 70’s followed a rich research period on AI with examples such as ELIZA, the first Natural Language Processing (NLP) model which simulated human communication of psychiatrist with a patient, or the General Problem Solver, a machine capable of solving the Hanoi towers problem (Kaplan & Haenlein, 2019). After a period of intense research and development, unfulfilled expectations, and skepticism from scientists such as James Lighthill, both the U.S. and U.K. governments cut funding for AI research during the 1970s. This period became known as the "AI Winter." It was not until 1997 that AI regained widespread attention when IBM's machine, Deep Blue, defeated the world's best chess player. (Toosi et al., 2021).

All the aforementioned developments in AI share a common characteristic: they were all based on rule-based algorithms. The approach to creating intelligent systems involved replicating human knowledge through logical structures that simulated and automated human tasks. These models, known as expert systems, lacked the ability to learn autonomously, leading some to argue that they should not be considered true AI. As a result, this approach has been referred to as "Good Old-Fashioned AI" (GOFAI). (Collins et al., 2021).

Along the 2000's decade another approach for artificial intelligence started to gain relevance, the use of statistical methods allowed to create computational models which were capable of statistically learn from databases and automatically generate algorithms based on that information which were able to do predictions. This concept of machines automatically learning from data is called Machine Learning (ML) coined by computer scientist Arthur Samuel (Brown, 2021). Machine learning models have become the most common general approach for developing artificial intelligence today. However, the term does not refer to a specific set of algorithms or methods, as these have evolved over time, incorporating different techniques and approaches. It is important to further study machine learning, focusing on its main characteristics, such as its statistical approach, and its implications for reliability and scalability, as well as the application of various algorithms and learning methods. The next section will explore machine learning in greater detail to establish a clearer foundation and better understand its role in architectural design.

3.03 Machine Learning: Statistical AI

Machine Learning (ML) is based on computational models which based on Data sets generates in an automated way algorithms based on observed patterns, capable of describing, predicting or prescribing (Malone et al., 2020). It is important to consider what ML capabilities are statistical based, it is capable of processing large amounts of data, observing correlations between the data which implies that rather than imitating the human understanding capabilities, it is capable of leaning from the world, 'instead of being told about it'(Bernstein, 2022). The use of machine learning in areas such as architecture presents a limitation, as the model is not capable of explaining the rationale behind the predictions it makes. Despite this limitation, ML models hold considerable potential, as they enable the analysis of large amounts of data in short periods of time. By applying this knowledge to different situations, they help improve problem understanding, predict outcomes, and facilitate better decision-making.

ML has numerous applications across various fields where description and prediction are valuable, improving the efficiency and effectiveness of workflows, increasing accuracy, and reducing time and costs. These benefits have the potential to be applied in architecture. ML can be utilized in different ways, such as generative design, simulations, automation, or visualization.

To better understand its potential in architecture, it's necessary to review the key components of machine learning. From a general perspective, ML models consist of two phases: the training phase, where the model is created based on provided data, and the application phase, where the trained model is used to describe, predict, and prescribe. Key elements involved include the data provided for training the model, the type of model (e.g., linear regression, decision trees, clustering, naïve Bayes, neural networks, or deep learning), and the algorithms employed (Han et al., 2011; Witten & Frank, 2005), Lastly, the output, which addresses the objective of the ML model, can take various forms, such as text, numbers, images, vectors, or other types of data.

A widely accepted way to classify machine learning models is based on the learning approach used to train the model. The different types include supervised learning, unsupervised learning, self-supervised learning, semi-supervised learning, and reinforcement learning. (Brown, 2021; Rose, 2023; Sarker, 2021; Z. Zhao et al., 2024). Different types of ML use different algorithm models and input data types, each with distinct applications. Supervised learning is trained with labeled data, where both the data parameters and the desired outcome variable are human-defined. It is commonly used for applications such as risk management, image recognition, and predictive analytics. (Belcic & Stryker, n.d.). An example would be a ML model trained with labeled images of cats and dogs, which objective is to distinguish between cats and dogs. Types of models use din Supervised learning are Regression, classification, Naïve bayes, Neural networks and Random Forest algorithms(China, 2023). Unsupervised learning focuses on finding patterns and correlations within unlabeled datasets, without a predefined outcome. An example of this is clustering images based on their similarities to better understand an image dataset. (Sarker, 2021). Examples of types of ML models used in unsupervised learning are K-means clustering, Hierarchical clustering or Probabilistic clustering(China, 2023). Self-supervised machine learning (SSL) involves providing an unlabeled dataset, which the model autonomously labels to learn from. These algorithms are commonly used in fields like Natural Language Processing and computer vision.

Reinforcement learning relies on human feedback to train the model, allowing it to learn and improve its performance over time.

Semi-supervised learning combines both supervised and unsupervised learning approaches. An example of semi-supervised learning is Generative Adversarial Networks (GANs), which consist of two models: a generator and a discriminator. The generator creates fake new data, while the discriminator classifies data as either fake or real. The objective is for the generator to learn how to create plausible data based on feedback from the discriminator about whether the data is realistic. (Google for developers, n.d.).

Different approaches of Machine Learning have different purposes and outcomes, however there are numerous other classifications of ML in the literature (Brown, 2021; China, 2023) in the context of design an important classification can be generative ML and non-generative ML. Its main difference is that generative models use what have learn from datasets, such as patterns and correlations to generate new plausible data, meanwhile non-generative models use what they learnt from datasets to classify, cluster, predict, and help take decision(Belcic, 2024). Example of generative ML are the above-mentioned GANs, Variational autoencoders (VAEs), diffusion models or flow models which are task-specific models or foundation models composed of large Language models, and large vision models.

All in all, ML models use data to obtain statistical conclusions that describe it. They are capable of predicting outcomes, generating new data, and prescribing actions to influence decision-making. However, there are other AI approaches beyond symbolic and statistical methods. For example, evolutionary models combine both symbolic and statistical AI. This type of AI is characterized by generating data based on human-defined parameters and constraints, then introducing random variations (mutations) and statistically determining the best-performing solution (fitness). The use of evolutionary models focuses on finding a wide spectrum of solutions and refining and optimizing them. (Vikhar, 2016).

There are numerous approaches to artificial intelligence, with capabilities and methods that vary widely. From a general perspective, these can be categorized into logical, statistical, and combined approaches, while acknowledging that sometimes logic-based algorithms are not considered AI due to their inability to autonomously learn from data. The capabilities described offer numerous benefits across many fields, and in the context of this paper, the focus is on architectural design. The next section will explore how AI capabilities are or could potentially improve architectural design.

3.04 AI in architecture:

Artificial Intelligence and Machine Learning tools have numerous applications in many fields, multiple approaches and examples have proven to be useful to improve efficiency and effectiveness in different processes, such as healthcare, agriculture or engineering(Xu et al., 2021). Architectural design is a complex process in which various stakeholders, objectives, and requirements play a decisive role. As discussed in the previous chapter, technologies such as Building Information Modeling (BIM) have already improved the design process by introducing new computational capabilities. In this context, artificial intelligence has the potential to enhance BIM capabilities by introducing technologies and benefits that can help overcome the existing limitations of current approaches.

The main capabilities of AI were discussed in the previous section. In the field of architecture, these capabilities can be applied in various ways, using different types of input and output data, which have the potential to bring benefits to different stages and workflows of the design process. In this thesis, the classification of AI capabilities in architecture will focus on generative design, simulation and analysis, optimization, and process automation.

This section will provide an overview of the main AI approaches for improving the design process, the key available tools, and the role they play in the design process, along with their benefits and limitations. Some AI design tools will be selected for exemplifying the role of AI in design.

AI applications for architecture have been in the spot since the last recent years(Bölek et al., 2023)The number of academic research papers, available AI-powered design tools, and interest from AEC professionals has significantly increased. However, it is important to acknowledge that AI computational tools in architecture have been of interest since the early stages of AI's general evolution. As early as 1964, architect Walter Gropius stated: “It will certainly be up to us architects to make use of them [computers] intelligently as means of superior mechanical control, which might provide us with ever-greater freedom for the creative process of design.” (Boston Architectural Center, 1964).

A clear example of early AI development in architecture is the researcher Nicholas Negroponte and its Architecture Machine Group (AMG) lab from the MIT, involved in Architecture, Artificial Intelligence, Computer science and electrical engineering. Negroponte published books such as “The architecture Machine” in 1970 and “Software architecture machines” in 1975 where he discussed the interaction between humans, computers and the built environment.

The early development of AI tools for design was limited by the still-developing state of computers. As computational capabilities increased, computer-aided design (CAD) tools became the standard during the 1980s. In the 2000s, Building Information Modeling (BIM) replaced CAD as the new standard. Since the 2020s, the increasing capabilities of digital computation have reintroduced artificial intelligence concepts in architecture, with new approaches and tools emerging. (Bernstein, 2022).

The introduction of AI brings the possibility of new predictive capabilities to architecture. However, if we consider the current landscape of AI tools used in architecture, many of them rely on rule-based AI rather than statistical-based approaches. It is important to note, however, that a significant portion of generative AI is also based on statistical models, particularly those that generate images and videos. Tools like Midjourney or Sora, however, could be argued to have limited benefits in improving design, particularly in terms of behavior and function, as described in the first chapter.

Author P. Bernstein (Bernstein, 2022), in his book *Machine Learning: Architecture in the Age of Artificial Intelligence*, presents a diagram called "Three Steps to AI-Enhanced Productivity" (Figure 04). In this diagram, Bernstein cross-references AI capabilities for architecture, described as automation, analysis, and prediction, with the incremental capabilities of a technology-driven design process, which are evaluate, simulate, and generate. He uses the example of design for code compliance, which is relevant as it aligns with the example discussed in the first chapter regarding constraint-based versus

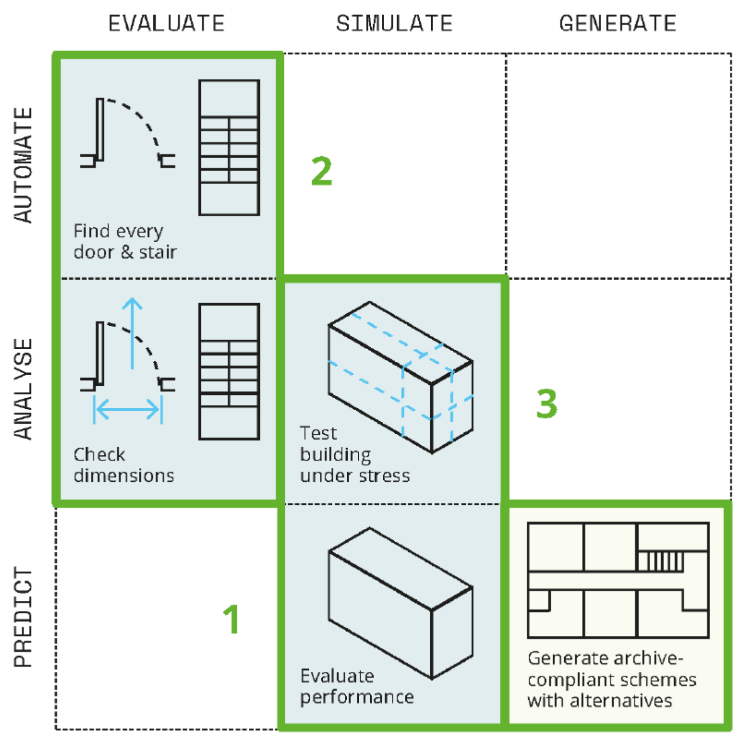


Figure 04. 'Three steps of AI-enhanced productivity' (Bernstein, 2022)

performance-based code compliance (Section 1.3). Bernstein divides his argument into three incremental steps.

Bernstein argues that AI capabilities for automation and analysis could be used to improve evaluation. For instance, in egress path evaluations, machine learning models could automate the identification of building elements relevant to egress, such as doors or stairs. Combined with rule-based analysis, this could ensure that these elements comply with requirements. The second step would involve AI simulating the actual behavior of egress elements, such as swing direction, fire ratings, and whether they are designed to handle the right number of occupants. This step combines analysis and predictive capabilities of AI. Finally, the third step would involve a model that, through learning, would acquire the ability to generate successful solutions based on behavior predictions.

This example from Bernstein provides a high-level overview of the potential AI capabilities in the design process, helping frame and understand how AI could enhance architectural design and improve the design process. In the following section, the main AI applications identified will be discussed, divided into four types: generative design, performance prediction, optimization, and automation.

04.1 Types of applications

04.1.1 Generative design

Generative AI capabilities that are useful to architecture are diverse and can be classified in various ways, such as based on the outcome, or the AI approach used. Based on the outcome produced, they can be distinguished into text, 2D images, and 3D models. Large language models, such as ChatGPT, are capable of interpreting and producing answers to language-based inputs. These models could potentially be useful for project requirements and predesign research; however, they exceed the scope of the current thesis.

Image generation based on machine learning models is one of the most popular uses of AI in architecture (RIBA, 2024). These models can be used to improve visualization as well as serve as a visual conceptual and inspiration tool. Generative image models have also been explored for producing 2D architectural floor plans. For example, GANs have been used to generate residential layouts, differentiating room usage (Chaillou, 2022).

The generation of 3D models is a widely explored approach for design options exploration. The most common AI approach for this purpose is rule-based algorithms. Examples of tools utilizing these capabilities include Testfit, Forma, and visual programming tools such as Dynamo and Grasshopper. These rule-based algorithms leverage parametric design to generate or modify design options based on human-defined program parameters. The next chapter's case study of Autodesk's Forma will explore its rule-based conceptual site generation tool.

While there has been considerable development in rule-based generative design tools, there have also been approaches using statistical ML models to generate 3D geometric models. For instance, the authors (Ampanavos & Malkawi, 2021) developed a generative model for early-stage conceptual design based on GANs, which generates conceptual designs that optimize sunlight exposure in an urban context.

04.1.2 Performance prediction

Performance prediction in architecture has been argued to be of great importance. Architectural design, within a functional framework, can consider the fulfillment of a functional goal as its main objective. AI prediction capabilities, as seen in other disciplines, have the potential to support informed decision-making in architectural design. On one hand, when considering the evolution of simulation tools in architecture, rule-based tools are not new. However, statistical AI capabilities offer a new dimension to behavior prediction in design. Machine learning (ML) models have the potential to analyze existing performance data and provide performance estimations for new cases. Examples of these models can be found in Autodesk's Forma design tools, where ML models are used to predict noise and wind performance.

It is important to acknowledge that statistical prediction has a significant limitation. While rule-based simulations are based on a logic model where the causal relationships and simplifications are known, the rationale behind statistical methods remains unknown. This 'black box' nature of statistical rationale limits its ability to provide certainty or explanatory logic behind the data. In architectural design, the explanation behind performance phenomena is crucial, as it helps to understand which design strategies could be effective and why. In current performance-prediction workflows, it is typically the designer or professional who is responsible for understanding the rationale behind a performance phenomenon and suggesting an appropriate solution or strategy.

04.1.3 Optimization

In the process of architectural design, the concept of optimization refers to the process of finding the best alternative among design proposals in terms of performance. A design proposal can be optimized for various factors, such as cost, sustainability, or specific use cases like educational environments. Optimization can focus on a single parameter, for example, designing a concrete beam that optimizes load transmission, or it can be multi-parameter, aiming to find the best combination of performance for all factors—such as optimizing a concrete beam for load transmission, fabrication cost, concrete usage, and ease of fabrication.

As discussed in the first chapter, the design problem can become complex and involve numerous behavioral interdependencies between elements and systems. Considering the Structure-Behavior-Function framework for design, it was argued that these interdependencies can lead to unexpected side effects. To illustrate the importance of these interdependencies in the optimization process, let's consider the example of optimizing a prefabricated façade panel layout. An optimization algorithm, such as a Genetic Algorithm, may be programmed to find the optimal geometric distribution that minimizes the number of customized panels. However, there are other behaviors affected by a particular layout design, such as the realignment of joints with support members for panel installation, the ease of installation by workers, or the presence of plumbing elements that should not interfere with the joints. If these parameters are not properly considered when optimizing for one or more factors, unintended side effects could arise, compromising the fulfillment of the desired functions.

Considering the potential for unexpected side effects, optimization possibilities are limited to relatively simple design problems where the boundaries of the design problem can be clearly defined. In artificial intelligence, there are algorithms that allow for multi-objective optimization. However, determining all possible objectives and side effects in an optimization process can become complex and time-consuming, which could potentially make optimization overly complex and inefficient as a solution.

04.1.4 Process automatization

Automatization in design has already been introduced into the design process through the use of digital tools, first with CAD and, more prominently, with BIM. BIM's centralized nature allows for the automation of changes across multiple views, saving time and effort while ensuring consistency throughout the project documentation. However, Artificial Intelligence (AI) statistical models bring new automation capabilities that can further streamline design workflows.

When considering other AI capabilities, such as generative design or performance prediction, artificial intelligence often leads to an automation effect. In the case of generative design, the explorative process of generating design alternatives is automated. Similarly, when predicting performance through statistical AI tools, the definition of parameters is simplified, and results are obtained more quickly, making it a form of automation.

In addition to these automation capabilities, Machine Learning (ML) models have also been applied to automate other aspects of design. These capabilities include transforming and interpreting data or analyzing and selecting data. For example, ML models can be used to vectorize a PDF or raster floor plan, or transform a point cloud model into a geometric BIM model. Furthermore, ML models can analyze a BIM design model and automatically select elements based on specific requests. (Zeitouny & Makhlouf, 2020).

04.2 Software applications examples

All four discussed capabilities—generative design, performance prediction, optimization, and automatization—can be either combined or stand alone in architectural design tools. Some tools primarily focus on generative design, while others concentrate on performance analysis. In many cases, other tools simply add capabilities to BIM software in the form of plug-ins. A selection of architectural design tools that incorporate Artificial Intelligence is provided, with a focus on early design stages. Early-stage design tools have been chosen for this study because many of them combine the four discussed

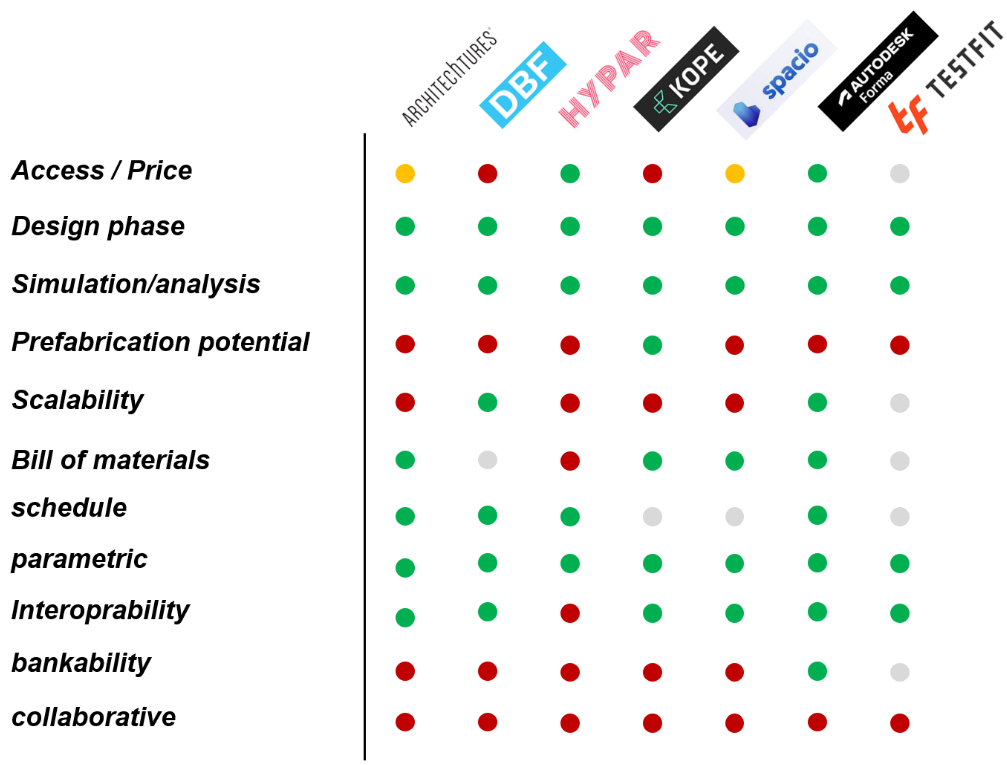


Figure 05. Comparative chart of AI early-stage design tools.

capabilities, providing a comprehensive approach to design development from the outset.

The different tools were analyzed based on the documentation provided on their respective webpages. Space, only Forma was tried with a complete license, while Hypar and Testfit were tested with limited licenses. A summary chart of the tools can be seen in

Figure 05. The main analysis focused on evaluating their capabilities, specifically identifying which ones utilize AI and which have the potential to improve the architectural design process. Some general insights from the analysis are:

- Beta versions and access limitations: Several tools are still in beta or have limited AI capabilities. For example, Digital Blue Foam, Hypar, Kope, Spacio, and Architechtures announce AI capabilities, but these are either unavailable or have limited accessibility. Some tools offer limited versions, while complete versions are available on a project-based billing model (e.g., Testfit). Autodesk Forma is the only tool with full access, available through the Autodesk student license. These access limitations suggest that many of the tools are still in development and not yet integrated into standard professional workflows.
- Rule-based vs. statistical AI: Many of the available tools primarily use rule-based AI. However, there are two tools that clearly mention the use of statistical AI approaches in their documentation—Forma (using ML models for performance prediction) and Kope (using genetic optimization algorithms). Other tools, such as Hypar (which generates BIM models from input prompts), also suggest the use of statistical AI algorithms, though this is not explicitly stated.
- Focus on early-stage generative design: Most tools for early-stage design focus on generative design capabilities based on parametric rule-based algorithms. These tools include Architechtures, DBF, Spacio, Forma, and Testfit. Some of these tools also include performance analysis, though the scope of analysis varies. For example, Forma, Spacio, and DBF offer more extensive performance analysis, while others, like Architechtures, plan to include performance analysis in the future.

This comparison was carried out to select a tool for further study and case analysis. The selected tool for this thesis is Autodesk Forma, due to its complete access and inclusion of both generative design and performance prediction tools in an automated manner. It was chosen because, in addition to rule-based AI, it also integrates statistical AI-based tools, providing a comprehensive solution for design and performance evaluation.

3.05 Discussion on AI in Architecture

During the AI-driven process of generative design or simulation, two AI approaches can be applied: those relying on a logical structure for generating and evaluating a design proposal, and those based on statistical learning from a reference dataset. On one hand, considering the complex nature of the architectural design process, which involves many considerations, possibilities, requirements, and conditions, it is challenging to define the design problem boundaries to obtain the "optimal" solution. Defining these boundaries can be difficult, costly, and time-consuming, potentially leading to oversimplifications that may overlook crucial factors, affecting the reliability and certainty of the results.

On the other hand, statistical approaches may be more reliable because they are based on actual data. By analyzing large datasets, these models can uncover a broader range of correlations and patterns that contribute to a more comprehensive solution. However, a significant limitation of statistical approaches is that, being statistical in nature, the rationale behind the output is often not transparent (Li et al., 2015). This lack of interpretability can limit the use of such models in architectural design, where understanding the reasoning behind design decisions is crucial for decision-making and ensuring that the final design aligns with intended goals and criteria.

Chapter 4. Case Study: Forma and C.Scale

4.01 Introduction

Forma is an early-stage online BIM design tool with a primary focus on modeling and performance assessment capabilities. It offers tools to enhance early-stage design workflows by integrating conceptual modeling with performance analysis, along with interoperability and integration options for widely used architectural BIM tools. In Chapter 3, the general applications of AI in architecture were described, including generative design, performance assessment, optimization, and process automation. Forma's capabilities include generative AI and AI-powered performance assessment.

Forma has been selected for this thesis as it incorporates both symbolic and statistical AI models for parametric generative design and performance prediction, respectively. It will serve as a case study to analyze and understand how AI-powered tools can improve the design process. Additionally, because Forma includes both AI and non-AI performance assessment tools, it enables a comparison of the differences, benefits, and limitations of each approach.

Although there are other commercially available AI-powered tools, most of them rely exclusively on generative design rule-based algorithms. Forma, however, incorporates a statistical machine learning model for performance prediction, combined with rule-based generative design. This enables the exploration of the role of statistical AI in architecture, which is expected to be one of Forma's most innovative features.

Forma was first released in 2016 by Håvard Haukeland Carl Christensen, and Anders Kvale in Oslo, Norway (Atomico, 2019) and was purchased by Autodesk in

2020(Autodesk PR, 2020). It first integrated AI-powered tools in 2019, and since then, new AI tools have been added. To better understand and frame the role of AI tools within Forma, a brief overview of its main elements and workflows will be provided. Forma's capabilities can be described as the collection of contextual data, parametric modeling of building geometries, including symbolic AI generative design, and performance assessment across various areas, such as environmental or sustainability parameters, using statistical AI—all within a collaborative and interoperable framework. The overview of Forma's capabilities will be divided into four main sections: Context data, building geometry modeling, performance assessment, and scalability.

Firstly, Forma provides access to context-related data, including building geometry, terrain, roads, parcels, trees, satellite images, and basemaps. This information can be accessed by selecting a site location and modified according to the project's requirements. The context data is not only important for documentation purposes but also serves as input for performance analyses, such as sunlight, daylight, noise, and wind. For example, the building's context geometry, along with the building and topography, is used to assess their impact on sunlight, noise, or wind around the building. Additionally, imported road data often includes traffic information, which is used for noise calculations, while site weather data is utilized for wind calculations.

Secondly, the modeling tools within Forma allow users to model buildings in the early conceptual stages based on general parameters and automate the exploration of design alternatives through parametric generative design. There are four options for modeling geometry. First, it is possible to model non-parametric shapes, which are considered generic masses. Additionally, parametric buildings can be manually drawn, allowing later modifications through the parameters. Parametric models enable better analysis of the building, allowing for the study of a greater number of design features, such as area metrics analysis (e.g., different building uses). Third, a set of parametric alternative building designs can be automatically generated. By providing a site and a set of parameter values, the tool can easily and rapidly visualize and produce options. This option is based on AI rule-based algorithms and generates results similar to the second modeling option.

Lastly, geometries can be imported as both generic masses and parametric masses, using Rhino and Revit. All four of these options for obtaining building geometric models can be used as input for performance assessment.

To better understand the modeling workflow in Forma, it is necessary to explain the three steps available when defining a building model. Figure 06 illustrates this workflow. Starting with a generatively defined building (Site automation), the overall footprint and height are defined and can be modified by the user through a set of high-level parameters, such as the total number of stories and the building's width. Once this stage is completed, the building's geometry can be "baked" into the next stage (Building automation) by clicking "release to zone," where parameters such as general use, circulation areas, and the number of stories of individual buildings can be modified. However, once this stage is done, the configuration type cannot be changed again, making this a non-reversible modification. Similarly, a third stage can be "baked" by clicking "release to basic building," where areas and uses for each floor plan can be defined. However, as with the previous stage, parameters such as the location of overall building circulation cannot be modified

Site Automation → **Building Automation** → **Basic Building**

Site Automation

- *Number of stories*
- *Building width*
- *Floor to floor height*
- *Tower width*

Building Automation

- *Circulation axis*
- *General building use*

Basic Building

- *Schematic floorplan*
- *Detailed uses by area*

Figure 06. Modeling workflow.

parametrically. This design workflow allows the building model to be defined in incremental steps of increasing detail.

The third Forma main capability is Performance Assessment. The performance assessment conducted is done using the input building model and a set of defined parameters. The different types of performance measured are described in Figure 07.

Name	What is measured	Input	Output
Sun hours	*Hours of Sun exposure of façade, floor and roof.*	*Geometric model, Date and time and location.*	*3D heat map, showing hours exposure, and pie chart statistics.*
Daylight potential	*Percentage of natural light that reaches the façade.*	*Geometric model, and location.*	*3D heat map, showing natural light percentage, and pie chart statistics*
Wind	• *Wind Speed based on 6 possible directions* • *Comfort based on wind speed, in different scales*	*Geometric model, location, and weather data*	*3D heat map, showing wind speed or comfort scale , pie chart statistics, and wind streams.*
Microclimate	*Temperature in roof and floor per date and hour.*	Wind and sun hours analysis	*3D heat map, showing temperature, and pie chart statistics*
Noise	*Noise estimation in Db for floor, roof and facades.*	*Geometric model, Streets and rail noise data.*	*3D heat map, showing noise in db, and pie chart statistics*
Solar analysis	PV panels potential energy production by area.	*Geometric model and location.*	*3D heat map, with energy production potential, and pie chart statistics*
Embodied carbon	Gas emission associated with building lifecycle in eCO_2t	*Geometric model, location and material and system definitions*	eCO_2t estimation expressed in total and by ft^2

Figure 07. Performance tools in Forma.

One of the main features of Forma's performance assessment, regarding AI, is the use of three types of performance measurements based on predictive machine learning models: rapid wind, rapid noise, and embodied carbon estimation. On the one hand, wind and noise offer rapid predictions in addition to the rule-based performance simulation. On the other hand, the embodied carbon estimation tool provides a carbon footprint estimation for the proposed building. The LCA estimation uses a third-party model called C.Scale, which also offers an online carbon footprint estimation based on the same model.

The fourth highlighted capability of Forma is its scalability, based on its collaborative and interoperable features. On one hand, the easy access web-based platform enhances collaboration and accessibility. On the other hand, its interoperability with widely-used tools in architectural design, such as Rhino and Revit, enables the integration of Forma's AI tools with other design stages and workflows. It is important to note that integration with Rhino and Revit not only allows the import and export of geometries and parameters but also generates a seamless back-and-forth workflow between Rhino/Revit and Forma.

All these four capabilities—context data, building modeling, performance assessment, and scalability—have the potential to significantly improve the design process. The next three sections will further discuss Forma's tools that use Artificial Intelligence: rule-based generative design, statistical performance prediction for rapid noise and wind, and embodied carbon estimation.

4.02 Geometric modeling: Generative Design

As discussed in the previous section, Forma allows for modeling 3D building geometry as generic models, 3D parametric geometries, or imported geometries. The automated generation of site building alternatives utilizes rule-based generative algorithms. This section will further analyze how "Site Automation," as it is called in Forma, works and highlight the main benefits and limitations of using it.

The generative conceptual building design tool is called Forma Site Automation. Its main workflow involves providing a set of building configuration alternatives for a site. The inputs include the delimited site and parameter values, which can be modified later. The process is divided into a series of steps or options, each with incremental detail, which generates a tree of options for the same site and helps easily explore different site configuration alternatives.

The different steps or levels of the generative process include the site outline delimitation, the site layout, the type of building, and the various building configuration options. In Figure 08, we can observe the different steps that generate branches of options.

Firstly, the layout defines the main lines that outline and subdivide the site into subareas. The layout options include empty, grid, or honeycomb. The first option generates a unique area on the site, the second creates a grid of lines with adjustable parameters such as grid width, height, and orientation, while the third option, honeycomb, generates layout lines that form a geometric pattern similar to a honeycomb. These automatically generated layout reference lines can also be modified manually by adding or removing lines.

Four types of building typologies can be selected: city block, linear building, tower, and a combination of linear and tower, referred to as 'mixed'. Based on the chosen building type and the defined layout lines, different configurations are automatically generated. These alternatives are based on preset configuration types for each building type, defining structural characteristics that adapt to the site and layout conditions. In Figure 08 the different building configuration types can be observed in the last column.

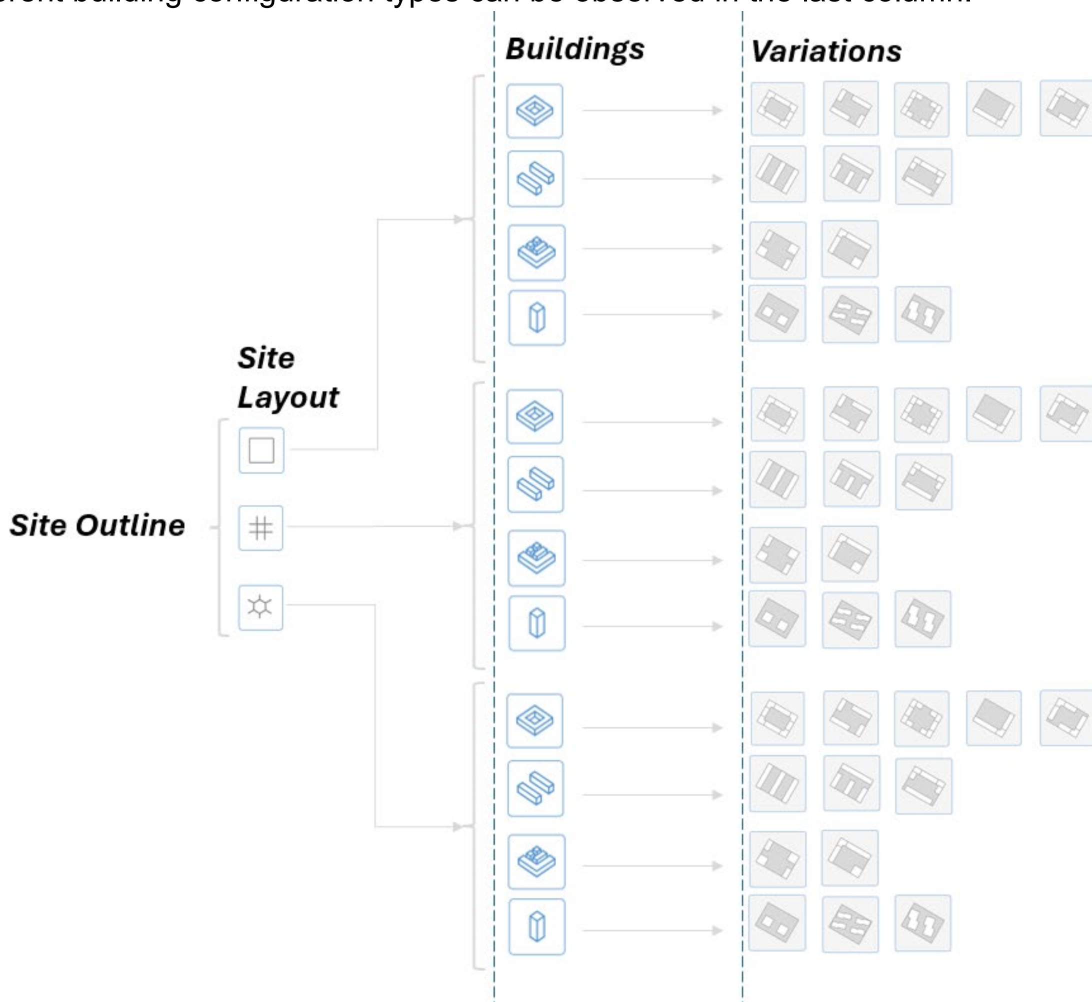


Figure 08. Site automation parameters diagram, showing relation of parameters to types and parameter values.

In addition, the generative process can be further defined and refined by the definition and modification of different parameters. Figure 09 shows the parameters available in site automation and its relationship to the layout and building type options. A total of 7 parameters for site layout and building type are grid width, height, and rotation, number of stories, floor height, building width and tower width.

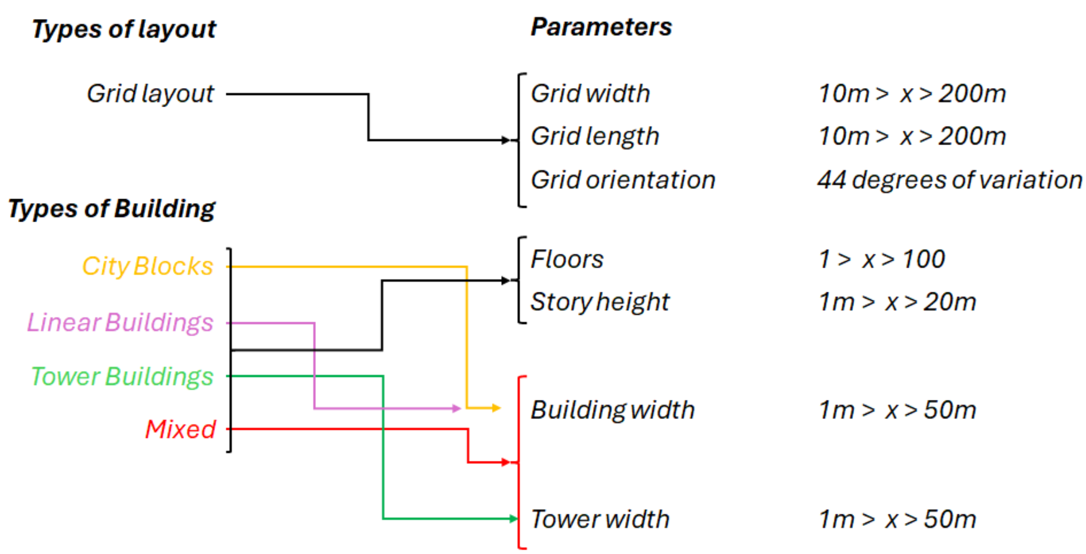


Figure 09. Diagram showing possible combinations in the Site Automation tool

The use of generative design offers multiple benefits, especially in early-stage design. By generating multiple site building configurations based on a minimal set of parameters, it allows for easy exploration of design alternatives. Early design stages are characterized by the flexibility to explore different options; the goal is to evaluate various alternatives and their potential implications in later stages of development.

Another benefit of Forma's generative design tool is that the geometric outcomes retain the ability to be modified and detailed through their parameters. This means that the generated design alternatives can be adjusted and refined, producing new alternatives based on performance assessment feedback or design intent.

However, generative design tools also have limitations. The generative algorithm is defined by a set of parameters and rules that may not account for all possible site configurations or deliver satisfactory results for certain sites and requirements. For example, in the Forma site generation tool, building typologies are limited to urban block, linear, and tower. If a project required a star-shaped building typology, the tool would not be suitable for that scenario.

Another limitation of Forma's site generation tool is that configuration alternatives can only be chosen during the initial, high-level stage of modeling. Once the building is "baked" into a more detailed stage, it is not possible to change the site configuration. This means that if a modification is required after further performance analysis or design development, the project would need to revisit the design alternatives or start with a different design proposal altogether.

Overall, the generative tool is useful for exploring early-stage site configuration alternatives, especially when combined with fast performance assessment and user-driven modifications. The automatic and rapid nature of the tool allows for quick access to alternatives without requiring many design parameters, providing project stakeholders with outputs they might not have considered or that would have otherwise taken more time and effort to explore.

Generative design tools become particularly relevant when integrated into a design workflow that includes fast, iterative performance assessment tools. The next section will explore performance assessment tools in Forma, with a focus on those based on predictive statistical models, which make them fast and accessible.

4.03 Performance analysis: Machine learning vs. Symbolic AI

Forma offers a total of 8 performance assessment categories, with an additional 8 optional analysis tools available as extensions. Among these performance categories, two—noise and wind—provide alternative methods for performance assessment. A more detailed simulation is available through rule-based algorithms, while a predictive model offers a faster assessment. These two models complement each other: the first rapid model gives a general idea of the potential performance outcome in near real-time, while the second provides a more reliable and detailed performance analysis.

Statistical predictions help identify the underlying phenomena behind performance outcomes, without the need to wait for the more time-consuming rule-based simulations. For example, in the case of wind performance predictions, the rapid analysis predicts wind speeds based on six different wind directions and provides an approximate plan of comfort levels. This prediction can often reveal wind phenomena such as downdraught effects, the Venturi effect, or upward deflection (D'Silva, 2024). When these predictions are used to make fast, iterative decisions during the design process, they have the potential to be combined with detailed simulations that either confirm or reject the predictions made. The main benefits of the two predictive tools included in Forma are the reduction in time, as the statistical prediction requires less computational power compared to rule-based simulations. Figure 10 outlines the advantages and disadvantages of both predictive and simulation models. In addition to the time and computational power required, it's important to highlight the lower reliability of predictions compared to simulations, as well as the degree of detail they provide. In some cases, the additional detail offered by simulations may be key to better understanding and studying the underlying phenomena that impact a building's performance, allowing for more informed decision-making.

	Rule-based Simulation	Statistical Simulation
Overview	• *Long simulation* • *Time depending on complexity* • *More detailed* • *More accurate*	• *Fast simulation* • *'live simulations'* • *less detailed* • *less accurate*
Forma Analysis tools	• *CFD analysis* • *Ray tracing light simulation* • *Isotropic Sky diffuse model* • physics-based noise propagation calculation (CNOSSOS standard)	• *ML Rapid wind Simulation* • *ML Rapid noise simulation* • *ML Energy simulation (ceased in 2024)* • *LCA ML C.Scale model*

Figure 10. Table of benefits and limitations of rule-based and statistical prediction models.

Both noise and wind predictions offer a floorplan with a color gradient scale and percentage estimates. In the case of wind, these predictions show different wind speeds based on wind directions and pedestrian comfort ranges, which can be expressed using the Lawson LDDC comfort scale. This is displayed in a circular area with a 150-meter to 350-meter diameter. For noise, a 200-meter diameter circular area is shown, highlighting different noise comfort levels and percentages of low, medium, and high discomfort, similar to the wind prediction.

The rule-based performance assessment provides a more detailed and precise outcome. In the case of wind, pedestrian comfort plans, including building roofs, are generated based on the persistence of wind speeds over time. These plans are categorized into six

	Sitting	Standing	Strolling	Walking	Uncomfort able
Lawson	1.8 m/s < 2%	3.6 m/s < 2%	5.3 m/s < 2%	7.6 m/s < 2%	7.6 m/s > 2%
Lawson LDDC	2.5 m/s < 5%	4 m/s < 5%	6 m/s < 5%	8 m/s < 5%	8 m/s > 5%
Lawson 2001	4 m/s < 5%	6 m/s < 5%	8 m/s < 5%	10 m/s < 5%	10 m/s > 5%
Davenport	3.6 m/s < 1.5%	5.3 m/s < 1.5%	7.6 m/s < 1.5%	9.8 m/s < 1.5%	9.8 m/s > 1.5%
NEN 8100	5 m/s < 2.5%	5 m/s < 5.0%	5 m/s < 10%	5 m/s < 20%	5 m/s > 20%
CSTB	3.6 m/s < 5%	N/A N/A	3.6 m/s < 10%	3.6 m/s < 20%	3.6 m/s > 20%

Figure 11. Wind comfort scale definitions available in Forma.

different comfort scales (Figure 11), which take into account varying wind speeds and their duration, helping to define different levels of comfort.

Additionally, wind speed ranges are provided for six different wind directions, including the building roofs. The wind streamlines for each direction can be analyzed using filters based on importance, height, and height variation, as well as parameters for amount and precision to better visualize the simulation.

In the case of noise simulations, a more detailed analysis is provided, including noise decibel (dB) range predictions for each façade and roof, in addition to the site floor. The simulations can be filtered by source type—train or road—and divided into day, evening, and night to better understand the noise effects at different times of the day. Figure 12 illustrates the models used, the timeframes, and the outcomes for each type of performance analysis related to wind and noise.

	Wind	Noise
Rapid Analysis	• *ML model* • *1-3 seconds* • *Wind speed and comfort estimation of ground floor*	• *ML model* • *1-20 seconds* • *Noise estimation on ground floor*
Detailed Analysis	• *Computational fluid dynamics (CFD)* • *40 – 200 min* • *Wind speed and comfort estimation of ground floor, and roofs*	• *physics-based noise propagation calculation (CNOSSOS)* • *5-20 min* • *Noise estimation on ground floor, roofs and facades*

Figure 12. main characteristics of rapid and detailed wind and noise performance tools.

Even though rule-based simulations offer more detailed and precise performance analysis, the time difference between prediction and simulation helps improve the design workflow by increasing the number of iterations and facilitating data-driven decision-making. The time required for detailed wind analysis ranges from 40 to 200 minutes, depending on the project complexity and the area of analysis. In contrast, the predictive model provides results in just 1 to 3 seconds. For noise analysis, detailed simulations take between 5 to 20 minutes, based on project complexity, while the rapid simulation provides results in 1 to 10 seconds.

The next section will further describe the statistical machine learning model used for rapid performance prediction, as well as the process by which it was trained.

03.1 Rapid Noise and Wind Machine learning prediction models

The rapid wind and noise prediction tools rely on statistical machine learning models using neural network technology. Both models require the same input parameters as the detailed simulations and provide less detailed but comparable outputs. Neural network models are structured so that, based on the provided dataset for training, an underlying, automatically generated, and generalizable algorithm is created (Holdsworth & Scapicchio, 2024), the model can make a prediction for different situations. In the case of Forma's predictive model, the dataset used to train the neural network is based on the outcomes of rule-based performance analysis models, under specific parameter values and building geometries. Figure 13 illustrates the potential structure and workflow of the machine learning model, where the initial training data set consists of the results from the rule-based simulations, and the output provides equivalent predictions for other case scenarios.

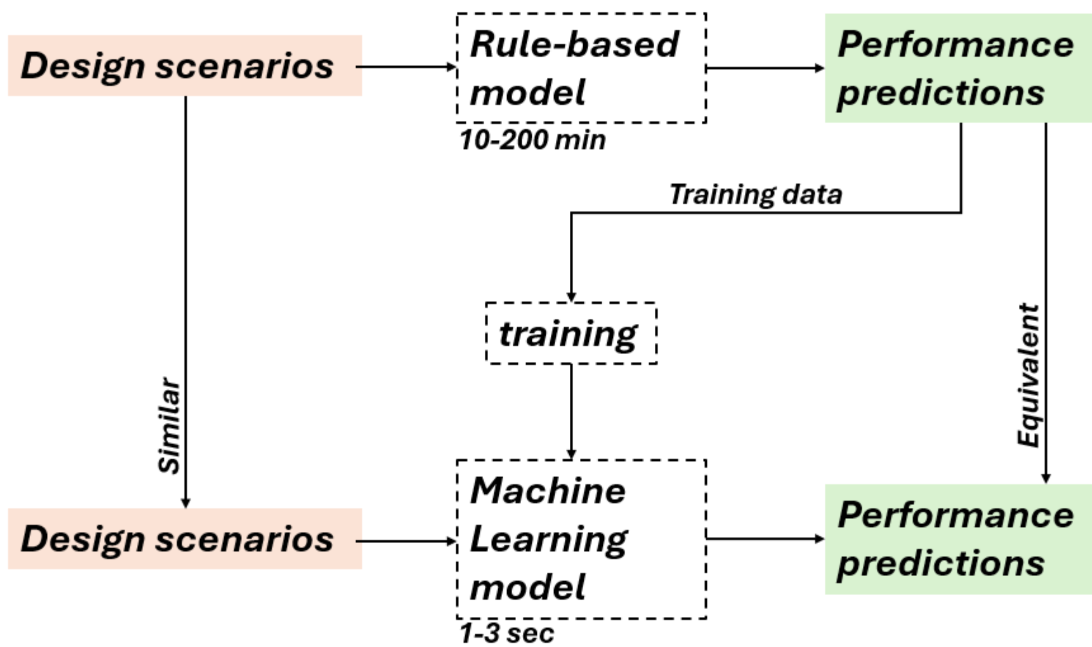


Figure 13. Rapid wind and noise statistical mode potential structure.

The underlying ML model was potentially trained with labeled data, making it a supervised training ML model. The parameters and parameters values of each case used for the training instance were associated with its performance analysis outcome. Potentially the parameters introduced in the training ML stage correspond to those that can be entered in the ML-based predictive tool, and the outcomes are equivalent to those associated with each set of parameters of the training data, The ML model found patters, and correlations between the provided parameter data and outcome so that it can replicate the rule-based logic performance prediction generation in an statistical way. Forma documentation provides a detailed description of accuracy parameters they have obtained by comparing the performance prediction by the ML model and the performance prediction obtained on the ruled-based models for the same set of conditions, Figure 14 shows both predictions for the same set of conditions.

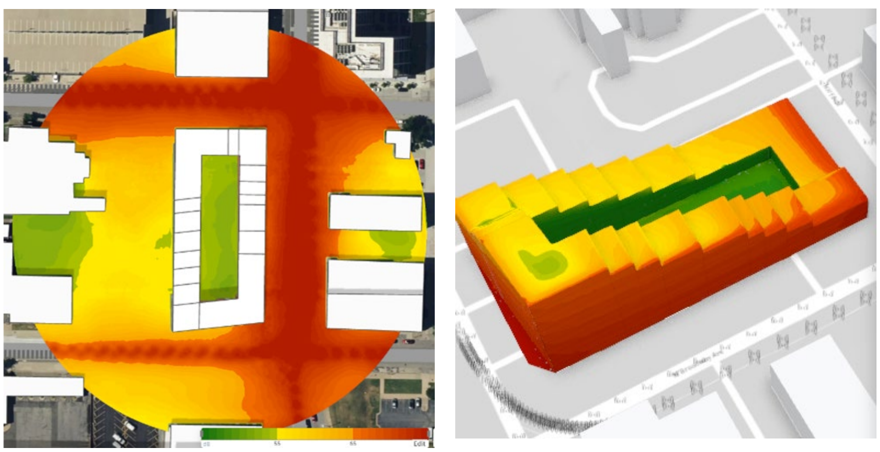


Figure 14. Rapid and detail performance prediction for the same set of conditions.

Currently there are only rapid predictions available to wind and noise. Prior to 2024 there was also an operational energy analysis tool, however, it was discontinued due to the oversimplification of the model used to generate the training data set which led to imprecise predictions, Autodesk has claimed to be actively working to provide a new more accurate version of the tool (Holdsworth & Scapicchio, 2024). The use of ML model to provide predictions has the potential to provide fast performance feedback for complex time-consuming rule-based simulations. It is important to acknowledge also that some performance assessments tools in Forma would potentially not benefit greatly from implementing ML models, at least in terms of time reduction, because the rule-based model tool is already fast. However, ML models could be potentially used to decrease computing time of more precise performance simulations models which may be more accurate.

4.04 C.Scale: Lifecycle assessment

Besides the wind and noise rapid analysis, there is another tool in Forma currently using statistical AI. The embodied carbon tool makes use of a machine learning model as a way of estimating and predicting the performance of the building in terms of total carbon emissions during production, transportation, maintenance, and end-of-life processes. This tool is based on a third-party model called C.Scale. C.Scale has available on their website a web-based tool which performs a whole-life building Lifecycle assessment estimation. This tool calculates embodied, operational, and landscape carbon emissions. The in-Forma embodied carbon tools provide an estimation of carbon dioxide equivalent tons (tCO2e), expressed in total and by area, and a distribution of the emissions in four systems: Envelope, structures, interiors, and MEP systems. C.Scale's more detailed web-based tool offers an estimation of tCO2e as well but in a more detailed manner, broken down by years, scope categories, and lifecycle stages. Moreover, it offers the possibility to study different scenarios by applying reduction strategies to the project and analyzing their effect.

The Autodesk Forma documentation describes the embodied carbon tool use scenarios as:

- Understanding the differences between different high-level choices

- Helping set project goals by setting reasonable tCO2e targets
- Helping non-carbon experts start conversations about sustainability with experts.

The C.Scale product documentation defines the use scenarios for its tools as:

- Identifying which carbon emissions reduction strategies a project should follow.
- Estimating embodied, operational, and landscape carbon emissions.
- Studying carbon emission reduction strategies in different scenarios to set a realistic carbon emissions budget.
- Approximating whole life carbon emissions when conducting an energy model and wbLCA analysis are not practical.

Overall, both alternatives offer the possibility to estimate or test strategies with the strict minimum of parameters defined. On the one hand, in the case of the Forma tool, the building geometry is provided as an input, and the parameters of the building program (commercial, education, hospital, residential, or warehouse), structural system (Wood Frame, Steel Frame, Reinforced Concrete, Mass Timber, Hybrid Concrete-Steel), and cladding system (Granite Veneer, Limestone Veneer, Brick Veneer, Exterior Insulation Finishing System (EIFS), Glass Fiber Reinforced Concrete (GFRC) Rainscreen, Aluminum Composite Panel Rainscreen, Terracotta Rainscreen, Fiber Cement Rainscreen, Formed Zinc Panel Rainscreen, Thin Brick Rainscreen, Formed Steel Panel Rainscreen, Hardwood Rainscreen) are defined. Moreover, the structure, interiors, envelope, and MEP levels of carbon intensities (from low carbon, best practices, conservative, or custom) are defined.

On the other hand, the C.Scale tool offered on their website has more input parameters. From the standpoint of defining the building geometry, the parameters are manually defined instead of obtained from an input geometry. The parameters include location, number of above and below-ground floors, total above and below-ground constructed area, building use, site area, electric grid future scenario, and emissions metrics (energy benchmark use intensity, benchmark fossil fuel use, energy code used, and average refrigerant leakage rates). Once the project parameters, or at least a minimum of them, are defined, the tCO2e estimations can be depicted by year and kind of emission (embodied carbon, refrigerant, electricity, fossil fuel emissions, biogenic carbon, avoided energy emissions, and net emissions), by scope category (energy use, structure, enclosure, interior, services, and sitework), and lifecycle stages (upstream product emissions, energy use, construction site emissions, end-of-life, in-use emissions, benefits beyond system boundary, replacement, and refurbishment), or by lifecycle stage and scope category.

Lastly, the tool offers the creation of different scenarios and inputting of different parameters for carbon reduction strategies to study how those may affect the carbon footprint of the building. The different categories of carbon reduction strategies are reuse, form and massing, energy use structure, carbon intensity, enclosure, interior, services, refrigerants, sitework, and jobsite. The figure 15 shows the different carbon reduction strategies that C.Scale offers.

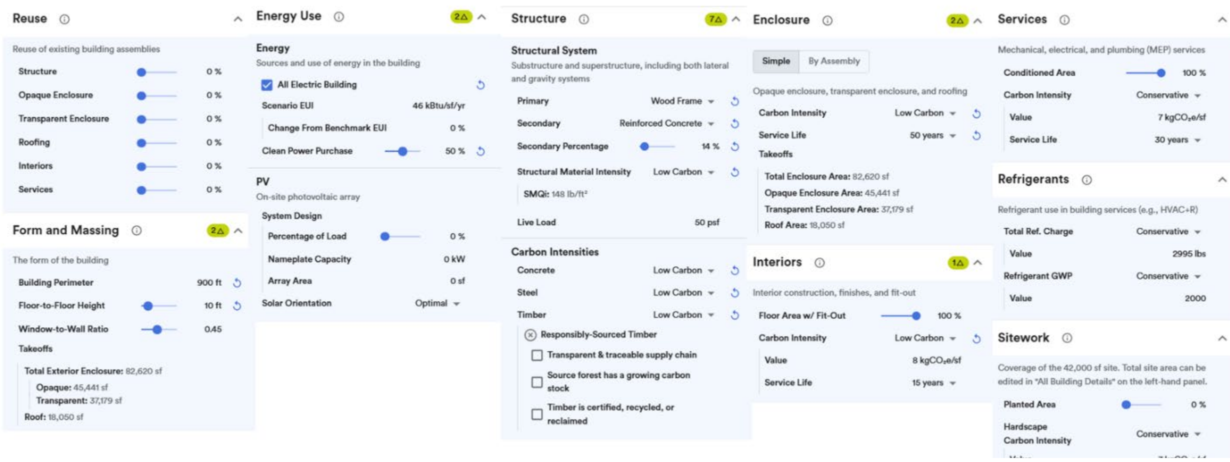


Figure 15. Carbon reduction strategies in C.Scale

C.Scale's estimation model is based on both machine learning and rule-based estimating algorithms. Both the Forma and C.Scale web-based tools make use of C.Scale's estimating model. The model provides estimations for the embodied carbon from different sources (structure and foundation, construction activities, cladding, glazing, roofing and their replacement over time, interior fit-outs and their replacement over time, MEP systems and their replacement over time, PV arrays and their replacement over time, regular landscape maintenance, assessed annually, and hardscape on the building site), operational carbon (combustion of methane, leakages, upstream emissions from electricity production delivered to the site, and refrigerant leakage), and stored carbon (in timber structures and site landscaping).

Of the scopes mentioned, the one that uses a machine learning model is the structure, particularly the estimation of the structure bill of materials. This ML model estimates the quantity of structural elements used for a building based on basic parameters such as areas, perimeter, use, or structure type. The ML model was trained with data from over 1200 buildings from C.Scale's internal sources and public sources. The model is regularly updated as new sources become available. It provides an estimate of quantities of structural material in typical buildings (Climate Scale inc., 2024). C.Scale claims that the model has been reviewed by industry professionals, such as those from MKA, the Carbon Leadership Forum, Autodesk, or Arup.

A benefit of using machine learning for this type of estimation is that, if it were rule-based, more details would probably be required at the beginning. Due to the larger number of parameters that would need to be introduced at the start, it may not be possible to gather enough input data, as much of it may not be defined yet. By making it a statistical estimation based on real information, a certain degree of reliability can be potentially achieved with a smaller number of parameters.

All in all, it could be said that AI capabilities in Forma and C.Scale have the potential to improve design by, on the one hand, helping explore design alternatives, and on the other hand, predicting how a building would perform from an early stage of design. This last capability is of great importance, as design has the goal of fulfilling a set of functions. The possibility that AI tools make it more accessible to better understand how these functions are met or not from an early stage has the potential to improve the result. The next section will look at how these work in the context of a design exercise.

4.05 Forma and C.Scale in practice: Multifamily residential project

Autodesk Forma and C.Scale have the potential to improve the design process, offering generative and performance analysis tools within a collaborative and interoperable platform. The following section will provide a case study to explore the benefits and limitations of the above-described capabilities of Forma and C.Scale tools through the development of an early-stage design exercise. This design exercise is based on a mixed residential building located in downtown Oklahoma City. The aim of this case study is to explore how Forma and C.Scale, particularly their AI-powered tools, work and have the potential to improve design workflows. Both generative symbolic AI tools, such as Forma Site Automation, and statistical performance prediction tools, including rapid wind and noise analysis and LCA tools, will be used. Additionally, rule-based performance tools for wind, noise, and daylight potential will be used to compare with the statistical performance tools.

The exercise is divided into five stages: predesign, conceptual design, option generation, performance assessment, and decision making. The figure 16 depicts the workflow that the exercise will follow, consisting of a simplified recreation of the early-stage design of a residential project. A residential project was chosen as the available tools for Forma are optimized for residential buildings. The first stage will determine the requirements of the project, including a simplified version of the building program, some general functions to be achieved, performance indicators and performance goals to measure them, and code requirements. The second phase will involve generating design options, from which a set of options will be selected and analyzed in the third phase using performance analysis tools for wind, noise, daylight, and LCA. Based on the results, an iterative process of refinement and further performance analysis will be used to decide which option to choose.

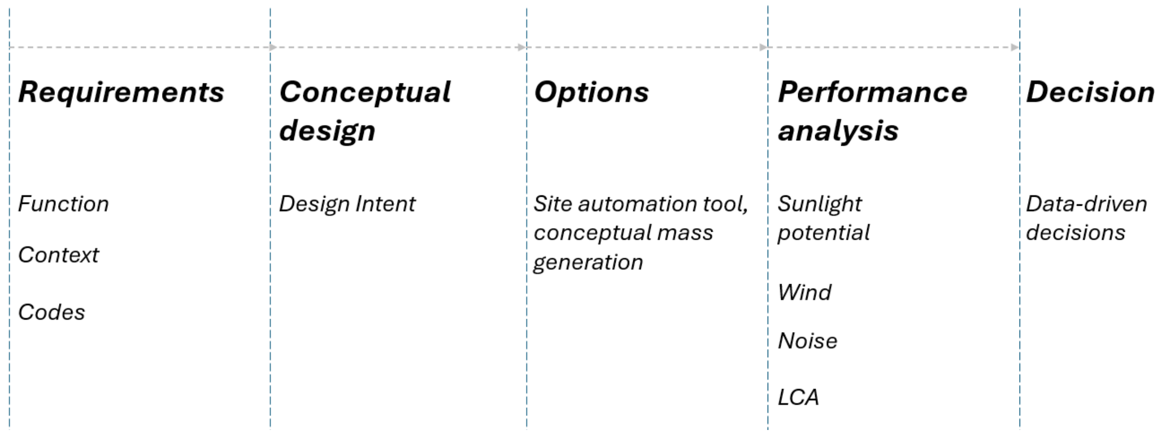


Figure 16. Workflow diagram followed to design exercise for Forma case study.

05.1 Predesign: Requirements.

The first stage of the exercise consists of defining the project requirements, which will determine the design strategies, development decisions, and how to measure the fulfillment of those requirements and determine when they are satisfied. To keep the exercise simple and achievable for this thesis, the predesign process will be simplified, acknowledging that not all functions, program necessities, or code requirements are considered. The building description is defined as follows: a mixed-use building with functional and comfortable, code-compliant residential units for multiple families, fostering sustainable design, combined with commercial facilities on the lower levels.

The building program chosen is for a residential building mixed with commercial use on the first floor. Figure 18 shows a description of the main general areas of the building (residential units, circulation, parking, plaza, amenities, and commercial) as well as the percentage of area they will occupy and an estimation of the area they will cover for a Floor Area Ratio (FAR) of 3 and 4. The building is considered to have a unit density per acre of 125 to 175. The different generated options will be preselected by looking at the FAR parameter in the Area Metrics analysis in Forma and will be considered compliant if the value is between 3 and 4.

Number of units: 125 - 175			
		Area in sq. ft	
Program	**%**	**FAR3**	**FAR 4**
Residential	60	75600	100800
Circulation	12	15120	20160
Commercial	8	10080	13440
Parking	10	12600	16800
Plaza	10	12600	16800
Total	100	126000	168000

Figure 18. Simplified building program with desired area ranges

Regarding code compliance, as the exercise scope is limited to early-stage design, only site code restrictions will be considered. For the selected location, the consultation code is the Oklahoma City Code Article 59 on zoning and planning. The extracted requirements are that the maximum height is 150’, the minimum height is 30’, and there is a maximum

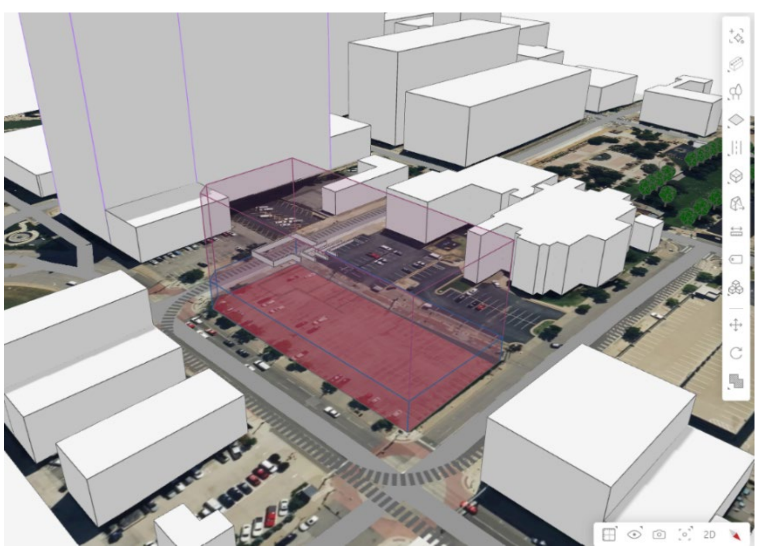


Figure 17.Visual volumetric site restrictions tool in Forma.

setback allowance of 40% on the street fronts. The Forma tools used for assessing maximum and minimum height will be analyzed using the Constrain Volume tool, which allows you to draw a volume and visualize whether the drawn building is inside or outside the constraints (Figure 17).

Lastly, based on the project description, a set of objectives and goals for the building will be defined, focusing on functionality, comfort, and sustainability. Once the goals are set, the performance indicators for measuring the fulfillment of these goals will also be established, along with the metrics or states of the performance indicators that define the success of the project.

For functionality, the FAR range of 3 to 4 will be established as an indicator, ensuring that all intended uses will have sufficient area. Comfort in the building will be measured by daylight potential, ensuring that enough natural light reaches the building's façades, noise produced by street vehicles and trams, and wind comfort, which assesses the comfort level of exterior spaces based on the persistence of wind speeds. These three indicators will be measured using Forma's performance analysis tools. The performance goals will include reducing areas where daylight potential is lower than 15% VSC (Vertical Sky Component) to a minimum, eliminating noise discomfort during nighttime hours on every façade, and minimizing wind discomfort areas while ensuring adequate airspeed for natural ventilation in terraces or interior plazas.

Lastly, to measure sustainability, the Forma carbon emission and C.Scale tools will be used. The goal will be to compare the final selected options to understand how different building shapes affect tCO_2e and to explore carbon emission reduction strategies to develop a realistic carbon footprint minimization plan.

All in all, two sets of requirements are extracted. First, the up-front code and urban conditions regarding maximum and minimum height, as well as the maximum percentage of street frontage, are established, along with the design intent of creating an interior plaza and avoiding view crossovers across the lot. The second set of requirements pertains to performance, focusing on functionality, comfort, and sustainability. The first set will be used to classify the automated design options, while the second will guide the study of the performance of the selected options.

05.2 Conceptual design and options generation

This phase marks the beginning of the design process. The goal of this section is to generate a set of design options and analyze them based on the established general upfront conditions, ultimately preselecting three base alternatives for further analysis. The tool used for this phase is Forma's Site Automation tool. The workflow is as follows: a site location is selected, parameters are input, and by choosing different layout types and building typologies, various automatically generated site configurations can be explored and selected.

The selected site for this exercise is located in downtown Oklahoma City, at Broadway St., lot 311, between 5th and 6th St. The selected area spans 42,000 sq ft. First, the site is selected, and parameters such as linear building width (40'), tower width (70'), number of stories (6), and floor height (10') are input. The next step is to choose the site layout option from empty, grid, or honeycomb. However, due to the lot size (330' x 140'), only the "empty" layout option can be selected. This combination of conditions and parameters generates a total of 13 options.

Once the 13 options are generated, they are analyzed based on the first set of established requirements. Some options are discarded, and others are selected for further analysis. The discarded options are those that fail to comply with the FAR between 3 and 4, exceed the 40% maximum street front setback, fail to generate an interior plaza, or allow views across the site. Figure 19 shows the discarded options, and the ones ultimately selected.

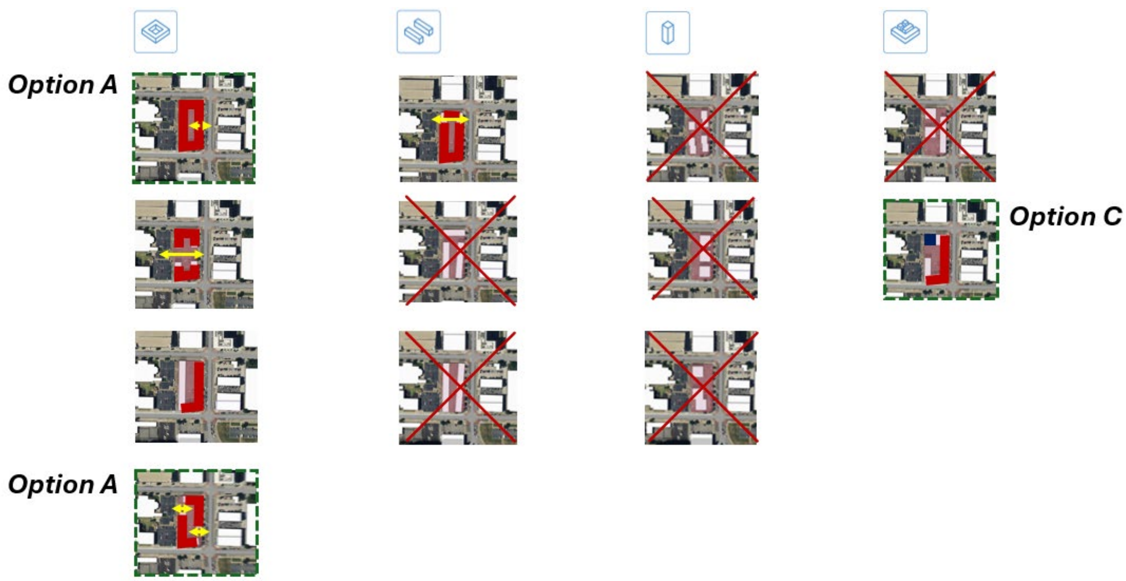


Figure 19.Site automation design alternatives automatically generated, showing discarded options (red X), and those three finally selected (Green dashed outline).

The main benefit observed is the ease and speed with which the tool generates design alternatives, as it takes less than a second to produce the options automatically. Another advantage for early-stage design is the minimal number of parameters required to generate options, which is convenient when some decisions regarding the building details have not yet been made. However, this low number of parameters limits the design space and may result in missing out on other potential alternatives. For example, the tool only allows a single height for all generated geometry and does not permit setting a maximum length for the linear buildings. Therefore, the tool's main potential lies in its role as an exploration tool, which can be used in combination with manual modifications and adjustments to meet more refined requirements.

05.3 Performance analysis

The third phase involves conducting performance analysis to make data-driven decisions. Ideally, all selected alternatives would be equally studied and compared. Based on each performance feedback, new modifications would be proposed and further analyzed. However, for the feasibility of this exercise, only the first option has been selected for further analysis. Wind, noise, and daylight analyses are first conducted on option A, which will be referred to as the base option. Based on the performance feedback from these three analyses, two new options will be proposed, and the three analyses will be repeated for these options. The base option, as well as options 1 and 2, will be compared, and the one that performs best will be selected. Lastly, a new option will be proposed and studied further to determine if it should be accepted or rejected.

To explore the effectiveness of predictive machine learning-based tools, the rapid noise and wind analysis will be used during the analysis, while only the rule-based detailed analysis will be used at the end to validate or reject the proposed design. The daylight potential tool is only available as a rule-based simulation. Due to the simplicity of the exercise, the result is provided in under one minute. However, Forma documentation notes that daylight potential simulations can take anywhere from ½ to 30 minutes.

The first steps in running the analysis for noise, wind, and daylight are shown in Figure 20, with results from the daylight, rapid noise, and rapid wind analyses. Since the rapid wind and noise tools are less detailed, the results provide data only for the street-level surface.

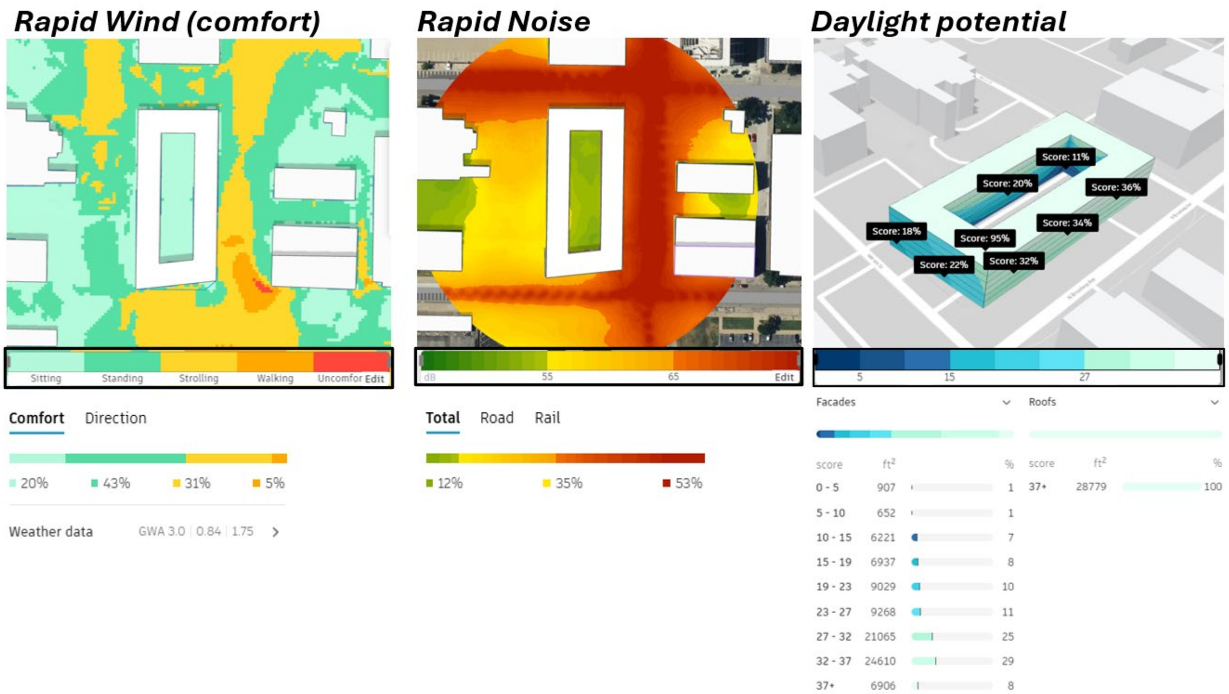


Figure 20. Analysis for noise, wind, and daylight results for selected option. The results are composed of heat map, color scale and performance results percentage distribution.

Based on the performance feedback, the following conclusions are drawn:

- **Wind**: A significant portion of the wind (40%) comes from the south. Due to the surrounding building geometries, the highest wind speeds, and therefore discomfort, originate from the southeast. The narrowing of the streets on Broadway is believed to cause an increase in wind speed due to the Venturi effect.
- **Noise**: The performance feedback indicated that Broadway is the highest source of noise, with 5th and 6th Streets also contributing a considerable amount of noise.

- **Daylight Potential**: Daylight potential measures the amount of light that a window can receive on a cloudy day. The simulation results show that the lower inner portions of the building receive the least amount of natural light.

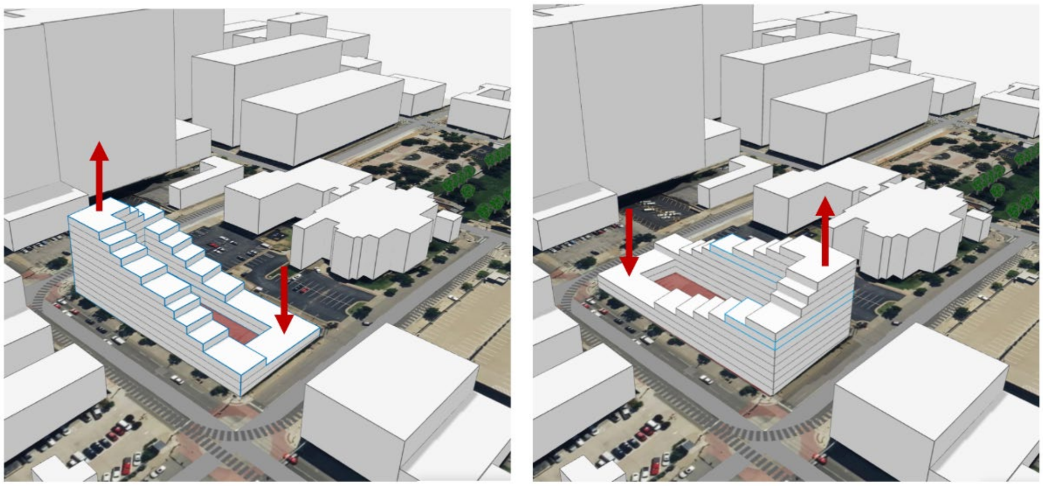
Considering these performance analysis results, the following strategies will be implemented:

- **Wind**: The southeast corner will be raised while the northwest section will be lowered, or vice versa, to create a barrier that mitigates the Venturi effect at the start of Broadway Street.

- **Noise**: The strategy is to separate the building as much as possible from the busy streets.

- **Daylight Potential**: The patio will be opened as much as possible to maximize natural light entry.

Based on the performance analysis feedback, two alternative designs will be generated: the first will raise the southeast corner and lower the opposite corner, while the second will raise the northwest corner and lower the southwest corner (Figure 21). Performance analysis will be conducted on both alternatives, evaluating wind, noise, and daylight.



Option 1 **Option 2**

Figure 21. Base selected desing modifications alternatives based on performance feedback.

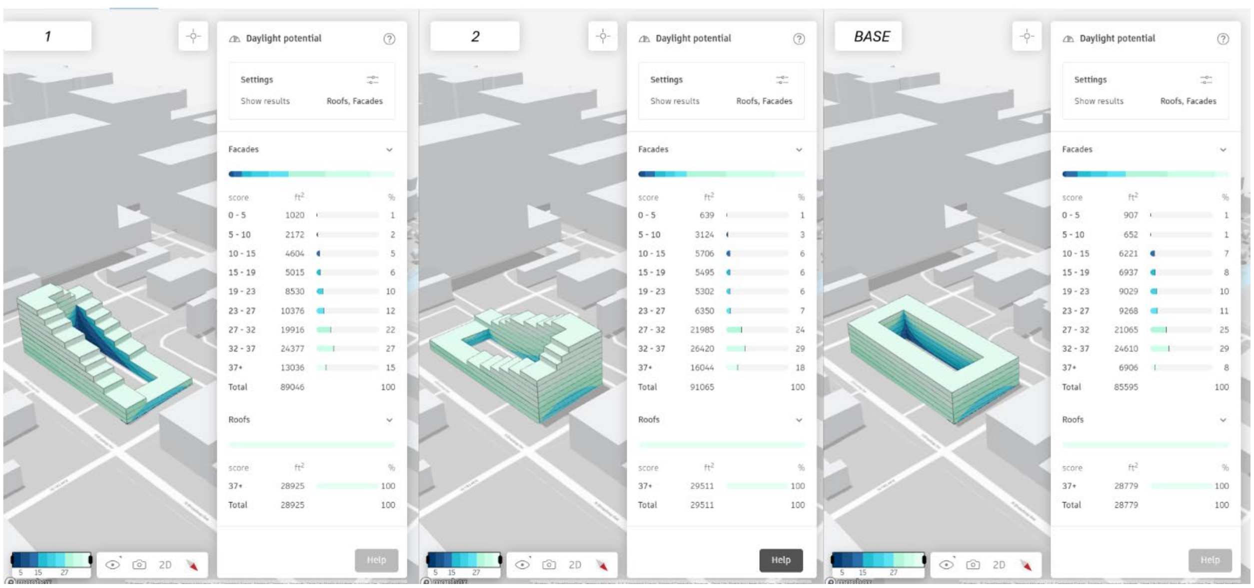
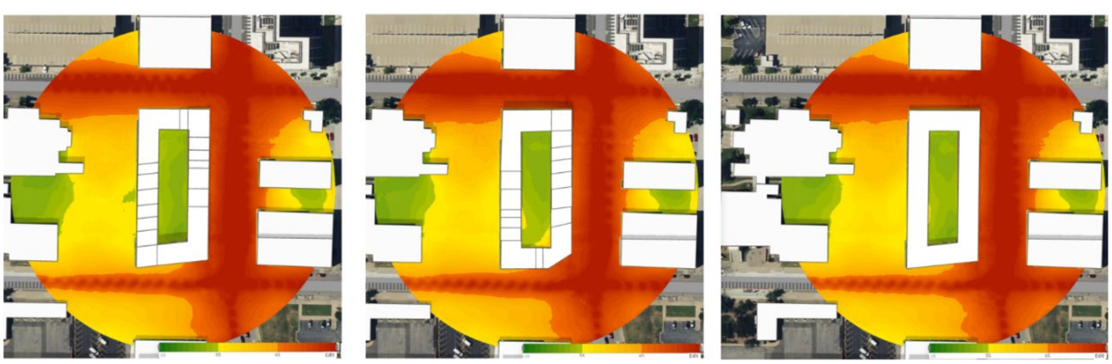


Figure 22. Daylight potential performance analysis results for Option 1, 2 and base.



Option 1 **Option 2** **Base**

Figure 23. Rapid noise performance analysis results for Option 1, 2 and base.

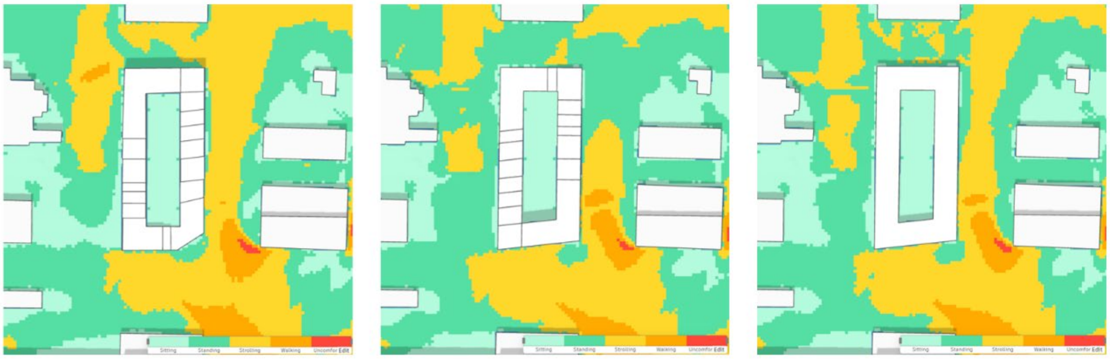


Figure 24. Rapid wind performance analysis results for Option 1, 2 and base.

Figures 22, 23 and 24 show the results for daylight, wind and noise for options 1 and 2, one the analysis has been generated, they need to be compared between each other to study which one is performing better and to the base option to judge the improvement of both. An adjustment needed to be made to this step in relationship to the original designed workflow, the statistical prediction of performance did not provide enough information to judge both options. The rapid analysis provided by Forma regarding wind and noise are only for the ground plane, however the footprint of both options is very similar and the main difference to study is the differences in height and the terraces created. Therefore, detailed analysis were conducted for both the option in noise and wind. Figure 25 shows the comparation between base option and option one and two with detailed wind predictions.

05.4 LCA Analysis

Life cycle assessment allows has been used in the exercise as a performance indicator for sustainability, both in-program embodied carbon estimator tool in Forma, and C.Scale webpage tool has been used in the current workflow. First, the Forma embodied carbon

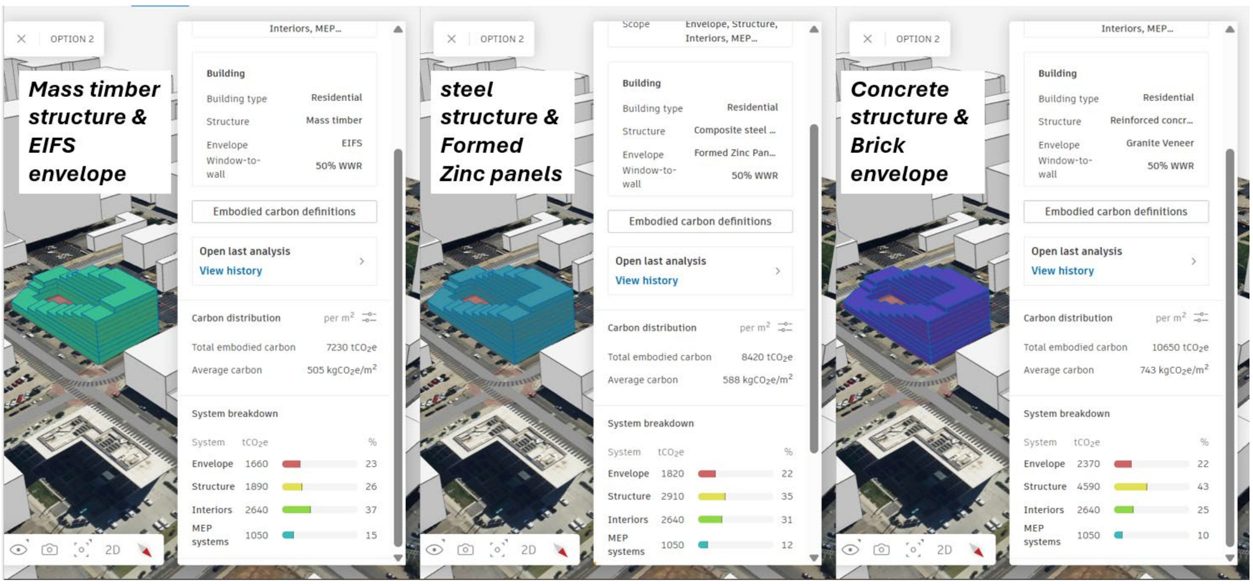


Figure 26. Forma Embodied Carbon performance analysis results for option1, 2 and base.

Figure 25. detailed wind performance analysis results for Option 1, 2 and base.

tool has been used to compare the effect that different options have in the amount of tCO_2e, Figure 26 shows the comparation of the embodied carbon of the different emissions.

The in-Forma tool has been used to compare the effect that different combinations of structural systems and envelope systems have on the embodied carbon emissions. Figure 26 shows that fort the same option a combination of mass timber and EIFS envelope has a considerable inferior carbon footprint that a concrete structure and brick envelope. This kind of insight can help improve early-stage design consideration for reducing the building's carbon footprint

The use of C.Scale webpage tools focuses on one of the design alternatives, these tools have been used to explore how different carbon reduction strategies can not only reduce the embodied carbon emissions but the whole building lifecycle assessment (wbLCA) emissions. The tool provides more possibilities and for example further alternative comparison between how would reusing different elements, using different energy sources or different possibilities for the different elements affect lifecycle emissions.

05.5 Discussion on Forma benefits and limitations

The present case study aims to explore and understand the capabilities and potential of AI in early-stage architectural design. Both the tool descriptions and the practical case study have highlighted several key benefits as well as limitations, which are always present in design tools and need to be acknowledged to avoid interfering negatively with their potential. Some of the general benefits observed in Forma, aside from the use of AI, include the integration of modeling and performance assessment within a web-based accessible platform. Forma's simple and minimalistic approach, while sometimes limiting for developing more detailed or unconventional design solutions, also works to its advantage by ensuring ease of use and a steep learning curve, particularly for users already familiar with other BIM tools.

Nevertheless, the primary focus of this thesis is the role that AI tools can play in design, with generative design tools and AI-based performance analysis tools being the main objects of study. On one hand, the generative design tool “Site Automation” provides a fast and automated way to explore and access a relatively large number of options, instantly generating results with a minimal set of parameters. However, simplifications such as the lack of building-use specificity, uniform height across the entire site, and the limitation to only three building typologies restrict the range of possibilities. The main potential of this tool has been identified in its combination with manual modeling, where the automated models function as high-level exploration tools providing a general base rather than a finalized design solution.

On the other hand, AI tools are used in performance analysis to provide performance estimations. Two main benefits have been observed in the use of these statistical estimation models. First, the reduction in the time required to obtain performance analysis results, which not only increases design efficiency but also allows for a smoother workflow and more data-driven decision-making, as all potential design iterations can receive real-time performance feedback. Second, performance estimation models offer the possibility of obtaining results with minimal input parameters. While rule-based models sometimes rely on oversimplified simulations, machine learning models can utilize real-world data to create statistical models that require fewer inputs. However, oversimplification can also be a drawback in statistical predictive models. A notable example is the withdrawn ML model for energy estimation, which was trained on oversimplified simulation data, resulting in poor generalizability and low accuracy in predictions.

The benefits that performance statistical tools offer also come with limitations or specific use cases where they are more effective. Predictive performance tools, being less precise, are more useful when evaluating options that differ significantly. For example, the information provided by the rapid wind analysis was not sufficient to differentiate between two similar footprint options. However, these tools could have been more effective when comparing two significantly different floor plan configurations.

Similarly, Figure 28 and Figure 27 both display rapid noise analysis results. In Figure 28, it is difficult to assess how variations in building height impact noise levels on each façade, as both results appear similar. In contrast, Figure 27 more clearly illustrates how different block configurations influence noise distribution within the interior of the block. In the second case, the ML-based rapid prediction is sufficient to conclude that the second option performs worse in terms of noise. However, in the first case, the ML model alone does not provide enough information to determine which option is superior, making a detailed noise analysis—one that offers precise noise levels on the façade—necessary.

Beyond the specific characteristics of Forma's tools, the broader question remains: how do AI tools represent and account for behavioral complexity in design problems? Two distinct conclusions can be drawn. On the one hand, statistical rapid wind and noise performance analyses differ from rule-based performance analyses primarily in terms of

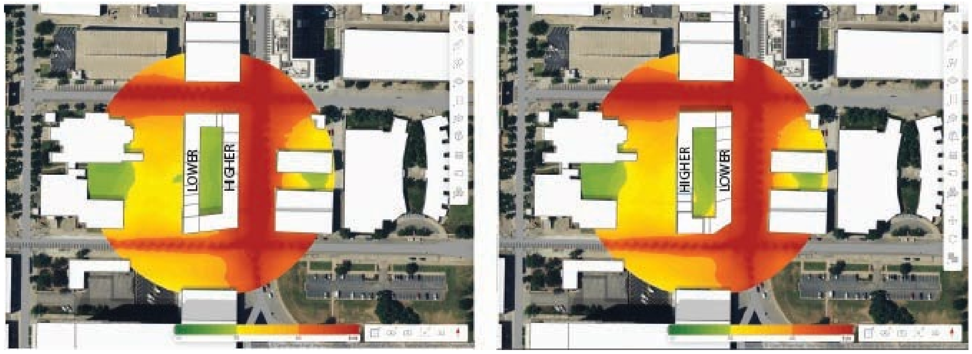


Figure 28. Rapid noise performance analysis of two similar options in footprint.

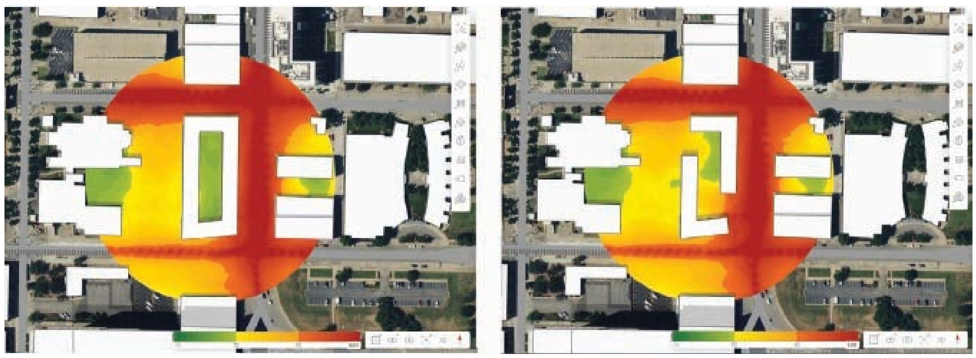


Figure 27. Rapid noise performance analysis of two different options in footprint.

time efficiency and computational demands, without incorporating additional behavioral considerations into the ML model. On the other hand, the ML model used to estimate LCA emissions introduces a more fundamental difference compared to rule-based analysis. Since this machine learning model is based on real performance data and considers a limited set of parameters, deep learning neural networks may identify patterns and correlations that rule-based models, constrained by simplifications, might overlook. The key distinction is that the rapid wind and noise performance models are trained on rule-based algorithm outputs, whereas the LCA estimation model is based on real-world data.

Despite the potential advantages of ML models on predicting performance, their statistical reasoning remains opaque. Unlike rule-based models, which follow a logic-driven causal framework, ML models function as a "black box," meaning their internal decision-making process is not explicitly interpretable. While the reliability of ML-generated results can be studied and assessed, their predictive capabilities remain inherently limited by their inability to explain the underlying reasoning behind their outputs. The lack of behavioral and causal relationships representation, limited to structural constraints, limits the possibilities of measuring different levels of performance. Due to this lack of representation in Forman it is not possible to assess the interdependences between different design decisions based on different performance requirements, considering different performance analysis outcome. For example, if based on a noise performance outcome, if the designers try to optimize a building design the tools would not provide feedback on how that modification affects, for example Floor to area ratio (FAR) requirements. The consideration of behavioral interdependencies and causal relationships existing behind design decisions rely on the designer knowledge and expertise, being AI-powered capabilities of limited help for addressing the behavioral complexity.

Chapter 5. Conclusions and further research

The architectural design process benefits significantly from BIM capabilities, yet BIM-supported workflows also present certain limitations. These include challenges in behavior representation, performance accessibility, user-friendliness, and interoperability. This thesis explores AI-powered tools to assess their contributions to BIM-supported design across various stages. This final chapter outlines the key benefits and limitations observed in AI-powered tools and their impact on different phases of the design process.

Predesign stage

During the predesign stage, AI enhances accessibility and user-friendliness in performance prediction tools, helping establish performance targets early in the process. For example, embodied carbon predictions based on area requirements or building type can assist in setting realistic sustainability goals before the design phase begins.

Conceptual design stage

In the conceptual design stage, strategies and alternatives are explored and compared to select the design candidates that would most likely meet the intended design outcomes. This stage, along with schematic design, provided the most insights in the case study, as the tools examined were primarily focused on early-stage design workflows. One of the main contributions of AI has been the capability to incorporate performance assessment at this stage, offering quick insights with minimal user input. Machine learning (ML) models generate predictions based on trained performance data, where high-level ballpark assessment is more crucial than accuracy. For this reason, some ML models tested (which one) where trained on rule-based simulation outcomes, rather than real-world data. In this approach, while computation is simpler and more efficient, ML models could replicate similar performance biases, along with uncertainty inherited from the rule-based models. Models have intrinsic and extrinsic uncertainty. A ML model based on another model, would most likely replicate if not magnify that uncertainty. However, while training models on real-world building performance data could increase accuracy and applicability, access to reliable, consistent data is currently an issue. Moreover, despite the advantages ML models still face limitations in explaining the reasoning behind their predictions, making them less reliable than rule-based simulations in cases where a good understanding of causal mechanisms is paramount.

Nonetheless, their speed and efficiency make them highly valuable in the early design phases.

A core advantage of BIM is its automation capabilities, and AI-driven tools further enhance this by reducing manual entry and iterations. AI-powered design exploration expands the range of viable alternatives, integrating rule-based parametric generative design with statistical approaches such as AI-generated floor plans or image-based design proposals.

Collaboration in early design stages is also essential, and AI may contribute to interoperability and coordination. While this capability has not been studied in this research, it is possible to anticipate that AI will also streamline data exchange workflows and interoperability between tools and stakeholders. For example, ML models could assist in recognizing and categorizing building elements automatically, improving workflow integration, by completing the specification of property types and values, ensuring data format consistency and other data constraints and requirements. However, AI's most significant impacts have been identified in other areas.

Schematic design

During the schematic design stage, AI-powered performance analysis plays a key role in benchmarking design alternatives. Rapid performance estimations facilitate comparative studies, though ML-based predictions become less reliable as designs advance in complexity. When performance differences between alternatives become subtle, approximate predictions may fail to capture them accurately.

One of AI's intended benefits is improving the representation of complex behaviors and interdependencies in design. However, current AI-powered tools offer only limited improvements in this area.

Design development and construction documentation

As projects move into design development and construction documentation, higher model definition and detailed documentation become essential. Performance assessments continue to guide decision-making, but the increasing level of development also makes workflows more suitable for automation. The combination of ML and rule-based automation enables the analysis and automatic selection of model elements, streamlining tasks based on predefined workflows. Documentation, in particular, presents opportunities for AI-driven automation, leveraging both statistical and rule-based AI capabilities. Additionally in this phase, tasks such as clash detection, building code automatic code checking and Design for Manufacturing and Assembly (DFMA) for prefabricated components could also be automated.

Remarks and Future Directions

In summary, while AI enhances certain aspects of BIM workflows, its integration into architectural design tools remains limited. Expanding AI capabilities could significantly improve behavior representation in BIM models, enhancing computational support for the development of models that provide better explanatory and predictive capabilities, especially during early phases of design. Such capabilities would provide designers with earlier and better insights into the impact of early design decisions, and the potential conflicts among different requirements. A major challenge for AI in design is the lack of a formal understanding of the causal relationships that drive specific performance outcomes, and the potential conflicts that arise among competing sets of requirements. To that end, it is necessary for BIM models to provide a more explicit, machine-readable representations of functions and behaviors associated to building elements. Such representation would enable AI to provide smarter recommendations on how to avoid or mitigate negative impacts of early design decisions, as well as to resolve functional conflicts emerging from different systems. In this way AI could become a more effective design decision support system.

However, the limited definition of those causal and behavioral relationships in current AI tools does not address the complexity of current design projects. As discussed in the first chapter the Structure-Behavior-Function design framework highlighted the importance of considering behavioral side effects or side behaviors as they can affect the fulfillment of the building functions and requirements, these become especially numerous and intricate in large and complex design projects. The current representation of these interdependence is currently limited to rule-based structural proxies. And even though, the accessibility and possibilities of performance assessment have increased with AI-powered capabilities such as those ML predictive models studied in Forma, the support for assessing and considering behavioral complexity has not been fully addressed by AI. AI powered tools do not currently address how decisions taken on design aspect may affect others, as discussed in the Forma chapter conclusion, the tools do not provide insights on how implemented design strategies affect other performance requirements.

In order to consistently address behavior in design, an ontological definition of high-level categories and relationships, would have to be considered. However, the statistical nature or Machine Learning presents limitations for making such definitions. Moreover, rule-based symbolic definitions as are not extensive and do not consider all possibilities in design scenarios, become brittle and cannot provide a successful solution either.

If Behavior definition wants to be addressed another approach needs to be taken. As none, rule-based or statistical approaches provide a complete solution, but they both contribute with benefits and strengths, if they could present a combined approach perhaps behavior could be considered in a more extensive but more logical and reliable way. ML data analysis and prediction could bring automatic capabilities for analyzing data, finding patterns and reaching statistical conclusions. Rule-based structures could provide a high-level structure which would provide a logic and reliable framework. The brittleness of rule-based algorithms could potentially be addressed by ML capabilities of considering large amounts of data and ML uncertainty could be addressed by being combined of rule-based algorithms.

Developing AI approaches which can help focus on considering behavioral in design complexity could perhaps direct current design efforts toward a more function-oriented design. The SBF framework highlights allowing functions as the ultimate goal of design, nowadays some architectural movements tend to focus on formalistic approaches. This may lead to the use of AI tools in a more form finding or inspirational way, not correctly addressing function and its importance for successful design outcomes.

Future research could improve AI prediction accuracy and reliability while making AI-driven tools more accessible across different design stages, further automation in BIM-supported workflows would also be beneficial. However, the most significant advancements would come from AI systems that better understand causal mechanisms and behavioral interdependencies. Strengthening behavior aware feedback mechanisms in design tools would potentially improve AI-generated insights and direct future design trends towards and improved function oriented improved design scenario.

Chapter 6. References

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