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AI-assisted Facade Optimization Tool

MASTER'S DEGREE THESIS IN
BUILDING AND ARCHITECTURAL ENGINEERING

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Abstract

The architecture, engineering, and construction (AEC) industry faces increasing pressure to integrate environmental sustainability into conceptual design phases, where decisions most significantly impact building performance. However, conventional physics-based simulation workflows are often fragmented, computationally demanding, and too slow to support the fluid, iterative nature of early-stage architectural development.

This thesis addresses these limitations by developing an AI-assisted computational workflow that integrates parametric design, environmental simulation, and machine learning (ML) to provide rapid façade performance evaluation.

The research investigates the efficacy of a surrogate model trained on high-fidelity simulation datasets to predict critical environmental metrics—specifically Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), point-in-time illuminance, and incident solar radiation—thereby circumventing the need for repetitive, time-intensive ray-tracing analyses.

The methodological framework involves the construction of a parametric façade model, the automated compilation of an exhaustive performance dataset, and the deployment of a Random Forest Regressor surrogate model embedded directly into a custom Rhino/Grasshopper design plugin. To validate the proposed workflow, a case study of the Il Sole 24 office building in Milan was conducted.

The results demonstrate that the AI-assisted system maintains acceptable predictive accuracy while delivering instantaneous performance feedback, significantly accelerating design iteration compared to traditional sequential workflows. This research contributes to the field of computational and sustainable architecture by bridging the gap between advanced environmental analysis technologies and the practical needs of conceptual architectural design, ultimately promoting a more responsive, performance-informed, and iterative design methodology.

Key-words: Performance-driven Design, Machine Learning, Computational Architecture, Façade Optimization, Daylight Simulation, Parametric Design

Abstract in Italiano

L'industria dell'architettura, dell'ingegneria e delle costruzioni (AEC) affronta una pressione crescente per integrare la sostenibilità ambientale nelle fasi di progettazione concettuale, dove le decisioni hanno il maggiore impatto sulle prestazioni dell'edificio. Tuttavia, i flussi di lavoro di simulazione basati sulla fisica convenzionale sono spesso frammentati, computazionalmente esigenti e troppo lenti per supportare la natura fluida e iterativa dello sviluppo architettonico nelle prime fasi.

Questa tesi affronta queste limitazioni sviluppando un flusso di lavoro computazionale assistito dall'IA che integra progettazione parametrica, simulazione ambientale e machine learning (ML) per fornire una rapida valutazione delle prestazioni della facciata.

La ricerca indaga l'efficacia di un modello surrogato addestrato su set di dati di simulazione ad alta fedeltà per prevedere metriche ambientali critiche — specificamente Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), illuminamento puntuale e radiazione solare incidente — aggirando così la necessità di analisi ray-tracing ripetitive e ad alta intensità di tempo.

Il quadro metodologico prevede la costruzione di un modello di facciata parametrico, la compilazione automatizzata di un set di dati sulle prestazioni esaustivo e l'implementazione di un modello surrogato Random Forest Regressor integrato direttamente in un plugin di progettazione personalizzato per Rhino/Grasshopper. Per convalidare il flusso di lavoro proposto, è stato condotto un caso studio dell'edificio per uffici 'Il Sole 24' a Milano.

I risultati dimostrano che il sistema assistito dall'IA mantiene un'accuratezza predittiva accettabile fornendo al contempo un feedback immediato sulle prestazioni, accelerando significativamente l'iterazione progettuale rispetto ai flussi di lavoro sequenziali tradizionali. Questa ricerca contribuisce al campo dell'architettura computazionale e sostenibile colmando il divario tra le tecnologie avanzate di analisi ambientale e le esigenze pratiche della progettazione architettonica concettuale, promuovendo in ultima analisi una metodologia di progettazione più reattiva, basata sulle prestazioni e iterativa.

Parole chiave: Progettazione guidata dalle prestazioni, Apprendimento automatico (Machine Learning), Architettura computazionale, Ottimizzazione delle facciate, Simulazione della luce naturale, Progettazione parametrica.

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1 Introduction

1.1. Background

The architecture, engineering, and construction (AEC) industry is currently facing increasing pressure to address environmental sustainability and reduce building-related energy consumption. Buildings are responsible for a significant portion of global energy use and carbon emissions, making the improvement of building performance a major priority within international climate strategies and European environmental policies [1], [2]. In response to climate change, energy insecurity, and the growing demand for sustainable development, the European Union has introduced regulations and initiatives aimed at improving the energy efficiency of buildings and reducing operational carbon emissions [3].

The foundation of this research emerged from the academic methodologies and environmental design approaches explored within the Sustainable Building Technologies (SBT) and Energy Efficient Buildings (EEB) courses at Politecnico di Milano. These courses emphasized the integration of computational simulations and environmental analysis into architectural workflows, highlighting the importance of performance-driven design strategies during the early stages of project development. Through daylight simulations, radiation analysis, and energy performance evaluations, the courses demonstrated how computational tools can support more informed architectural decision-making processes.

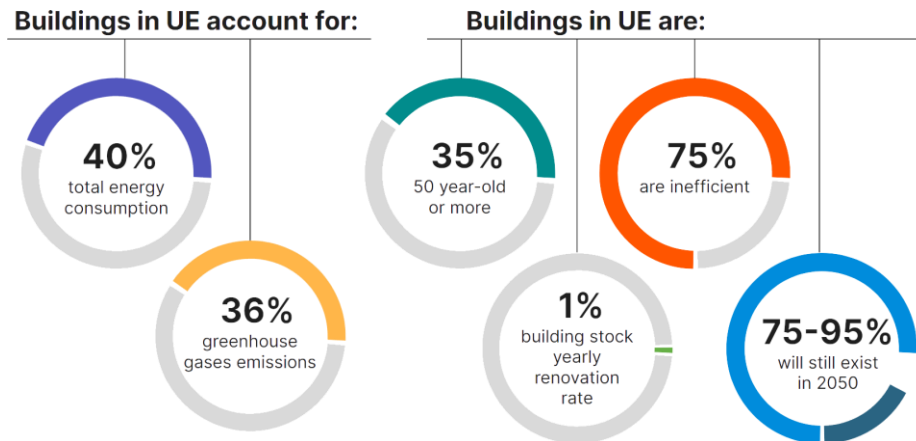


Figure 1-1 – Building Energy Consumption Diagram

Research in sustainable architecture consistently demonstrates that the majority of a building's environmental performance is determined during the conceptual and early design phases [5]. Decisions related to building orientation, massing, glazing ratio, shading systems, and facade geometry significantly affect solar heat gain, daylight penetration, thermal comfort, and annual energy demand. Once projects move into advanced development stages, modifications become increasingly difficult and expensive. Consequently, integrating environmental analysis into early-stage design has become essential for achieving sustainable building performance.

Within this context, the building facade plays a critical role as the interface between indoor and outdoor environments. The facade regulates the exchange of heat, light, and air between the building and its surroundings while directly influencing occupant comfort and energy efficiency [6]. Traditionally considered primarily as an architectural and aesthetic element, contemporary facades are increasingly understood as high-performance environmental systems capable of improving building sustainability and operational efficiency.

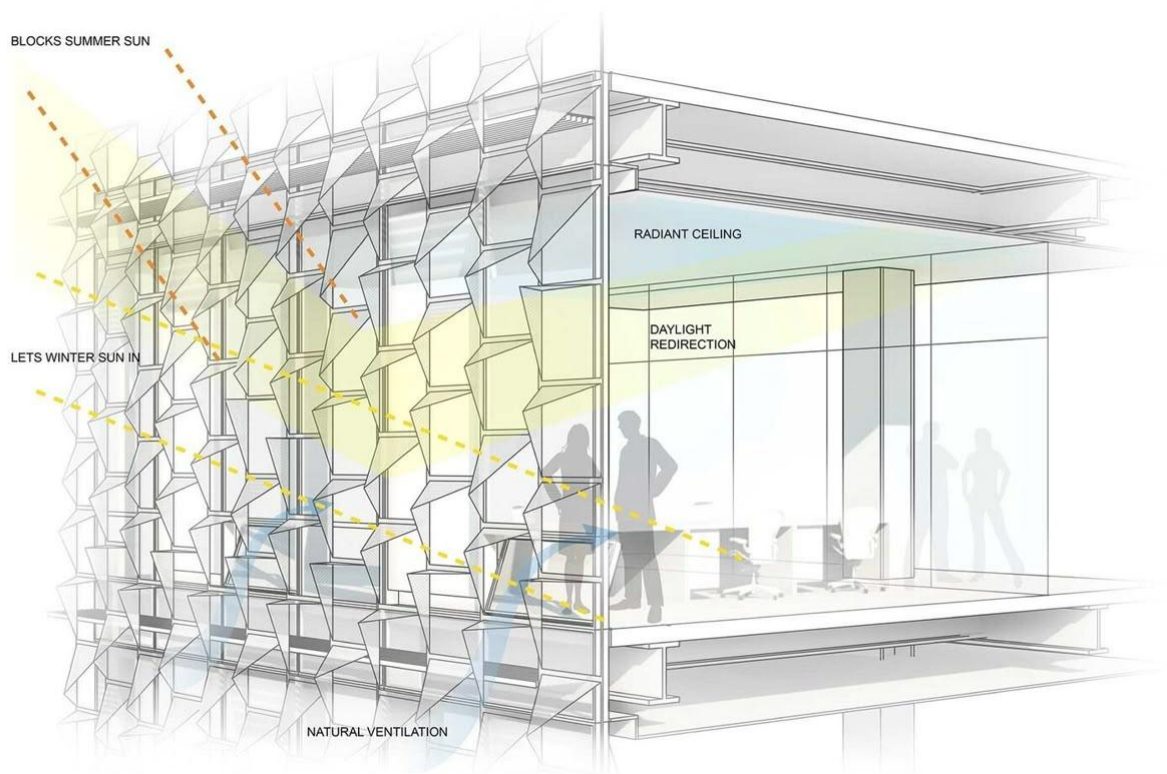


Figure 1-2 – Facade as Environmental Interface[57]

The importance of facade performance has become even more significant following the recent European energy crisis and the instability of global energy markets. Rising energy prices and growing concerns regarding energy dependency have reinforced the need for energy-efficient buildings and responsive envelope systems across Europe [3]. As a result, facade optimization has become an important area of research and professional practice within sustainable architectural design.

Simultaneously, advances in computational design technologies have enabled architects and engineers to evaluate environmental performance with greater precision than ever before. Parametric modeling tools, environmental simulation engines, and optimization algorithms now allow designers to analyze multiple facade alternatives based on measurable environmental criteria such as daylight autonomy, solar exposure, and energy demand [7]. These technologies have expanded the possibilities of performance-driven architectural design and computational optimization.

However, despite these advancements, integrating environmental simulations into conceptual design workflows remains challenging. Existing simulation processes often require extensive model preparation, interoperability between multiple software

platforms, and long computational times, limiting the ability of designers to rapidly explore and evaluate multiple alternatives during early-stage design [8]. Consequently, many architects still rely on intuition or simplified assumptions rather than iterative environmental analysis during conceptual development.

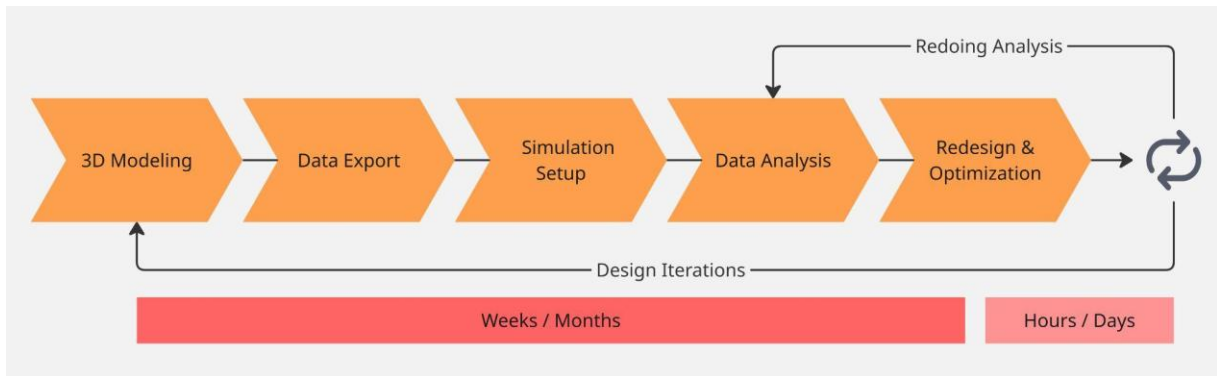


Figure 1-3– Traditional Simulation Workflow

Recent developments in artificial intelligence (AI), machine learning, and data-driven optimization methods have introduced new opportunities for accelerating environmental performance evaluation within architectural workflows [9]. Predictive computational systems trained on simulation-generated datasets have the potential to provide faster performance estimations while supporting iterative design exploration. This emerging intersection between architecture, computational design, and AI-assisted optimization forms the foundation of this research.

This research is positioned within this evolving intersection between architecture, environmental performance, computational design, and AI-assisted optimization. The study investigates how facade performance evaluation workflows can be improved to support faster and more efficient decision-making during conceptual architectural design. By focusing on the optimization of facade modeling and environmental analysis processes, the research aims to contribute toward the development of more accessible and responsive tools for sustainable architectural design.

1.2. Problem Statement

The integration of environmental performance analysis into architectural design processes has become increasingly important due to growing sustainability requirements and energy efficiency regulations. In particular, facade systems play a major role in determining building performance because they directly influence

daylight penetration, thermal behavior, solar heat gain, and operational energy demand [6].

Although environmental simulation tools have advanced considerably in recent years, their integration into early-stage architectural workflows remains limited. Existing simulation processes often depend on complex computational workflows involving multiple software environments, detailed geometric preparation, and computationally intensive analyses [7]. While these methods can provide accurate environmental evaluations, they are frequently too slow and fragmented to effectively support rapid conceptual design exploration.

One of the main challenges in facade performance evaluation is the excessive time required to conduct environmental simulations. Accurate daylight and energy analyses generally require repeated simulation cycles whenever facade parameters such as geometry, opening ratios, shading systems, or material properties are modified. As the number of design alternatives increases, the simulation workflow becomes increasingly repetitive and time-consuming [8].

This issue becomes particularly problematic during early-stage design phases, where architects need immediate performance feedback to support iterative decision-making. Conventional simulation workflows are often unable to provide real-time or near real-time environmental evaluation within the pace of conceptual design development. Consequently, designers may reduce the number of tested alternatives or rely on intuition instead of comprehensive performance-based analysis [5].

Another significant limitation is the fragmentation of current workflows. Environmental analysis commonly requires interoperability between parametric modeling software, simulation engines, visualization platforms, and data-processing tools. Managing information exchange between these systems can interrupt the design process, increase technical complexity, and reduce workflow efficiency [7].

Furthermore, existing optimization approaches frequently prioritize simulation accuracy over design efficiency. While high-fidelity simulations provide reliable environmental data, they often lack the speed and flexibility required for iterative architectural exploration. This creates a gap between the capabilities of environmental simulation technologies and the practical needs of architects during conceptual design stages.

Recent developments in AI-assisted prediction models and machine learning methods suggest the possibility of accelerating performance evaluation by reducing dependency on repetitive simulations [9]. Predictive systems trained on

environmental simulation datasets may provide significantly faster estimations while maintaining acceptable analytical reliability for early-stage decision-making.

Therefore, the primary problem addressed by this research is the lack of a fast, integrated, and designer-oriented workflow for facade performance evaluation during conceptual architectural design. Existing methods remain too slow, fragmented, and computationally demanding to effectively support rapid iterative facade optimization processes.

1.3. Research Aim

The aim of this research is to develop an optimized computational workflow for facade performance evaluation that supports faster, more efficient, and performance-informed decision-making during the early stages of architectural design. The research addresses the limitations of conventional environmental simulation workflows, which are often characterized by long computation times, fragmented software interoperability, and reduced compatibility with iterative conceptual design processes [7], [8]. By improving the speed and accessibility of facade performance analysis, the study seeks to support architects in integrating environmental considerations more effectively during the phases where design decisions have the greatest impact on building performance.

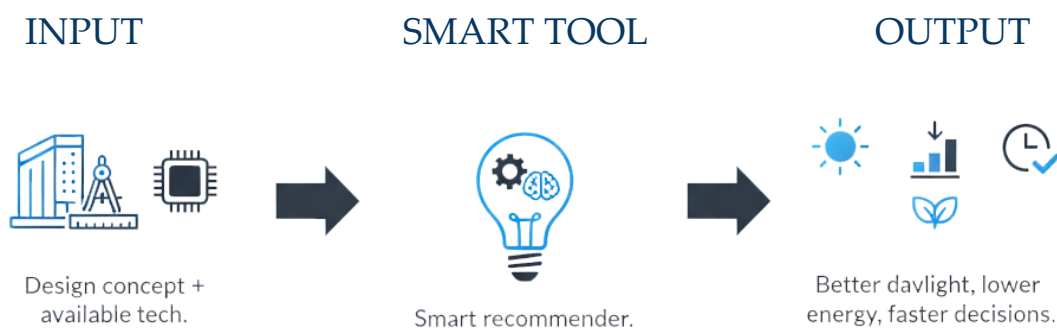


Figure 1-4– General workflow

The research focuses specifically on the relationship between facade design, environmental performance, and computational optimization. Since facade systems directly influence daylight penetration, solar radiation exposure, thermal behavior, visual comfort, and operational energy demand, they represent one of the most critical components in sustainable building design [6]. At the same time, facade development during conceptual design often involves the rapid exploration of multiple geometric and material alternatives. Conventional simulation workflows are generally unable to support this level of iterative experimentation efficiently due to the computational cost associated with repeated environmental analyses.

To address this challenge, the research aims to investigate the integration of parametric modeling techniques, environmental simulation tools, and AI-assisted predictive methods within a unified workflow framework. The proposed system seeks to create a more responsive design process capable of providing rapid environmental performance feedback while minimizing dependency on repetitive and computationally intensive simulation cycles. Instead of relying exclusively on traditional simulations for every facade variation, the study explores the potential of predictive computational models trained on simulation-generated datasets to estimate environmental performance outcomes more efficiently [9].

Another important aim of the research is to improve the compatibility between performance-driven analysis and architectural creativity during conceptual design stages. Existing environmental simulation workflows can interrupt the fluid and exploratory nature of design processes because they often require complex setup procedures, detailed geometric preparation, and extensive technical knowledge [7]. This research therefore aims to develop a workflow that is more integrated, designer-oriented, and supportive of iterative exploration without sacrificing analytical relevance.

The study also seeks to contribute to the broader field of computational and sustainable architecture by examining how AI-assisted prediction methods can enhance environmental decision-making within architectural practice. Through the creation of a parametric facade dataset and the implementation of predictive evaluation techniques, the research investigates how machine learning approaches may reduce analysis time while maintaining acceptable levels of environmental performance accuracy for early-stage applications.

Furthermore, the research aims to establish a workflow that can support rapid comparison between multiple facade alternatives based on measurable environmental criteria such as daylight availability, solar radiation exposure, and energy-related

performance indicators. By enabling faster evaluation and optimization processes, the proposed system intends to encourage a more iterative and data-driven design methodology within architectural workflows.

Ultimately, the research aims to demonstrate how the integration of computational design, environmental simulations, and AI-assisted optimization can improve facade performance evaluation processes and support the development of more sustainable, efficient, and responsive architectural design strategies. The study aspires to bridge the gap between advanced environmental analysis technologies and the practical requirements of early-stage architectural design by proposing a workflow that balances computational accuracy with design efficiency and usability.

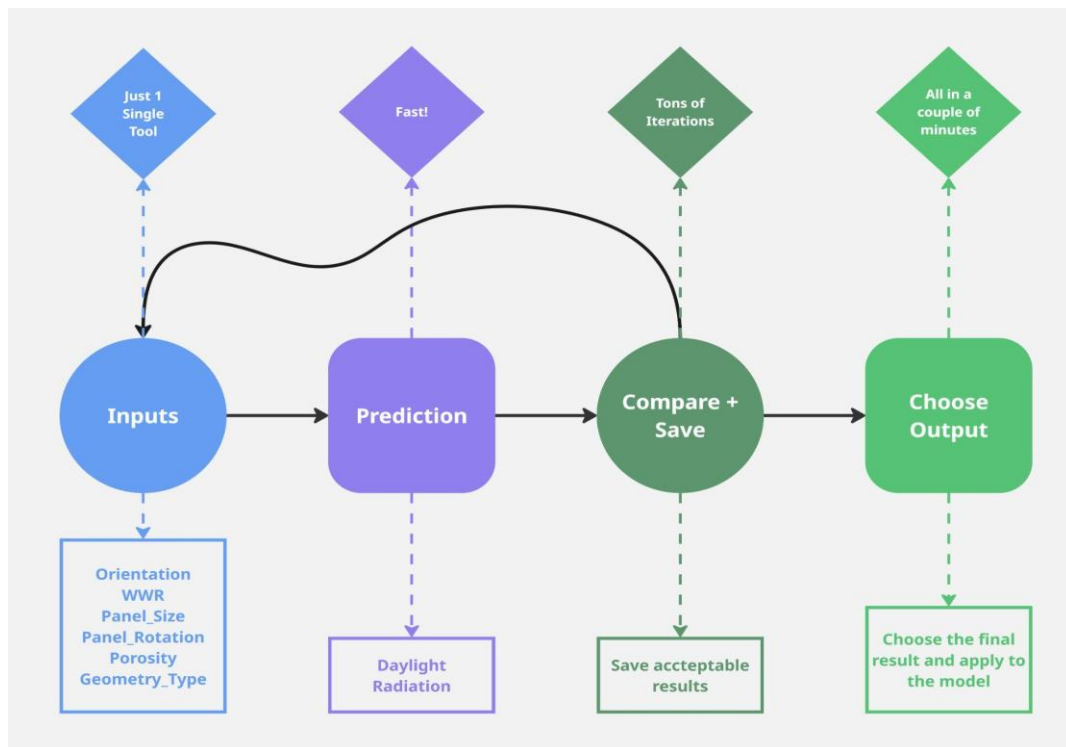


Figure 1-5 – Integrated Computational Workflow for Early-Stage Facade Performance Evaluation

1.4. Research Objectives

Objectives

The primary objective of this thesis is to develop an AI-assisted computational workflow for façade optimization. By seamlessly integrating parametric design, environmental simulations, and Machine Learning (ML), the proposed system aims to make façade design decision-making significantly faster and more efficient. To fulfill this overarching goal, the research is driven by six specific operational objectives:

1. Development of a Parametric Façade Model: The first objective is to construct a dynamic, rule-based parametric model within the Rhino/Grasshopper visual programming environment. This framework must be capable of systematically generating diverse architectural façade scenarios by manipulating critical design variables, specifically focusing on Window-to-Wall Ratio (WWR), shading geometries, and building orientation [5].

2. Evaluation of Façade Performance via Simulations: The second objective focuses on accurately assessing the environmental behavior of the generated façade configurations. This involves executing rigorous daylighting and energy simulations to evaluate each design scenario's impact on spatial visual quality and operational energy consumption, capturing the complex physical behaviors of the building skin [6].

3. Generation of a Simulation-Based Dataset To bridge the gap between physics-based analysis and data-driven prediction, the third objective is to establish an automated pipeline to compile a comprehensive, structured dataset. By employing an exhaustive, full-factorial approach, this dataset will aggregate every possible discrete combination of parametric design inputs and their corresponding simulated performance outputs, serving as a highly robust and blind-spot-free ground truth for the machine learning phase.

4. Training and Validation of a Machine Learning Model: The core technical objective is to train a machine learning algorithm capable of predicting façade performance metrics based on the established dataset. Once trained, the surrogate model's predictive accuracy will be rigorously validated against the actual simulation results to ensure its reliability and analytical precision as a predictive tool [8].

5. Integration into an Interactive Design Tool: To ensure practical utility for architects, the fifth objective is to embed the validated predictive model directly back into the native Rhino/Grasshopper workspace. This integration aims to create an

interactive decision-support tool that provides instantaneous, real-time performance feedback as the user manipulates geometric design parameters [9].

6. Comparative Analysis with Traditional Workflows: The final objective is to critically evaluate the success of the proposed AI-assisted workflow by comparing it against conventional, multi-software simulation methods. This comparative analysis will assess the new system based on computational speed, workflow usability, and overall efficiency during the conceptual design phase.

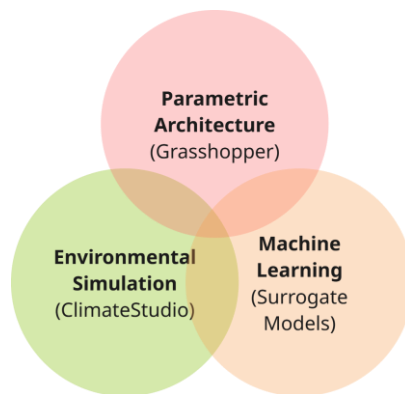


Figure 1-6 – Research Scope

1.5. Research Questions

The transition from traditional, physics-based simulation environments to an AI-assisted predictive workflow introduces critical methodological inquiries. To evaluate the success, reliability, and practical utility of the proposed interactive decision-support tool, this research is structured around three fundamental questions:

1. Predictive Accuracy and Simulation Fidelity: To what extent can a Machine Learning surrogate model accurately predict environmental façade performance (specifically daylighting and energy metrics) when compared directly to the ground-truth data generated by traditional, physics-based simulations? Establishing this baseline addresses Objective 4, as surrogate models must prove they can capture complex, non-linear environmental behaviors with an acceptable margin of error for early-stage design exploration [10].

2. Workflow Efficiency and Comparative Acceleration: How does the proposed AI-assisted workflow, compare to conventional, multi-software simulation methods in terms of computational speed, iteration capacity, and overall efficiency during the

conceptual design phase? This question directly addresses Objective 6, seeking to quantify the exact temporal savings of deploying instantaneous machine learning inferences over computationally heavy raytracing algorithms [11].

3. Interactive Design and Decision-Making: In what ways does embedding a real-time predictive model directly into the native Rhino/Grasshopper modeling environment influence the architect's ability to optimize building skins? Addressing Objective 5, this question investigates the practical impact of the tool on usability, examining whether instantaneous, interactive feedback successfully encourages a more effective "optioneering" approach without interrupting the creative flow [12].

1.6. Thesis Structure

To systematically address the established research questions and objectives, this thesis is organized into seven interconnected chapters. The written workflow is structured as follows:

Chapter 1: Introduction This chapter establishes the foundational context of the research by outlining the environmental and operational challenges within early-stage façade design. It defines the problem statement, articulates the primary research aims and objectives, and formulates the core questions guiding the study.

Chapter 2: Literature Review The second chapter provides a comprehensive review of existing academic literature across domains such as building energy performance, daylighting, parametric design, and machine learning in architecture. It critically evaluates current simulation tools and optimization methods to identify the existing research gap, ultimately justifying the need for the proposed AI-assisted workflow.

Chapter 3: Methodology This chapter details the technical framework of the study, mapping the complete workflow from parametric geometry generation to automated dataset extraction and preprocessing. It extensively describes the architecture and training protocol of the machine learning surrogate model, concluding with its integration into the Rhino/Grasshopper environment as an interactive design tool.

Chapter 4: Case Study The fourth chapter introduces a specific architectural project to practically apply and test the developed computational workflow. It defines the base building model and establishes the various parametric façade scenarios that will undergo both traditional simulation and AI-driven evaluation.

Chapter 5: Results This chapter presents the quantitative findings of the study, rigorously validating the predictive accuracy of the machine learning model against the baseline, physics-based simulation data. It provides a comparative analysis highlighting the computational time saved by the AI workflow and identifies the most optimized façade outcomes for the selected case study.

Chapter 6: Discussion The sixth chapter interprets the generated results, analyzing how individual geometric parameters influence overall building performance and evaluating the systemic strengths of the proposed tool. It addresses the practical limitations and methodological challenges encountered during development, while proposing viable directions for future research and tool expansion.

Chapter 7: Conclusion The final chapter synthesizes the core findings of the thesis, directly answering the established research questions. It highlights the study's overall contribution to the fields of computational design and sustainable architecture, reaffirming the value of real-time predictive modeling in conceptual practice.

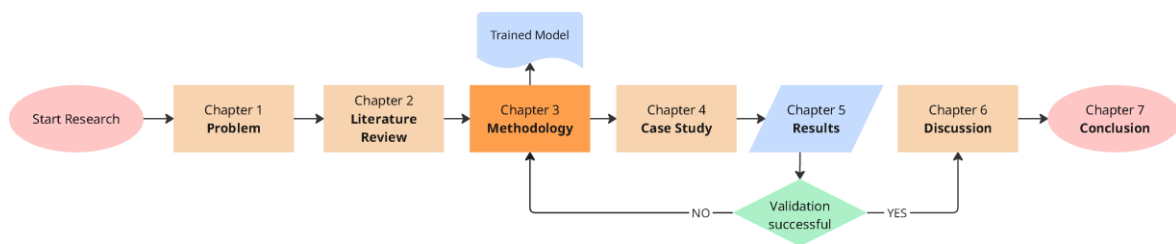
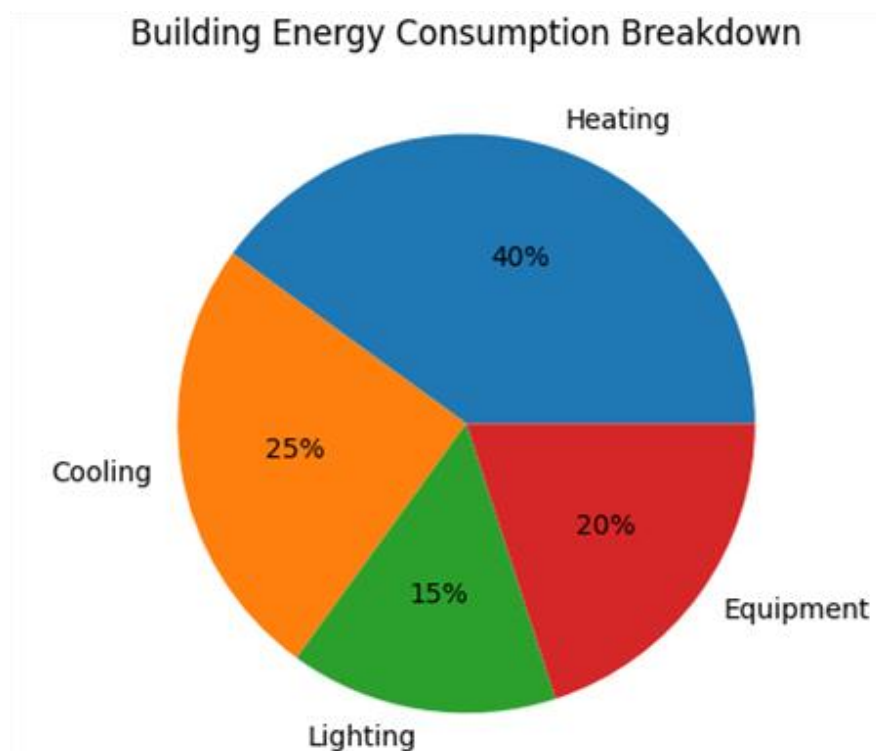


Figure 1-7 – Thesis structure flow chart

2 Literature Review

2.1. Building Energy Performance

Building energy performance refers to the assessment of the energy required for the operation of a building, including heating, cooling, ventilation, lighting, and plug loads. It represents a fundamental indicator of building efficiency and environmental impact, particularly in the context of global sustainability goals. The building sector is recognized as one of the largest consumers of energy worldwide, accounting for approximately 30–40% of total energy use and a significant share of greenhouse gas emissions, as reported by the International Energy Agency [2]. This has led to



increasing attention toward improving building performance through both design strategies and technological innovation.

Figure 2-1 – The relative contribution of different energy uses in buildings

The evaluation of building energy performance is inherently complex, as it depends on multiple interrelated factors. Among these, climatic conditions play a primary role, influencing heating and cooling demands throughout the year. For example, buildings located in colder climates typically require higher heating loads, while those in warmer regions demand more cooling energy. Consequently, climate-responsive design has become a key approach in reducing energy consumption by adapting building form and systems to local environmental conditions [13]. This includes strategies such as optimizing solar gains, enhancing natural ventilation, and reducing thermal losses.

The building envelope is one of the most critical components affecting energy performance. It acts as a thermal barrier between indoor and outdoor environments, regulating heat transfer and solar radiation. Key parameters include insulation levels, material properties, glazing type, and Window-to-Wall Ratio (WWR). The WWR, in particular, has a significant impact on both thermal and visual performance. Higher WWR values can improve daylight availability and reduce the need for artificial lighting, but they may also increase unwanted heat gains in summer or heat losses in winter, depending on the climate and orientation [14]. Therefore, optimizing WWR is a crucial aspect of façade design and energy efficiency.

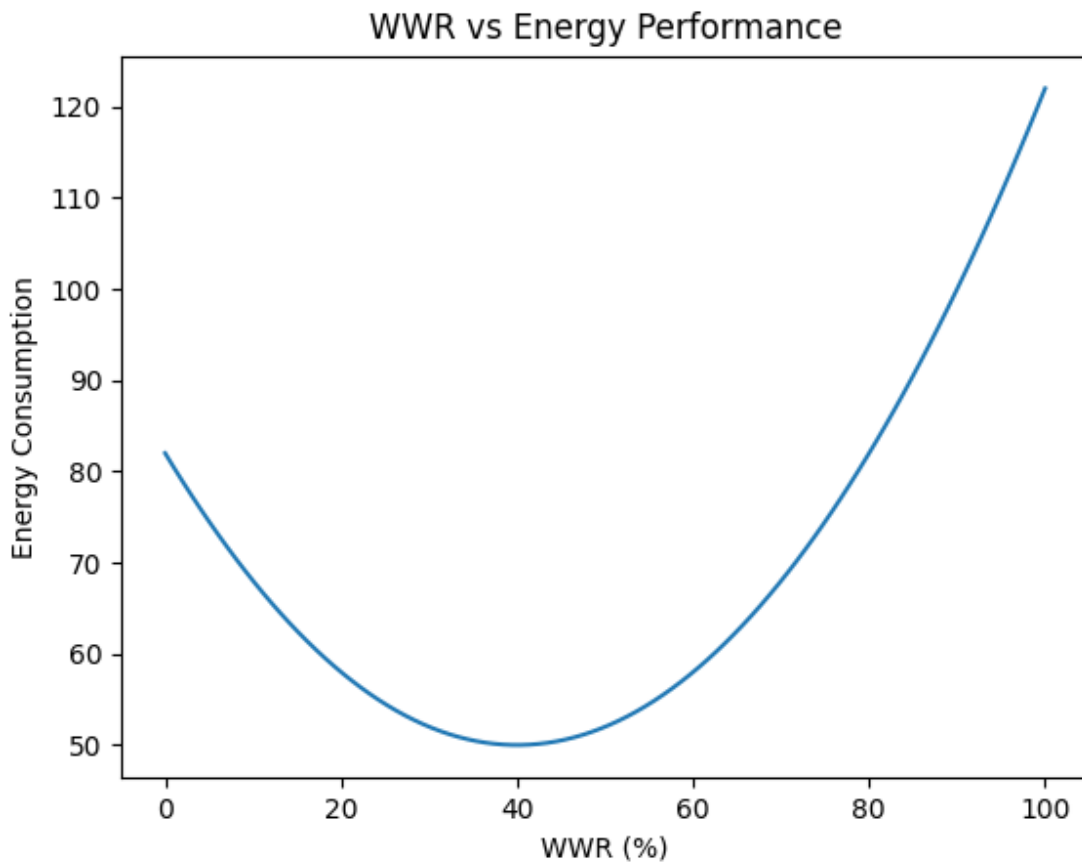


Figure 2-2– The relationship between WWR and overall energy consumption

In addition to envelope characteristics, building orientation strongly influences energy performance. Orientation determines the amount and distribution of solar radiation received by different façades over time. In the northern hemisphere, south-facing façades typically receive the highest solar exposure, which can be advantageous for passive heating during winter months. However, without proper shading strategies, excessive solar gains can lead to overheating and increased cooling demand during summer [15]. As a result, the integration of shading devices and façade articulation becomes essential in balancing solar access and thermal comfort.

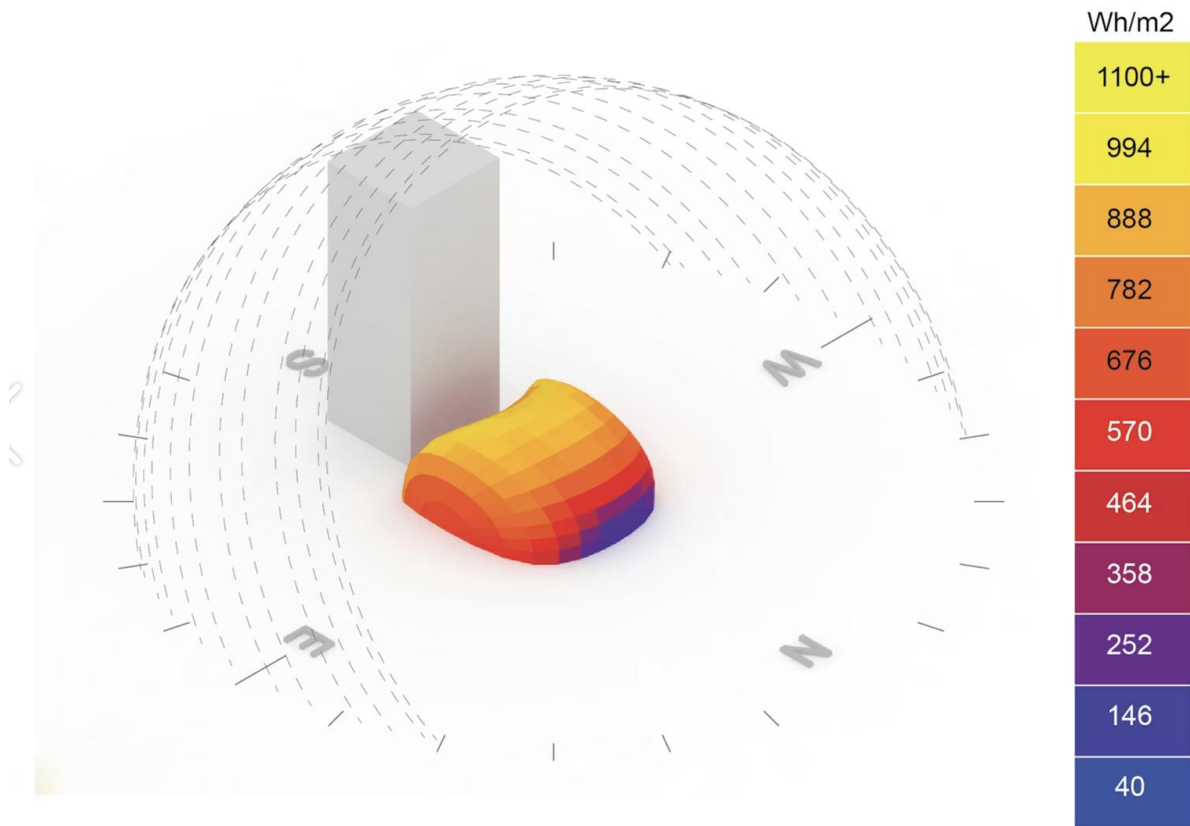


Figure 2-3 – The variation of solar exposure based on façade orientation

Another important aspect of building energy performance is the role of internal loads and occupancy patterns. Human activities, equipment usage, and lighting systems contribute to internal heat gains, which can significantly affect thermal conditions. In highly occupied or equipment-intensive buildings, internal gains may reduce heating demand but increase cooling requirements. Therefore, accurate representation of occupancy schedules and internal loads is essential in performance evaluation models [16].

To assess and predict building energy performance, simulation-based methods have become standard practice in both research and professional applications. Tools such as EnergyPlus enable detailed modeling of building physics, including heat transfer, air flow, and system operations. These tools rely on numerical methods and time-step calculations to simulate building behavior under varying environmental conditions. While they provide highly accurate results, they require detailed input data and significant computational resources, which can limit their usability during early design stages [17].

The integration of simulation tools into the design process has significantly improved the ability of architects and engineers to evaluate performance before construction. However, traditional simulation workflows are often time-consuming and require specialized expertise. This creates a gap between design exploration and performance evaluation, particularly in early phases where multiple design alternatives must be tested rapidly. As noted in guidelines developed by ASHRAE, early design decisions have a substantial impact on overall building energy consumption, yet they are often made with limited performance feedback [18].



Figure 2-4– A typical workflow for building energy simulation

In response to these challenges, there has been a growing emphasis on performance-driven design approaches. These approaches aim to integrate energy analysis directly into the design process, allowing designers to evaluate and optimize building performance iteratively. Parametric design tools and optimization algorithms have been increasingly used to explore a wide range of design configurations and identify high-performance solutions. This shift reflects a broader transition from prescriptive design methods toward data-informed and performance-based strategies [11].

Furthermore, the concept of high-performance buildings has evolved in recent decades, leading to the development of low-energy and nearly zero-energy buildings (nZEB). These buildings aim to minimize energy demand through passive design strategies and efficient systems, while also incorporating renewable energy sources to offset consumption. The European Union, in particular, has established regulations requiring new buildings to meet nZEB standards, emphasizing the importance of energy performance in contemporary architectural practice [4].

Despite the advancements in simulation and design methodologies, a key limitation remains the trade-off between accuracy and computational efficiency. High-fidelity simulation tools provide reliable results but are not always suitable for rapid evaluation of multiple design options. This limitation becomes especially critical in parametric design contexts, where hundreds or thousands of design variations may be generated. To address this issue, recent research has explored the use of surrogate models and data-driven techniques, including machine learning, to approximate simulation results with significantly reduced computation time [19].

These emerging approaches offer the potential to transform building performance analysis by enabling real-time feedback and supporting decision-making during early design stages. By learning from large datasets of simulation results, machine learning models can predict energy performance based on input parameters such as geometry, orientation, and material properties. This capability is particularly relevant in the context of façade design, where complex geometries and multiple variables interact to influence performance outcomes. As a result, the integration of data-driven methods represents a promising direction for improving both the efficiency and accessibility of building energy analysis.

2.2. Daylighting in Architecture

Daylighting refers to the controlled use of natural light in buildings to illuminate interior spaces, with the aim of reducing energy consumption and improving indoor environmental quality. It is a fundamental aspect of sustainable architecture, as it directly reduces the need for artificial lighting while enhancing occupant comfort and well-being. According to the International Energy Agency, lighting accounts for a significant portion of electricity use in buildings, making daylighting strategies essential for energy-efficient design [2]. In addition to energy savings, daylight has been shown to positively affect human health, productivity, and circadian rhythms [20].

The contribution of daylight to reducing artificial lighting demand in buildings is illustrated in Figure. 2.5.

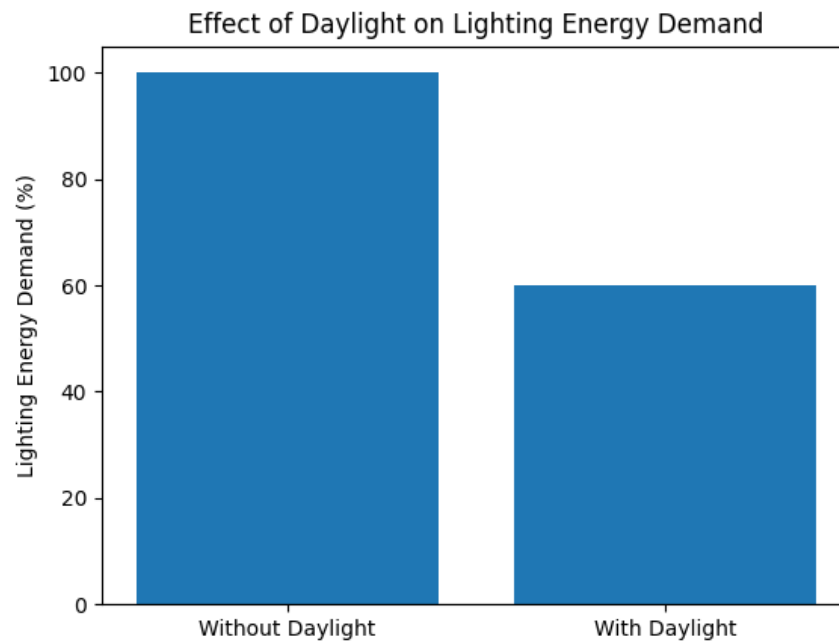


Figure 2-5 – Contribution of daylighting to reducing artificial lighting energy demand in buildings (Source: author)

The performance of daylighting in buildings depends on several design parameters, including window size, glazing properties, orientation, and interior layout. Among these, the Window-to-Wall Ratio (WWR) plays a crucial role in determining the amount of daylight entering a space. Larger window areas generally increase daylight penetration but may also introduce issues such as glare and excessive solar heat gain. Therefore, achieving a balance between sufficient daylight and visual comfort is essential. The geometry of the space, including room depth and surface reflectance, also significantly influences daylight distribution [21].

The relationship between window size and daylight penetration is shown in Figure. 2.6.

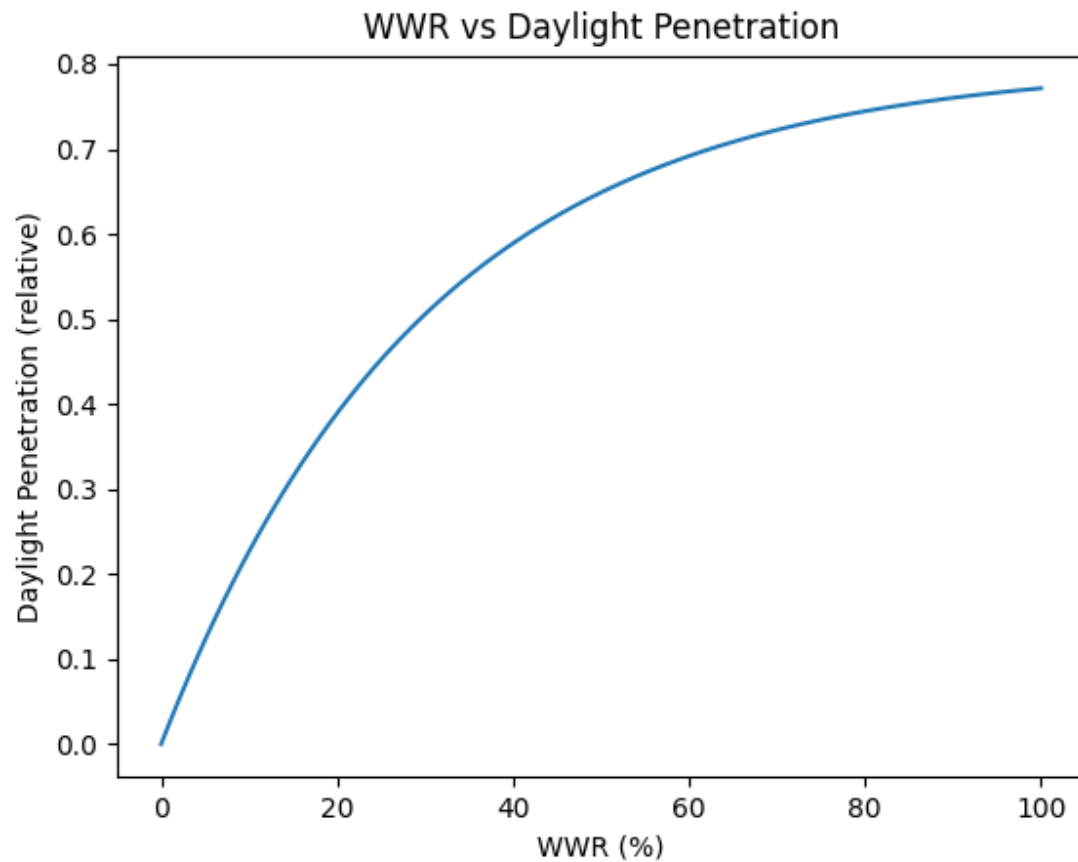


Figure 2-6 – Impact of Window-to-Wall Ratio (WWR) on natural light penetration in interior spaces (Source: author)

To evaluate daylight performance, several quantitative metrics have been developed. Among the most widely used are Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE), defined by the Illuminating Engineering Society. sDA measures the percentage of occupied floor area that receives sufficient daylight levels (typically 300 lux) for a specified portion of the year, while ASE quantifies the risk of excessive sunlight exposure that may cause glare or overheating [22]. These metrics provide a more comprehensive assessment compared to traditional static measures, as they consider annual variations in daylight availability.

The evaluation metrics for daylight performance are summarized in Figure. 2.7.

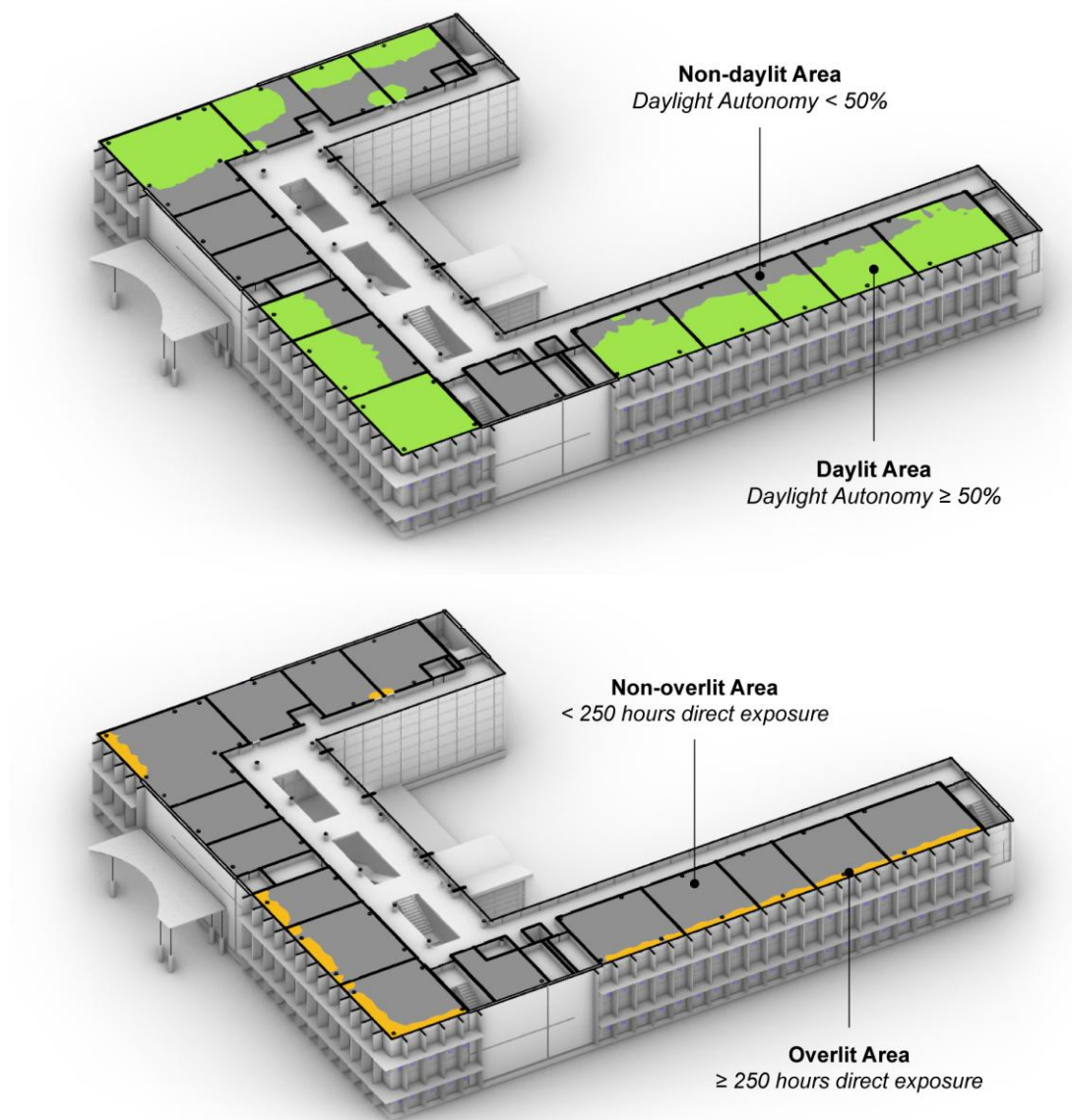


Figure 2-7 – Comparative Visualization of Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (Source: author)

Daylighting design must also address potential challenges such as glare, non-uniform illumination, and thermal discomfort. Excessive daylight can lead to visual discomfort and increased cooling loads, particularly in climates with high solar radiation. To mitigate these issues, shading devices such as louvers, blinds, and secondary façades are commonly used. These elements help control the amount and direction of incoming light, improving both visual and thermal performance. The integration of

dynamic or adaptive shading systems has further enhanced the ability to respond to changing environmental conditions [14].

The effect of shading devices on daylight control is illustrated in Figure. 2.8.

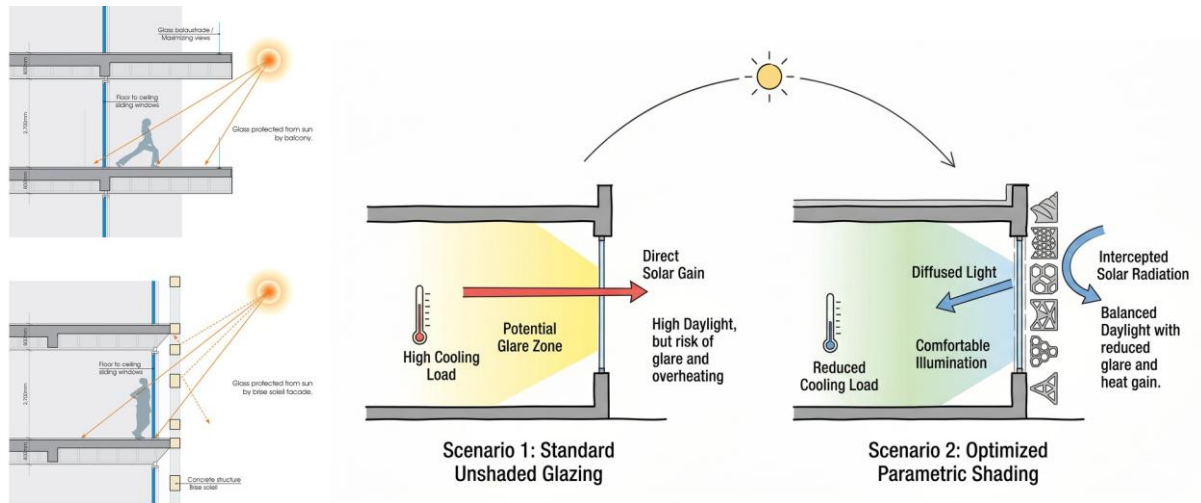


Figure 2-8 – Impact of shading devices on daylight penetration and glare control (Source: adapted from Tzempelikos [14])

Simulation tools play a critical role in daylighting analysis, allowing designers to predict lighting conditions and optimize design parameters. Software such as Radiance is widely used for physically-based daylight simulation, providing accurate results for illuminance, glare, and light distribution [23]. These tools enable detailed analysis but often require significant computational effort and expertise. As a result, similar to energy performance analysis, their use is sometimes limited in early design stages.

A typical workflow for daylight simulation is shown in Figure. 2.9.

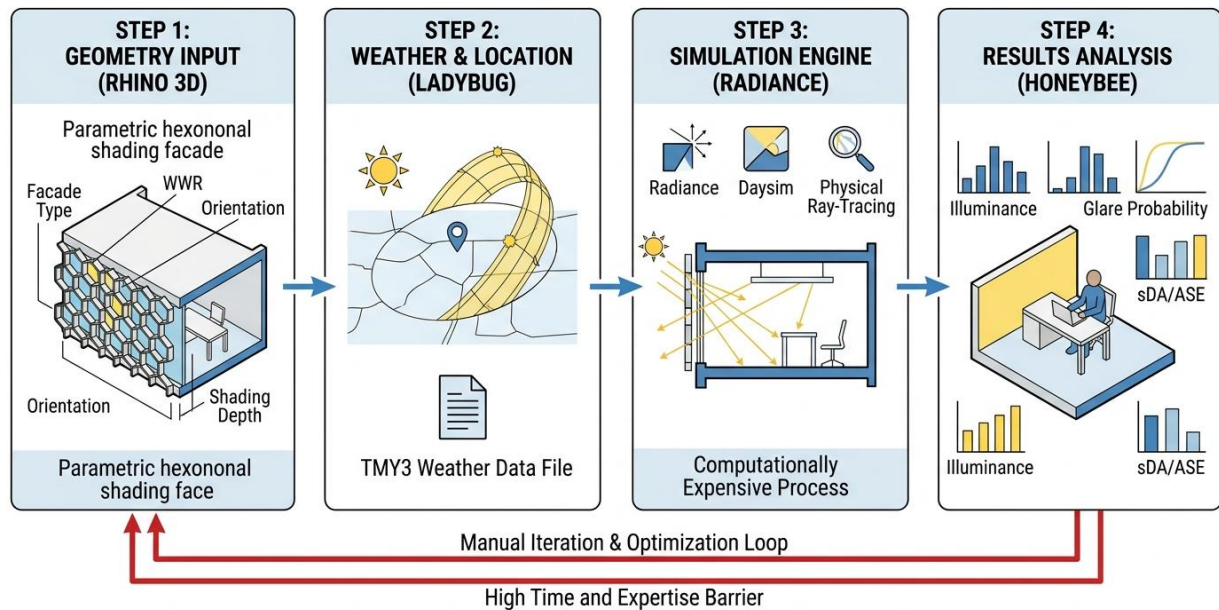


Figure 2-9 – Workflow of daylight simulation from geometry input to performance metrics output (Source: author)

In recent years, there has been increasing interest in integrating daylight analysis into parametric and performance-driven design workflows. This allows designers to explore multiple design alternatives and evaluate their daylight performance in a more efficient manner. However, the computational cost of repeated simulations remains a challenge, particularly in complex geometries such as parametric façades. This limitation has encouraged the development of alternative approaches, including simplified models and data-driven techniques.

The integration of daylight performance with other criteria, such as energy consumption and thermal comfort, is essential for holistic building design. Rather than optimizing daylight in isolation, contemporary approaches aim to balance multiple performance objectives. This is particularly relevant in façade design, where decisions related to geometry, materiality, and shading simultaneously affect both daylight and energy performance. Consequently, daylighting is not only a visual design concern but also a key component of building performance optimization.

2.3. Façade Design Strategies

The building façade represents one of the most influential elements in architectural design, functioning as the interface between indoor and outdoor environments.

Beyond its aesthetic role, the façade directly affects energy consumption, daylight availability, thermal comfort, and indoor environmental quality. In contemporary sustainable architecture, façades are no longer considered static envelopes but dynamic systems capable of regulating environmental performance [24]. As buildings account for a large share of global energy use, façade design has become a critical aspect of performance-driven architecture.

The role of the façade as an environmental mediator between interior and exterior conditions is illustrated in Figure. 2.10.

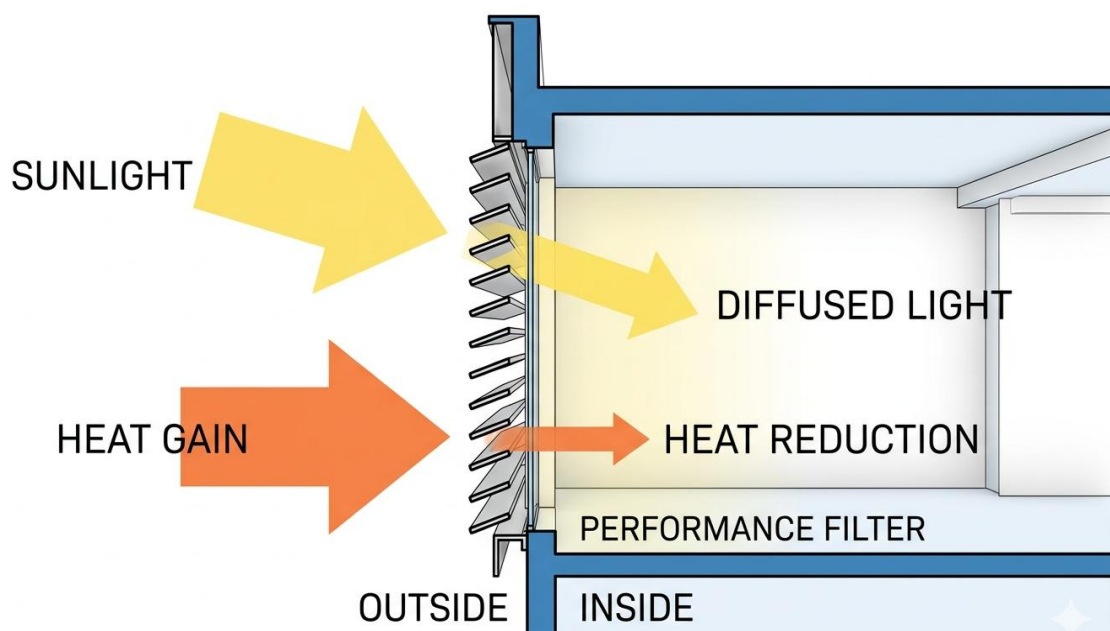


Figure 2-10 – Building façade as an interface controlling solar radiation, daylight, and thermal exchange (Source: author)

One of the primary objectives of façade design is controlling solar heat gain while maintaining adequate daylight penetration and visual connection with the outdoor environment. Several façade parameters influence building performance, including glazing ratio, material properties, shading systems, and geometric configuration. Among these, the Window-to-Wall Ratio (WWR) is widely recognized as a key factor affecting both daylight and energy performance. Large glazed surfaces can improve transparency and daylight autonomy but may simultaneously increase cooling loads and glare risk [14]. Therefore, façade optimization requires balancing multiple and often conflicting performance objectives.

The relationship between façade transparency and building performance is illustrated in Figure. 2.11.

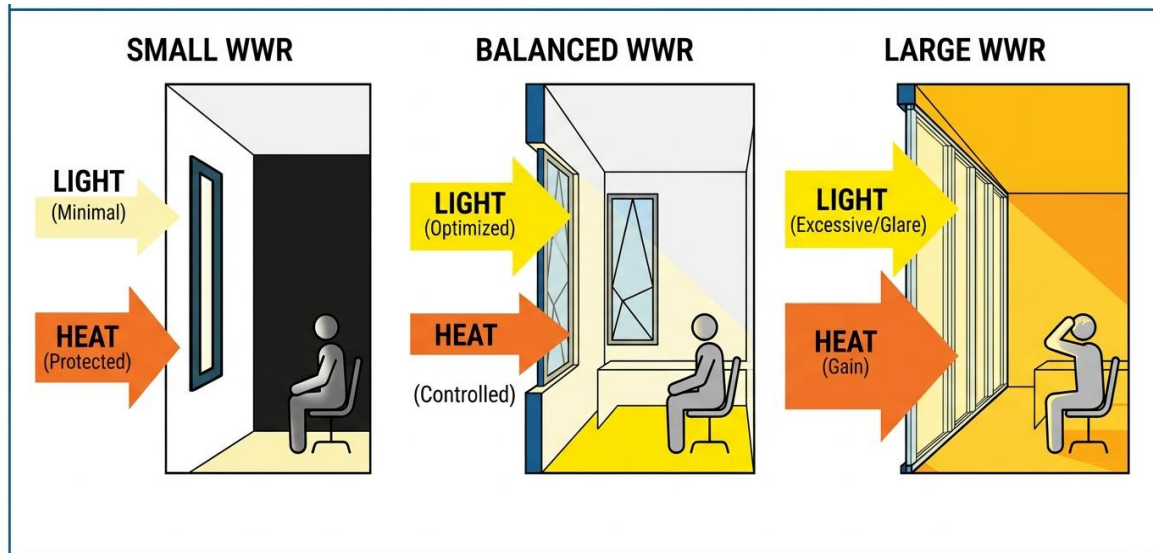


Figure 2-11 – Influence of Window-to-Wall Ratio (WWR) on daylight availability and thermal performance (Source: author)

Shading devices are among the most commonly used façade strategies for improving environmental performance. Horizontal louvers, vertical fins, perforated panels, and secondary skins can reduce excessive solar radiation while maintaining daylight access. The effectiveness of shading systems depends on several factors, including orientation, geometry, depth, angle, and material characteristics. For example, horizontal shading devices are generally more effective on south-facing façades, whereas vertical fins perform better on east and west orientations due to lower sun angles [15]. Consequently, climate-responsive shading design plays a significant role in reducing cooling demand and improving occupant comfort.

Different façade shading strategies based on orientation are presented in Figure. 2.12.

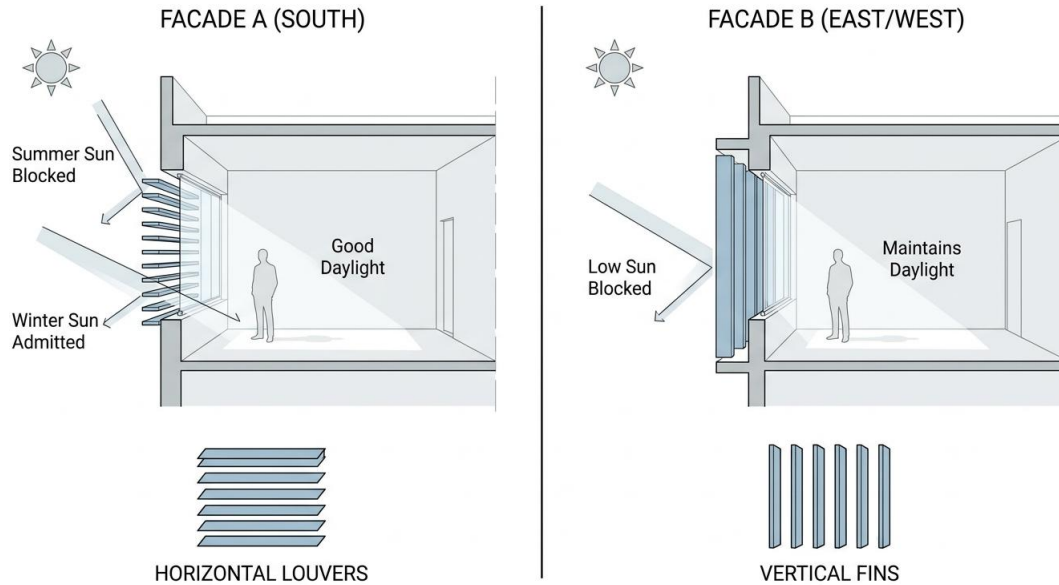


Figure 2-12 – Comparison of horizontal and vertical shading devices for different façade orientations (Source: author)

In recent decades, double-skin façades and adaptive façade systems have emerged as advanced strategies for enhancing building performance. Double-skin façades typically consist of two layers of glazing separated by an air cavity, which acts as a thermal buffer and can improve insulation and ventilation performance [25]. Adaptive façades, on the other hand, are capable of changing their configurations in response to environmental conditions. These systems may include movable panels, kinetic elements, or responsive shading devices controlled through sensors and automation systems. Such approaches aim to optimize daylight, thermal comfort, and energy efficiency dynamically throughout the day.

Examples of advanced façade systems are illustrated in Figure. 2.13.

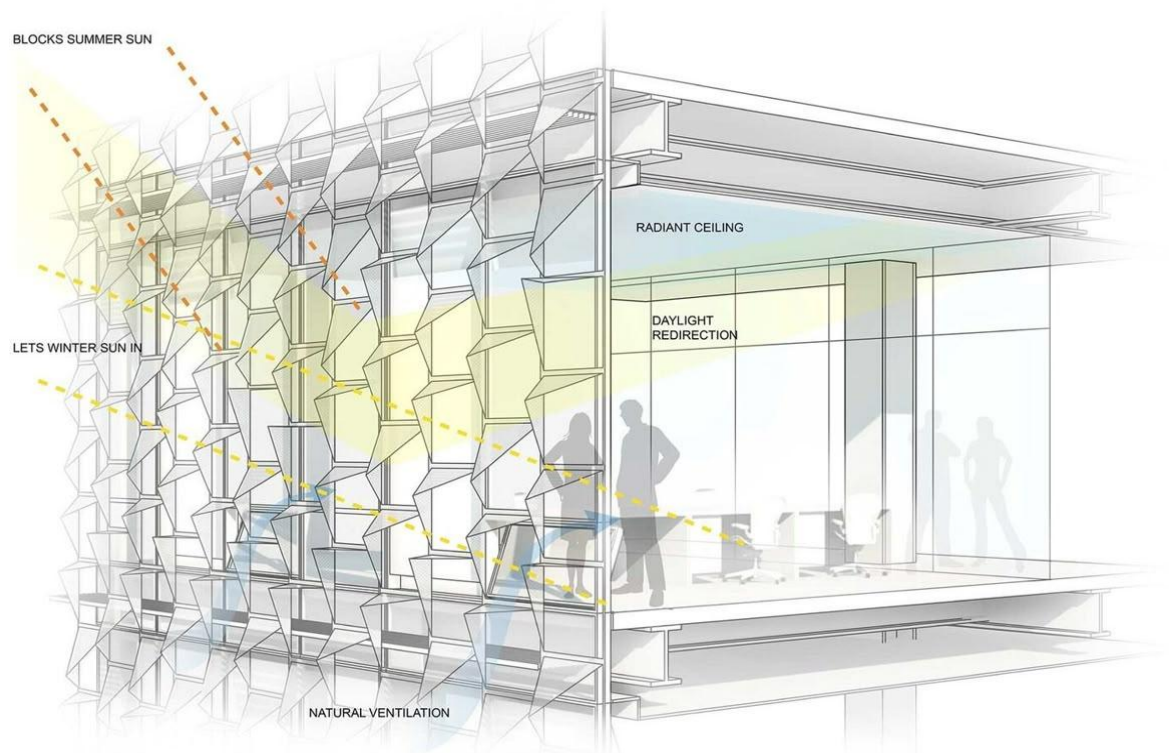


Figure 2-13 – Examples of double-skin and adaptive façade systems in contemporary architecture [57]

The development of computational design tools has significantly transformed façade design methodologies. Traditional façade design processes often relied on manual iteration and designer intuition. However, the introduction of parametric modeling has enabled designers to generate and evaluate multiple façade configurations rapidly. Parameters such as panel size, opening ratio, shading angle, porosity, and geometric pattern can now be systematically controlled and optimized [26]. This shift has facilitated the emergence of performance-driven façade design, where environmental analysis directly informs geometric development.

The integration of parametric modeling into façade design workflows is shown in Figure. 2.14.

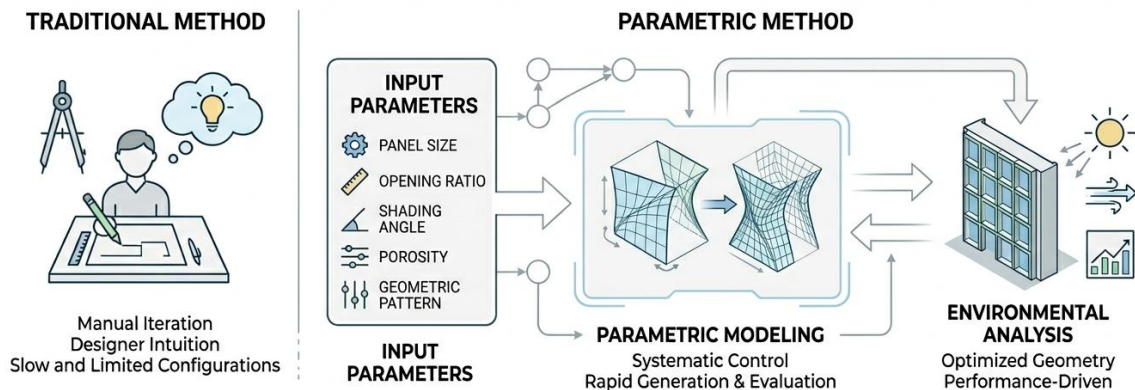


Figure 2-14 – Parametric façade design workflow integrating geometry generation and performance evaluation (Source: author)

Parametric façade systems have become particularly relevant in contemporary architecture due to their ability to handle complex geometries and environmental adaptation. Geometric patterns such as triangular, hexagonal, and cellular structures are increasingly used not only for aesthetic purposes but also for environmental optimization. Through parametric control, designers can manipulate opening sizes, panel rotation, and porosity to achieve desired daylight and energy performance outcomes. This approach enables a more integrated relationship between architectural expression and environmental functionality [27].

In addition to geometric flexibility, computational façade design enables integration with environmental simulation tools. Software platforms such as Grasshopper, often combined with environmental plugins, allow designers to evaluate façade performance iteratively during early design stages. However, evaluating large numbers of façade variations through simulation can become computationally expensive and time-consuming, particularly when dealing with complex geometries and multiple performance indicators.

As a result, recent research has increasingly focused on combining façade design with optimization techniques and machine learning approaches. These methods aim to accelerate performance prediction while supporting rapid exploration of design alternatives. In this context, façade systems are no longer treated solely as architectural elements but as data-driven and performance-responsive components within an integrated computational workflow.

2.4. Parametric Design in Architecture

Parametric design is a computational design methodology in which geometric relationships are defined through parameters, rules, and algorithms rather than fixed forms. In architecture, this approach enables designers to generate, modify, and optimize complex geometries efficiently by controlling variables and their interdependencies. Unlike conventional modeling methods, where geometry is manually edited, parametric systems allow dynamic modification of design elements through adjustable parameters [26]. This capability has significantly transformed contemporary architectural practice, particularly in projects involving complex forms, adaptive systems, and performance-driven design processes.

The fundamental concept of parametric design based on relationships between parameters and geometry is illustrated in Figure. 2.15.

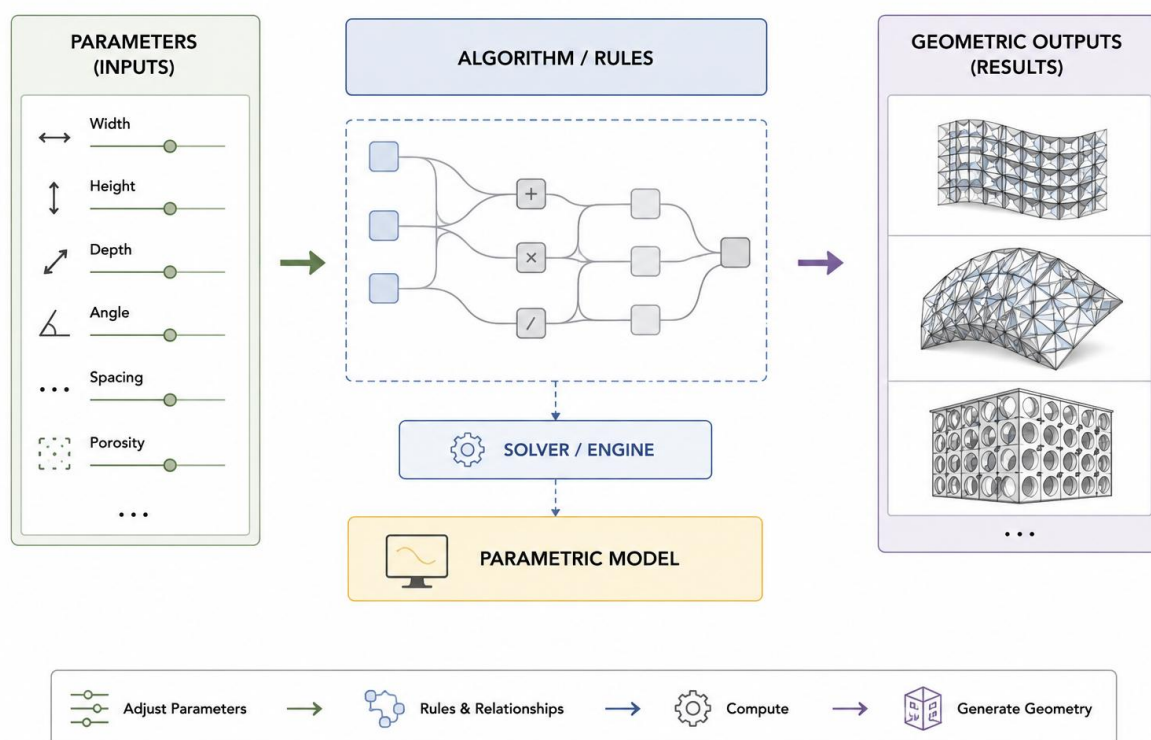


Figure 2-15 – Conceptual framework of parametric design linking parameters, algorithms, and geometric outputs (Source: author)

The emergence of parametric design is closely associated with advancements in computational technologies and digital fabrication. Early applications focused primarily on formal exploration and complex geometries that were difficult to achieve

using traditional design methods. However, parametric design has evolved beyond purely formal experimentation and increasingly incorporates environmental, structural, and functional performance criteria into the design process [27]. This transition has enabled architects to integrate analytical feedback directly into geometry generation and optimization workflows.

One of the key advantages of parametric design is its ability to support iterative exploration. Designers can rapidly generate multiple design alternatives by modifying parameters such as dimensions, proportions, angles, or material properties. This approach facilitates a more flexible and responsive design process compared to conventional static modeling methods. In façade design, for example, parameters such as opening size, panel orientation, shading depth, and porosity can be adjusted dynamically to evaluate their impact on energy and daylight performance [28].

The iterative nature of parametric design and generation of multiple alternatives is shown in Figure. 2.16.

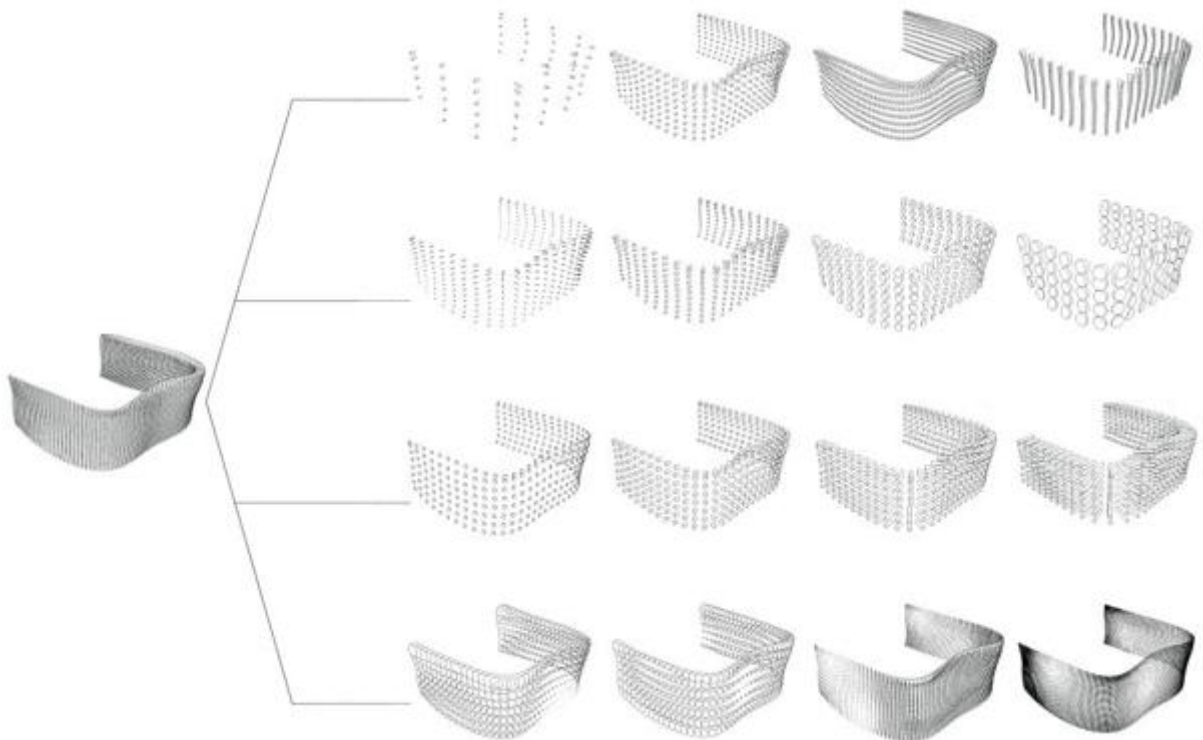


Figure 2-16 – Iterative generation of architectural alternatives through parametric variation

Software environments such as Grasshopper, integrated with Rhinoceros 3D, have become widely used tools for parametric modeling in architecture. These platforms

use node-based visual programming systems that allow designers to construct relationships between geometric operations and input parameters without extensive programming knowledge. Such tools provide high flexibility and facilitate integration with environmental simulation software, optimization algorithms, and digital fabrication workflows [29].

A typical node-based parametric workflow using Grasshopper is illustrated in Figure 2.17.

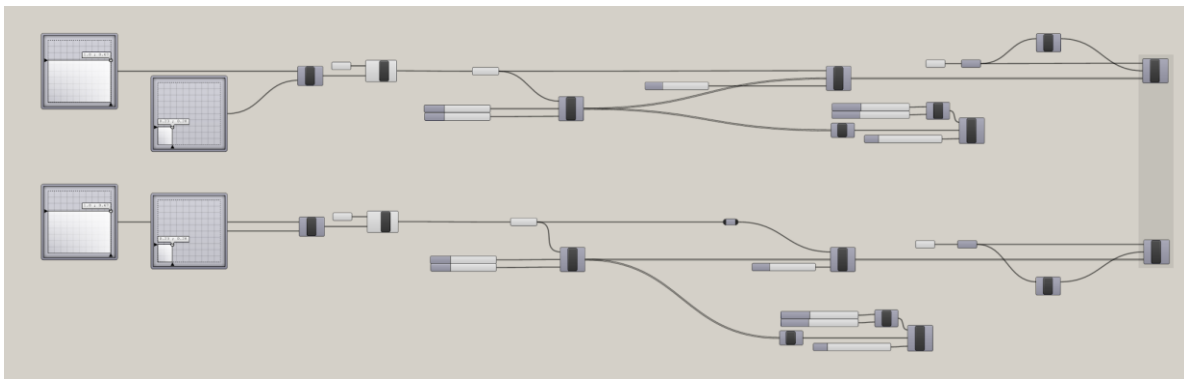


Figure 2-17 – Example of a node-based parametric workflow in Grasshopper for façade generation (Source: author)

Parametric design has become particularly important in performance-driven architecture, where design decisions are informed by measurable criteria such as energy consumption, daylight availability, structural efficiency, and thermal comfort. In this context, geometry is no longer developed solely based on aesthetic considerations but also according to environmental performance objectives. The integration of simulation tools into parametric workflows allows designers to evaluate performance continuously throughout the design process [30].

This integration has led to the emergence of optimization-based design approaches. Optimization algorithms such as genetic algorithms and evolutionary solvers are often combined with parametric models to identify high-performance design solutions automatically. By evaluating numerous design iterations against predefined objectives, these methods support multi-objective optimization and informed decision-making. However, simulation-based optimization workflows can become computationally expensive, especially when dealing with large parametric spaces and high-resolution analyses [11].

The integration of parametric modeling, simulation, and optimization processes is presented in Figure 2.18.

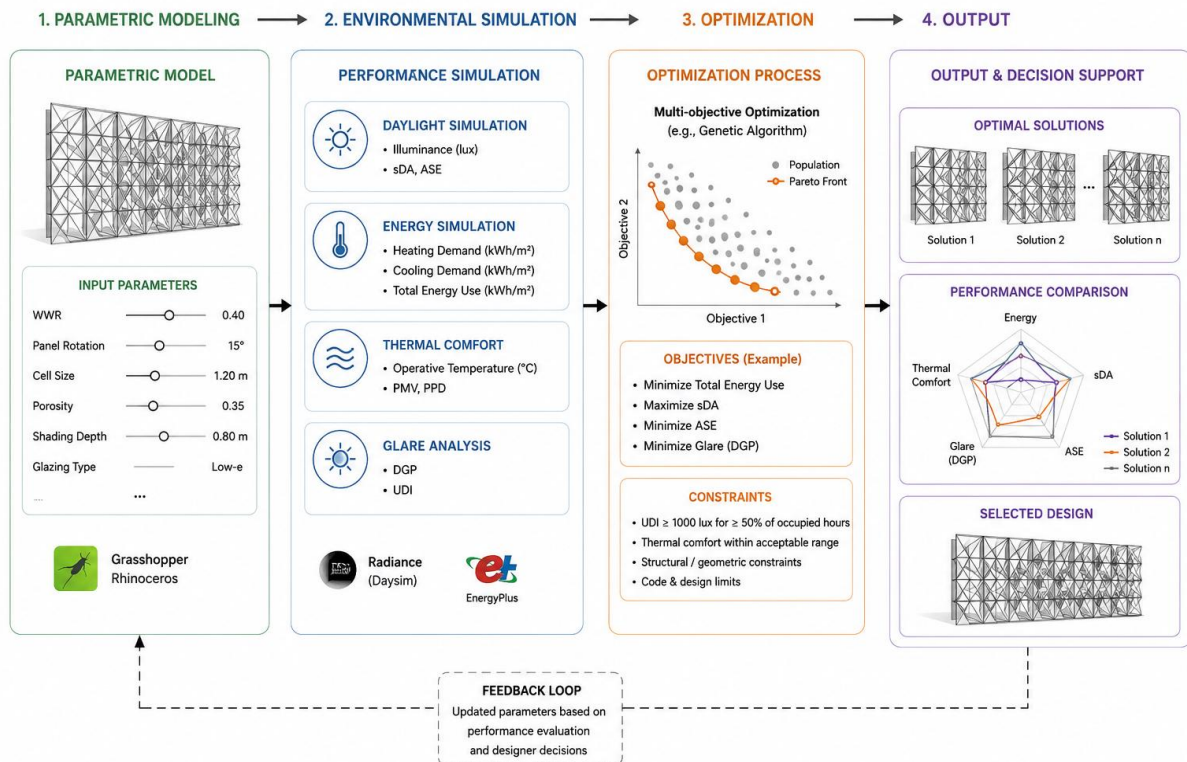


Figure 2-18 – Integration of parametric modeling with environmental simulation and optimization workflows (Source: author)

In façade design applications, parametric methodologies enable the development of adaptive and responsive systems capable of addressing environmental conditions dynamically. Geometric patterns such as triangular, hexagonal, and cellular tessellations can be parametrically controlled to regulate solar radiation, daylight penetration, and thermal performance. This flexibility allows designers to explore a broad range of façade configurations while maintaining relationships between design variables [31]. Consequently, parametric design supports both architectural creativity and environmental responsiveness.

Despite its advantages, parametric design also presents several challenges. Increasing geometric complexity often leads to longer simulation times and higher computational requirements. As the number of parameters increases, the design space becomes more difficult to manage and evaluate efficiently. In performance-driven workflows, evaluating hundreds or thousands of design alternatives through detailed simulation can become impractical within typical design timelines [32].

These limitations have encouraged the exploration of data-driven approaches and machine learning techniques capable of accelerating performance prediction within

parametric workflows. Instead of relying exclusively on repeated simulations, machine learning models can learn relationships between input parameters and performance outputs from existing datasets. This approach enables faster evaluation of design alternatives and supports real-time feedback during the design process. As a result, the combination of parametric design and machine learning has emerged as a promising direction in computational architecture research.

2.5. Simulation Tools

Simulation tools have become essential components in contemporary architectural design processes, enabling designers to predict and evaluate building performance before construction. These tools provide quantitative assessments of energy consumption, daylight availability, thermal comfort, airflow, and solar radiation, supporting more informed design decisions. In sustainable and performance-driven architecture, simulation software allows architects and engineers to analyze the environmental impact of design alternatives and optimize building performance throughout the design process [32].

The role of simulation tools in evaluating environmental building performance is illustrated in Figure. 2.19.

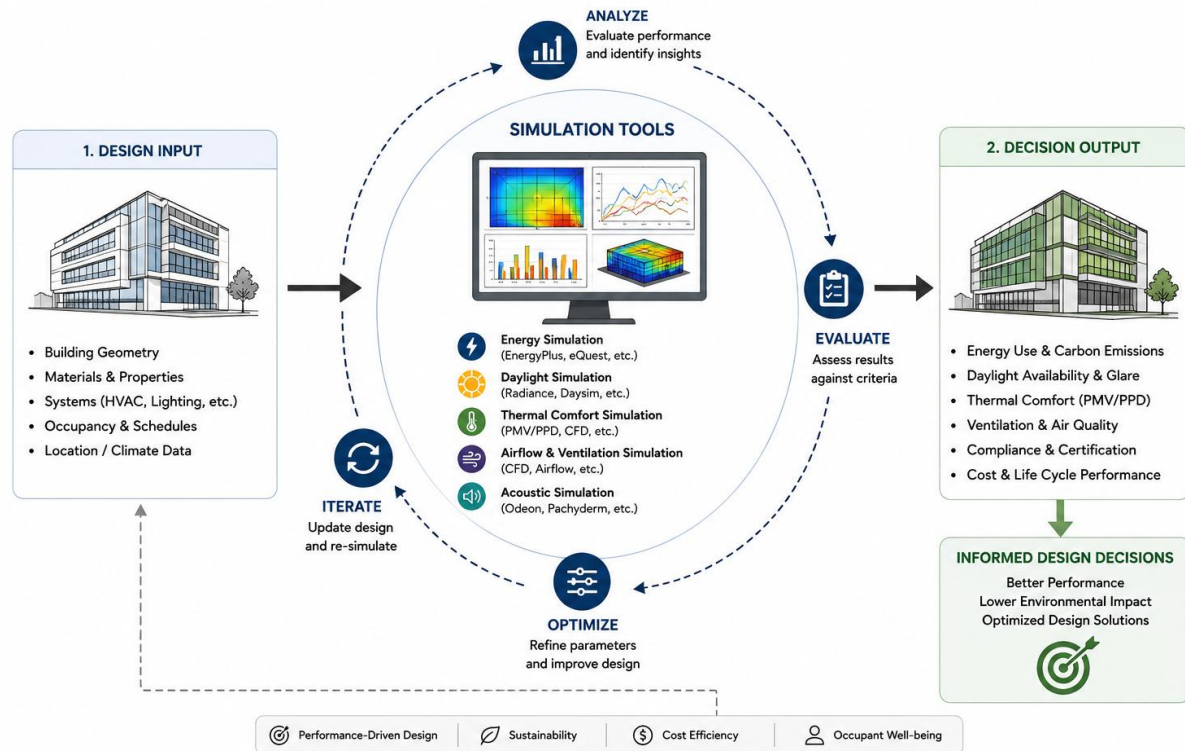


Figure 2-19 – Integration of simulation tools within the architectural design process (Source: author)

Building performance simulation generally relies on physics-based computational models that represent interactions between environmental conditions, building geometry, materials, and mechanical systems. These simulations typically use climate data, occupancy schedules, and material properties to estimate performance indicators over time. Among the most commonly analyzed aspects are energy consumption, daylight availability, thermal comfort, and solar radiation [33]. Such analyses are particularly important during early design stages, where design decisions have the greatest impact on long-term building performance.

Energy simulation tools are widely used to estimate heating and cooling loads, annual energy consumption, and thermal behavior of buildings. One of the most established platforms is EnergyPlus, developed by the United States Department of Energy. EnergyPlus performs detailed calculations related to heat transfer, HVAC systems, internal loads, and thermal zones [17]. Due to its high accuracy and flexibility, it has become a standard tool in both academic research and professional practice.

The workflow of building energy simulation using EnergyPlus is shown in Figure 2.20.

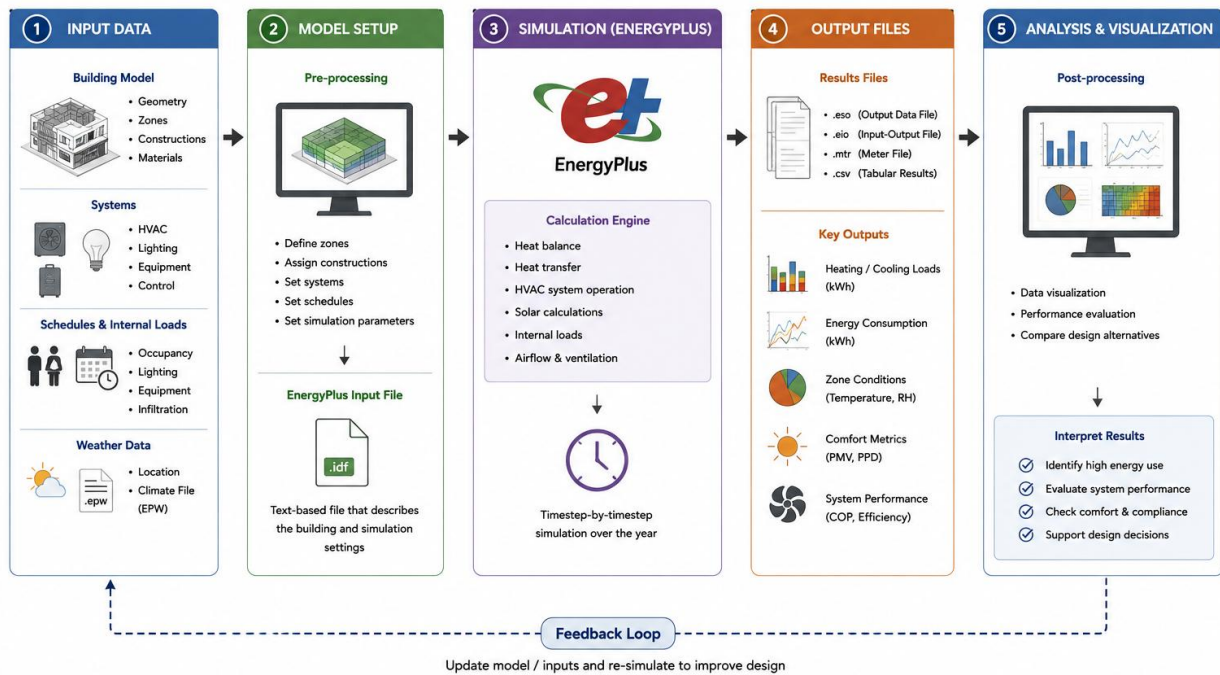


Figure 2-20 – Typical workflow of building energy simulation using EnergyPlus (Source: author)

In parallel with energy simulation, daylight analysis tools are used to evaluate natural lighting conditions within buildings. Software such as Radiance performs physically-based lighting calculations to predict illuminance levels, glare probability, and daylight distribution [23]. Radiance has been extensively validated and is widely recognized for its accuracy in daylight simulation studies. Through annual climate-based simulations, designers can assess metrics such as Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), and Useful Daylight Illuminance (UDI).

Climate-based daylight simulation metrics and workflows are illustrated in Figure 2.21.

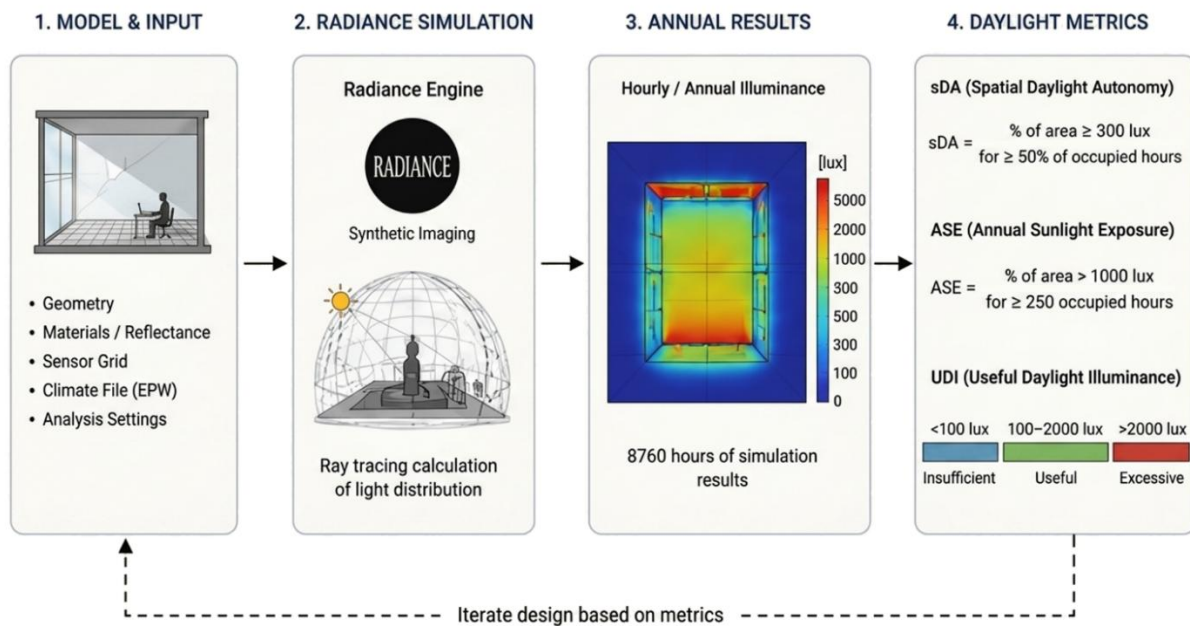


Figure 2-21 – Daylight simulation workflow and performance metrics using Radiance-based tools (Source: author)

To facilitate accessibility and integration within design environments, several simulation plugins have been developed for parametric modeling platforms. Plugins such as Ladybug and Honeybee, integrated within Grasshopper, enable architects to connect geometry generation directly with environmental analysis tools [34]. These platforms simplify workflows by linking design parameters with simulation engines such as EnergyPlus and Radiance. As a result, designers can evaluate environmental performance iteratively during the design process without leaving the modeling environment.

The integration of simulation plugins within parametric design environments is presented in Figure. 2.22.

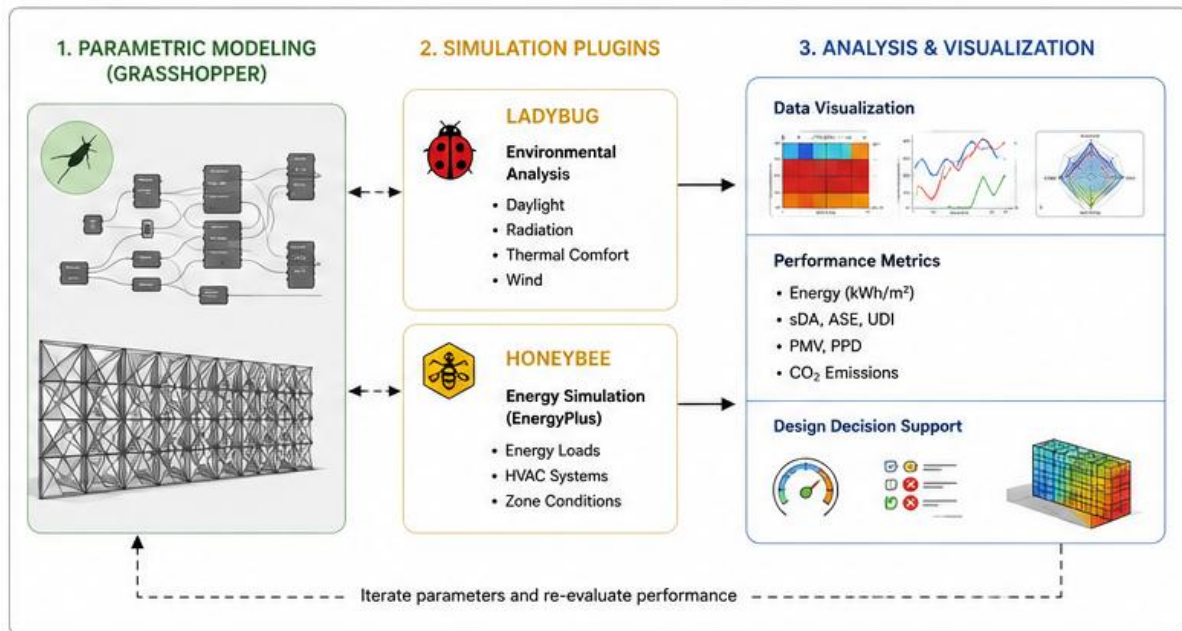


Figure 2-22 – Integration of Grasshopper with environmental simulation plugins such as Ladybug and Honeybee (Source: author)

Despite their capabilities, simulation tools present several limitations, particularly regarding computational cost and workflow complexity. High-resolution simulations often require detailed geometric models, accurate material definitions, and extensive climate data. When multiple design iterations are evaluated, simulation times can increase significantly, especially in optimization-based workflows [11]. This challenge becomes more critical in parametric design contexts, where hundreds or thousands of design alternatives may be generated and analyzed.

Another limitation involves the expertise required to operate simulation tools effectively. Accurate performance evaluation depends not only on software capabilities but also on proper model setup and interpretation of results. Errors in geometry, material definitions, or simulation settings may lead to inaccurate predictions. Consequently, simulation-based workflows often require collaboration between architects, engineers, and environmental consultants [35].

To address these challenges, recent research has explored methods for accelerating simulation workflows through surrogate modeling and machine learning techniques. Instead of performing detailed simulations for every design iteration, predictive models can approximate simulation outputs based on previously generated datasets. This approach reduces computational time while maintaining acceptable levels of accuracy [19]. In performance-driven façade design, where multiple geometric and

environmental parameters interact simultaneously, such methods offer significant potential for real-time analysis and design support.

The integration of simulation tools with machine learning and parametric modeling represents a major shift in computational architectural workflows. Rather than relying solely on traditional sequential simulation processes, contemporary approaches increasingly emphasize interactive, data-driven, and optimization-oriented systems. These developments are particularly relevant for complex façade systems, where rapid evaluation of daylight and energy performance is essential for informed decision-making during early design stages.

2.6. Machine Learning in Architecture

Machine Learning (ML) is a branch of artificial intelligence that enables computers to identify patterns and make predictions based on data without being explicitly programmed for every task. In recent years, machine learning has gained increasing attention in architecture, engineering, and construction due to its ability to process large datasets, automate analysis, and support decision-making processes [36]. Within the field of architecture, ML has been applied to various domains including energy prediction, daylight analysis, occupancy modeling, structural optimization, urban analysis, and generative design.

The general workflow of machine learning processes in architectural applications is illustrated in Figure. 2.23.

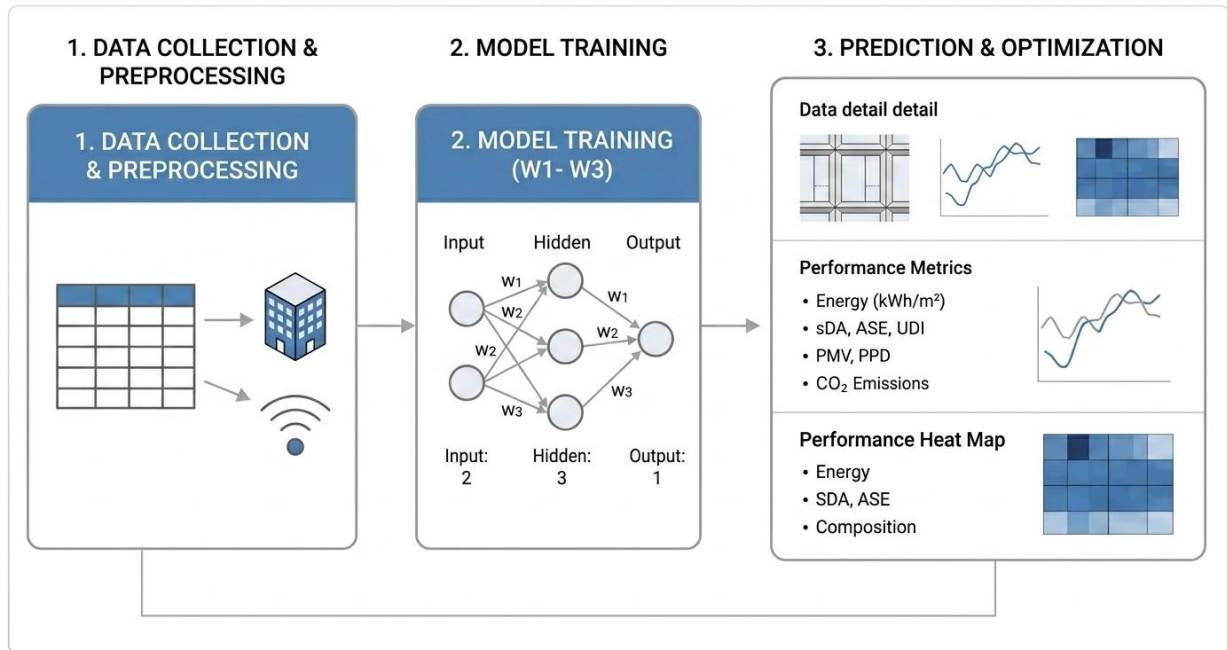


Figure 2-23 – General workflow of machine learning applications in architecture from data collection to prediction (Source: author)

Traditional building performance analysis methods rely heavily on physics-based simulations such as energy and daylight simulations. Although these methods provide accurate results, they are often computationally intensive and time-consuming, especially when evaluating multiple design alternatives. In parametric design workflows, where hundreds or thousands of variations may be generated, repeated simulations can become impractical within typical design timelines [11]. This limitation has motivated researchers to investigate data-driven approaches capable of accelerating performance evaluation.

Machine learning models can learn relationships between input variables and performance outputs by training on previously generated datasets. In architectural applications, input parameters may include building geometry, orientation, material properties, glazing ratio, shading configurations, and climatic conditions, while outputs may involve energy consumption, daylight metrics, thermal comfort, or solar radiation values [32]. Once trained, ML models can predict performance outcomes rapidly, enabling near real-time feedback during the design process.

The relationship between architectural input parameters and predicted performance outputs is illustrated in Figure. 2.24.

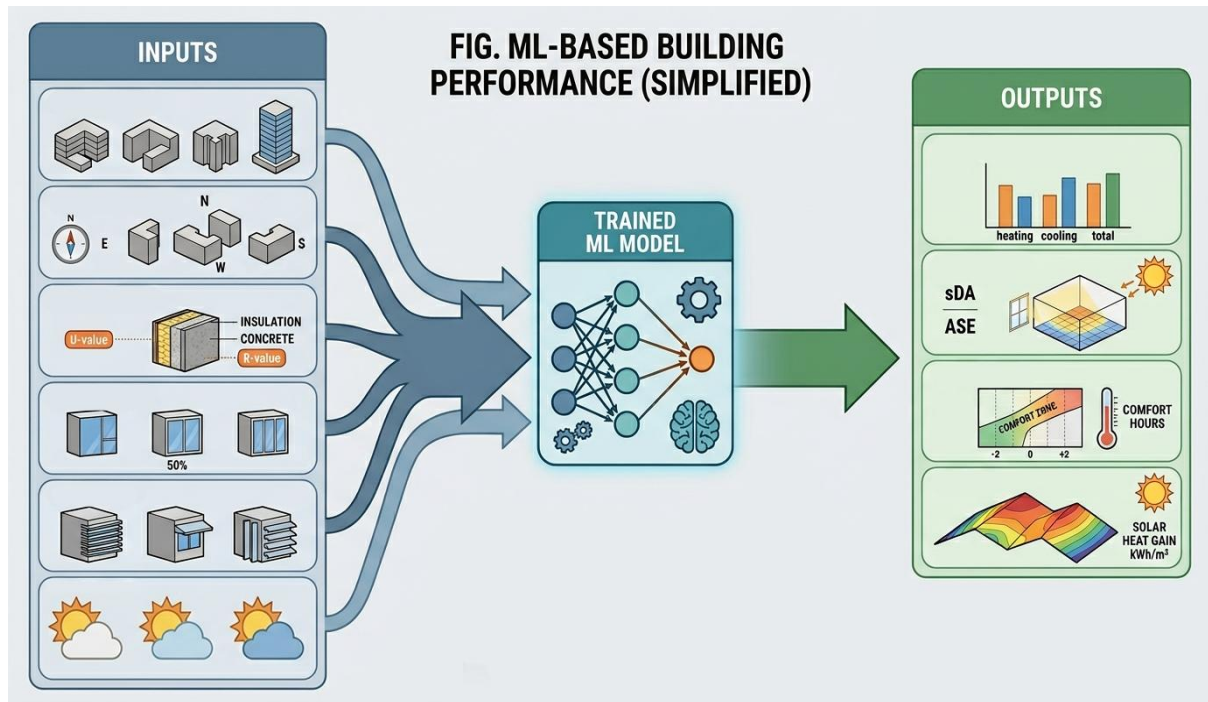


Figure 2-24 – The relationship between architectural input parameters and predicted performance outputs

Several machine learning techniques have been applied in architectural and environmental performance studies. Among the most commonly used methods are Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees, Random Forests, and Deep Learning models [37]. Artificial Neural Networks, inspired by the structure of biological neural systems, are particularly effective in capturing complex non-linear relationships between variables. Due to their flexibility and predictive capability, ANNs are widely used for building energy consumption forecasting and environmental performance prediction.

A simplified structure of an Artificial Neural Network used for performance prediction is presented in Figure. 2.25.

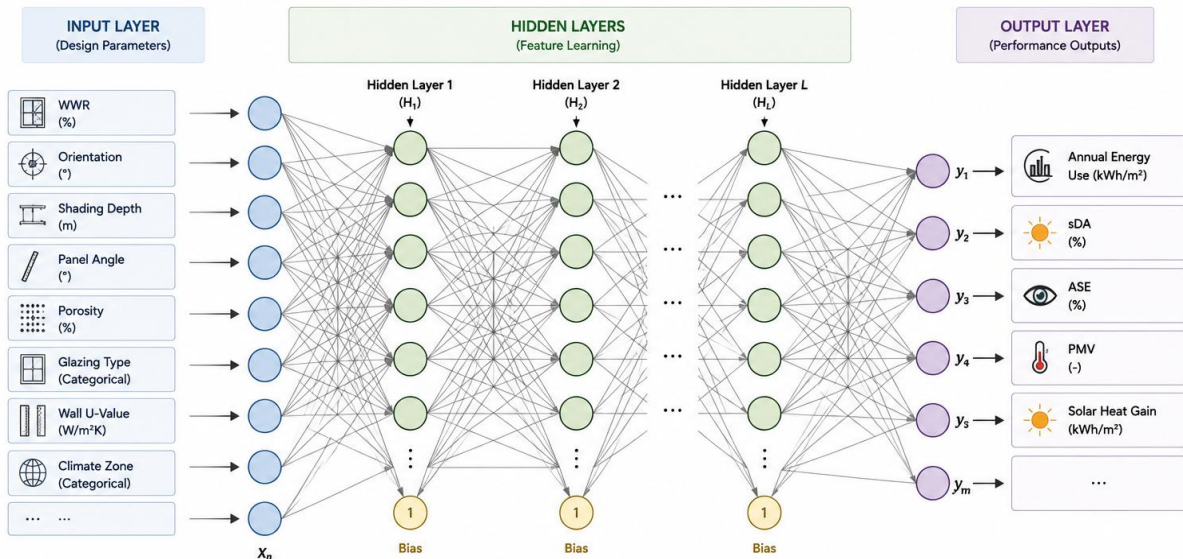


Figure 2-25 – Simplified architecture of an Artificial Neural Network for building performance prediction (Source: author)

One of the major advantages of machine learning in architecture is the significant reduction in computational time compared to repeated simulation workflows. Instead of running full simulations for every design iteration, trained models can generate predictions within seconds. This capability is particularly beneficial in early design phases, where rapid evaluation and exploration of alternatives are essential. Machine learning also supports optimization workflows by enabling designers to evaluate larger design spaces more efficiently [19].

However, the accuracy of machine learning models strongly depends on the quality and quantity of training data. Reliable datasets are essential to ensure that the model can generalize effectively to new design conditions. In building performance applications, datasets are commonly generated through large numbers of simulation runs, where different combinations of input parameters are systematically evaluated [38]. The preparation of training datasets therefore becomes a critical component of ML-based workflows.

In recent years, the integration of machine learning with parametric and generative design tools has become an important research direction in computational architecture. Platforms such as Grasshopper enable designers to combine geometry generation, simulation workflows, and predictive models within a unified environment. This integration allows architects to receive rapid performance feedback while interactively modifying design parameters [29]. As a result, machine learning is

increasingly viewed not only as an analytical tool but also as an active component of the design process itself.

Machine learning has shown particular potential in façade design applications due to the high number of interrelated variables involved. Parameters such as geometry type, opening ratio, shading depth, panel angle, porosity, orientation, and climatic conditions collectively influence daylight and energy performance. Evaluating these variables through conventional simulations alone can be computationally demanding. ML-based predictive models offer an alternative approach capable of supporting rapid decision-making and optimization in complex façade systems [31].

Despite its advantages, machine learning in architecture also faces several limitations and challenges. Model accuracy may decrease when predictions are applied outside the range of training data, and some ML models operate as “black-box” systems with limited interpretability. Furthermore, preparing datasets and training models require technical expertise in data processing and computational methods. Consequently, machine learning is generally considered a complementary tool rather than a complete replacement for physics-based simulations [39].

Nevertheless, the integration of machine learning, parametric modeling, and environmental simulation represents a major advancement in computational architectural workflows. By combining predictive intelligence with generative design systems, ML-based approaches enable faster exploration of design alternatives and more informed decision-making during early design stages. These developments have established machine learning as a promising methodology for performance-driven architectural design and optimization.

2.7. Optimization Methods in Building Design

Optimization methods have become increasingly important in contemporary building design due to the growing complexity of environmental, functional, and energy-related performance requirements. In performance-driven architecture, designers must often balance multiple criteria simultaneously, including energy efficiency, daylight availability, thermal comfort, visual quality, and façade aesthetics. Traditional trial-and-error approaches are generally insufficient for evaluating large numbers of design alternatives, particularly in parametric workflows involving numerous interdependent variables [32]. Consequently, computational optimization methods have emerged as essential tools for supporting efficient and informed decision-making during the design process.

The integration of optimization processes within performance-driven architectural workflows is illustrated in Figure. 2.26.

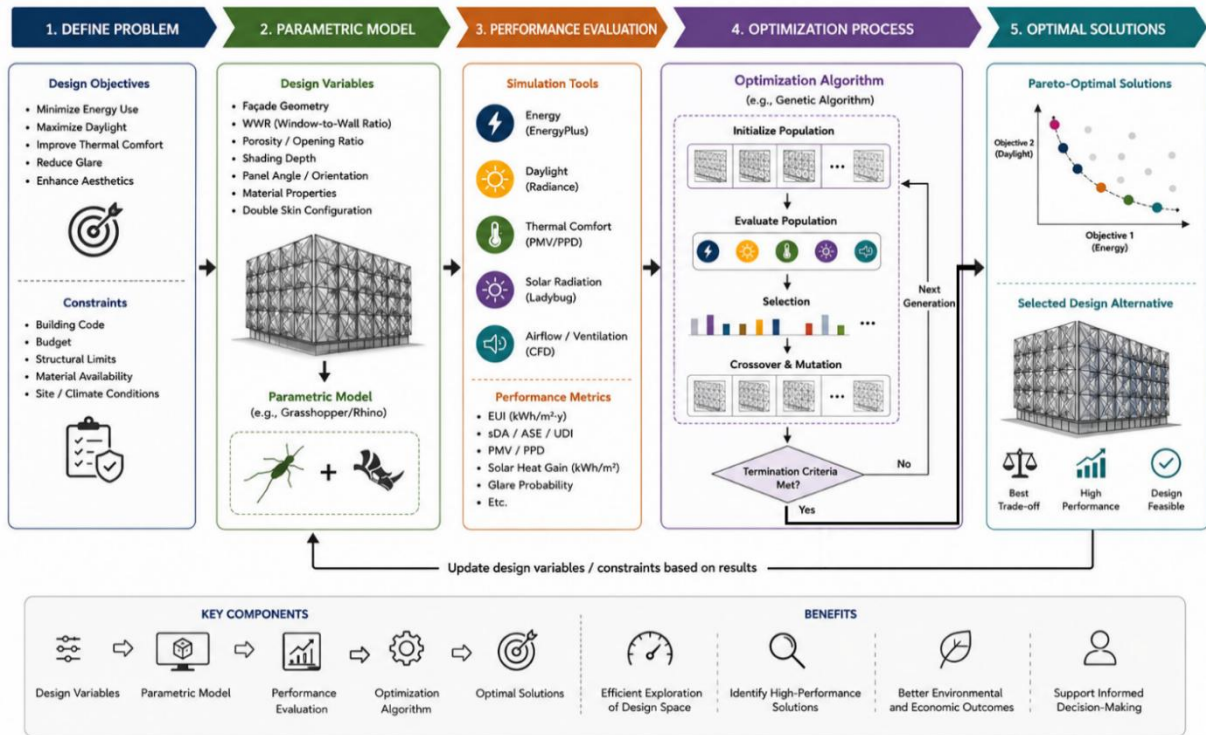


Figure 2-26 – Integration of optimization methods within parametric and performance-driven architectural design workflows (Source: author)

Optimization in building design typically involves defining objective functions, design variables, and performance constraints. Design variables may include façade geometry, Window-to-Wall Ratio (WWR), shading depth, porosity, panel angle, orientation, and material properties, while objective functions often focus on minimizing energy consumption or maximizing daylight performance [40]. Since these variables strongly influence one another, identifying high-performance solutions requires systematic exploration of complex design spaces.

In façade design applications, optimization methods are particularly relevant because façade systems directly affect both daylight and energy performance. Parametric façade systems containing adjustable geometric patterns, secondary skins, and shading devices generate a large number of possible design variations. Evaluating these alternatives manually through simulation becomes highly time-consuming and computationally demanding. Therefore, optimization algorithms are increasingly used to automate the exploration and evaluation process [30].

The relationship between façade parameters and optimization objectives is illustrated in Figure. 2.27.

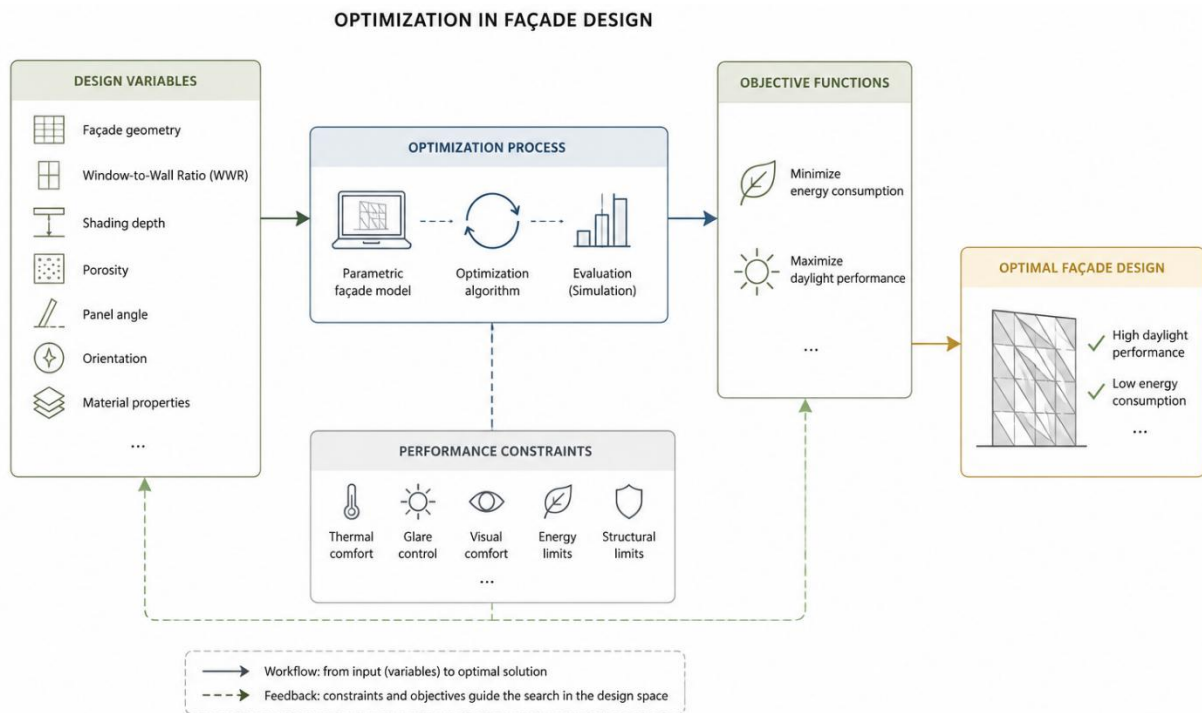


Figure 2-27– Interaction between façade variables and environmental performance objectives in optimization workflows (Source: author)

Among computational optimization techniques, Genetic Algorithms (GA) are one of the most widely used approaches in building performance optimization. Genetic Algorithms are inspired by biological evolution processes such as selection, crossover, and mutation [41]. In this method, each design solution is represented as an individual within a population, and the algorithm iteratively evolves the population toward higher-performing solutions according to predefined fitness criteria.

In parametric façade optimization, design parameters such as geometry type, opening ratio, panel angle, porosity, shading depth, and orientation can be encoded as optimization variables. Simulation tools evaluate the environmental performance of each iteration, while the algorithm identifies and reproduces favorable design characteristics over successive generations [42]. This approach enables systematic exploration of large parametric design spaces that would be impractical to evaluate manually.

The workflow of Genetic Algorithm optimization applied to parametric façade systems is presented in Figure. 2.28.

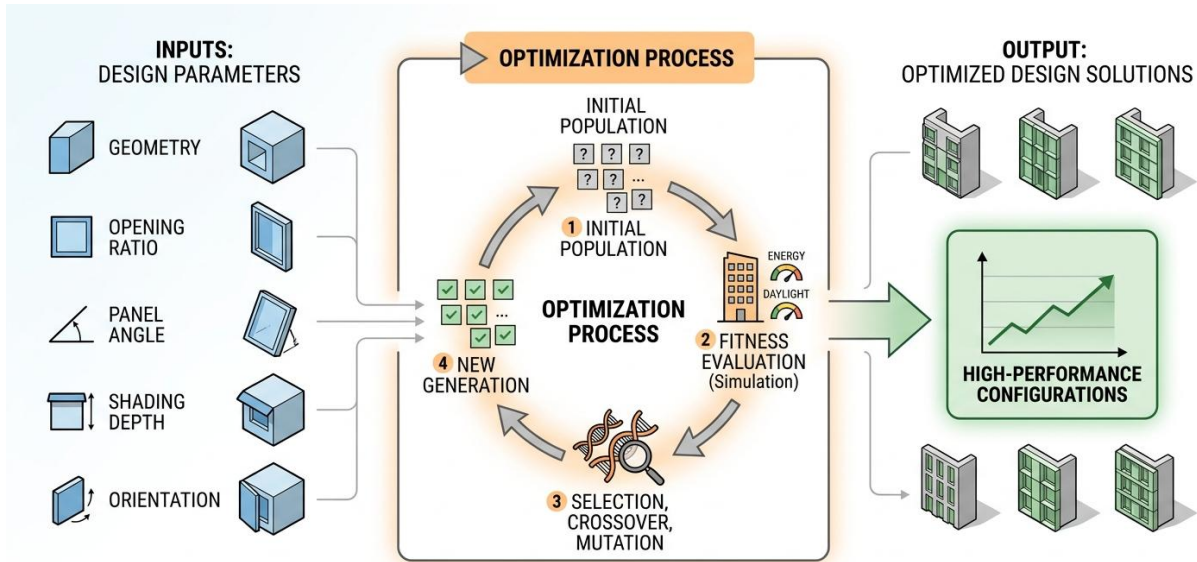


Figure 2-28 – Genetic Algorithm workflow for optimization of parametric façade configurations (Source: author)

In architectural applications, optimization problems are often multi-objective in nature because improving one performance criterion may negatively affect another. For example, increasing façade porosity can improve daylight penetration while simultaneously increasing solar heat gain. Similarly, deeper shading devices may reduce cooling demand but also decrease interior illuminance levels. As a result, optimization processes frequently aim to balance competing objectives rather than produce a single optimal solution [11].

Multi-objective optimization methods commonly rely on Pareto-based approaches, where solutions are evaluated according to trade-offs between different performance indicators. A Pareto front represents a set of non-dominated solutions in which improving one objective would reduce performance in another objective [43]. Instead of generating a single result, this approach provides designers with a range of high-performance alternatives that can support more informed design decisions according to project priorities.

A conceptual Pareto front representing trade-offs between daylight and energy performance is illustrated in Figure. 2.29.

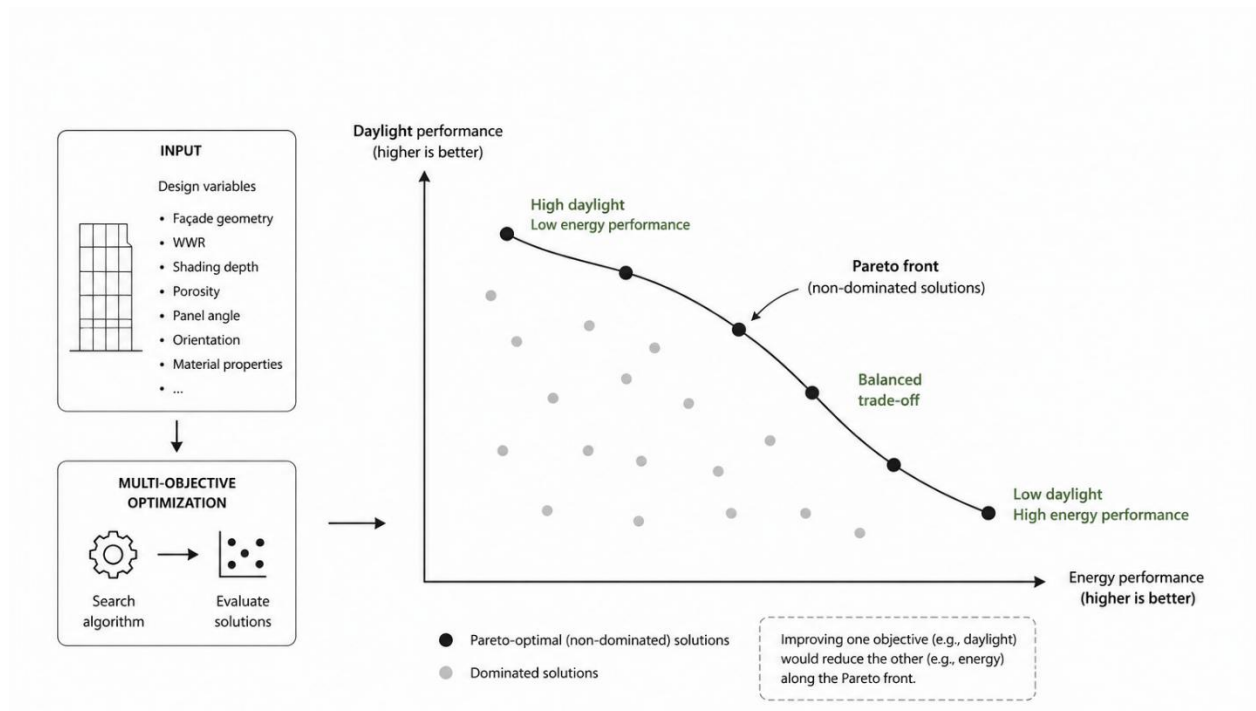


Figure 2-29 – Pareto-based multi-objective optimization balancing daylight and energy performance criteria (Source: author)

Optimization methods are increasingly integrated with parametric design platforms such as Grasshopper. Tools such as Galapagos, Wallacei, and Octopus allow designers to combine parametric geometry generation, environmental simulation, and optimization algorithms within a unified workflow [44]. This integration enables automated generation and evaluation of numerous façade alternatives according to predefined performance objectives.

However, simulation-based optimization workflows often require extensive computational resources because each iteration must be evaluated through detailed environmental simulations. In complex façade systems involving multiple parameters and performance indicators, optimization processes may require hundreds or thousands of simulations runs [45]. This challenge becomes particularly significant in early-stage design workflows, where rapid feedback is essential for iterative exploration.

To overcome these limitations, recent research has explored the integration of machine learning models into optimization workflows. Instead of performing full simulations for every iteration, predictive models can estimate performance outcomes rapidly

based on previously generated datasets [19]. This significantly reduces computational time and allows more efficient exploration of large parametric design spaces.

In façade design applications, the integration of optimization methods, parametric modeling, environmental simulation, and machine learning creates a highly efficient workflow for performance-driven design exploration. By enabling rapid evaluation of complex façade configurations, these approaches support more informed decision-making and facilitate the development of environmentally responsive architectural systems.

2.8. Research Gap and Motivation

Despite the significant advancement of environmental simulation tools and parametric design workflows, several limitations remain in the integration of performance analysis within architectural design processes. Existing simulation platforms such as EnergyPlus, Radiance, and simulation plugins integrated with Grasshopper provide accurate environmental analysis capabilities for evaluating daylight and energy performance. However, these workflows are often time-consuming, computationally demanding, and difficult to integrate efficiently into early-stage architectural design processes [32].

In conventional workflows, designers must first develop detailed digital models including façades, openings, floors, material definitions, and environmental parameters before performing simulations. Each environmental analysis, such as Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), illuminance levels, or solar radiation, typically requires separate simulation processes and repeated model preparation [11]. When multiple façade alternatives are explored, designers must manually modify design parameters, rerun simulations, record outputs, and compare results individually. Consequently, evaluating large numbers of design alternatives becomes highly inefficient and difficult within typical design timelines.

The limitations of conventional simulation-based workflows in façade performance analysis are illustrated in Figure. 2.30.

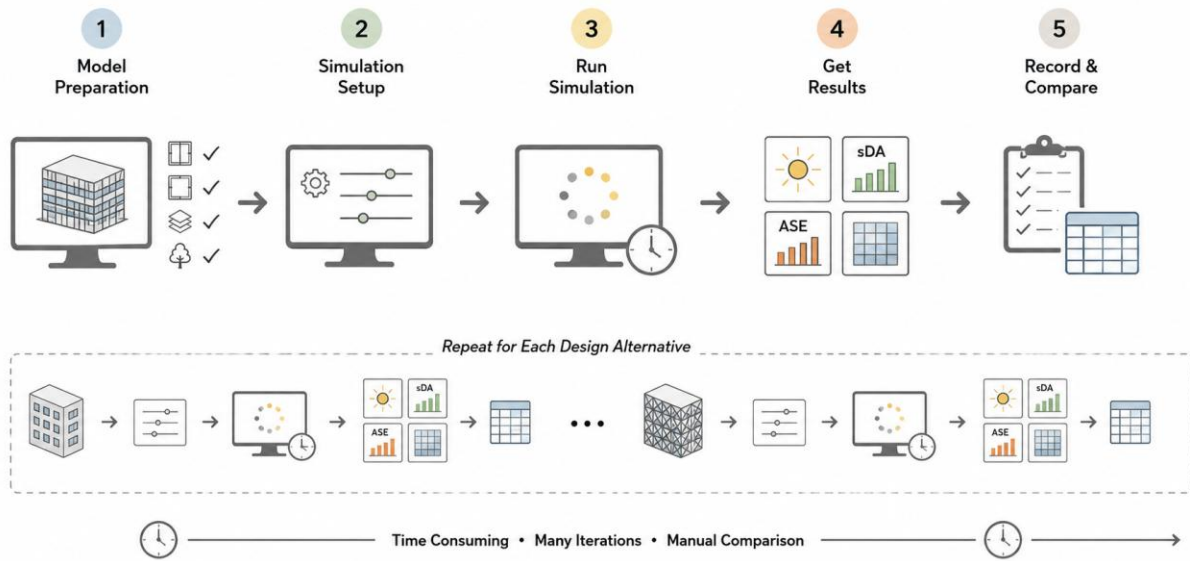


Figure 2-30 – Conventional workflow of environmental simulation requiring repeated model preparation and analysis iterations (Source: author)

Another important limitation of existing simulation tools is that they mainly function as post-design evaluation systems rather than design-support systems. In many cases, environmental analysis is performed after substantial design decisions have already been made. As a result, designers may discover performance problems only after completing significant portions of the project, requiring extensive redesign and modification of façade configurations[30]. This creates a lack of effective decision-support tools for early-stage or pre-design architectural workflows.

Furthermore, existing simulation platforms generally provide analytical outputs without actively guiding designers toward optimization strategies. While designers can obtain numerical performance results, they must independently determine which façade parameters should be modified to improve environmental performance. For example, simulation software typically does not indicate whether daylight performance could be improved by increasing Window-to-Wall Ratio (WWR), modifying façade porosity, adjusting shading depth, changing panel orientation, or selecting alternative geometric configurations. This process requires substantial expertise and repeated trial-and-error experimentation.

The difference between conventional post-analysis workflows and predictive pre-design workflows is illustrated in Figure. 2.31.

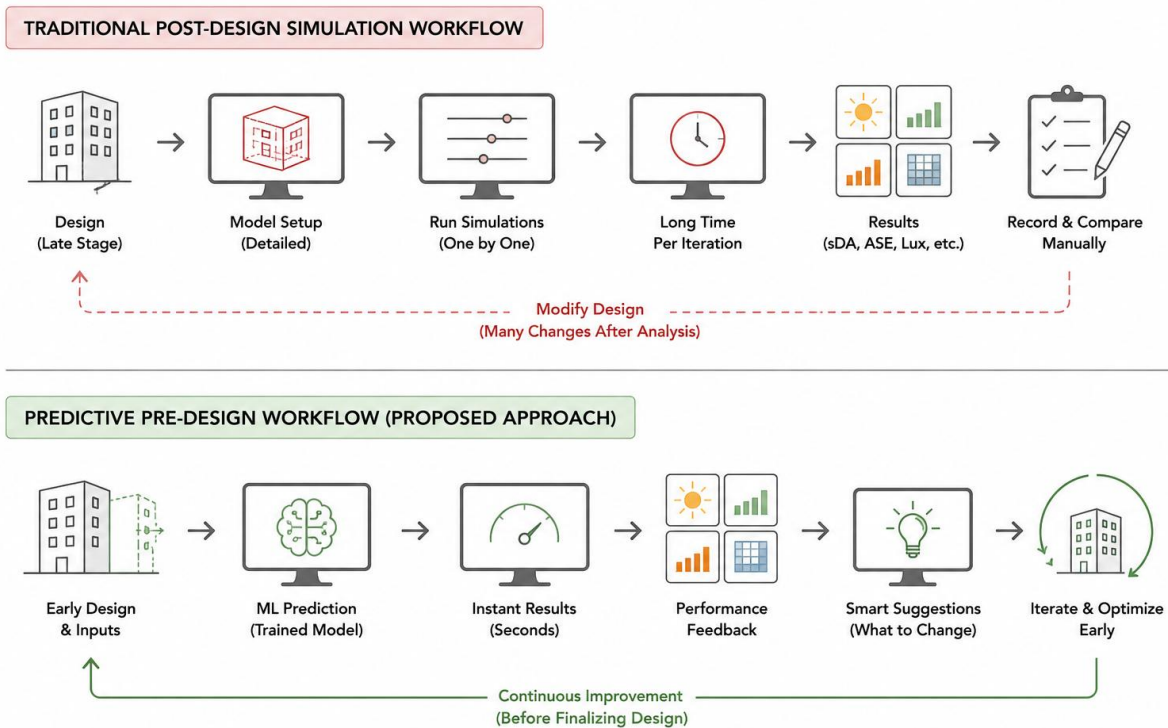


Figure 2-31 – Comparison between traditional post-design simulation workflows and predictive pre-design analysis approaches (Source: author)

The present research addresses these limitations through the development of a machine learning-assisted predictive design tool integrated within the Rhino environment. Unlike conventional workflows requiring repeated simulations, the proposed system enables real-time prediction of daylight and energy-related performance indicators directly during the design process. The developed model was trained using a dataset of approximately 2000 simulation samples generated through Rhino, parametric modeling workflows, and Climate Studio simulations. This dataset includes multiple façade configurations and environmental conditions associated with parametric secondary façade systems.

The proposed workflow supports both conventional façade configurations and parametric secondary façade systems within a unified predictive framework. Users can evaluate environmental performance either with or without secondary façade panels according to project requirements and design intentions. In addition to standard façade variables such as Window-to-Wall Ratio (WWR), orientation, and opening configurations, the system also enables exploration of parametric secondary façade geometries including triangular, circular, and hexagonal panel systems.

Through custom parametric components developed within Grasshopper, users can dynamically modify parameters such as panel size, façade porosity, shading depth, panel orientation, and geometric typology. This flexibility allows designers to compare the environmental impact of different façade strategies, ranging from simple single-skin façades to more complex double-skin and parametric shading systems. These variables are used as inputs for the machine learning prediction model to generate real-time environmental performance feedback.

The integration of parametric façade generation, simulation datasets, and machine learning prediction is shown in Figure. 2.32.

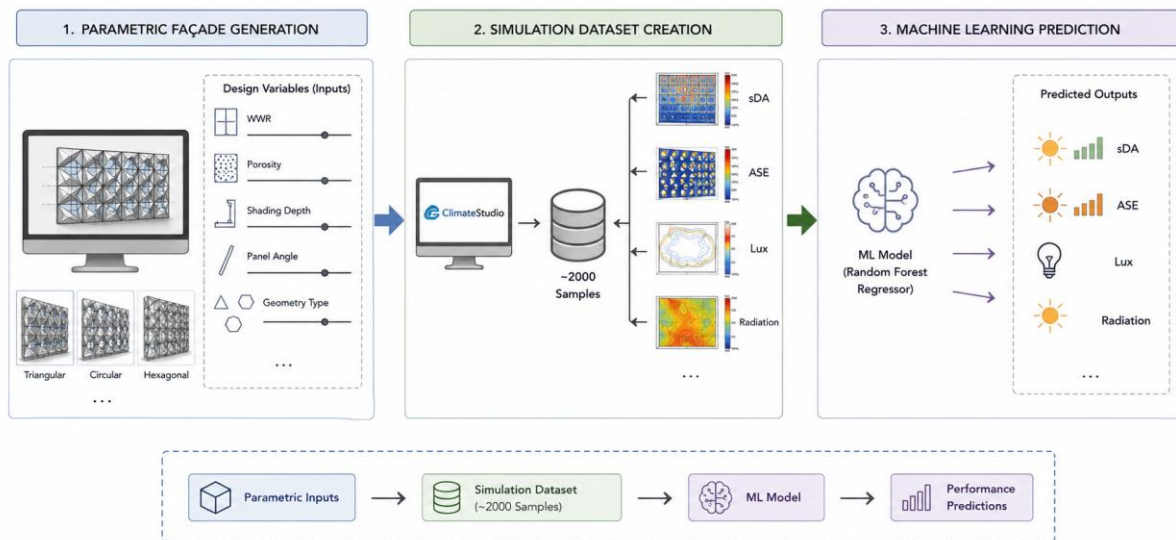


Figure 2-32 – Workflow integrating parametric façade generation, simulation dataset creation, and machine learning prediction (Source: author)

The machine learning model predicts multiple environmental performance outputs including Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), illuminance levels, and solar radiation values. In contrast to conventional simulation workflows that may require several minutes or longer for each analysis iteration, the proposed system provides feedback within a few seconds. This significantly accelerates exploration of design alternatives and supports rapid iterative optimization during early design stages.

Another important contribution of the developed system is the integration of performance feedback and design guidance within the user workflow. In addition to presenting environmental performance predictions, the tool provides suggestions regarding possible façade modifications that may improve results. For example, the

system may recommend increasing or decreasing Window-to-Wall Ratio, adjusting façade porosity, modifying panel orientation, or changing geometric configurations according to predicted performance outcomes. This transforms the workflow from passive analysis toward active design support.

Real-time prediction and design feedback within the Rhino-based workflow are illustrated in Figure. 2.33.

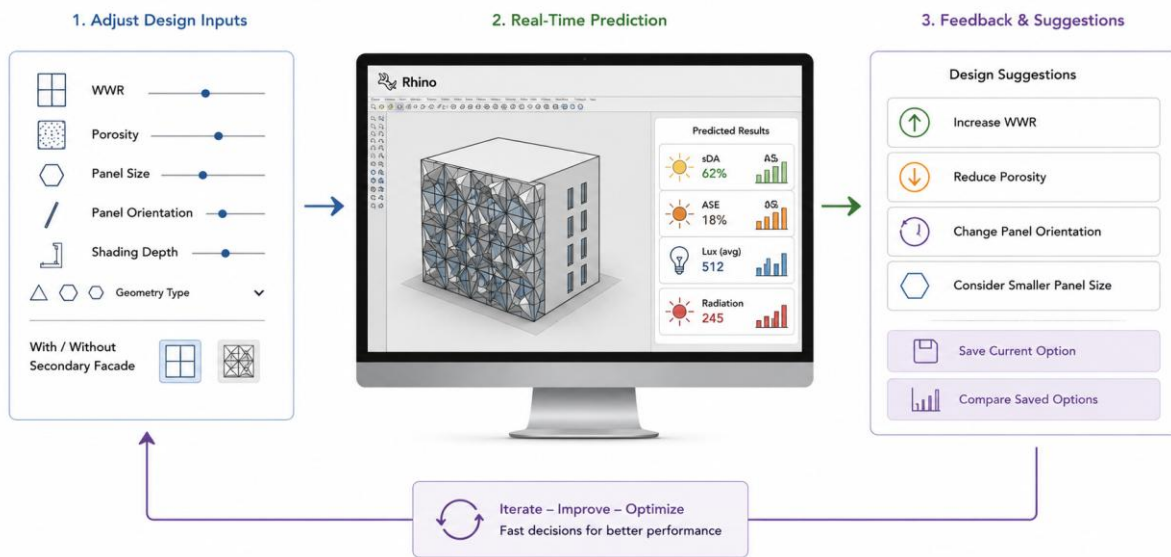


Figure 2-33 – Real-time environmental prediction and design feedback within the Rhino parametric workflow (Source: author)

An additional advantage of the proposed system is the integration of design and analysis within a single digital environment. Since the tool is implemented as a Rhino-based plugin, users do not need to repeatedly export, rebuild, or redefine models in separate simulation software environments. Designers can directly modify façade parameters and instantly evaluate performance outcomes within the same modeling workflow. This integration improves usability and reduces interruptions during iterative design processes.

The proposed framework is also expandable and adaptable for future developments. Although the current study focuses primarily on Milan climate conditions and a specific set of façade geometries, the dataset and predictive workflow can be extended through the inclusion of additional city locations, climatic conditions, façade typologies, and environmental performance indicators. Future expansions may include outputs such as cooling loads, glare analysis, thermal comfort metrics, or

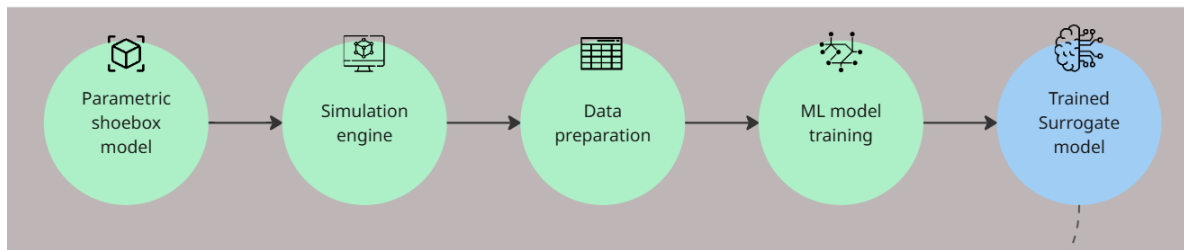
additional façade systems. This scalability increases the long-term applicability and research potential of the developed framework.

Therefore, the primary research gap identified in this study lies in the lack of integrated, real-time, machine learning-assisted façade design tools capable of supporting environmental decision-making during early-stage architectural design processes. Existing workflows rely heavily on repetitive simulation procedures and post-design evaluation, while limited research addresses predictive and interactive pre-design optimization workflows integrated directly within parametric architectural environments. The present research aims to address this gap by developing an interactive predictive framework capable of accelerating façade performance evaluation and supporting informed design exploration during the early stages of architectural design.

3 Methodology

3.1. Workflow

Phase 1: Data generation and machine learning



Phase 2: Interactive design workflow

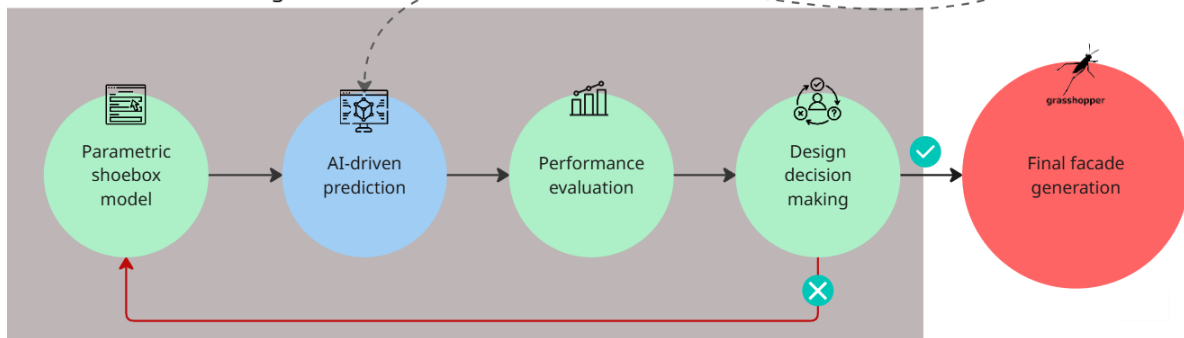


Figure 3-1 – General workflow divided by phases

The workflow presents a streamlined approach to integrating Artificial Intelligence into the architectural design process through surrogate modeling.

The Development Phase (phase1): This stage focuses on generating a dataset using a **Parametric shoebox model** and a **Simulation engine** (Climate Studio) to produce performance metrics. These data are then processed through **Data preparation** and used for **ML model training**, resulting in a **Trained Surrogate model** capable of rapid performance estimation.

The Application Phase (phase2): This phase begins with **Custom Geometry Inputs** provided by the architect. These inputs are processed by the **AI-driven prediction** unit, which replaces slow traditional simulations with instantaneous performance data. This speed enables a real-time **Performance evaluation** and an iterative **Design decision-making** loop.

Finally, the optimized solution is transferred to Grasshopper for **BIM integration**, where the final facade system is generated and implemented.

3.2. Parametric Façade Model

The parametric façade model was developed in Rhino/Grasshopper to systematically generate multiple façade configurations based on a set of controllable design parameters [46]. The model enables rapid exploration of facade alternatives by adjusting key variables that influence building performance.

The primary parameters include Window-to-Wall Ratio (WWR), shading device depth, and façade orientation. These parameters were selected due to their significant impact on both energy consumption and daylight performance, as identified in the literature.

The façade geometry is generated through a rule-based logic. The base building volume is first defined as a simplified rectangular mass. Openings are then applied to the façade according to the specified WWR. External shading elements are parametrically added based on the shading measurement variables.

The model is structured to maintain geometric consistency while enabling continuous variation of parameters. This ensures that all generated configurations remain comparable and suitable for performance evaluation.

The parametric model serves as the input generator for the subsequent simulation process, enabling the automated creation of multiple design scenarios.

3.2.1. Design Variables and Parameters

Building upon the theoretical principles established in the literature review, this section defines the operational variables used to construct the parametric façade model. The selected parameters are translated into computational inputs within the Grasshopper environment, establishing the boundaries of the design search space.

To ensure a comprehensive evaluation of the façade's performance, the variables are categorized into two primary scales: **Global Building Parameters** (affecting the overall massing and exposure) and **Local Façade Parameters** (governing the detailed geometry and material properties of the skin).

Global Building Parameters

- **Orientation:** Represents the building's rotation relative to the True North. This is a critical continuous variable for assessing solar radiation and daylighting across different directions.
- **Window-to-Wall Ratio (WWR):** Controls the proportion of the glazed area relative to the total exterior wall area. It is formulated as a domain parameter to scale the openings dynamically while maintaining geometric constraints.

Local Façade Parameters

- **Panel Type:** A categorical variable that dictates the architectural morphology of the shading modules (e.g., circular, triangular or hexagonal geometries). This parameter triggers different geometric generation algorithms within the script.
- **Panel Size:** Controls the dimensional density of the façade grid (radius/edge of the modules), directly impacting the frequency of shading elements across the elevation.
- **Panel Rotation:** Determines the deployment angle of the shading elements relative to the façade plane. This continuous variable is crucial for calculating daylight penetration.
- **Porosity:** Defines the physical gap size or spacing distance between adjacent shading panels. Rather than internal voids, this parameter controls the spatial distribution and separation of the modules across the façade.
- **Glass Transparency:** Represents the Visual Light Transmittance (VLT) of the glazing system. It is modeled as two different glass types to ensure the simulation remains grounded in constructible realities.

The precise ranges, steps, and data types for all computational inputs are summarized in Table 1. These specific bounds were selected to represent realistic architectural scenarios.

Table 3-1 - Design parameters

Parameter Category	Variable Name	Data Type	Computational Range / Values	Unit
Global	Orientation	Categorical	North East South West	Index
Global	WWR	Continuous	10 to 90 (Step: 20)	Percentage (%)
Local	Panel Type	Categorical	Circular (C01) Triangular (T01) Hexagonal (H01)	Index
Local	Panel Size	Continuous	20 to 60 (Step: 20)	Centimeters (cm)
Local	Panel Rotation	Continuous	0 to 60 (Step: 30)	Degrees (°)
Local	Porosity	Continuous	10 to 40 (Step: 15)	Percentage (%)
Local	Visible Light Transmittance (VLT)	Categorical	40, 80	Percentage (%)

3.2.2. Geometry Generation Logic

The geometric modeling of the façade is executed within the Rhino /Grasshopper visual programming environment. The algorithm is designed hierarchically, ensuring that macro-scale building parameters dictate the boundary conditions for micro-scale façade details. The computational sequence is divided into three primary stages: Base Volume Definition, Fenestration Logic, and Shading System Generation.

1. Base Volume and Host Surface Definition: The generation sequence initiates with the definition of a baseline architectural massing, often represented as a "shoebox". This foundational geometry provides the host surfaces (the primary elevations) upon which the parametric skin is constructed. The global parameter of **Orientation** is applied at this stage, rotating the entire base volume relative to the environmental north to simulate various solar exposures.

2. Fenestration and WWR Implementation: Following the definition of the host surface, the **Window-to-Wall Ratio (WWR)** is parametrically applied. Rather than relying on static drawing methods, the fenestration is generated through a dynamic scaling algorithm. The script extracts the centroid and boundaries of the host wall, and scales an inner surface based on the target WWR percentage. This ensures that the window remains perfectly centered and topologically consistent. Then the algorithm maps the **Glass Transparency** properties onto the generated fenestration surface.

3. Façade Shading Generation: The core of the constructive model lies in the generation of the modular shading system, which is executed through a continuous algorithmic sequence. The process begins with module instantiation, where specific geometric logic is applied to the surface to construct the physical shading elements based on the selected panel type (e.g., circular, triangular, or hexagonal geometries) and panel size variables. Once these base panels are generated, the algorithm applies local parametric transformations and spacing rules. Specifically, the panel rotation parameter controls the pivot angle of the elements relative to the façade plane, while the porosity parameter concurrently governs the spacing logic, adjusting the spatial distribution of the modules along the surface to define the exact gap dimensions between consecutive elements.

Through this sequential logic, the script transforms abstract numerical inputs into a fully detailed, quantifiable, and 3D constructible façade model, ready for downstream evaluations.

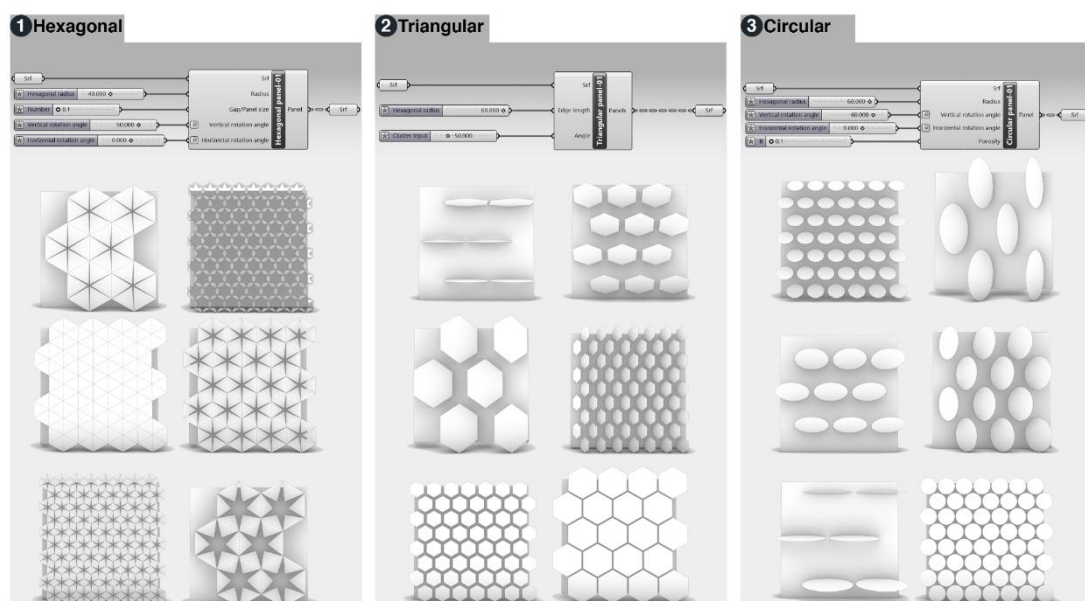


Figure 3-2– Grasshopper script for parametric panel generation



Github repository related to the grasshopper components

<https://github.com/mohammadmrml/facade-shading-components.git>

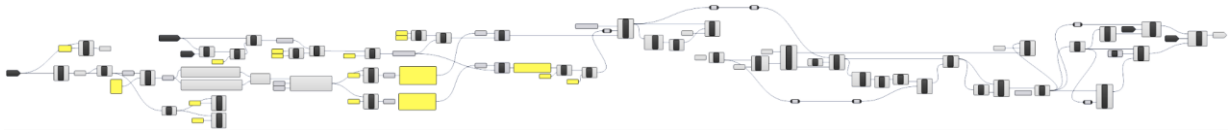


Figure 3-3 – Grasshopper cluster for parametric hexagonal panel generation

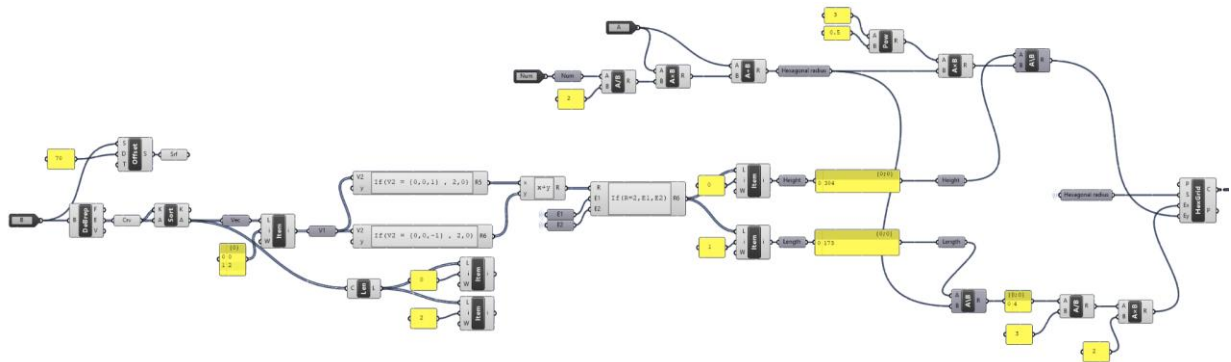


Figure 3-4 – Initial surface partitioning for parametric hexagonal panel generation

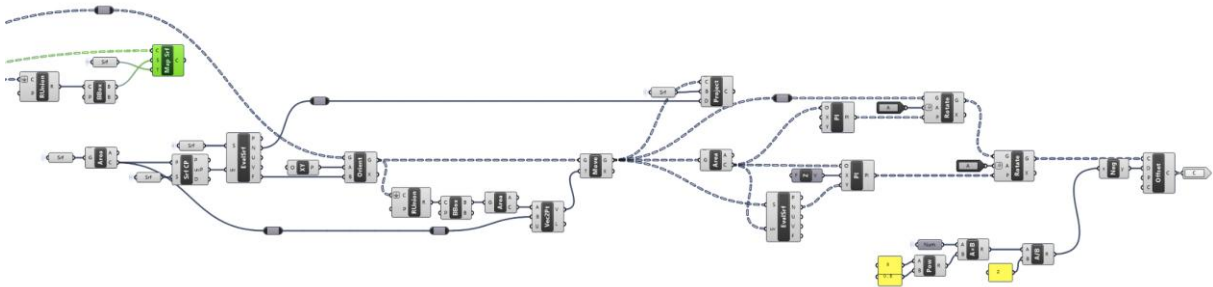


Figure 3-5– Parametric hexagonal surface mapping, illustrating the parametrization of panel rotation and size.

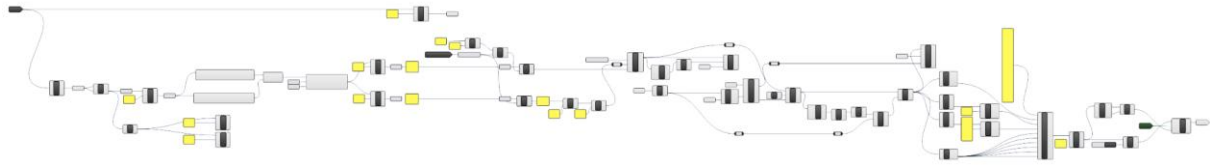


Figure 3-6– Grasshopper cluster for parametric triangular panel generation

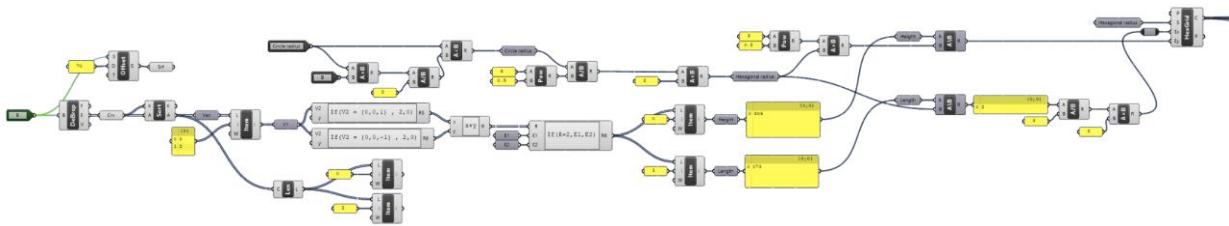


Figure 3-7 – Initial surface partitioning for parametric circular panel generation

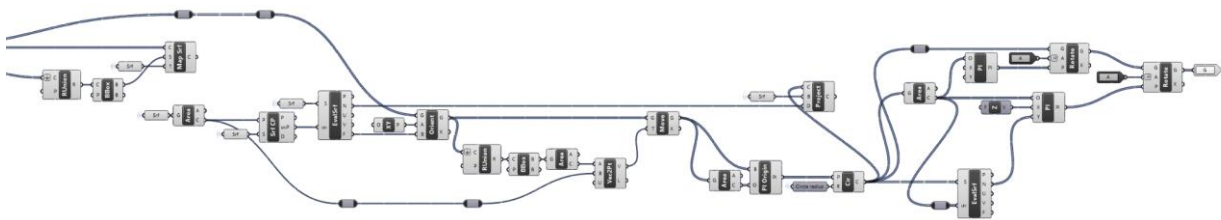


Figure 3-8 – Parametric circular surface mapping, illustrating the parametrization of panel rotation and size.

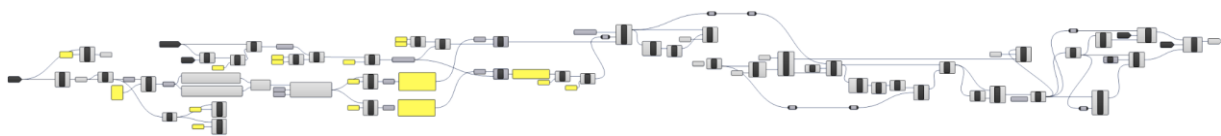


Figure 3-9 – Grasshopper cluster for parametric circular panel generation

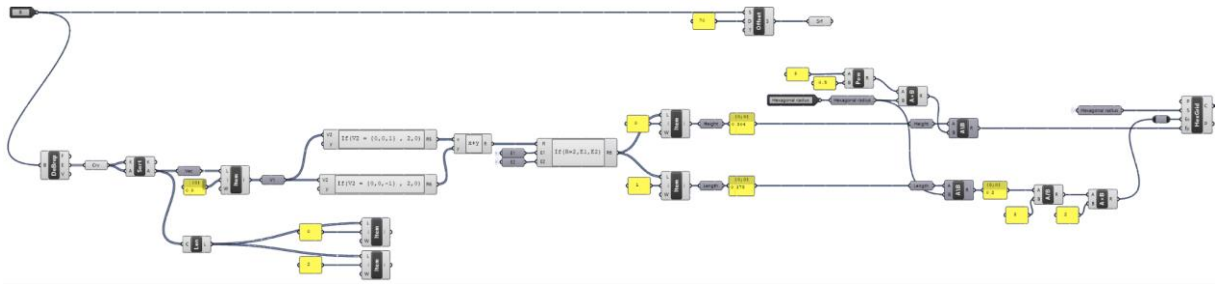


Figure 3-10 – Initial surface partitioning for parametric triangular panel generation

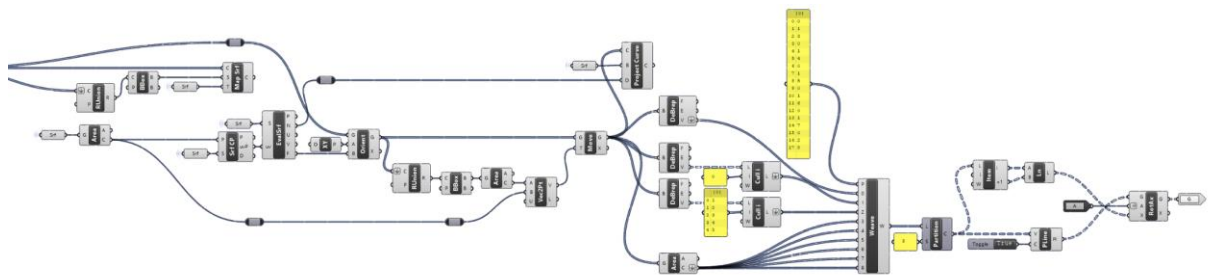


Figure 3-11 – Parametric triangular surface mapping, illustrating the parametrization of panel rotation and size.

3.2.3. Simulation setup

The final stage of the parametric modeling process is the preparation of the generated geometry for environmental evaluation. The model is configured to output simulation-ready data without requiring any manual intervention between iterations.

The raw Grasshopper geometries (Breps and surfaces) are algorithmically converted into recognized simulation objects—such as shading surfaces—compatible with engines like Climate Studio. Material properties, including the categorical Visible Light Transmittance (VLT) variables and the opaque wall constructions, are automatically assigned to their respective surfaces. This allows for a seamless transition to the simulation phase without manual intervention, ensuring a high-speed and error-free data generation process.

3.3. Simulation Framework

This section outlines the environmental simulation framework utilized to evaluate the parametric façade iterations. The objective is to establish an automated pipeline that

calculates specific performance indicators, which will subsequently serve as the benchmark data for training the machine learning surrogate model.

3.3.1. Computational Tools and Pipeline

To achieve an optimal balance between computational efficiency and physical accuracy, the simulation framework is embedded directly within the Rhino/Grasshopper visual programming environment. This integration establishes a seamless computational bridge between dynamic parametric geometry generation and validated environmental analysis. Specifically, Climate Studio is deployed as the primary simulation engine to rigorously evaluate daylighting, energy performance, and visual comfort. Powered by an accelerated, path-tracing Radiance engine, Climate Studio facilitates highly accurate, multi-threaded calculations for both annual and point-in-time metrics. Consequently, this setup delivers robust environmental training data at a fraction of the computational time typically required by conventional CPU-based workflows.

3.3.2. Input-to-Output Mapping

The automated pipeline acts as a direct computational bridge between the geometric variables defined in Section 3.2 and the target environmental performance indicators.

1. Simulation Inputs: As the optimization loop generates a new iteration, the global parameters (**Orientation** and **WWR**) and local façade variables (**Panel Type**, **Panel Size**, **Panel Rotation**, **Porosity**, and **Glass Transparency**) automatically update the physical model. The script algorithmically converts these surfaces into analytical objects:

- Opaque walls and shading panels are assigned specific reflectance values.
- The fenestration surfaces are assigned optical properties based on the selected glass transparency (Visual Transmittance).
- An analysis grid with virtual sensors is established at a standardized working plane height (0.8m above the floor) across the interior zone.

2. Simulation Outputs: Once the inputs are initialized, the workflow triggers Ladybug and ClimateStudio to execute the simulations without manual intervention [34]. The pipeline extracts four distinct performance metrics per iteration, serving as the high-fidelity training targets:

Visual Comfort and Daylighting Metrics:

- **Spatial Daylight Autonomy (sDA):** Evaluates the annual sufficiency of daylight within the space. It measures the percentage of the analyzed floor area that receives a minimum target illuminance of 300 lux for at least 50% of the annual occupied hours. Maximizing sDA is a primary objective to ensure adequate natural lighting and reduce reliance on artificial fixtures.
- **Annual Sunlight Exposure (ASE):** Quantifies the potential risk of visual glare and excessive solar heat gain. It measures the percentage of the floor area exposed to direct sunlight exceeding a specific threshold of 1000 lux for more than 250 hours per year. Minimizing ASE is critical for maintaining visual comfort and preventing localized overheating [22].
- **Point-in-Time Illuminance (Lux):** Measures the absolute raw light intensity arriving at designated sensor grids on the working plane under specific sky conditions (e.g., equinox or solstice design days). Analyzing raw lux distributions provides granular insight into the spatial uniformity of daylight across the room depth.

Environmental Exposure Metrics:

- **Incident Solar Radiation (kWh/m²):** Quantifies the total cumulative solar energy striking the exterior façade panels and penetrating the glazing system. Tracking solar radiation is essential for evaluating the blocking efficiency of different panel rotations and porosity, serving as a direct proxy for passive thermal loads.

The simultaneous evaluation of sDA, ASE, and raw illuminance ensures a balanced internal daylighting condition, while the solar radiation metric evaluates the external skin's capacity to intercept unwanted thermal energy.

Table 3-2 - Simulation outputs

Metric	Scope	Target Objective	Primary Unit
sDA	Daylight Sufficiency	Maximize	Percentage (%)
ASE	Reduce Overlit Areas	Minimize	Percentage (%)
Illuminance (lux)	Spatial Light Distribution	Optimize (Range)	Lux
Radiation	Solar Energy Exposure	Control	kWh/m ²

3.4. Dataset Generation and Preprocessing

Translating high-fidelity environmental simulations into a structured format suitable for machine learning requires a systematic approach to automated data collection and formatting. This section outlines the logic used to execute the design iterations and the preprocessing steps applied to prepare the final simulation tables for model training.

3.4.1. Full Factorial Parametric Execution

To ensure a comprehensive and highly granular representation of the architectural search space, an exhaustive **full-factorial simulation approach** is employed. Rather than utilizing statistical or algorithmic sampling strategies (which only test a subset of possibilities), this framework evaluates every possible permutation of the defined design variables.

To make this computationally viable, all continuous domains are discretized into specific, evenly spaced intervals. For instance, the Window-to-Wall Ratio (WWR) is not treated as an infinite continuous range (0–100%), but is instead broken down into fixed incremental spans (e.g., 10%, 30%, 50%, 70%, and 90%). By applying this discretization logic to all continuous parameters (WWR, Panel Size, Panel Rotation, and Porosity) and combining them with the categorical variables (Orientation, Panel Type, and Glass Transparency), a finite matrix of distinct architectural states is established.

The Grasshopper script systematically iterates through this entire matrix, generating every single unique façade configuration. For each iteration, the automated pipeline triggers ClimateStudio and Ladybug to compute the environmental metrics and outputs the numerical results. This exhaustive execution guarantees that the final dataset maps the entire parametric boundaries without any untested combinations or theoretical blind spots.

3.4.2. Data Aggregation and Formatting

Rather than applying automated data filtering at this stage, all executed simulation results are directly aggregated to establish a complete raw operational record. The input variables and their corresponding outputs (sDA, ASE, Lux, and Solar Radiation) are compiled into centralized tabular datasets (formatted as **.csv** files).

Structuring the data into clear input-to-output tables ensures that the exact physical behavior calculated by the simulation engines is preserved. Validation and error analysis are intentionally reserved for the post-ML phase, where the surrogate model's predictions are directly compared against these baseline simulation tables to evaluate inference accuracy.

3.4.3. Feature Encoding and Dataset Splitting

Before the tabulated data is fed into the machine learning algorithms, standard mathematical transformations are applied to ensure the models process the architectural features correctly:

Encoding Categorical Variables: Discrete architectural inputs, such as **Panel Type**, **Orientation**, and **Glass Transparency**, are converted into machine-readable formats using **Categorical Encoding**. This process transforms text-based geometric or material states into specific discrete identifiers (e.g., mapping a triangular panel to 'T01'). This allows the machine learning algorithm to recognize and group distinct architectural morphologies as separate classes, without incorrectly interpreting them as continuous physical measurements or assigning unphysical numerical weights.

Dataset Splitting: Finally, the formatted table is partitioned to train the algorithm. A standard split is allocated: **80%** of the tabulated data is used for training the model's internal weights, while the remaining **20%** is withheld as an unseen testing set to rigorously assess the model's predictive performance and ensure it generalizes well to new, untested façade configurations.

3.5. Machine Learning Model

To bypass the computational bottleneck of traditional raytracing and thermal proxy simulations during the iterative design phase, a machine learning algorithm is deployed as a **surrogate model** [48]. This section outlines the architecture selection, the training protocol using the tabulated simulation data, and the mathematical metrics used to evaluate the model's predictive accuracy.

3.5.1. Surrogate Model Architecture

The primary objective of the machine learning model is to establish a multi-output regression mapping between the architectural design space and the environmental performance indicators. Because the dataset contains both continuous variables (, WWR, Panel Size, Panel Rotation, Porosity) and encoded categorical features (Orientation, Panel Type, and Glass Transparency), an algorithm capable of capturing complex, non-linear dependencies is required.

For this framework, a **Random Forest Regressor** architecture is selected [49]. This approach is highly effective at modeling multidimensional physical interactions without assuming linear correlations. The input layer of the model corresponds directly to the dataset defined in Section 3.4, while the output layer is configured to simultaneously predict the four target environmental metrics: Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), Point-in-Time Illuminance (Lux), and Incident Solar Radiation.

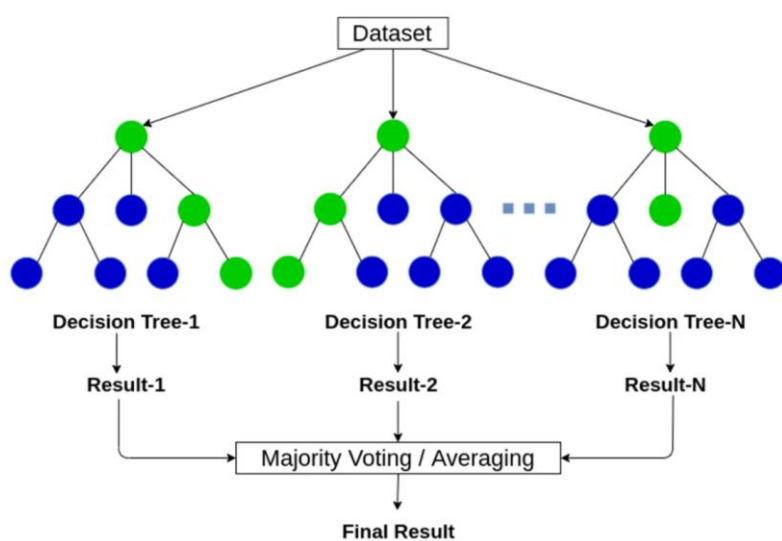


Figure 3-12 – Random Forest Overview

3.5.2. Training Protocol and Optimization

The learning process is driven by the preprocessed tabular dataset established in Section 3.4. Using the designated training partition (80% of the total dataset), the algorithm iteratively learns the underlying physical mapping calculated by Climate Studio.

During the training phase, the model's internal weights and biases are optimized to minimize the prediction error between the surrogate outputs and the ground-truth simulation targets. The training protocol utilizes Model Error: 16992.288373354208 as the primary loss function.

3.5.3. Predictive Accuracy Evaluation

Once the surrogate model is trained, its predictive capability must be rigorously validated using the 20% withheld testing dataset to ensure it can reliably support architectural decision-making. Rather than relying solely on abstract statistical loss, the framework evaluates performance across three highly interpretable, practical tiers:

The predictive accuracy of this model is evaluated using the **Mean Squared Error (MSE)**. This metric measures the average of the squares of the errors, which means it quantifies the average squared difference between the predicted values and the actual target values. A lower MSE indicates a more accurate model.

While the **Root Mean Squared Error (RMSE)** was also mentioned, it was calculated using a hard-coded value. I will add a corrected cell to calculate the RMSE directly from the MSE, which is a more standard and accurate approach. RMSE is useful because it's in the same units as your target variable, making it easier to interpret.

3.5.4. Model Deployment

Following training and validation, the finalized Random Forest surrogate model was serialized and exported as a reusable prediction asset. This deployment step enabled the trained model to be integrated into the Rhino/Grasshopper design environment while preserving the predictive relationships learned from the ClimateStudio-generated dataset.

The deployed model acts as the computational core of the proposed workflow. During operation, geometric and façade parameters extracted from the Rhino environment are automatically transferred to the prediction engine, which returns estimated environmental performance indicators without executing new simulation calculations. This architecture allows the machine learning model to function as a lightweight

surrogate for computationally intensive daylight simulations during early-stage design exploration.

By separating the training process from the prediction process, the workflow enables the trained model to be reused across multiple design sessions while maintaining rapid response times suitable for interactive architectural applications. The deployed prediction engine forms the foundation of the Rhino-integrated tool described in the following section.

3.6. Tool Integration (Rhino/Grasshopper Plugin)

3.6.1. Integration Strategy

The final stage of the research methodology focuses on integrating the trained surrogate model into a practical architectural design environment capable of supporting real-time interaction and iterative decision-making. Rather than functioning as an isolated analytical system, the machine learning framework is embedded directly within the Rhino/Grasshopper environment through a custom-developed plugin workflow. This integration transforms the surrogate model into an active design-support tool capable of providing immediate environmental feedback during conceptual architectural development.

Rhino and Grasshopper were selected as the host platform because of their widespread adoption within computational architectural practice and their flexibility for parametric geometry generation, visual scripting, and performance-driven workflows [30]. Embedding the predictive system directly into this ecosystem allows the workflow to maintain continuity between geometric modeling, environmental evaluation, and facade optimization.

The integration strategy establishes a direct relationship between:

- Parametric facade generation,
- AI-assisted environmental prediction,
- Real-time visualization,
- Iterative design exploration,
- BIM-oriented geometry development.

This unified computational environment minimizes workflow fragmentation and enables designers to evaluate facade performance without leaving the modeling platform.

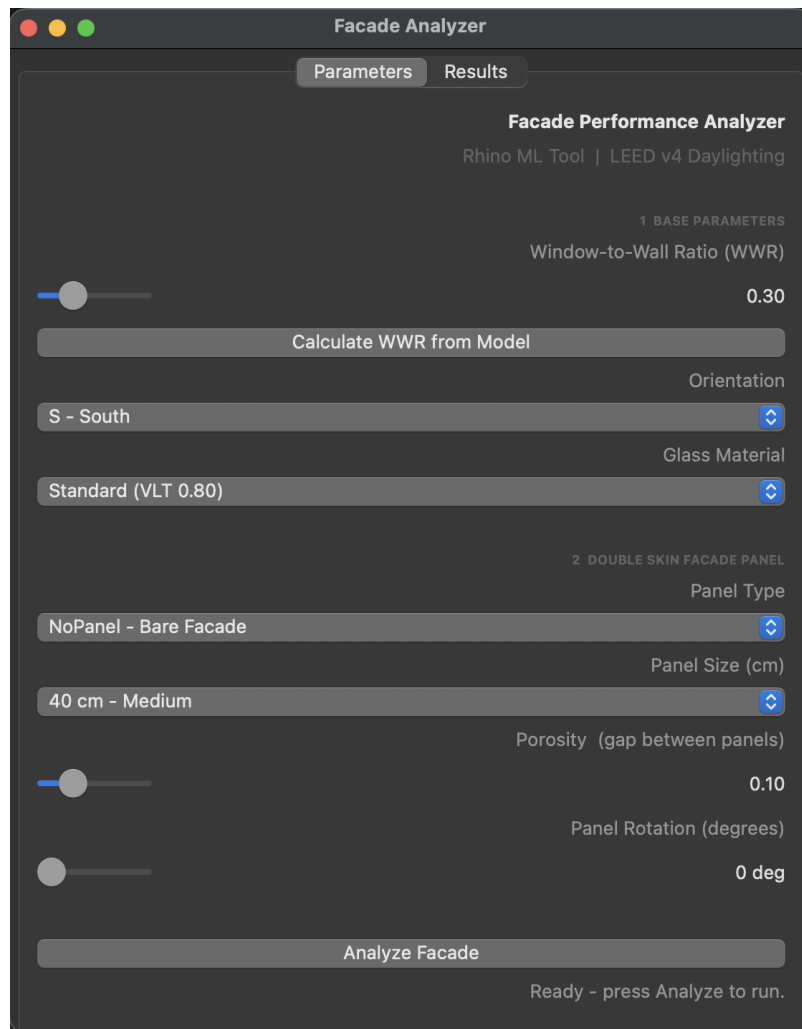


Figure 3-13 – Screenshot of Rhino plugin - Parameters tab



Facade Performance Analyzer — Rhino ML Plugin Demo video

<https://youtu.be/qRqQzm9Ae1Y>



Github repository related to the Smart Façade Recommender

https://github.com/mohammadmrml/Smart_Facade_Recommender.git

3.6.2. Plugin Architecture and Workflow

The Rhino plugin operates as an intermediary computational layer between the facade modeling environment and the deployed surrogate prediction engine. The workflow begins with the architect manipulating facade parameters directly within the Grasshopper interface. These parameters include:

Window-to-Wall Ratio (WWR),

Orientation,

Panel Type,

Panel Size,

Panel Rotation,

Porosity,

Glass Transparency.

To improve flexibility and compatibility with different modeling approaches, the system supports two alternative methods for defining the Window-to-Wall Ratio (WWR) parameter.

The first method is a manual parametric input workflow, where the designer controls the WWR directly through an interactive slider within the Grasshopper interface. This approach is primarily intended for rapid conceptual exploration, allowing the user to dynamically adjust the glazing ratio and immediately observe the predicted environmental performance response.

The second method enables automatic WWR calculation directly from custom architectural geometry modeled within Rhino. In this workflow, the user first explodes the facade geometry into its constituent surfaces. The opaque facade surfaces are then assigned as wall elements, while the opening geometries are separately identified and referenced as glazing surfaces. Once these surfaces are defined, the plugin automatically calculates the Window-to-Wall Ratio by comparing the total opening area against the overall facade surface area. This automated process allows the system to work with custom facade configurations beyond the predefined parametric shoebox model and improves compatibility with more advanced architectural geometries.

After the facade parameters are defined through either manual or automatic workflows, the script extracts the numerical parameter values and transfers them to the predictive engine. Instead of triggering conventional environmental simulations,

the trained surrogate model instantly estimates the environmental performance outputs.

The plugin workflow can therefore be summarized as:

Parametric Inputs / Custom Geometry Inputs,

Parameter Extraction,

AI Prediction Engine,

Environmental Performance Outputs

By supporting both parametric slider-based workflows and geometry-based automatic WWR recognition, the plugin accommodates multiple architectural design approaches while maintaining real-time environmental feedback capabilities.

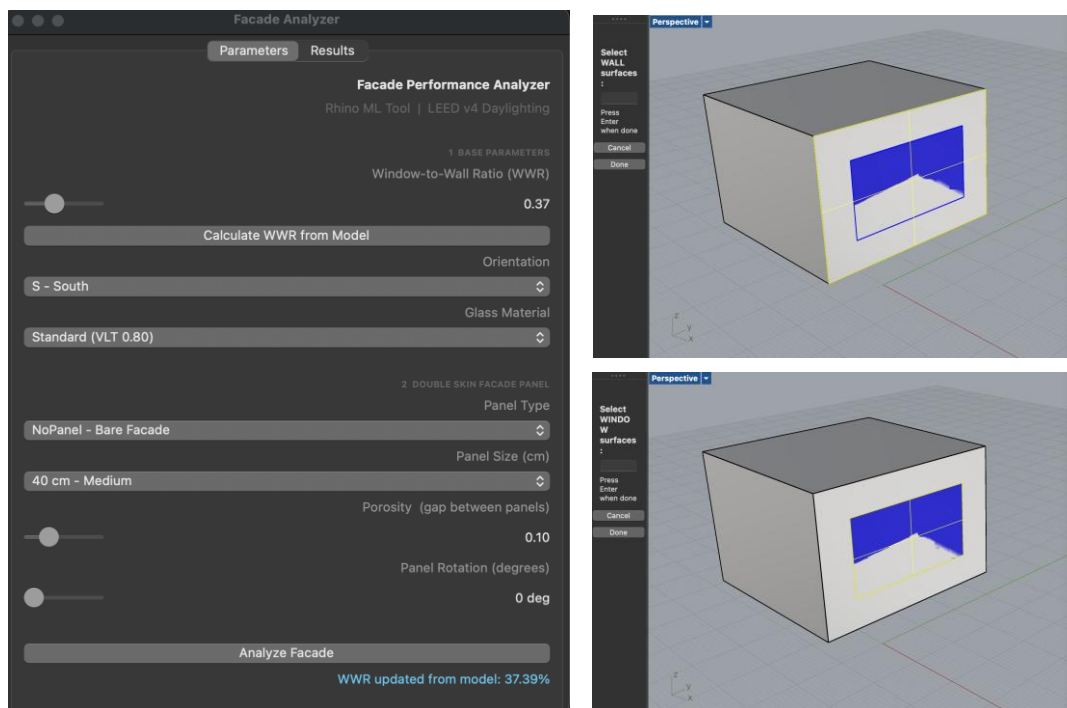


Figure 3-14– Integrating a custom façade design into the plugin interface

3.6.3. Instantaneous Forecasting Interface

The real-time prediction interface serves as a core element of the plugin, facilitating a seamless communicative bridge between the architect and the surrogate machine learning model.

As designers adjust various façade parameters via interactive menus and sliders, the system provides immediate feedback.

3.6.4. Real-Time Prediction Interface

One of the primary components of the plugin is the real-time prediction interface. This interface acts as the communication layer between the designer and the machine learning model.

As the user manipulates facade parameters through sliders and selection menus, the system immediately updates the predicted environmental metrics without launching external simulations. The interface continuously evaluates the facade configurations and displays:

Spatial Daylight Autonomy (sDA),

Annual Sunlight Exposure (ASE),

Point-in-Time Illuminance,

Incident Solar Radiation.

The predictions are visualized numerically and graphically to improve interpretability during conceptual design stages. This immediate feedback mechanism allows architects to understand the environmental consequences of geometric modifications while maintaining the fluidity of the design process.

The real-time nature of the interface significantly increases the number of facade alternatives that can be explored within limited design timeframes. Instead of waiting

for lengthy simulation calculations, designers can rapidly iterate between multiple solutions and evaluate performance interactively.

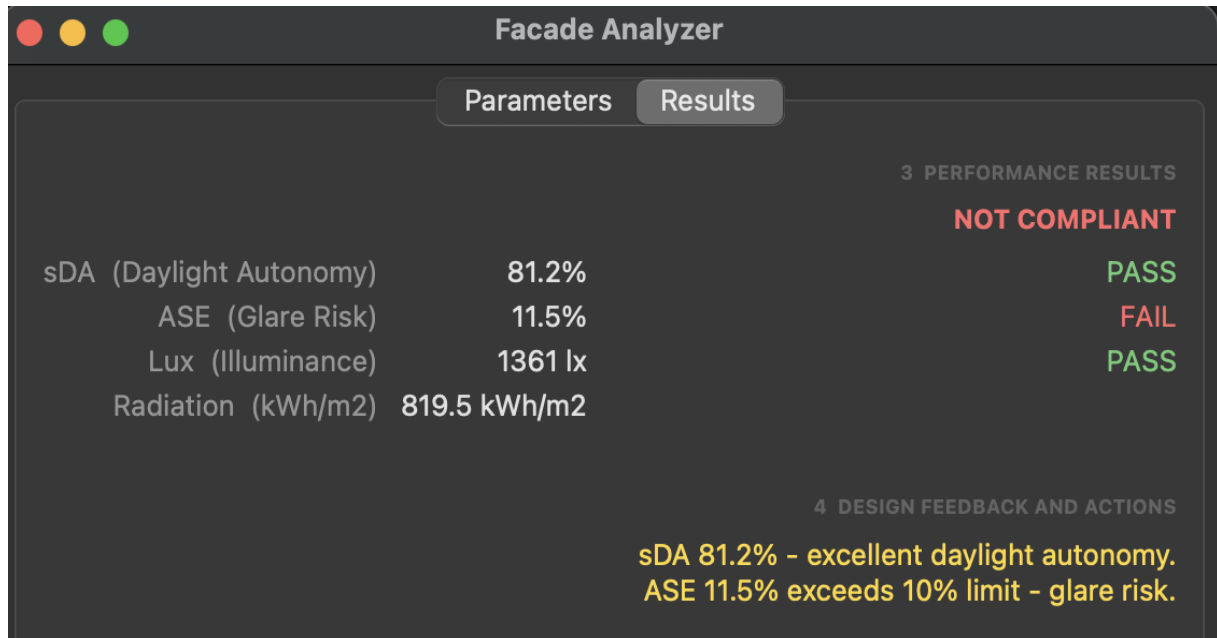


Figure 3-15 – Real-time daylight and radiation performance prediction in the results tab

3.6.5. Geometry Visualization and Analytical Feedback

Beyond predicting environmental performance metrics, the plugin incorporates a recommendation-based feedback mechanism designed to support architects during the early stages of façade design exploration. Following each prediction cycle, the system analyzes the estimated performance indicators and generates context-specific design suggestions intended to improve daylight availability, reduce excessive solar exposure, or achieve a more balanced environmental response.

The recommendation engine evaluates the predicted outputs, including Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), Point-in-Time Illuminance (Lux), and Incident Solar Radiation, and compares them against predefined performance objectives. Based on this assessment, the system proposes potential design actions such as adjusting the Window-to-Wall Ratio (WWR), modifying panel rotation, changing façade porosity, revising glazing transparency, or exploring alternative façade configurations.

Rather than automatically modifying the geometry, the plugin preserves designer control throughout the process. Recommendations are presented within the user interface as interactive design suggestions that can be selected by the user. When a

recommendation is activated, the corresponding parameter values are automatically updated within the prediction interface and a new environmental prediction is generated. This enables designers to immediately evaluate the potential impact of the proposed modification without manually reconfiguring all input parameters.

The workflow therefore establishes an interactive feedback loop between environmental evaluation and design refinement. Designers remain responsible for developing and modifying the façade geometry, while the plugin acts as an intelligent decision-support system that highlights potential performance improvements and enables rapid assessment of alternative parameter configurations.

By embedding recommendation-based feedback directly within the prediction workflow, the system transforms environmental analysis from a passive reporting process into an active design-support mechanism. This approach enables faster exploration of design alternatives while maintaining architectural flexibility and designer-driven decision-making.

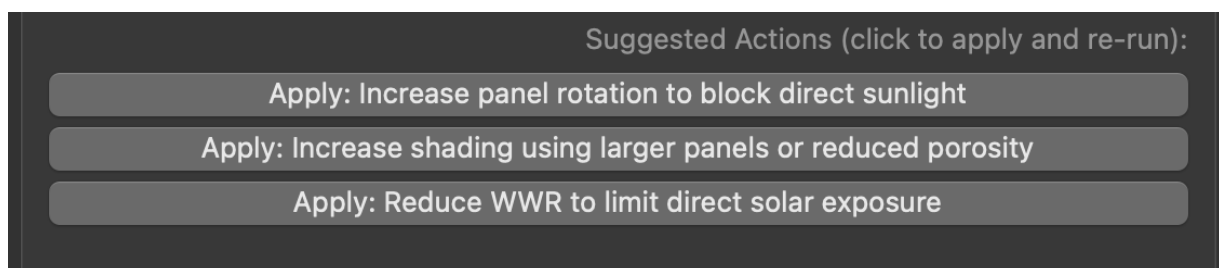


Figure 3-16 – AI-assisted recommendation interface for façade performance improvement.

3.6.6. Iterative Design Exploration Support

A central objective of the plugin integration is to support iterative façade exploration during the conceptual design stage. Traditional environmental analysis workflows often interrupt the design process because each design modification requires a new simulation cycle, resulting in considerable computational time and reduced exploration capacity [53]. In contrast, the AI-assisted prediction workflow provides near-instantaneous environmental feedback, allowing designers to evaluate alternative façade configurations without repeatedly executing detailed simulations.

The workflow establishes a continuous relationship between:

- Design modification,
- Environmental prediction,
- Performance evaluation,

- Design iteration comparison.

Following each prediction cycle, users can store the evaluated façade configurations together with its associated environmental performance outputs. The saved iteration records include both the input parameters and the predicted performance indicators, creating a structured history of explored design alternatives throughout the development process.

This functionality enables designers to compare multiple façade options and track the impact of parameter modifications on environmental performance. Rather than relying on memory or manually documenting design changes, architects can review previously evaluated alternatives and assess their relative performance during the decision-making process.

The iterative workflow encourages performance-informed experimentation by reducing the effort required to evaluate successive design variations. As a result, designers can investigate a broader range of façade strategies and parameter combinations while maintaining a clear record of the explored solutions and their predicted environmental outcomes.

By facilitating rapid evaluation and systematic comparison of design alternatives, the plugin supports a more informed and efficient façade development process while preserving full control of design decisions within the hands of the architect.

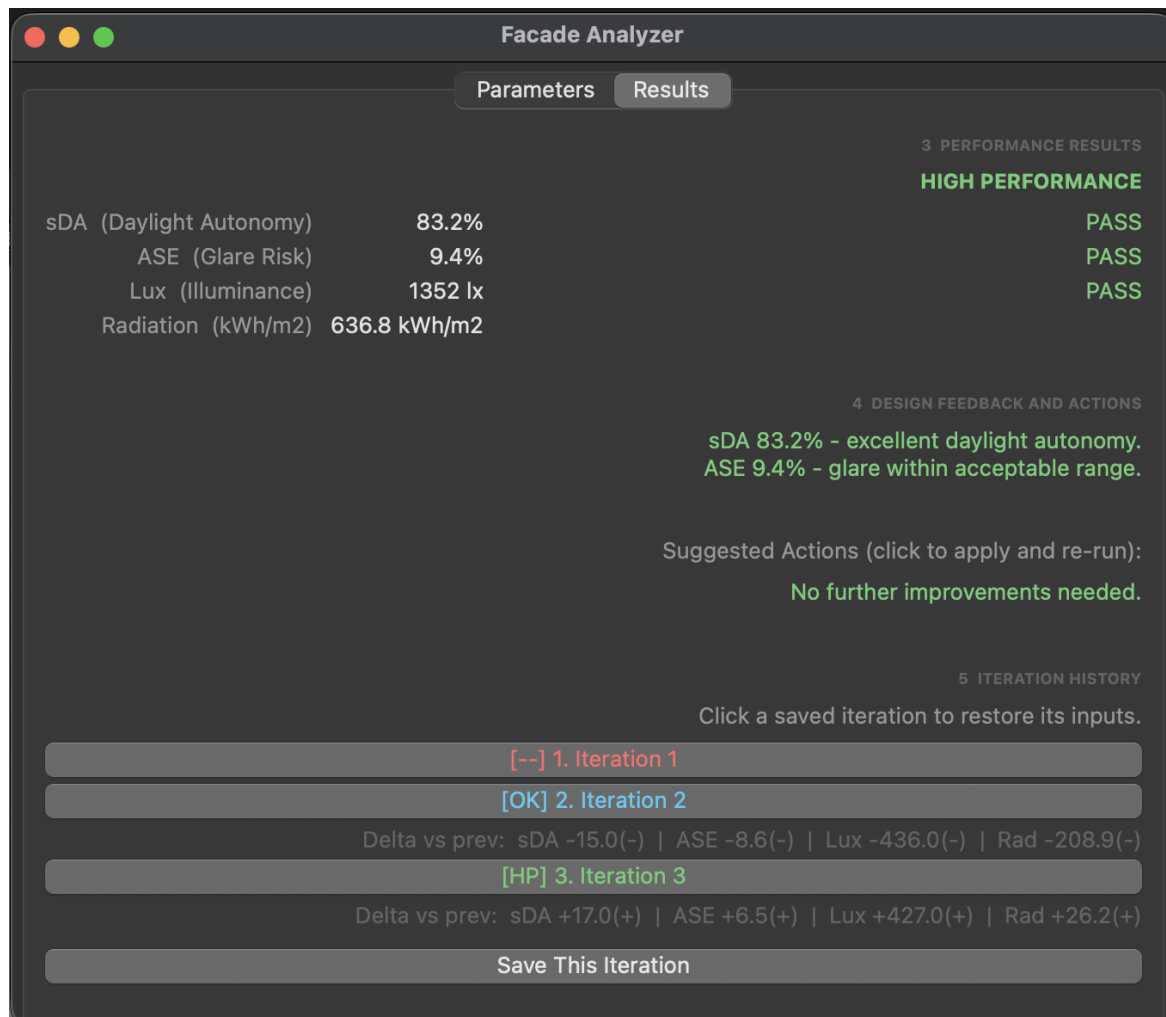


Figure 3-17 – Iteration loop workflow

3.6.7. Workflow Continuity and BIM Compatibility

An additional advantage of the proposed Rhino-based workflow is its compatibility with existing architectural modeling and BIM-oriented development processes. Since the prediction system is integrated directly within the Rhino and Grasshopper environment, architects can evaluate façade performance without transferring geometry to external platforms during the early stages of design exploration.

The workflow preserves the continuity between geometric modeling, environmental evaluation, and subsequent design development. Designers remain free to modify and refine façade geometries using their preferred Rhino and Grasshopper workflows while simultaneously receiving performance predictions through the integrated AI-assisted tool.

Because the design process remains within a common computational environment, interoperability issues and repetitive data transfer operations are reduced. This allows the environmental evaluation workflow to be incorporated into established architectural design practices without disrupting existing modeling procedures.

Once a preferred façade solution has been identified, the corresponding geometry can continue through conventional BIM and documentation workflows for further development, detailing, and project delivery. In this way, the proposed system supports the integration of environmental performance assessment within the broader architectural design process while maintaining compatibility with downstream design and documentation stages.

3.6.8. Justification for Rhino Plugin Integration Instead of Web Application

The research intentionally prioritizes a Rhino-integrated plugin workflow rather than a standalone web application. Although web-based systems provide accessibility and platform independence, they introduce several limitations when applied to computational architectural workflows.

Architectural facade design depends heavily on direct geometric manipulation, parametric relationships, and continuous interaction with complex 3D modeling environments. These operations are significantly more efficient within native modeling platforms such as Rhino and Grasshopper, where geometry generation and parameter control already exist as integrated components of the design workflow [50].

Another major advantage of the Rhino-based approach is interoperability with existing computational design practices. Since Rhino and Grasshopper are already widely adopted within architectural offices and academic research environments, embedding the predictive model directly into this ecosystem minimizes workflow fragmentation and eliminates repetitive geometry export/import operations.

From a computational perspective, local plugin integration also reduces latency associated with cloud communication and remote processing. Because the predictive workflow operates locally within the modeling environment, the system can provide faster interaction and more responsive real-time feedback during iterative design sessions.

Finally, the Rhino integration supports a stronger connection between conceptual design, environmental optimization, and BIM-oriented development. This continuity would be significantly more difficult to achieve through a simplified external web-based platform.

4 Case Study

4.1. Project Description

The selected case study for this research is *Il Sole 24*, an office building located in Milan. This project was chosen due to its representative office typology and extensive glazed façade surfaces, which are highly exposed to the climatic conditions of Northern Italy. Milan is characterized by a humid subtropical climate with warm summers and cold winters, resulting in significant seasonal solar variations. In such office buildings, excessive solar gains frequently increase cooling loads and cause visual discomfort, while insufficient daylight availability drives up dependency on artificial lighting. Consequently, façade design becomes a fundamental interface for balancing daylight performance, visual comfort, and operational energy efficiency [51], [14].

The primary objective of this case study is to evaluate the baseline daylight performance of the original façade and investigate the effectiveness of parametric double-skin façade (DSF) systems generated through the developed AI-assisted tool. The building geometry was reconstructed using Rhino 3D and Grasshopper, while physical daylight simulations were conducted in ClimateStudio, utilizing the Radiance engine for climate-based analysis [52]. By comparing the original façade against multiple AI-generated parametric configurations and validating those results through physical simulation, this chapter evaluates both the architectural effectiveness of the design interventions and the predictive reliability of the surrogate machine learning model.



Figure 4-1 – Il Sole 24 case study building within the urban context of Milan, Italy.



Figure 4-2– Il Sole 24 case study building within the urban context of Milan.



Figure 4-3 – Exterior view and primary façade of the Il Sole 24 office building.

4.2. Baseline Model Setup

This section defines the foundational computational and environmental parameters established for the unoptimized reference building. It describes the comprehensive reconstruction of the architectural geometry, the specification of material surface boundary conditions within the simulation engine, and the initial integration of the baseline model into the custom plugin environment prior to any parametric optimization.

4.2.1. Geometric Modeling and Design Strategy

The base model represents the original condition of the *Il Sole 24* office building prior to any optimization interventions. The geometry was comprehensively reconstructed in Rhino 3D, capturing the specific architectural massing, floor divisions, and exact solar orientation. Special analytical attention was directed toward the South, East, and West façades, as these highly glazed elevations experience significant annual solar exposure and directly dictate the interior daylight behavior [12]. The original architectural strategy relies on a continuous, high-transparency glass curtain wall system lacking any external shading devices. To establish an accurate baseline reference, the initial 3D model isolates this unshaded state, capturing the exceptionally high Window-to-Wall Ratios (WWR) averaging approximately 88% across these primary exposures.

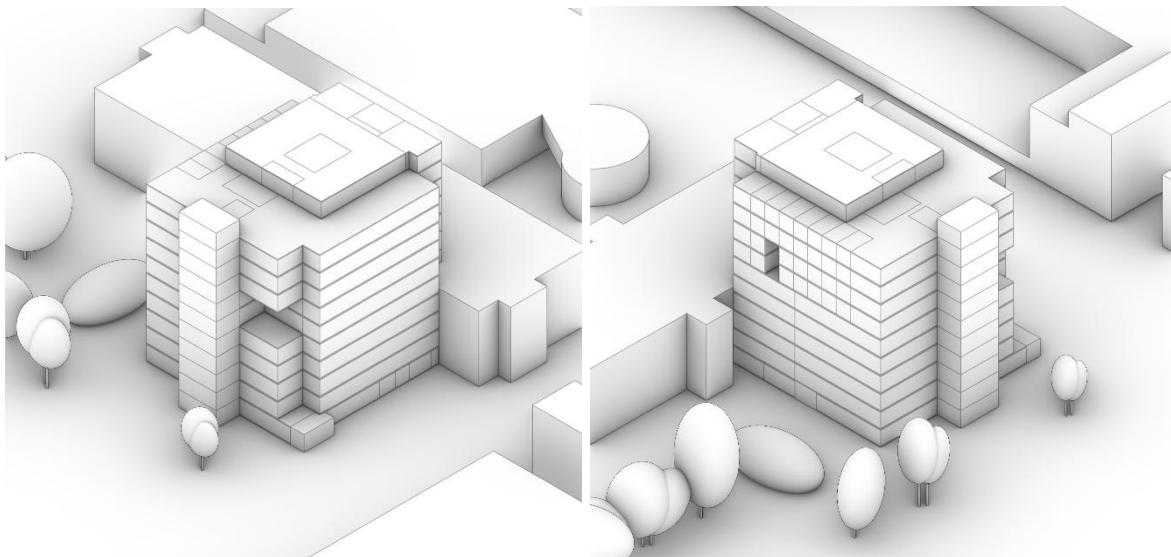
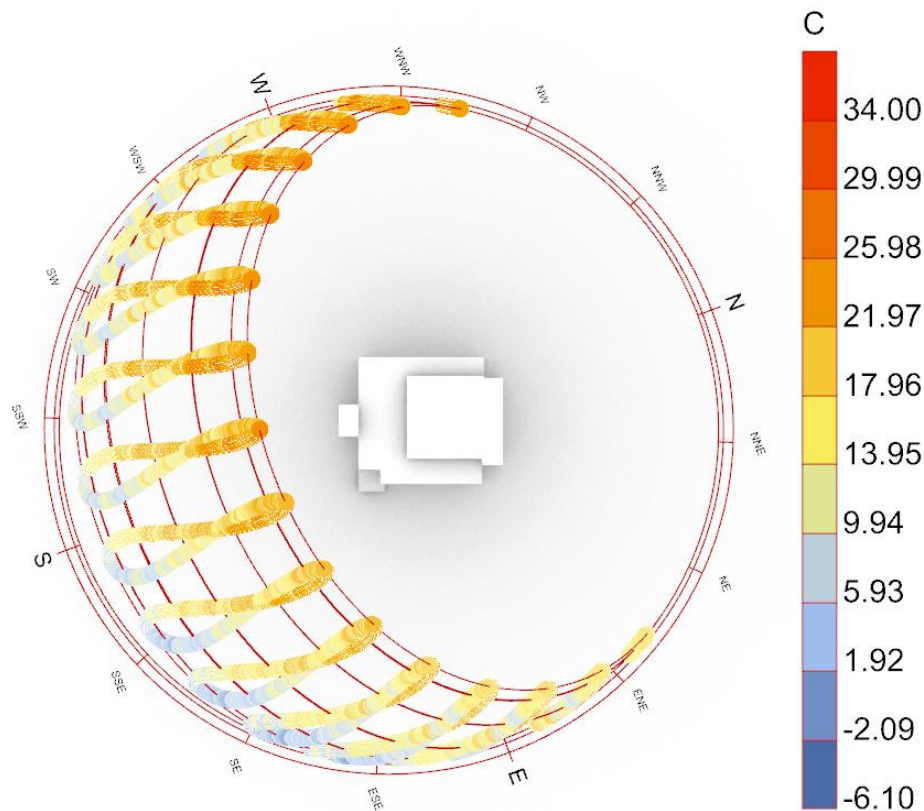


Figure 4-4 – Reconstructed 3D geometric massing of the case study building and its immediate urban context within the Rhino environment.



Dry Bulb Temperature (C)
 source: SRC-TMYx
 city: Milano-Linate.AP
 time-zone: 1.0
 country: ITA

Figure 4-5 – Stereographic sun path diagram and annual solar orientation analysis for the building envelopes in Milan, Italy.

4.2.2. ClimateStudio Simulation Configurations

To evaluate the physical baseline performance, the unshaded geometric model was configured within ClimateStudio, leveraging the Radiance engine for physically accurate, climate-based daylight modeling (CBDMM) [23]. Simulations utilized the standard EPW weather file corresponding to Milan. The analytical grid was established at a standard office working plane height of 0.80 meters with a 0.50-meter spacing, operating under a standard weekday schedule (8:00 AM to 6:00 PM). To accurately simulate the high-transparency characteristics of the existing structure, the primary glazing layers were assigned a high Visible Light Transmittance (VLT) value of 0.88, alongside standard internal reflectance values for floors, walls, and ceilings.

The baseline analysis specifically focused on mapping three primary metrics: Spatial Daylight Autonomy (sDA) to evaluate overall daylight sufficiency, Annual Sunlight Exposure (ASE) to identify localized overlighting risks, and Point-in-Time Illuminance (Lux) to assess absolute light distribution [22], [53].

Table 4-1– Baseline environmental simulation parameters, sensor grid bounds, and

Parameter	Value
Location	Milan, Italy
Weather Data	EPW Climate File
Simulation Type	Annual Daylight Simulation
Workplane Height	0.80 m
Sensor Grid Spacing	0.50 m
Occupancy Schedule	Office Working Hours (8 am - 6 pm - Working days)
Simulation Engine	Radiance via ClimateStudio

occupancy schedules configured in ClimateStudio.

Layer	Material	VLT	VLR
Floor	Concrete Floor	-	29%
roof	Concrete Exterior Floor	-	18%
neighbors	Wall LM83	-	50%
walls	White Painted Concrete wall	-	89%
glass wall	Clear	88%	8%
window	Azuria - Solarban 67 (3) (Krypton)	41%	11%
▼ CSTree Sparse Short	Fagus Sylvatica / LengthOfDay	-	9%
Leaves Detailed	Acer Platanoides / LengthOfDay	-	0%
Trunk	Bark	-	15%
Twig	Bark	-	15%
Tree	Fagus Sylvatica / LengthOfDay	-	9%

ITA_MILANO-LINATE_160800_IW2	
Climate Zone	
Koppen climate zone:	Temperate, No Dry Season, Hot Summer (Cfa)
ASHRAE climate zone:	Mixed (4)
Average annual temperature:	14 °C
Annual total solar radiation:	1,318 kWh/m ²
Average annual wind speed:	1 m/s
Heating Design Conditions	
Coldest month:	December
Coldest week:	12/22 - 1/5
Typical winter week:	1/ 6 - 1/12
Annual HDD for 18 °C is:	2,175
Design temperature 0.04 %:	-5.2 °C

Cooling Design Conditions	
Hottest month:	July
Hottest week:	6/29 - 7/ 5
Typical summer week:	8/10 - 8/16
Annual CDD for 18 °C is:	570
Design temperature 99.6 %:	31 °C
Time Zone	
IANA Name:	Europe/Rome
Standard Time:	W. Europe Standard Time
UTC Offset:	+1.0 hours
Has Daylight Savings:	Yes
Start:	Mar 26
End:	Oct 28
Shift:	+1.0 hours

Figure 4-6 – Material surface reflectance assignments and baseline glazing layer setups within the ClimateStudio interface.

4.2.3. Rhino Plugin Integration

Following the geometric definition, the original façade configurations was processed through the AI-assisted Rhino plugin interface. The baseline model was structured on an orientation-by-orientation basis, parsing the specific properties of the South, East, and West envelopes. The plugin's geometry-parsing algorithms successfully recognized the unshaded configurations and the extensive ~88% WWR. By processing these initial geometric inputs through the trained machine learning surrogate model, the system generated instantaneous preliminary predictions for sDA, ASE, and Lux. This crucial step establishes a consistent reference framework within the plugin environment, verifying the initial boundaries of the predictive model and providing the necessary comparative foundation to evaluate the optimized parametric scenarios developed in the subsequent phases.

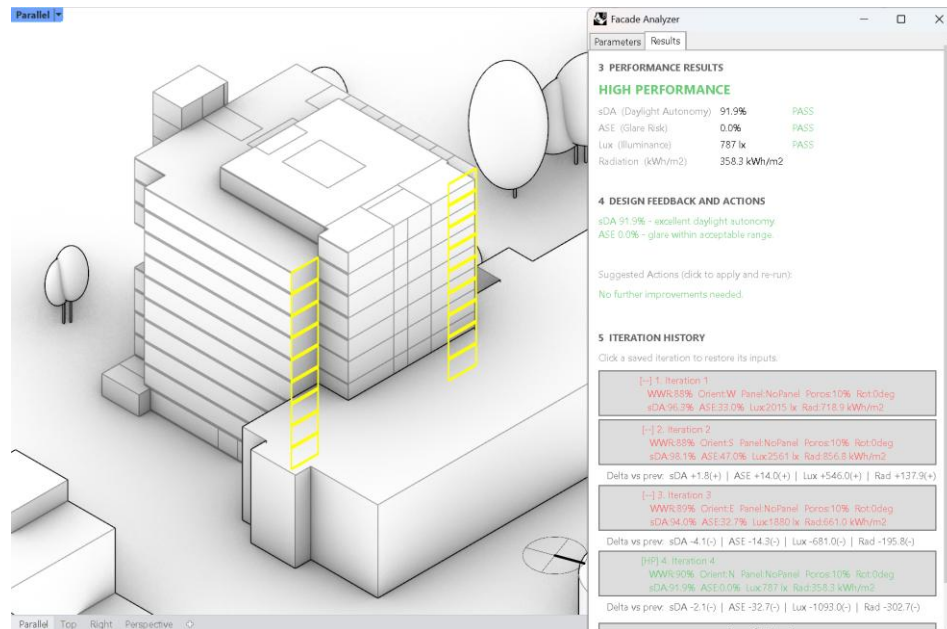


Figure 4-7 – Rhino plugin configurations for the Base Model on the North façade.

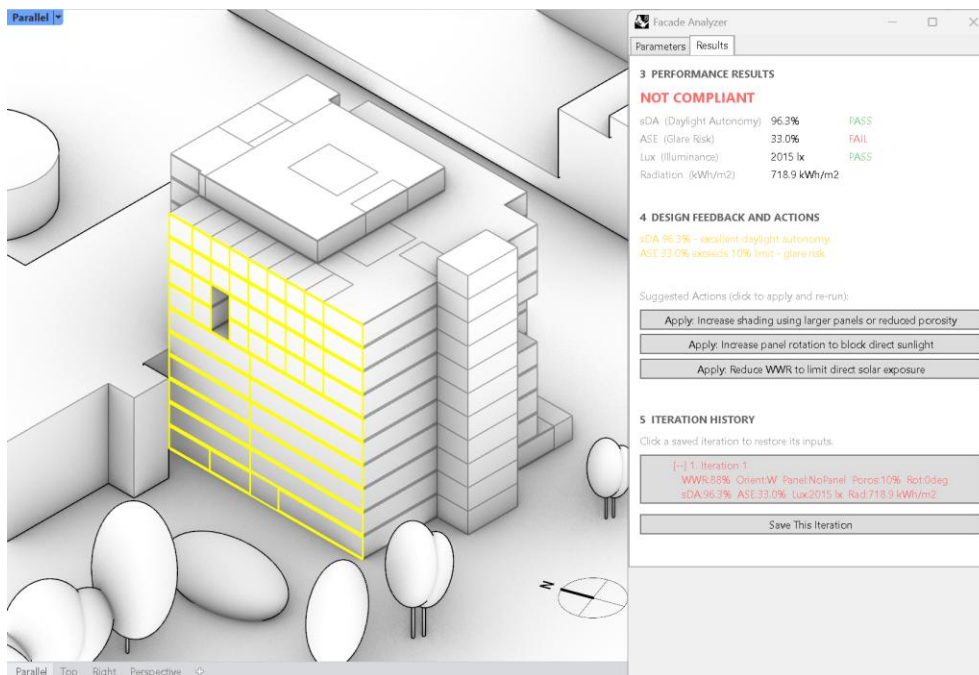


Figure 4-8 – Rhino plugin configurations for the Base Model on the West façade.

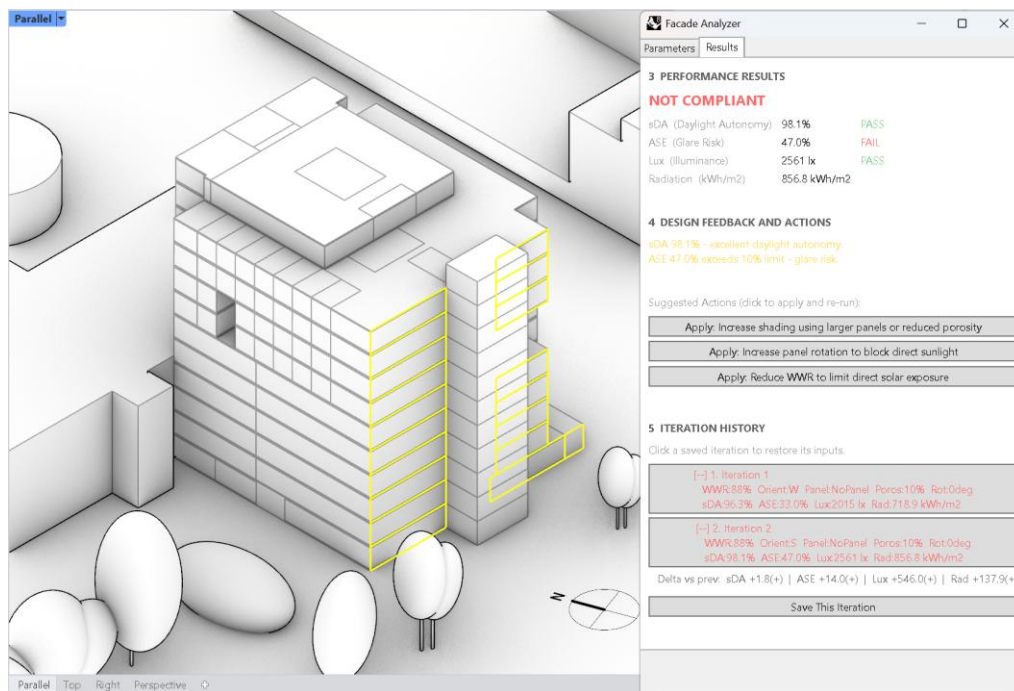


Figure 4-9 – Rhino plugin configurations for the Base Model on the South façade.

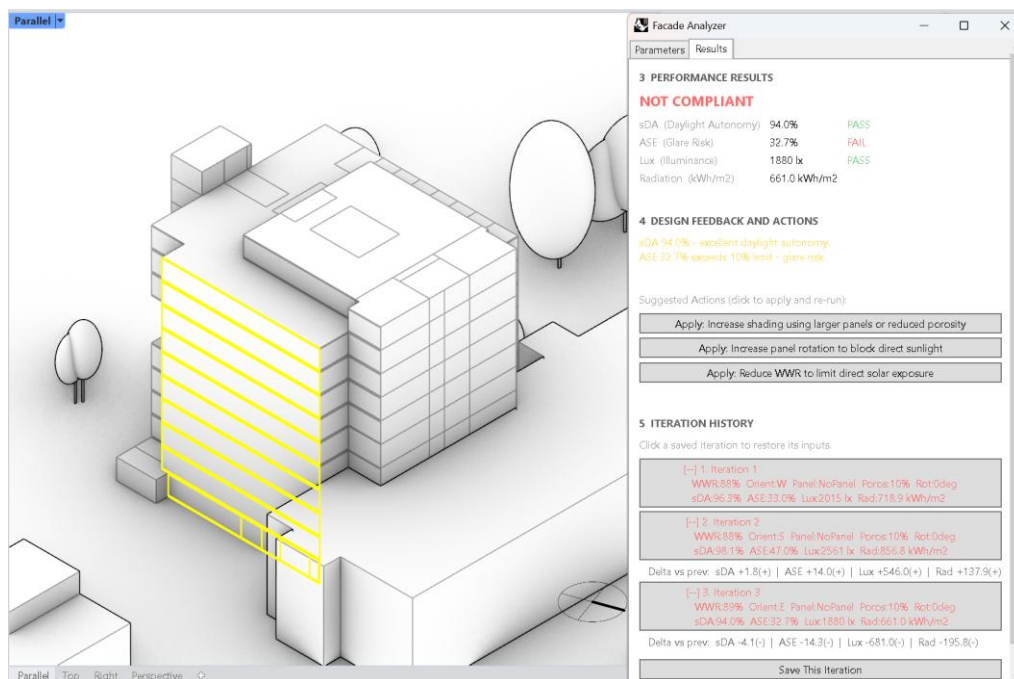


Figure 4-10 – Rhino plugin configurations for the Base Model on the East façade.

4.3. Façade Exploration Scenarios

Following the baseline daylight analysis, multiple double-skin façade (DSF) scenarios were generated using the developed AI-assisted optimization tool. The proposed workflow integrates parametric façade generation in Grasshopper and manual drafting methodologies with machine learning-based daylight prediction, culminating in an interactive customization environment within Rhino. Unlike dynamic adaptive façades that mechanically respond to environmental conditions in real time, the systems developed in this research are digitally static and parametric; their geometries are controlled through adjustable design parameters defined by the architect during conceptual development. This approach facilitates the rapid generation and environmental evaluation of diverse façade alternatives [30], [54]. To maximize its practical utility and adapt to authentic architectural workflows, the tool supports two distinct exploration paths: the automated evaluation of predefined parametric façade systems, and the instant performance evaluation of custom façade designs created directly by the user.

4.3.1. Scenario A: Parametric Hexagonal Panel System

The first exploration scenario allows for the rapid generation of parametric DSF systems based on a predefined geometric typology: the hexagonal panel. This specific morphology was selected for its high potential for parametric variation, aesthetic articulation, and structural effectiveness in solar control [30], [54]. The hexagonal panel system utilizes a continuous tessellation logic, enabling controlled variations in façade openness; due to its angular geometry, it provides highly balanced daylight diffusion and effective solar filtering.

4.3.1.1. Geometric Modeling and Parameterization

The hexagonal skin is globally governed by a set of independent, adjustable variables managed within the Grasshopper environment: module size, rotation angle, and porosity. By dynamically manipulating these core parameters, the designer can systematically investigate how geometric variations influence spatial daylight distribution, direct solar exposure, visual comfort, and overall façade transparency across the varying solar angles of the southern, eastern, and western elevations [14].

Table 4-2 – Multi-variable design matrix defining the explicit operation bounds, step sizes, and ranges for the hexagonal modules.

Parameter	Description
Panel Size	Controls the dimensions of façade modules
Rotation Angle	Influences shading behavior and façade openness
Porosity	Regulates transparency and daylight penetration
Panel Distribution	Controls façade density and module arrangement

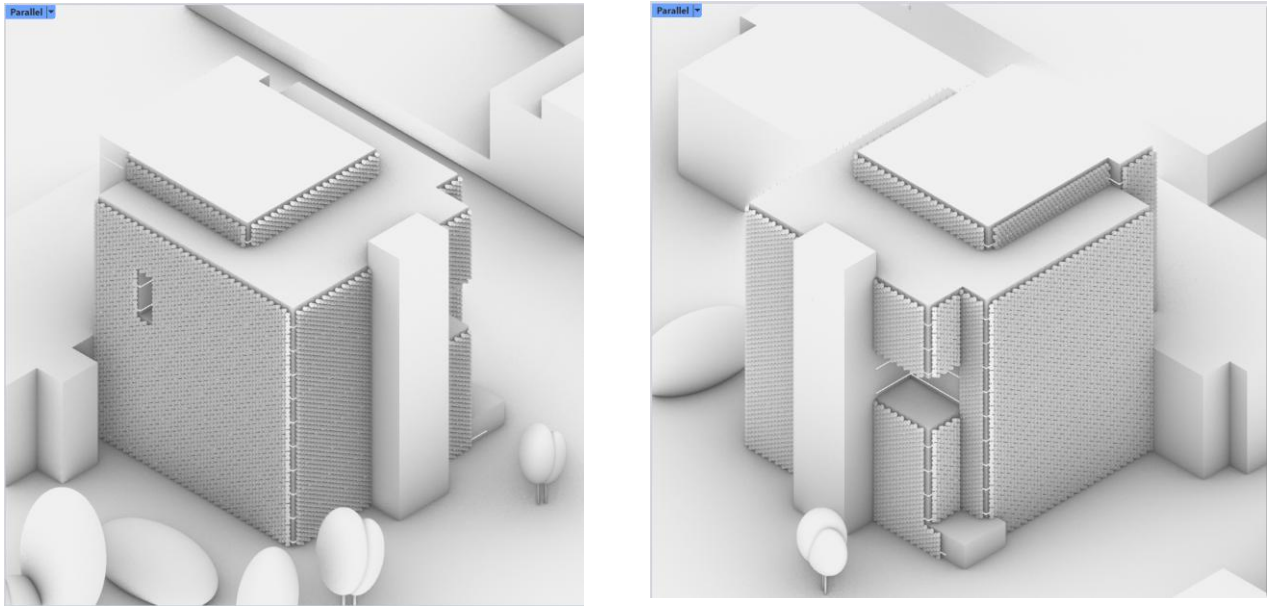


Figure 4-11 – Scenario A: Hexagonal Panel System

4.3.1.2. Rhino Plugin Integration

Concurrently, the shifting hexagonal parameters were mapped directly to the customized Rhino interface of the developed tool. This connection empowers the system's core algorithms to route the varying porosity and rotation metrics directly into the pre-trained surrogate machine learning model before any rigorous simulation takes place. This integration bypasses time-intensive physical simulation loops, generating instantaneous performance predictions for sDA, ASE, and Lux to support a highly interactive, real-time optimization session. By providing rapid estimations, the plugin acts as a proactive guide, allowing the architect to narrow down the vast parametric search space and identify the most promising geometric combinations.

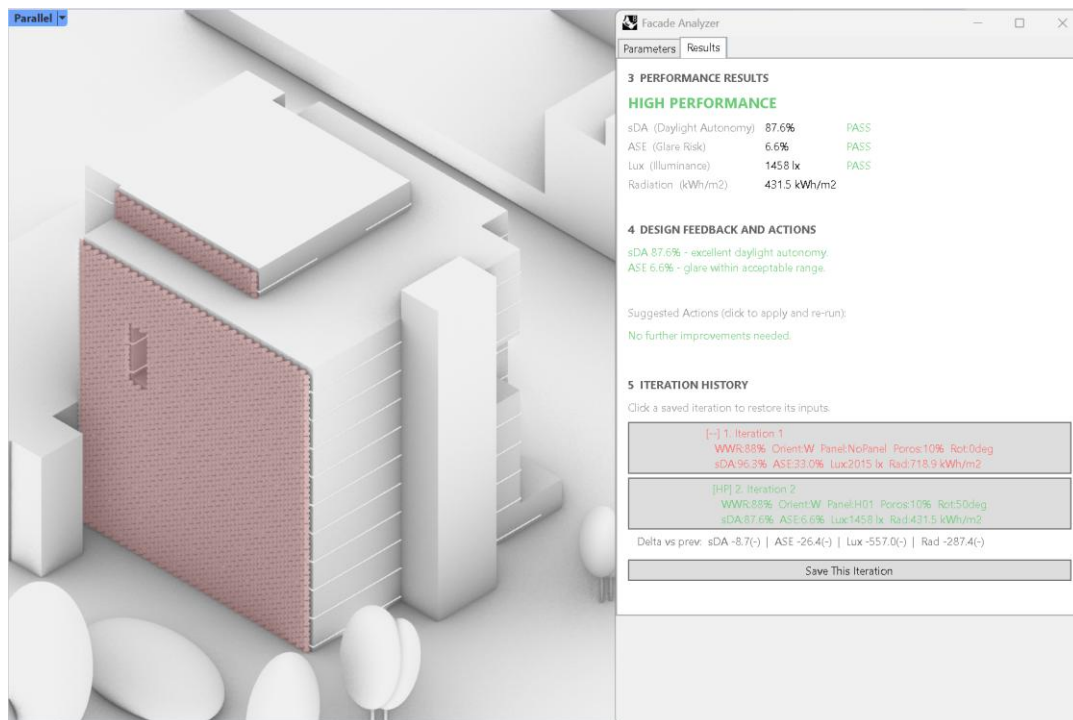


Figure 4-12 – Rhino plugin configurations for Scenario A (Hexagonal Panel System) on the west façade.

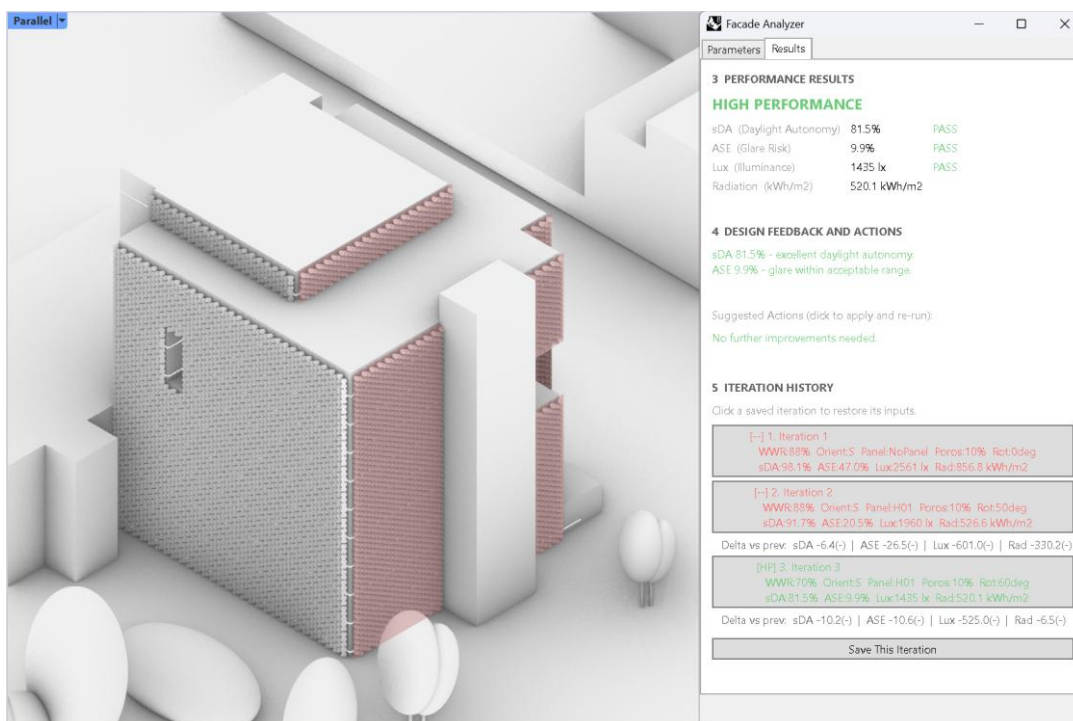


Figure 4-13 – Rhino plugin configurations for Scenario A (Hexagonal Panel System) on the south façade.

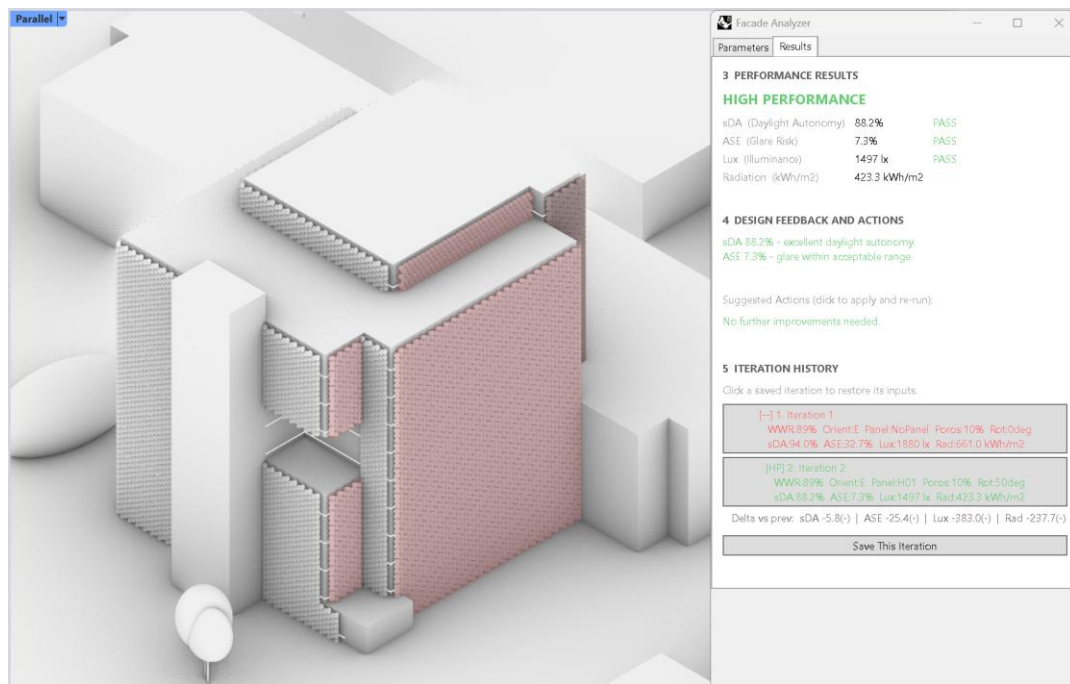


Figure 4-14 – Rhino plugin configurations for Scenario A (Hexagonal Panel System) on the east façade.

4.3.1.3. ClimateStudio Simulation Configurations

Following the AI-assisted parameter optimization, the finalized parametric hexagonal geometries generated in Grasshopper were seamlessly integrated into ClimateStudio to establish a rigorous physical benchmark. This validation setup maintained the identical baseline constraints, including the Milan EPW weather file, sensor grid density, and office schedules, while introducing the specific material reflectance properties of the secondary skin. Furthermore, this configuration involved a variable glazing Visible Light Transmittance (VLT) testing loop (evaluating profiles from 0.4 to 0.8) paired with the exterior shading panels to definitively validate the balance between climate-based daylight sufficiency (sDA) and exposure mitigation (ASE) under exact physical ray-tracing equations.

Layer	Material	VLT	VLR
Floor	Concrete Floor	-	29 %
panels	Aluminium Grey Exterior Clading	-	48 %
roof	Concrete Exterior Floor	-	18 %
neighbors	Wall LM83	-	50 %
Panel-O1	Aluminium Grey Exterior Clading	-	48 %
walls	White Painted Concrete wall	-	89 %
glass wall	Clear	88 %	8 %
window	Azuria - Solarban 67 (3) (Krypton)	41 %	11 %
Tree	Fagus Sylvatica / LengthOfDay	-	9 %

ITA_MILANO-LINATE_160800_IW2

Climate Zone	
Koppen climate zone:	Temperate, No Dry Season, Hot Summer (Cfa)
ASHRAE climate zone:	Mixed (4)
Average annual temperature:	14 °C
Annual total solar radiation:	1,318 kWh/m ²
Average annual wind speed:	1 m/s

Heating Design Conditions	
Coldest month:	December
Coldest week:	12/22 - 1/5
Typical winter week:	1/6 - 1/12
Annual HDD for 18 °C is:	2,175
Design temperature 0.04 %:	-5.2 °C

Cooling Design Conditions	
Hottest month:	July
Hottest week:	6/29 - 7/5
Typical summer week:	8/10 - 8/16
Annual CDD for 18 °C is:	570
Design temperature 99.6 %:	31 °C

Time Zone	
IANA Name:	Europe/Rome
Standard Time:	W. Europe Standard Time
UTC Offset:	+1.0 hours
Has Daylight Savings:	Yes
Start:	Mar 26
End:	Oct 28
Shift:	+1.0 hours

Figure 4-15 – ClimateStudio simulation setup for Scenario A: Hexagonal Panel System

4.3.2. Scenario B: Custom Façade Design

Moving beyond rigid algorithmic templates, the second exploration scenario introduces a custom façade evaluation workflow that allows architects to analyze their own bespoke façade designs directly within the Rhino environment.

4.3.2.1. Geometric Modeling and Design Strategy

In this non-parametric workflow, the architect manually defines the façade composition using a systematic, performance-informed drafting methodology. The process begins by establishing a base architectural grid, dividing each elevation using reference lines spaced at 1-meter intervals. This grid serves as a geometric framework to accurately distribute the custom transparent and opaque surfaces based on the exact Window-to-Wall Ratio (WWR) required for the space.

Beyond the simple distribution of openings, specific architectural interventions were applied to respond to the unique solar exposure of each orientation. On the East and West façades, the window openings were strategically rotated and angled within the 1-meter grid to maximize functional daylight capture during morning and afternoon hours while mitigating low-angle direct glare. Conversely, on the highly exposed South façade, a continuous horizontal cantilever with a depth of 2 meters was introduced as a primary structural shading element. This deep cantilever was specifically designed to intercept high-angle summer sun, strictly controlling the Annual Sunlight Exposure (ASE) without compromising the overall façade transparency.

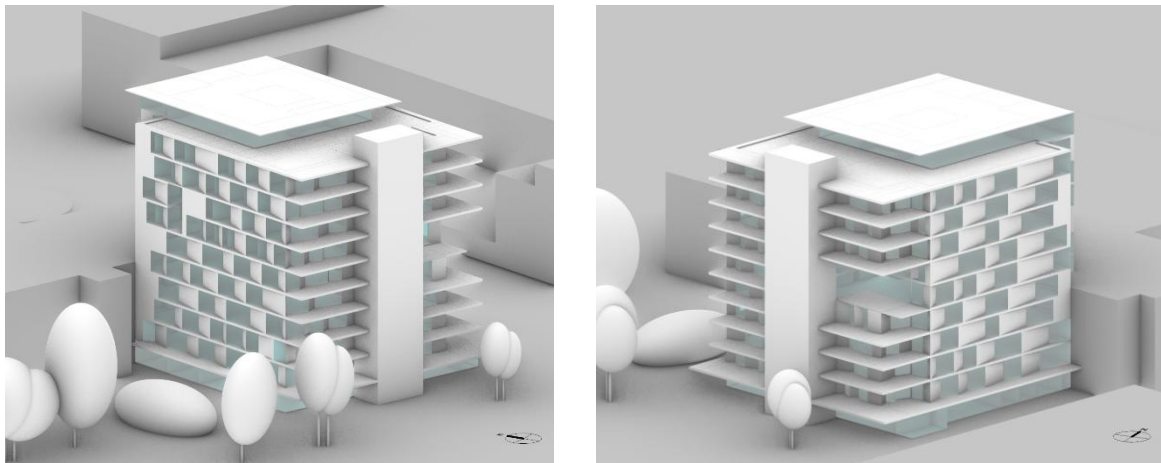


Figure 4-16 – Scenario B: Custom-Designed facade

4.3.2.2. Rhino Plugin Integration

The tool's backend system is utilized to continuously guide the custom drafting process before any definitive simulations are run. Initially, the plugin was used to rapidly test various opening percentages through the pre-trained surrogate machine learning model, allowing the designer to identify the optimal target WWR for each specific façade orientation based on predicted daylight sufficiency.

Once the optimal WWR was established and the designer explicitly mapped the transparent elements across the 1-meter grid, the plugin's geometry-parsing algorithms automatically extracted the final composition. The surrogate model then instantly predicted the expected environmental performance of the customized façade, outputting daylight autonomy tendencies and localized solar exposure behaviors. This rapid feedback loop transforms the developed system into an advanced decision-

support tool, enabling the architect to iteratively refine bespoke geometric features—such as the cantilever depth or opening angles—during early-stage decision-making without requiring full annual simulations for every conceptual adjustment [30], [56].

AI-assisted Facade Optimization Tool

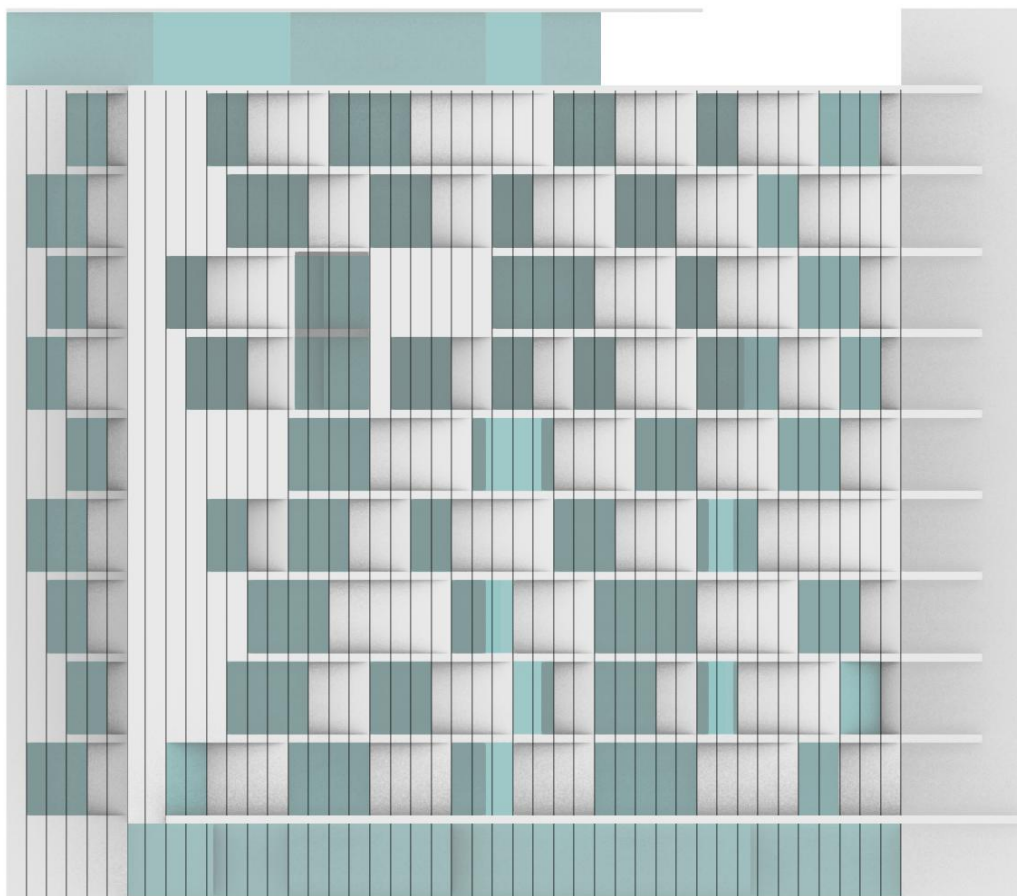
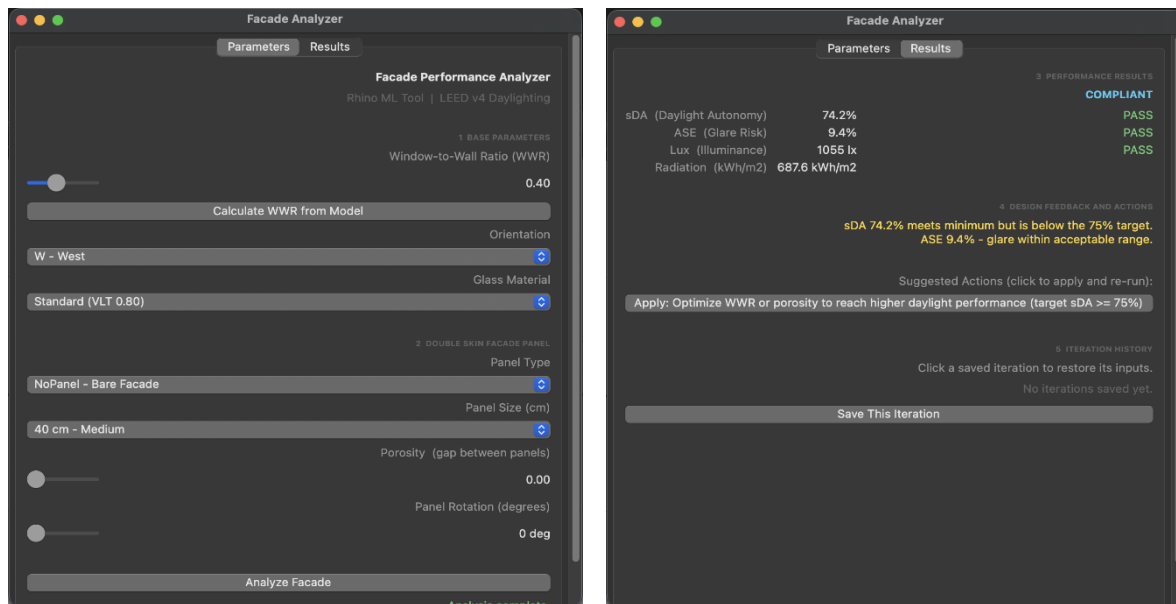


Figure 4-17 – Application of the Rhino plugin for the optimization of Scenario B: Custom-Designed Façade (West Orientation)

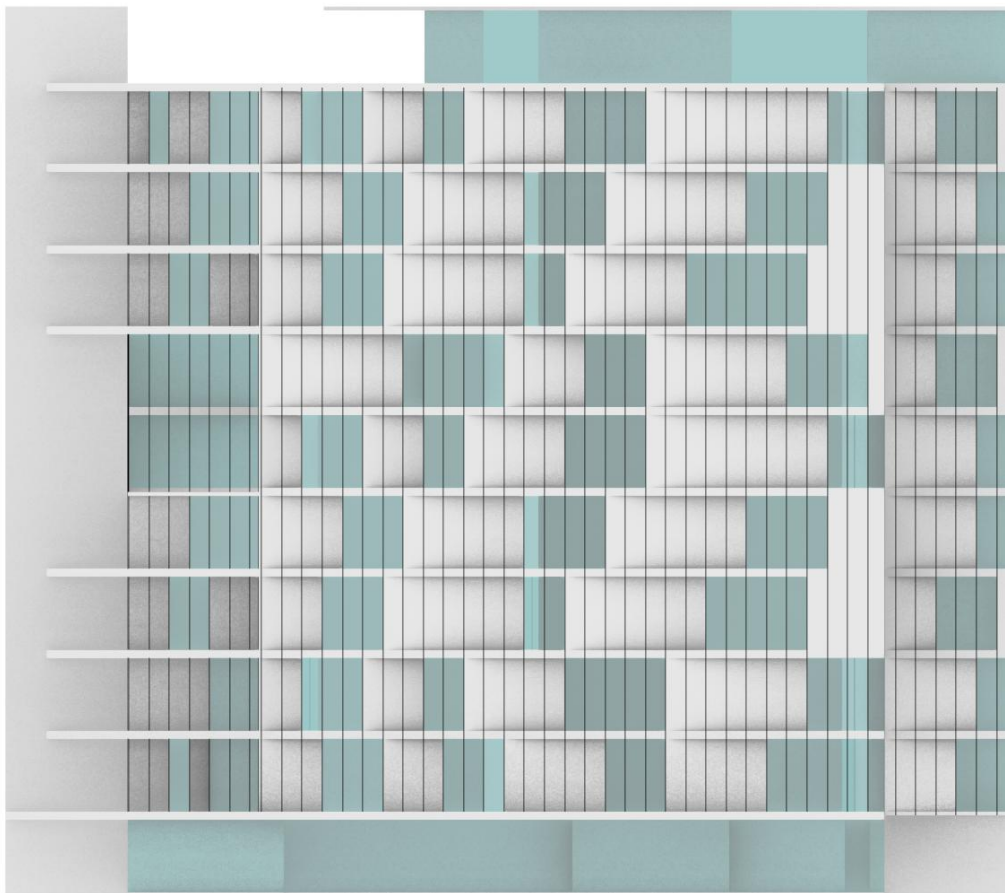
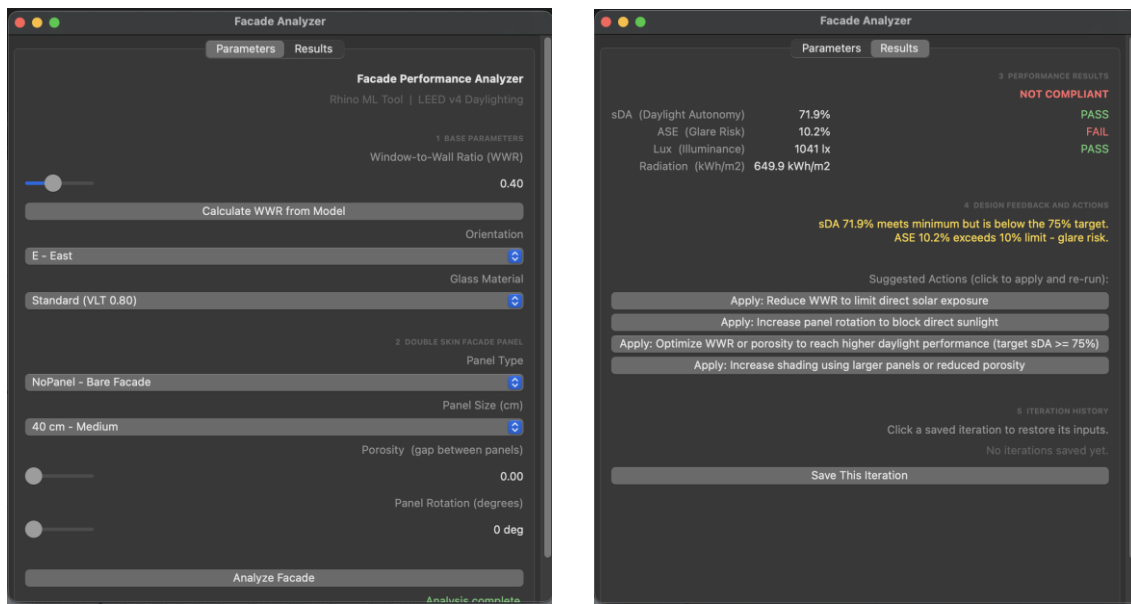


Figure 4-18 – Application of the Rhino plugin for the optimization of Scenario B: Custom-Designed Façade (East Orientation)

AI-assisted Façade Optimization Tool

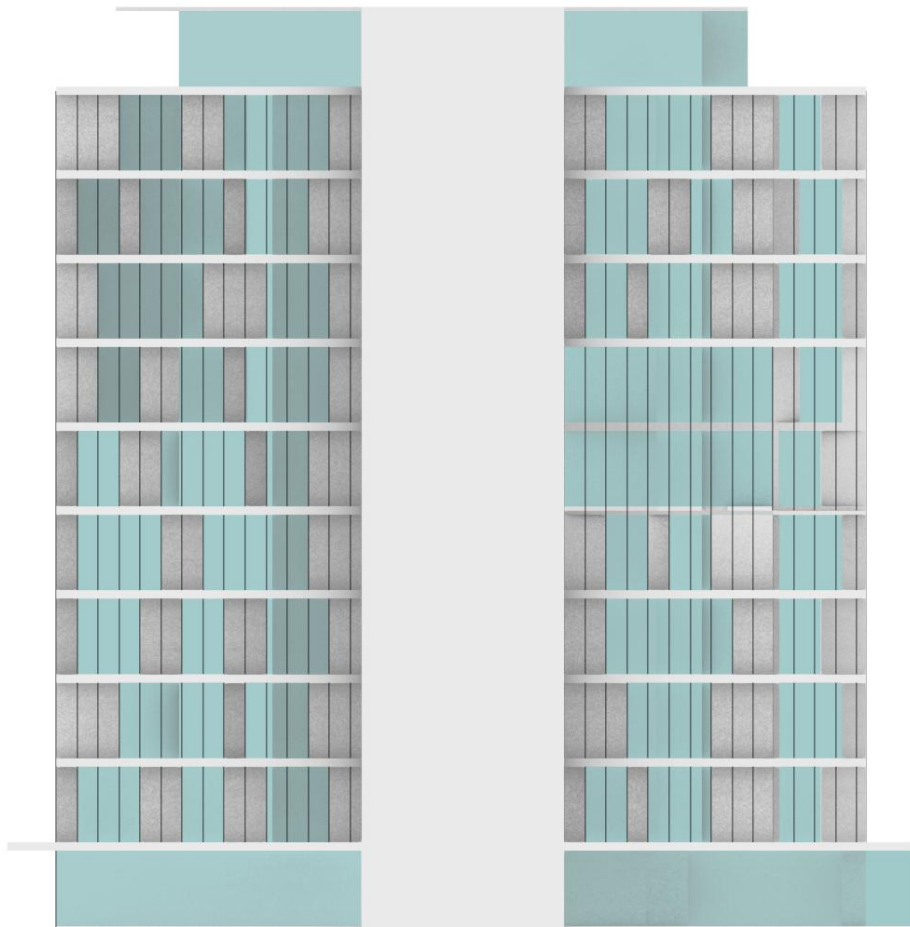
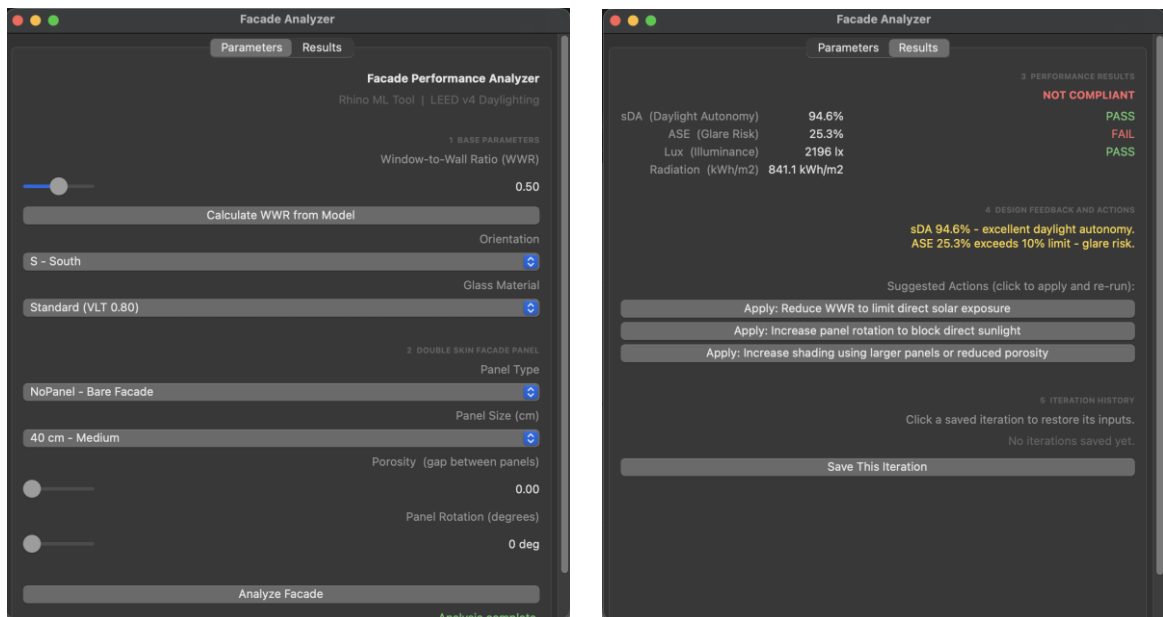


Figure 4-19 – Application of the Rhino plugin for the optimization of Scenario B: Custom-Designed Façade (South Orientation)

4.3.2.3. ClimateStudio Simulation Configurations

Following the AI-assisted design optimization, the final manually drafted custom façade geometry is converted into native ClimateStudio simulation layers to definitively verify the physical performance of the architect's intuition. This configuration applies the identical baseline physics bounds, internal reflects, and standard high-VLT glazing properties to run an exact, rigorous annual ray-tracing validation of the bespoke design, accurately capturing the specific shading impacts of the rotated windows and the 2-meter southern cantilever.

Layer	Material	VLT	VLR
Floor	Concrete Floor	-	29%
roof	Concrete Exterior Floor	-	18%
neighbors	Wall LM83	-	50%
Interior_Walls	White Painted Concrete wall	-	89%
Interior glass wall	Clear	88%	8%
window	Starphire - Sungate 400 (3) on Starphire (Krypton)	80%	14%
CSTree Sparse Short	Fagus Sylvatica / LengthOfDay	-	9%
Tree	Fagus Sylvatica / LengthOfDay	-	9%
Windows_HighVLT	Starphire - Sungate 400 (3) on Starphire (Krypton)	80%	14%
Exterior_Walls	White Painted Concrete wall	-	89%
East_O2_Windows	Starphire - Sungate 400 (3) on Starphire (Krypton)	80%	14%
South_O2_Windows	Starphire - Sungate 400 (3) on Starphire (Krypton)	80%	14%
West_O2_Windows	Starphire - Sungate 400 (3) on Starphire (Krypton)	80%	14%
Shadings	Exterior White Painted Concrete Slab	-	82%

ITA_MILANO-LINATE_160800_IW2	
Climate Zone	
Koppen climate zone:	Temperate, No Dry Season, Hot Summer (Cfa)
ASHRAE climate zone:	Mixed (4)
Average annual temperature:	14 °C
Annual total solar radiation:	1,318 kWh/m ²
Average annual wind speed:	1 m/s
Heating Design Conditions	
Coldest month:	December
Coldest week:	12/22 - 1/5
Typical winter week:	1/6 - 1/12
Annual HDD for 18 °C is:	2,175
Design temperature 0.04 %:	-5.2 °C

Cooling Design Conditions	
Hottest month:	July
Hottest week:	6/29 - 7/5
Typical summer week:	8/10 - 8/16
Annual CDD for 18 °C is:	570
Design temperature 99.6 %:	31 °C
Time Zone	
IANA Name:	Europe/Rome
Standard Time:	W. Europe Standard Time
UTC Offset:	+1.0 hours
Has Daylight Savings:	Yes
Start:	Mar 26
End:	Oct 28
Shift:	+1.0 hours

Figure 4-20 – ClimateStudio simulation setup for Scenario B: Custom-Designed facade

5 Results and Analysis

This chapter presents the quantitative and qualitative results obtained from annual daylight simulations and machine learning predictions for the *Il Sole 24* case study in Milan. The primary objective of this section is to evaluate the environmental effectiveness of the proposed parametric double-skin façade (DSF) configurations and rigorously validate the predictive capabilities of the developed AI-assisted workflow. To achieve this, the analysis establishes a direct performance comparison between the building's original unshaded façade configurations, the generated parametric scenarios, and the validated simulation results obtained through ClimateStudio. Furthermore, this chapter investigates the operational differences between conventional physics-based simulation pipelines and the developed AI-assisted design workflow in terms of computational efficiency, prediction accuracy, and early-stage design exploration capacity.

5.1. Simulation Results

This section details the annual climate-based daylight simulation results obtained through ClimateStudio for both the baseline façade configurations and the selected parametric DSF scenarios generated by the tool. To ensure absolute consistency and comparability across the entire exploration matrix, all scenarios were evaluated using identical environmental boundary conditions, sky models, and internal material schedules. The performance analysis targets three primary validated architectural metrics: Spatial Daylight Autonomy (sDA) to confirm daylight sufficiency, Annual Sunlight Exposure (ASE) to map overlighting and excessive direct sunlight exposure, and Point-in-Time Illuminance (Lux) to evaluate interior light distribution uniformity [22].

5.1.1. Baseline Simulation Results

The initial simulation phase was conducted on the original, unoptimized building envelope to establish a definitive baseline reference condition prior to any optimization interventions. The baseline analysis revealed that while the extensive, unprotected glazing allowed deep daylight penetration into the core floor plates, resulting in a high initial sDA percentage, it simultaneously introduced severe overlighting risks. Specifically, the perimeter office zones directly adjacent to the southern and western glass exposures exhibited elevated ASE percentages and

excessive raw Lux levels that significantly exceed standard comfort thresholds. These findings confirm that the original curtain wall lacks necessary solar control features, creating highly overexposed workspaces near the perimeter and validating the necessity of an engineered double-skin intervention to balance daylight autonomy with overlighting mitigation.

Table 5-1 – Baseline performance metrics

Metric	Result
sDA (Daylight Autonomy)	74.9%
ASE (Annual Sunlight Exposure)	40.6%
Point-in-Time Illuminance (Lux)	1854

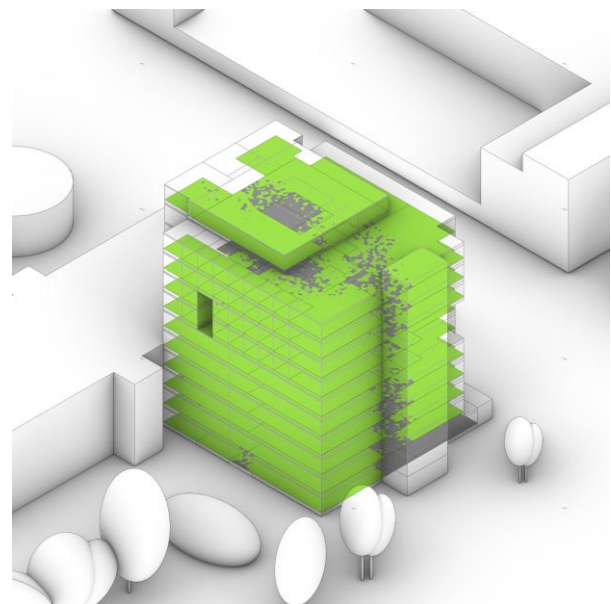
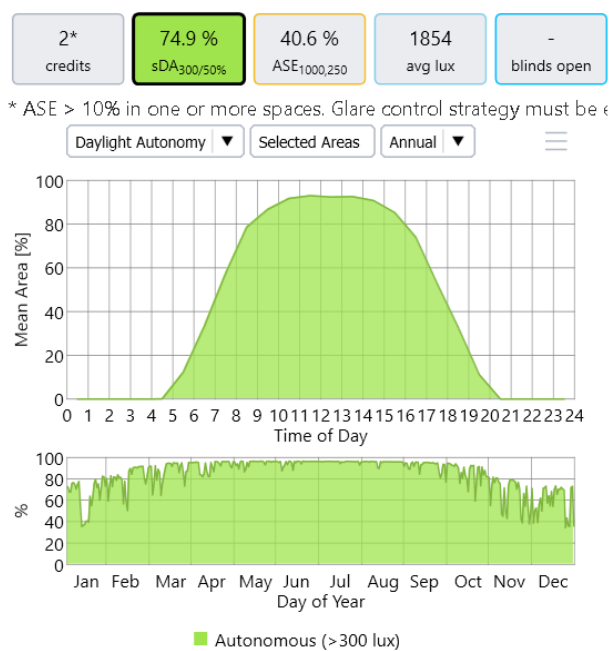


Figure 5-1 – Baseline Spatial Daylight Autonomy (sDA) analysis map.

AI-assisted Façade Optimization Tool

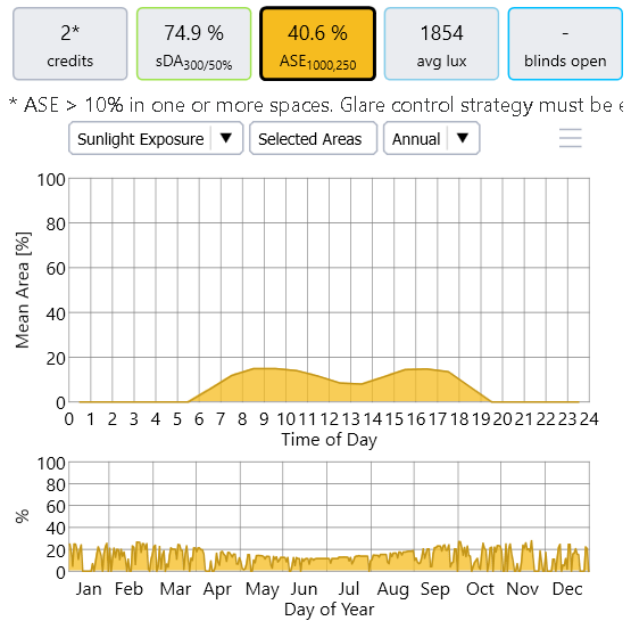


Figure 5-2 – Baseline Annual Sunlight Exposure (ASE) visualization.

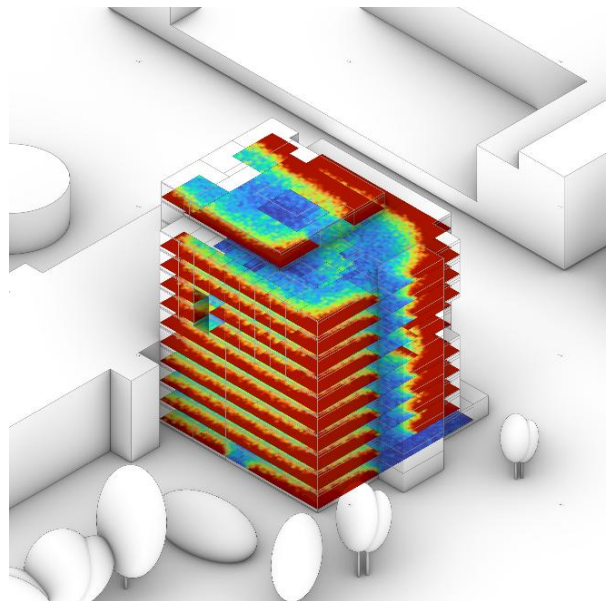
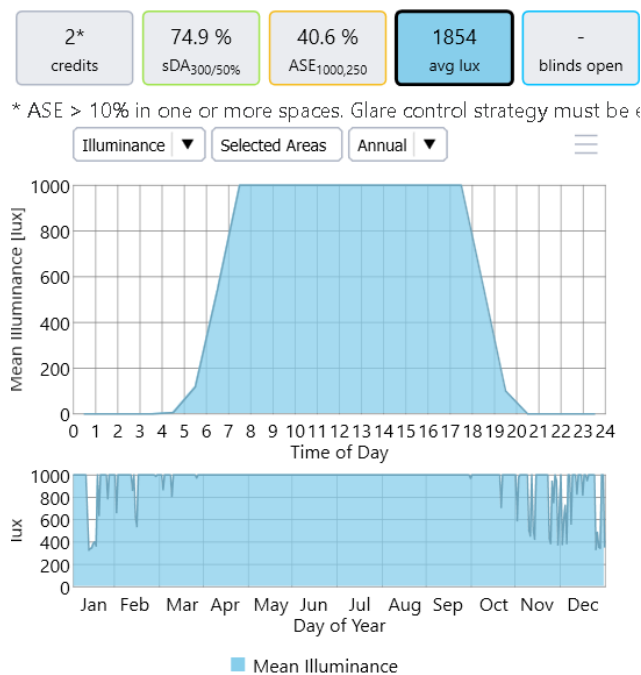


Figure 5-3 – Interior Point-in-Time Illuminance (Lux) under original façade configurations

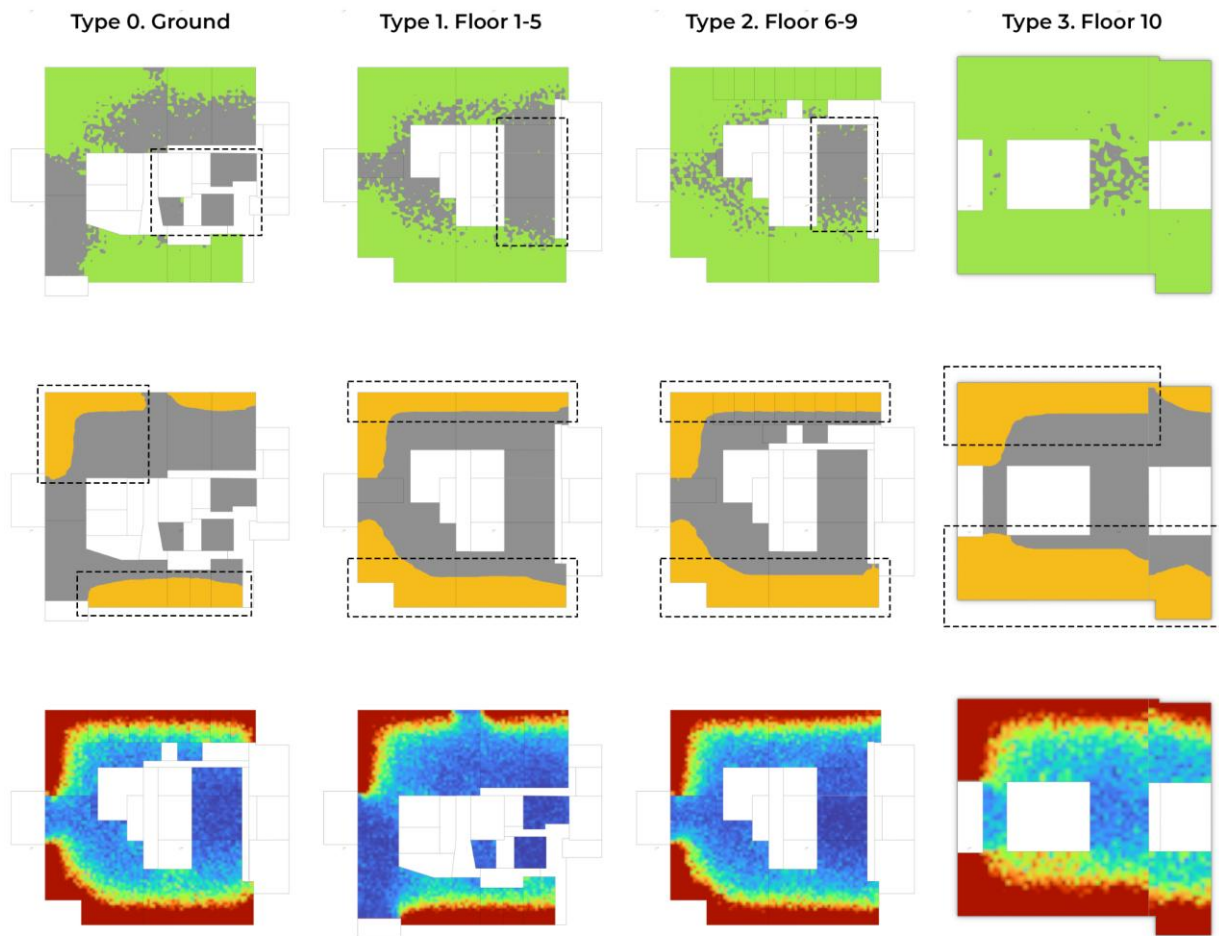


Figure 5-4 – Multi-level spatial performance maps illustrating annual sDA, annual ASE, and point-in-time Illuminance (Lux) distributions across typical floor plans: Marked areas (sDA) show underlit zones justified with design decisions. Marked areas(A



Figure 5-5 – Urban context perspective of the Il Sole 24 base model

5.1.2. Evaluation of Optimized Façade Scenarios

This subsection outlines the simulation performance for the selected optimized façade configurations, focusing on two distinct architectural workflows: an automated parametric panel system and a fully custom user-defined envelope.

5.1.2.1. Scenario A – Hexagonal Panel System (Predefined Parametric Workflow):

The hexagonal façade variant represents the tool's capability to generate and evaluate structured, automated multi-layered envelopes. This configuration utilizes a continuous modular grid wrapped around the primary glass surfaces of *Il Sole 24*. Crucially, the baseline diagnostics confirmed that the North-facing elevation experienced no problematic Annual Sunlight Exposure (ASE) values and functioned optimally with a fully open glazing configuration. Consequently, the secondary parametric skin was deliberately omitted from the North façade, and the shading panels were exclusively applied to the South, East, and West orientations.

The optimization process for Scenario A was systematically conducted in two primary iterations to achieve an optimal balance between daylight sufficiency and exposure control. The initial configurations (**Iteration A.1**) evaluated the hexagonal system (WWR 40%, Panel Porosity 40%, and orientation-specific rotations) paired with a standard glazing Visible Light Transmittance (VLT) of 0.4. While this conservative setup successfully mitigated overlighting, reducing the ASE to an exceptional 6.1%, the low VLT severely restricted global daylight penetration. This resulted in an insufficient sDA of 45.8% and a low average illuminance of 609 Lux, indicating that the interior workspaces had become excessively dark.

To resolve this underexposure while maintaining geometric shading efficiency, a subsequent evaluation (**Iteration A.2**) was executed by increasing the glazing VLT from 0.4 to 0.8. The ClimateStudio results indicate that this refined configuration achieves an exceptional performance balance compared to the unshaded baseline. The sDA improved dramatically to 74.9%, and the average illuminance stabilized at 1487 Lux, ensuring a well-lit interior core. Simultaneously, by restricting direct solar penetration on the highly exposed southern and western orientations, the parametric geometry effectively maintained safe Annual Sunlight Exposure values (11.9%). The primary advantage of this system lies in its structural geometry, which naturally acts as a calibrated spatial filter to regulate excessive exposure without causing underexposure in the deep interior core.

Table 5-2– Scenario A daylight performance results

Metric	Result A.1	Result A.2
sDA (Daylight Autonomy)	45.8 %	74.9 %
ASE (Annual Sunlight Exposure)	6.1 %	11.9 %
Point-in-Time Illuminance (Lux)	609	1487

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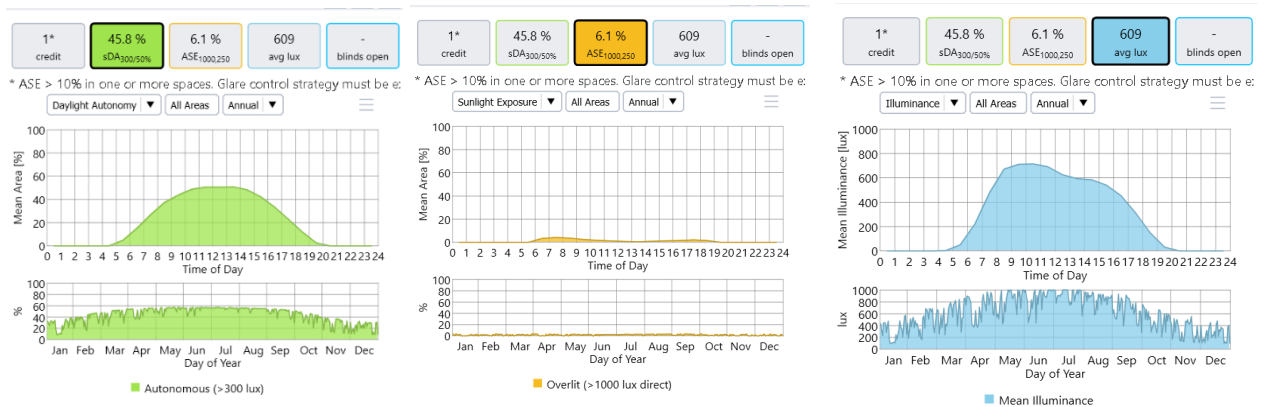


Figure 5-6 – ClimateStudio simulation results for Scenario A.1: Hexagonal Panel System

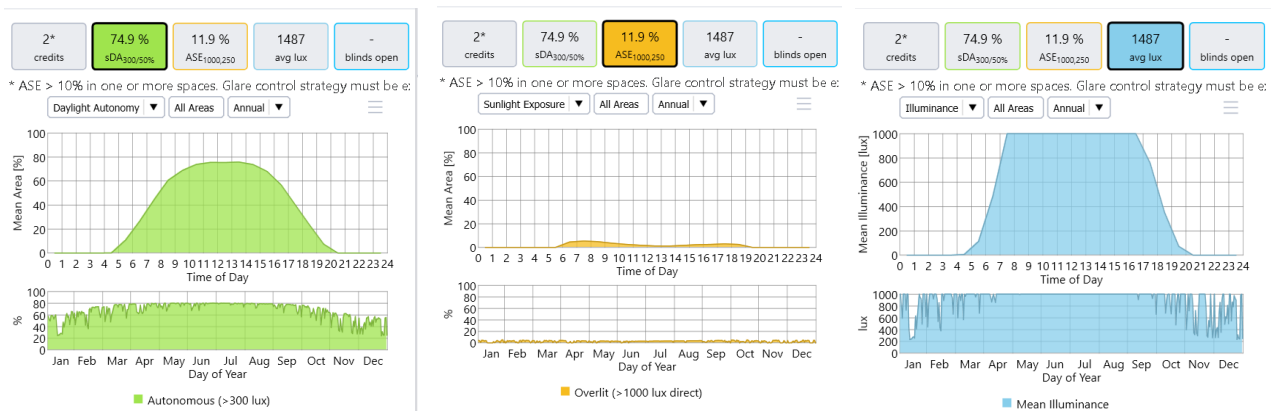


Figure 5-7 – ClimateStudio simulation results for Scenario A.2: Hexagonal Panel System

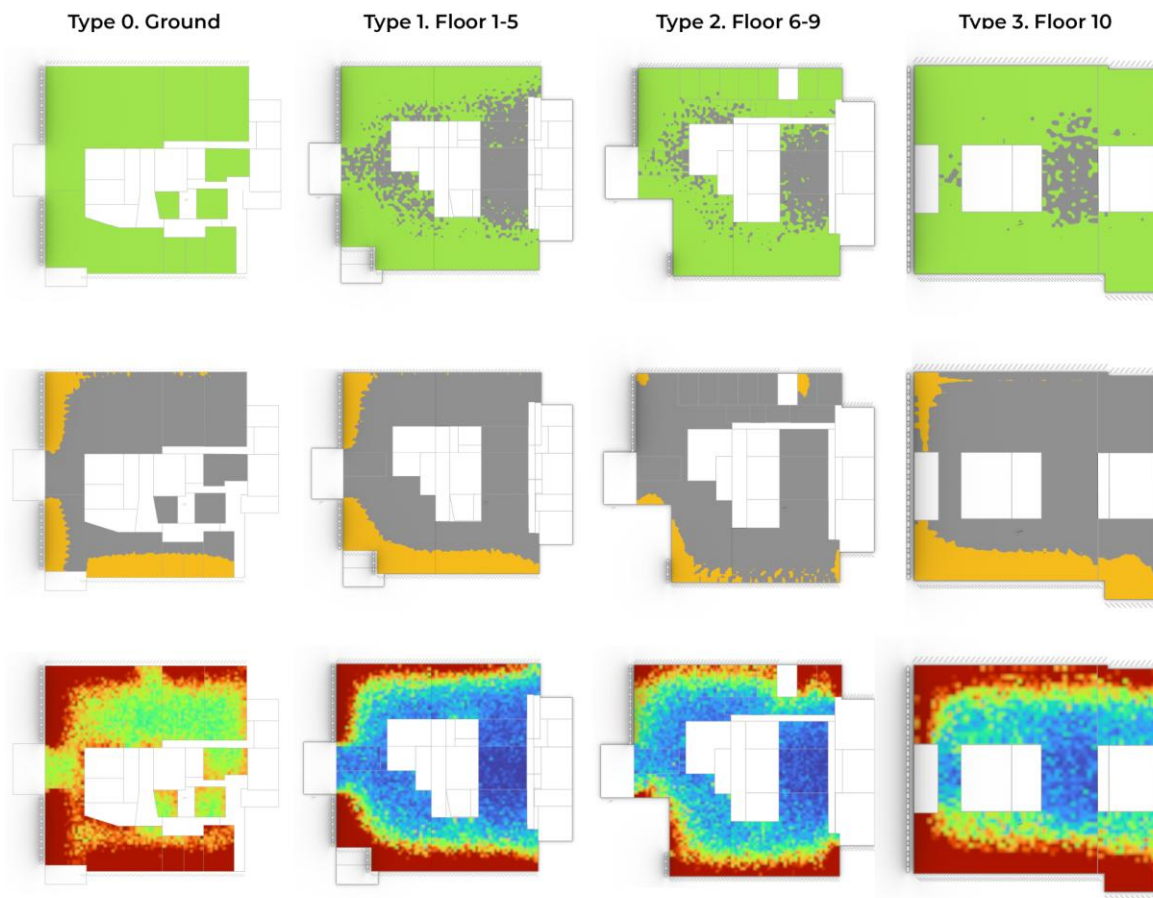


Figure 5-8 – Annual daylight performance analysis (sDA, ASE, Lux) for Scenario A: Hexagonal Panel System, categorized by floor plan type.

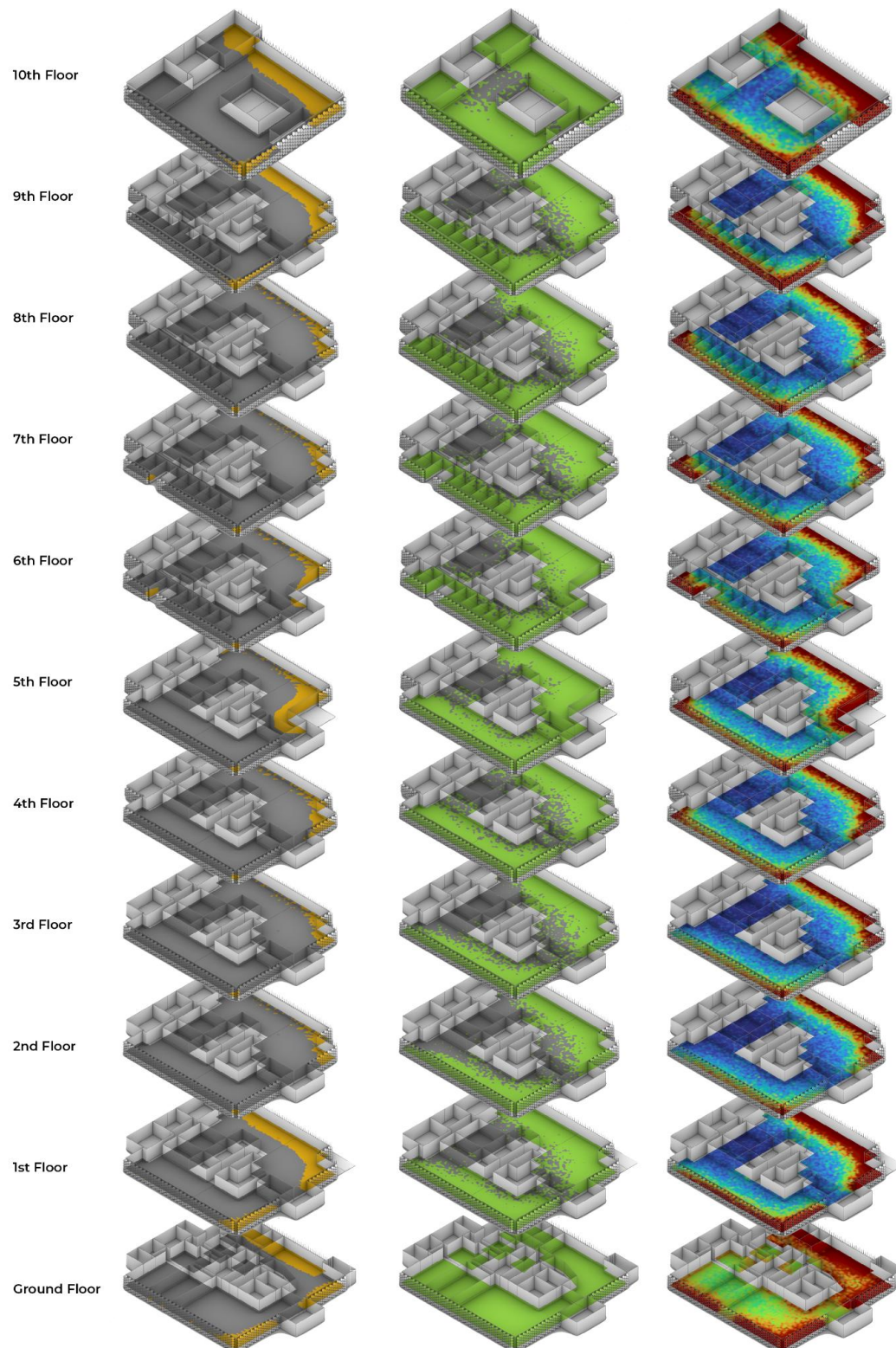


Figure 5-9 – Annual daylight performance analysis (sDA, ASE, Lux) for Scenario A: Hexagonal Panel System, categorized by floor plans 0 to 10.



Figure 5-10 – Urban context perspective of the Il Sole 24 Scenario A - Hexagonal Panels

5.1.2.2. Scenario B – Custom Architect-Designed Façade (User-Defined Workflow):

To evaluate the tool's flexibility beyond rigid algorithmic templates, a completely unique façade configurations was manually modeled within the Rhino environment using the custom evaluation pipeline. In this workflow, the designer possesses total formal freedom, drawing opaque wall zones, tailored glazing distributions, and floor plates directly in the viewport. The integrated plugin automatically parses this custom input, calculates the resulting absolute Window-to-Wall Ratio (WWR), and routes the architectural features through the pre-trained surrogate machine learning model to estimate performance instantly.

Regarding the façade design strategy, the south-facing elevation exhibited the highest potential for excessive solar exposure. To address this issue while maintaining adequate daylight penetration, a secondary shading system was incorporated above the upper glazing zones, reducing direct solar gains during periods of high sun angles. In addition, the east and west façades were designed with angled window openings

oriented in relation to the predominant solar path. These inclined openings increase self-shading and limit direct sunlight penetration during morning and afternoon hours, when low-angle solar radiation is typically more difficult to control. The opaque façade portions were also geometrically articulated to create additional shading effects around the glazing elements, enhancing solar protection while preserving visual continuity across the façade composition. Together, these interventions demonstrate how the custom design workflow can support architect-driven façade solutions that integrate daylight access, solar control, and formal design intentions within a unified performance-informed design process.

Table 5-3 – Scenario B daylight performance results

Metric	Result
sDA (Daylight Autonomy)	70.6 %
ASE (Annual Sunlight Exposure)	15.7 %
Point-in-Time Illuminance (Lux)	1544

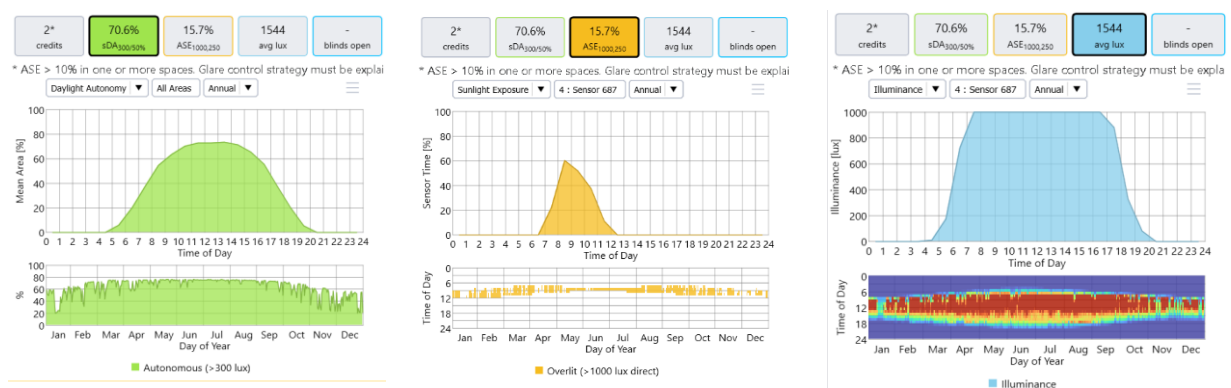


Figure 5-11 – ClimateStudio simulation results for Scenario B: Custom-Designed facade

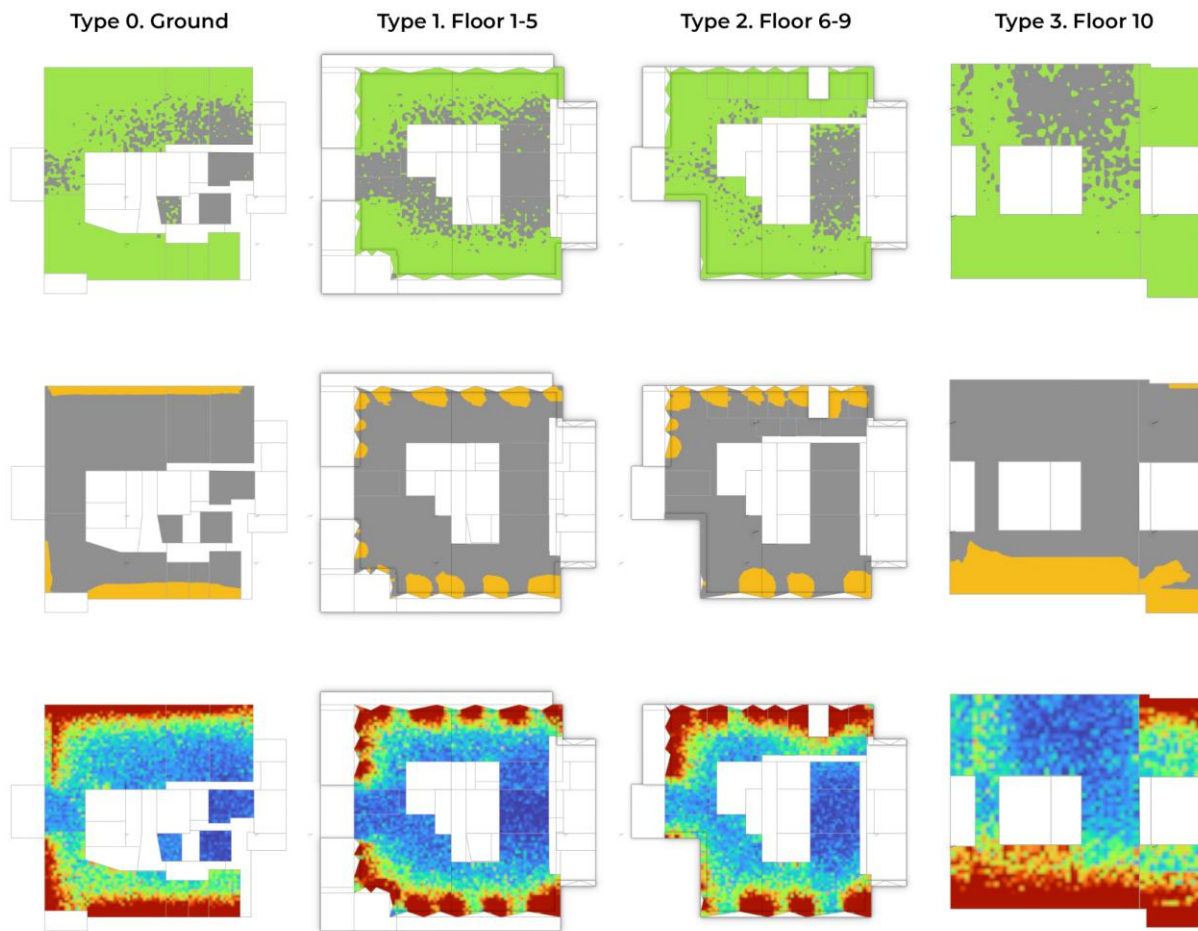


Figure 5-12 – Annual daylight performance analysis (sDA, ASE, Lux) for Scenario B: Custom-Designed Facade, categorized by floor plan type.

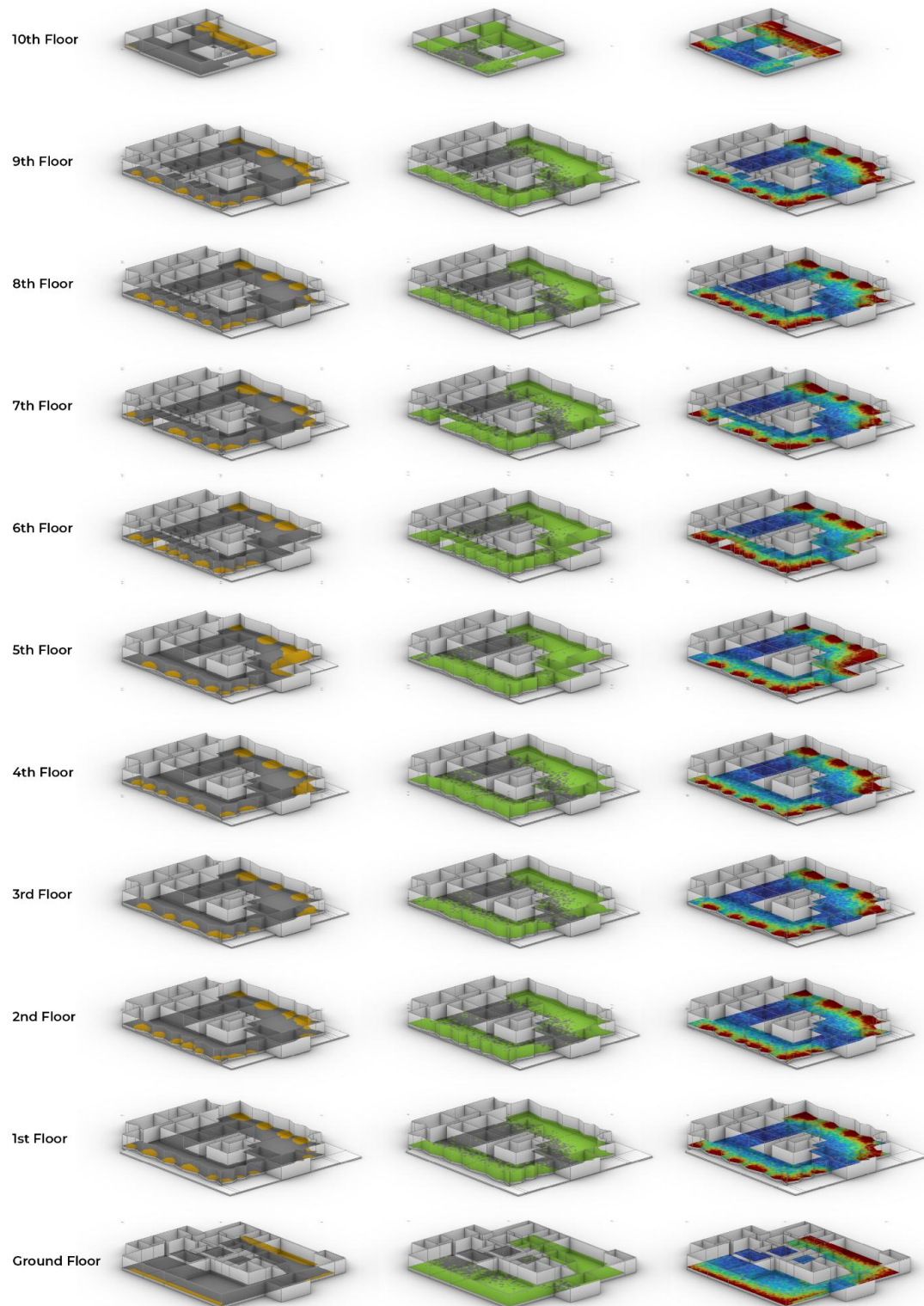


Figure 5-13 – Annual daylight performance analysis (sDA, ASE, Lux) for Scenario B: Custom-Designed Facade, categorized by floor plans 0 to 10.



Figure 5-14 – Urban context perspective of the Il Sole 24 Scenario B - Custom-Designed Façade

5.1.3. Performance Evaluation: Baseline vs. Optimized Scenarios

To evaluate the effectiveness of the proposed workflow, the daylight performance of the baseline building was compared with two façade configurations generated and assessed through the developed Rhino plugin: the Hexagonal Panel System and the Custom Façade. The comparison was conducted using Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), and average illuminance values [22].

The baseline model achieved an sDA of 74.9% and an ASE of 40.6%, indicating adequate daylight availability but a considerable level of excessive solar exposure. The average illuminance value for the baseline case was 1854 lux.

Both optimized scenarios demonstrated a significant reduction in ASE while maintaining acceptable daylight autonomy levels. The Hexagonal Panel System

preserved the baseline sDA value of 74.9% while reducing ASE to 11.9%. Similarly, the Custom Façade achieved an sDA of 70.6% and reduced ASE to 15.7%. These results indicate that the generated façade solutions were successful in controlling excessive sunlight exposure without substantially compromising daylight availability within the space.

The average illuminance values were reduced to 1487 lux and 1544 lux for the Hexagonal Panel System and Custom Façade, respectively. This reduction reflects a more controlled daylight distribution compared to the baseline case, which exhibited higher levels of solar penetration.

Overall, the results demonstrate that the developed Rhino plugin was capable of generating façade configurations that improved daylight performance relative to the original design. Through the integration of machine learning predictions and parametric façade generation, the workflow enabled the exploration of alternative façade solutions that reduced excessive sunlight exposure while maintaining satisfactory daylight conditions. These findings validate the effectiveness of the proposed approach as a decision-support tool for early-stage façade design and daylight optimization.

Table 5-4 – Comparative daylight simulation results for all façade scenarios

Scenario	sDA (%)	ASE (%)	Lux
Baseline	74.9%	40.6%	1854
Hexagonal Panel System	74.9 %	11.9 %	1487
Custom Façade	70.6 %	15.7 %	1544

5.2. Machine Learning Prediction Validation

This section assesses the precision of the machine learning surrogate model by benchmarking its predicted daylight performance values against empirical results from ClimateStudio simulations.

The primary goal of this validation is to determine if the AI-driven workflow can deliver reliable daylight estimations during the early phases of design exploration [4]. By doing so, the workflow aims to minimize the necessity for frequent, computationally expensive simulations.

Comparative analysis was performed across three key daylight performance metrics:

- Spatial Daylight Autonomy (sDA),
- Annual Sunlight Exposure (ASE),
- and Point-in-Time Illuminance (Lux).

This assessment covers both the established parametric façade systems and the bespoke architect-designed façade scenario to evaluate:

- the surrogate model's predictive reliability,
- the alignment between predicted data and simulated outcomes,
- and the overall utility of the workflow in conceptual architectural design.

5.2.1. Prediction vs Simulation Comparison

Table 5.7 presents a comparison between the daylight performance values predicted by the machine learning model and the corresponding results obtained through ClimateStudio simulations.

It is important to note that the objective of the surrogate model is not to replace detailed daylight simulations, but rather to provide rapid performance estimations during the early stages of façade design [4]. While ClimateStudio requires complete geometric definition and computationally intensive simulations [4], the developed Rhino plugin offers immediate feedback on the expected daylight performance of alternative façade configurations. This allows designers to evaluate multiple options before committing to detailed simulation workflows.

The comparison shows that differences exist between the predicted and simulated values, particularly for sDA. However, the predicted results consistently reflected the overall daylight performance tendencies of the evaluated façade configuration. The

model successfully distinguished between different design alternatives and provided performance estimates that were sufficiently representative for preliminary design assessment.

For ASE, the predicted values showed close agreement with the simulation results, with differences ranging from 0.7 to 3.9 percentage points. For sDA, larger deviations were observed, particularly in the baseline case. Nevertheless, the predictions remained within a range that enabled meaningful comparison between façade alternatives and supported informed design decisions during the conceptual phase.

From an architectural design perspective, the value of the workflow lies in its ability to significantly reduce the number of simulation-based iterations required during façade development. Instead of repeatedly modifying a façade design and running time-consuming ClimateStudio analyses, designers can use the Rhino plugin to rapidly explore multiple façade configurations and identify promising solutions based on predicted daylight performance. Detailed simulations can then be reserved for the final evaluation and verification of selected alternatives.

Therefore, although the machine learning predictions do not exactly match the simulation outputs, the validation results demonstrate that the developed workflow provides a practical and efficient decision-support tool for early-stage façade design. By shortening the feedback loop between design generation and performance evaluation, the proposed approach helps architects make informed daylight-related design decisions while reducing computational effort and design iteration time.

Table 5-5 – Comparison between machine learning predictions and ClimateStudio simulation results

Scenario	Metric	ML Prediction (mean value)	Simulation Result	Difference (percentage points)
Baseline Model	sDA	96%	74.9%	21.1
Baseline Model	ASE	38%	40.6%	2.6
Scenario A: Hexagonal Panel System	sDA	85%	74.9%	10.1
Scenario A: Hexagonal Panel System	ASE	8%	11.9 %	3.9
Scenario B: Custom Façade	sDA	80%	70.6 %	9.4
Scenario B: Custom Façade	ASE	15%	15.7 %	0.7

5.3. Comparative Analysis of Traditional and AI-Assisted Workflows

This section compares the conventional daylight-driven façade design workflow with the proposed AI-assisted workflow in terms of computational time, design iteration capability, workflow efficiency, and feedback speed during the early stages of design development.

Traditional daylight-informed design workflows typically rely on repeated simulation cycles using physically based simulation engines such as Radiance and ClimateStudio [4]. These tools provide highly accurate performance assessments and remain essential for detailed analysis and final design validation [4]. However, because each simulation requires model preparation and computational processing, evaluating multiple façade alternatives can become time-consuming, particularly during conceptual design phases where numerous iterations are explored.

The proposed AI-assisted workflow is not intended to replace simulation-based tools. Instead, it functions as a complementary pre-design decision-support system that provides rapid daylight performance estimations based on machine learning predictions. By offering immediate feedback on the expected performance of different façade configurations, the workflow allows designers to explore a larger range of alternatives before conducting detailed simulations.

This approach shortens the iterative cycle between façade generation and performance evaluation, enabling architects to identify promising design directions more efficiently. Detailed ClimateStudio simulations can then be reserved for the verification and refinement of selected solutions, reducing the number of computationally intensive analyses required throughout the design process.

The following comparison evaluates the practical impact of integrating machine learning-assisted prediction into the façade design workflow and examines its potential to support faster and more informed decision-making during early-stage architectural design.

5.3.1. Workflow Time Comparison

This subsection compares the practical efficiency of the conventional simulation-based workflow and the proposed AI-assisted workflow during the façade design exploration process.

In a traditional daylight-informed design workflow, each façade modification requires the preparation and execution of a new ClimateStudio simulation [4]. Although this approach provides highly accurate performance assessments, the time required for model updates, simulation execution, and result interpretation can significantly limit the number of design alternatives evaluated during the early stages of design.

The developed AI-assisted workflow introduces a rapid feedback mechanism through the integration of a machine learning surrogate model within the Rhino environment. Following the modification of façade parameters or the creation of a custom façade configurations, daylight performance indicators can be predicted almost instantaneously, allowing designers to assess multiple alternatives without repeatedly running detailed simulations.

Table 5-6 – Comparison between traditional simulation workflow and AI-assisted workflow

Parameter	Traditional Workflow	AI-Assisted Workflow
Average Iteration Time	Several minutes per simulation run	A few seconds per prediction
Number of Explored Scenarios	Limited by simulation time	Significantly higher due to rapid feedback
Computational Cost	High	Low
Feedback Speed	Delayed	Real-Time
Design Exploration Capability	Limited	Extensive

Primary Purpose	Detailed performance validation	Early-stage design exploration and guidance
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Rather than replacing ClimateStudio or other physically based simulation tools, the proposed workflow serves as an intermediate design-support layer between conceptual design generation and detailed performance validation. By providing immediate performance estimates, the workflow enables architects to identify promising façade configurations before investing time and computational resources in comprehensive simulations.

As shown in Table 5.6, the AI-assisted workflow substantially improves feedback speed and design exploration capability while reducing computational effort. This allows a larger number of design alternatives to be investigated within the same design timeframe, supporting a more iterative and performance-informed design process. Detailed simulations remain essential for final verification; however, the number of simulation cycles required to reach an optimized solution can be significantly reduced through the use of the proposed workflow.

6 Discussion

6.1. Interpretation of Results

The daylight performance of the *Il Sole 24* case study reveals a strong dependency between façade geometry and indoor light distribution. The baseline results indicate that Window-to-Wall Ratio (WWR) and orientation act as primary drivers of daylight availability, consistent with established findings in building performance literature [55]. While the original high-transparency façade allows deep daylight penetration, it simultaneously leads to significant risks of overlighting, particularly on the South and West orientations where elevated ASE values and high illuminance peaks are observed [12], [22].

The results further suggest that introducing a secondary shading layer can effectively mitigate extreme exposure conditions. In particular, configurations with reduced WWR combined with controlled panel porosity appear to improve the balance between daylight sufficiency and overexposure. The influence of panel rotation is not uniform across orientations; higher rotation angles on South and West façades are more effective in limiting direct solar gains, whereas lower angles on East and North façades help preserve adequate daylight levels without introducing underlit conditions.

Overall, the case study highlights that façade performance emerges from a trade-off between global geometric parameters and local shading strategies. Rather than acting independently, these variables interact in a coupled system where optimization requires balancing competing daylight objectives such as exposure control and daylight autonomy[14].

6.2. Strengths of the Proposed System

The primary strength of the proposed AI-assisted workflow lies in its capacity to transform the traditional relationship between environmental performance evaluation and the creative architectural design process [30]. Conventional architectural workflows rely on a linear sequence where any modification to the façade geometry requires a complete re-execution of high-fidelity physical simulation engines, creating a major time bottleneck [12]. By embedding a pre-trained surrogate machine learning model directly within the design workspace, this framework completely overcomes

these computational constraints. The most significant advancement of this system is its high speed and computational efficiency, which compresses annual daylight calculation times from several minutes down to fractions of a second [12]. This rapid processing capability provides instantaneous performance feedback without compromising scientific validity, effectively removing the heavy computational burden associated with traditional ray-tracing workflows.

This dramatic shift in calculation speed provides unprecedented support during the early stages of design, a phase where architectural decisions have the greatest impact on final building performance but are rarely guided by data due to time limitations and geometric uncertainty [56]. The proposed system resolves this challenge through a seamless integration of computational tools, linking parametric modeling interfaces, machine learning algorithms, and physical validation engines within a unified digital environment [54]. This integrated architecture allows designers to execute real-time evaluations without constantly switching between different software platforms or manually reformatting geometric data. Consequently, the workflow ensures a significantly reduced reliance on repetitive physical simulations. Instead of executing hundreds of slow, parallel simulation loops to test minor geometric alterations, the designer uses the machine learning model as the primary predictive core, reserving physical simulation engines strictly as a final step for definitive validation.

Furthermore, this workflow enables a highly interactive decision-making process that stands in sharp contrast to fully automated optimization algorithms that isolate the user from the design process [30]. The system operates as a responsive design assistant, instantly displaying how manual alterations or parametric shifts influence spatial daylight metrics like sDA, ASE, and Lux. This real-time feedback loop establishes a dynamic dialogue between human intuition and scientific logic, significantly expanding the overall design exploration capability. Architects are no longer restricted to evaluating a few safe alternatives due to schedule pressures; instead, they can fluidly test hundreds of diverse formal and parametric variations in a single working session [54]. By separating simulation accuracy from processing latency, the proposed system successfully transforms environmental analysis from a retrospective check into a proactive, performance-driven design methodology [12], [30].

6.3. Limitations and Challenges

The development and validation of the proposed AI-assisted workflow, while successful, are subject to several specific limitations and developmental constraints that must be acknowledged.

Dataset and Model Generalization: The iterative development of the surrogate machine learning model revealed early challenges regarding computational efficiency and predictive reliability. Initial experiments demonstrated that a limited simulation dataset was insufficient to accurately map the highly non-linear relationships between façade geometry and spatial daylight metrics [12]. Consequently, the data generation pipeline was expanded. Generating additional simulation scenarios and extending the domain of geometric parameters successfully improved the model's robustness, ensuring reliable predictions without overfitting to a constrained geometric library [55], [56].

Scope of Validation: While the developed workflow establishes a robust methodology, its empirical validation is bounded by a distinct architectural and geographic scope. The validation phase was strictly limited to the *Il Sole 24* office building, representing a single typology of building within the specific urban context of Milan [12]. Therefore, applying the pre-trained surrogate model to radically different building typologies, distinct macro-climates, or constrained urban environments would require careful recalibration to ensure continued predictive accuracy [55].

Dependence on Simulation Assumptions: The reliability of the predictive engine is inherently tied to the assumptions of the physical simulations used during dataset generation [12]. The training data relied on the EPW climate file for Milan, standardized office occupancy schedules, and fixed simulation settings such as sensor grid density and internal reflectance properties [23], [22]. Because the algorithm learns from these predetermined environmental bounds, significant deviations in real-world conditions or localized microclimatic shifts would introduce margins of error.

Evolution of the User Interface: Translating the computational backend into an intuitive architectural tool also presented development challenges. An early version was developed as a standalone web application to externalize the prediction environment. To support fluid, real-time design exploration, the system's architecture was fundamentally restructured and integrated directly into a Rhino and Grasshopper plugin, successfully consolidating the form-finding and evaluation processes [30].

Design Freedom and User Control: This integration prompted a critical re-evaluation of architectural design freedom. Initially, the generative capabilities were restricted to a predefined library of three specific parametric panel typologies [30], [54]. Recognizing that this constrained the creativity of the designer, the workflow was significantly expanded to accommodate custom, user-drawn geometries. This modification enabled users to manually define arbitrary transparent and opaque

surfaces to achieve specific custom Window-to-Wall Ratios (WWR), reinforcing a "designer-in-the-loop" paradigm that acts as an extension of creative intuition rather than a parametric restriction [55].

Limitations of ML-Based Prediction: Finally, although the trained machine learning model demonstrated highly satisfactory accuracy, it remains an algorithmic approximation of high-fidelity ray-tracing simulations [12]. The predicted metrics are reliable estimations meant to rapidly guide early-stage conceptual iterations. Therefore, the developed workflow functions as an advanced decision-support tool to accelerate design exploration, rather than a complete replacement for the rigorous physical daylight simulations required during final architectural documentation [23].

6.4. Future Work

The architectural flexibility and predictive framework established in this research provide several clear trajectories for subsequent computational development. To address the current boundaries of the system and expand its utility as an early-stage design tool, future research should focus on the following key areas.

Dataset Expansion and Model Generalization: The current predictive framework relies on a dataset calibrated for a specific geometric and environmental context. Future iterations of this research must prioritize dataset expansion to enhance the machine learning model's generalization capabilities. By automating data generation pipelines to produce vastly larger and more diverse training matrices, the surrogate model can learn more complex non-linear relationships, thereby reducing statistical approximation errors across a much broader spectrum of architectural variations.

Validation Across Multiple Climates and Building Types: To eliminate the current geographical and programmatic boundaries of the framework, subsequent studies should validate the system across diverse global climates and structural typologies. Retraining the algorithms on a multitude of diverse EPW weather files and varying functional layouts—such as educational, healthcare, or residential floor plans—will transition the tool from a localized case-study application into a universally applicable design-support engine [12], [55].

Multi-Objective Performance Evaluation: While the present study successfully optimizes Spatial Daylight Autonomy (sDA) and mitigates spatial overexposure via ASE and Lux monitoring, future development should scale the workflow into a comprehensive multi-objective optimization engine. Integrating real-time machine learning predictions for internal thermal comfort profiles, whole-building mechanical

cooling loads, and the embodied carbon metrics of secondary skin materials will ensure that early-stage conceptual form-finding is completely aligned with holistic building decarbonization targets [14], [56].

Expansion to Additional Façade Systems: The creative utility of the interface can be significantly broadened by expanding the underlying façade typology database. While the current tool successfully handles structured modular geometries (such as hexagonal grids), integrating a wider spectrum of parametric morphologies—including kinetic louvers, origami-inspired folding plates, and adaptive generative meshes—will provide architects with a vastly enriched vocabulary for performance-driven form-finding [30], [54].

Enhanced Design Freedom and User Customization: Finally, future updates to the Rhino and Grasshopper evaluation workflow should focus on maximizing geometric flexibility to further solidify the "designer-in-the-loop" paradigm. Enhancing the core geometry-parsing algorithms to seamlessly support highly irregular, non-orthogonal, or doubly-curved custom surfaces will grant architects absolute design freedom. This evolution will ensure the AI-assisted tool acts as a fluid extension of human creative intuition rather than a rigid parametric constraint, ultimately bridging the gap between rigorous building physics and conceptual architectural expression.

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