Design Problem Optimization with Multi-Objective Evolutionary Algorithms

Presented by:

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Declaration

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Farzana Haque Toma

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Abstract

Complex design challenges involve conflicting objectives and require robust optimization techniques. They commonly arise in engineering, building design, robotics, drug design, and energy systems, among others, where balancing competing criteria is essential. Sunshade optimization is also a complex design problem as it has many conflicting objectives. Sunshades significantly influence a building's thermal performance, daylight quality, occupant comfort, and energy usage. However, traditional sunshade designs typically focus on a limited set of objectives—often ignoring broader considerations such as cost efficiency and outside-view obstruction. This thesis addresses that gap by implementing and comparing two advanced multi-objective evolutionary algorithms—Multi-Objective Covariance Matrix Adaptation Evolution Strategy (MO-CMA-ES) and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II)—to optimize sunshades across five key objectives: thermal comfort, energy consumption, Useful Daylight Illuminance (UDI), cost, and outside-view obstruction.

A single-room office model was used as a test bed, with parameterized sunshades simulated through Honeybee, EnergyPlus, and Radiance. Experiments were conducted in four distinct climate zones—Cape Town (moderate), Nairobi (hot), Colombo (hot-humid), and Oslo (cold)—to ensure broad applicability. Both algorithms consistently outperformed traditional, manually designed sunshades in reducing thermal discomfort and energy usage while also improving UDI. Gains in cost and view preservation were more modest, primarily because minimal overhang sunshades can already be inexpensive and unobtrusive. Statistical tests indicated no systematic performance advantage of one algorithm over the other; NSGA-II tended to produce larger Pareto fronts, whereas MO-CMA-ES explored a broader range of objective values. The main contribution of this research is the use of two advanced multi-objective evolutionary algorithms to optimize sunshade designs based on five key objectives, tested in four climate zones representing both the northern and southern hemispheres, as well as regions below and above the equator, demonstrating clear advantages over traditional, manually designed sunshades in achieving a balanced trade-off among competing performance criteria.

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Abbreviations

AC	Air Conditioning
ANNs	Artificial Neural Networks
ASHRAE	The American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BFO	Building Façade Optimization
BIM	Building Information Modeling
CAD	Computer-Aided Design
CMA-ES	Covariance Matrix Adaptation Evolution Strategy
DRL	Deep Reinforcement Learning
EAs	Evolutionary Algorithms
ENVLOAD	Envelope Energy Load
EPW	EnergyPlus Weather
EUI	Energy Use Intensity
GAs	Genetic Algorithms
HVAC	Heating, Ventilation, and Air Conditioning
IDF	Input Data File
LCC	Life Cycle Costs
MaOEAs	Many-Objective Evolutionary Algorithms
ML	Machine learning

MO-CMA-ES	Multi-Objective Covariance Matrix Adaptation Evolution Strategy
MOEAs	Multi-Objective Evolutionary Algorithms
MOO	Multi-Objective Optimization
NSGA	Non-dominated Sorting Genetic Algorithm
NSGA-II	Non-dominated Sorting Genetic Algorithm II
nZEB	nearly zero-Energy Building
OTTV	Overall Thermal Transfer Value
PACS	Performance of Air Conditioning Systems
PAES	Pareto Archived Evolution Strategy
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied
SPEA	Strength Pareto Evolutionary Algorithm
SPEA-2	Strength Pareto Evolutionary Algorithm 2
SVMs	Support Vector Machines
TDP	Thermal Discomfort Percentage
UDI	Useful Daylight Illuminance

Chapter 1

Introduction

In architectural design, sunshades are important elements that serve multiple functions, including enhancing thermal comfort, regulating natural light, reducing energy consumption, and maintaining aesthetic appeal (Al-Masrani et al., 2018). These architectural features are significant in controlling the amount of solar radiation that enters a building, which influences the indoor environmental quality and the overall energy performance of structures. Sunshades come in various forms, such as fixed louvers, adjustable blinds, and dynamic shading systems, each offering unique advantages in different climatic and structural contexts (Raheem et al., 2014).

Traditional sunshade designs have mostly relied on manual, heuristic approaches, which often involve iterative testing and expert judgment to balance these many objectives. Architects and designers typically employ trial-and-error methods, guided by their experience and qualitative assessments, to determine the optimal configuration of sunshades for specific building types and environments. While effective to a degree, these methods can be time-consuming and may not always provide optimal solutions, especially when confronted with the complex interplay of various performance criteria (Sönmez, 2018). The subjective nature of manual design processes also introduces variability and potential biases, which can affect the consistency and reliability of the outcomes.

A research gap exists in the comprehensive optimization of sunshade designs that simultaneously consider a broad spectrum of objectives. Most existing studies focus on optimizing two or three objectives, such as thermal comfort, energy consumption, and daylight provision, but rarely address additional critical factors such as cost and obstruction of the outside view in a unified framework (Li et al., 2024). This limitation restricts the applicability of such studies to real-world scenarios where multiple performance metrics must be balanced to achieve sustainable and user-centric building designs, particularly under diverse location-based climatic conditions characterized by varying temperature, humidity, and solar irradiance, which significantly influence occupant comfort and energy performance. Furthermore, the application of advanced many-objective optimization algorithms, specifically MO-CMA-ES, remains unexplored in the context of sunshade optimization (Shan & Junghans, 2023). This gap underscores the need for innovative approaches that can handle the complexity and interdependencies of multiple performance metrics in sunshade design.

Advancements in computational optimization techniques offer promising avenues for overcoming the limitations of manual design processes. Multi-Objective Optimization (MOO) algorithms, such as the NSGA-II (Ma et al., 2023) and Covariance Matrix Adaptation Evolution Strategy (CMA-ES) (Hansen & Ostermeier, 2001), have demonstrated significant potential in exploring extensive design spaces and identifying Pareto-optimal solutions that balance conflicting objectives. These algorithms employ evolutionary principles and statistical adaptations to efficiently navigate the vast landscape of possible designs; this can result in convergence towards high-quality configurations that satisfy multiple criteria (Coello, 2007). By leveraging these computational tools, designers can achieve a more comprehensive and objective assessment of sunshade performance, facilitating informed decision-making and enhancing the overall quality of architectural designs (Keough & Benjamin, 2010).

This thesis aims to evaluate the performance of NSGA-II and CMA-ES in the context of sunshade design by comparing them against traditional manually designed sunshades. The evaluation is based on five key objectives: thermal comfort, Useful Daylight Illuminance (UDI) (Nabil & Mardaljevic, 2006), energy consumption, cost, and outside view obstruction. By leveraging real-world weather data, the study ensures that the assessment of these objectives is grounded in practical and relevant environmental conditions. Specifically, the research focuses on office environments, which are prevalent in urban settings and have significant energy demands due to heating and cooling requirements (Jung et al., 2018). The study encompasses four distinct climate zones to capture a wide variety of environmental conditions, ensuring that the optimized sunshade designs are adaptable and effective across different geographical contexts.

Simulations are conducted over an entire year to account for seasonal variations in weather, such as daytime temperature and humidity, which significantly impact thermal comfort for room occupants (Cao et al., 2021). The ability to control the entering solar radiation through sunshades directly influences thermal comfort; for instance, on colder days, allowing more sunlight to enter can reduce the reliance on heating systems, thereby decreasing energy consumption (Karlsen et al., 2016). Conversely, on hotter days, restricting sunlight helps maintain cooler indoor temperatures, reducing the need for air conditioning (Xue et al., 2019). This dynamic control of solar exposure not only enhances occupant comfort but also contributes to energy efficiency, aligning with broader sustainability goals in building design (Xiang & Matusiak, 2022).

In addition to thermal regulation, sunshades play a crucial role in managing daylight within the workspace. Achieving optimal UDI ensures that occupants receive adequate lighting without excessive glare, enhancing visual comfort and productivity (Baker et al., 2013). Proper daylight management reduces the dependency on artificial lighting, further lowering energy consumption and operational costs (González & Fiorito, 2015). These optimizations must be balanced against the need to preserve unobstructed views to the outside, which are essential for occupant well-being and satisfaction.

Moreover, the cost of implementing and maintaining sunshade systems is a vital consideration for the feasibility and scalability of such solutions (Araújo et al., 2016). While advanced shading systems may offer superior performance in terms of energy savings and occupant comfort, their initial installation and maintenance costs can be prohibitive. Therefore, it is imperative to evaluate the economic implications of different sunshade designs alongside their environmental and comfort-related benefits. By incorporating cost as a key objective, this study provides a holistic assessment of sunshade performance, ensuring that the optimized designs are not only effective but also economically viable (Okeil, 2010).

The integration of real-world weather data into the optimization process enhances the robustness and applicability of the study (Mehta & Fung, 2013). By using actual climate patterns, the simulations reflect realistic operating conditions, ensuring that the optimized sunshade designs perform reliably throughout the year (Heidari Matin & Eydgahi, 2022). This data-driven approach enables the identification of design configurations that are resilient to climatic variations, promoting long-term sustainability and reducing the risk of performance degradation over time (Krelling et al., 2024).

In summary, this thesis seeks to reduce the existing research gap by using advanced many-objective optimization algorithms to design sunshades that simultaneously address multiple performance criteria. By comparing algorithmically optimized designs with traditional manual approaches, the study aims to show the advantage and efficiency of computational methods in achieving superior architectural design outcomes. The findings are expected to inform architects and engineers about the advantages of adopting MOO techniques in sunshade design, ultimately contributing to the development of more sustainable, cost-effective, and user-centric building environments.

1.1 Motivation

The design and implementation of effective sunshades are important in modern architectural practices, particularly in enhancing the sustainability and comfort of office environments. Sunshades serve as critical components in managing solar radiation, influencing the thermal and visual comfort of building occupants. By controlling the incoming sunlight, sunshades play a significant role in regulating indoor temperatures and managing natural light levels, which are essential factors in reducing energy consumption and creating conducive workspaces (Coetzee & Nitschke, 2019). Despite their importance, the optimization of sunshade designs remains a complex challenge due to the many-objectives that must be simultaneously addressed.

A research gap exists in the comprehensive optimization of sunshade systems that consider a broad spectrum of performance criteria. While numerous studies have explored the optimization of sunshades, most have focused on optimizing two or three objectives, such as thermal comfort, energy consumption, and daylight provision (Ma et al., 2023). However, there is a notable absence of research that integrates additional factors like cost and outside view obstruction into the optimization framework. This omission limits the practical applicability of existing studies, as real-world scenarios require a balanced consideration of multiple, often competing, objectives to achieve sustainable and user-centric building designs.

Furthermore, the application of advanced many-objective optimization algorithms, specifically the MO-CMA-ES, has not been explored in the context of sunshade optimization. Traditional sunshade designs have been primarily based on manual heuristic approaches that involve iterative testing and expert judgment (Ma et al., 2023). These methods, while useful, are inherently time-consuming and may not consistently yield optimal solutions, especially when navigating the intricate trade-offs between diverse performance metrics. The introduction of Evolutionary Algorithms (EAs) like NSGA-II and MO-CMA-ES offers a promising alternative, providing systematic and efficient exploration of extensive design spaces to identify Pareto-optimal solutions that balance conflicting objectives (Wang et al., 2023b).

The motivation behind this research is driven by the need to bridge these gaps by employing advanced many-objective optimization techniques to design sunshades that address five key objectives: thermal comfort, UDI, energy consumption, cost, and outside view obstruction. By integrating all these objectives into a unified optimization framework, this study aims to develop sunshade designs that are not only energy-efficient and cost-effective but also enhance the overall quality of the indoor environment and preserve the aesthetic and functional aspects of building facades.

Office environments, characterized by their significant energy demands for heating and cooling, present an ideal setting for this research. Optimizing sunshade designs in such settings can lead to substantial energy savings and improved occupant comfort, thereby contributing to both economic and environmental sustainability (Xiang & Matusiak, 2022). The use of real-world weather data across four distinct climate zones ensures that the optimized designs are adaptable and effective in diverse geographical contexts, enhancing their practical relevance and scalability.

Moreover, the application of EAs like NSGA-II and MO-CMA-ES is expected to outperform manually designed sunshades by providing location-specific solutions that are tailored to the unique environmental conditions of each climate zone. These algorithms facilitate the identification of high-quality design configurations that balance multiple objectives, offering a level of precision and efficiency that manual methods cannot achieve (Shan & Junghans, 2023). By using these computational tools, architects and engineers can make more informed and objective design decisions, ultimately leading to the development of more sustainable and user-centric building environments.

In essence, this research is motivated by the need to develop optimized sunshade solutions that meet the complex and varied demands of modern office buildings. By addressing the existing research gaps and using the power of advanced optimization algorithms, this study aims to contribute significantly to the field of architectural optimization, promoting energy efficiency, cost-effectiveness, and enhanced occupant well-being. Consequently, the integration of multiple performance criteria and the opportunity to apply advanced MOEAs provide the rationale for selecting sunshade optimization as the design problem of this thesis.

1.2 Research Questions

This study explores the effectiveness of integrating advanced computational methodologies, specifically MOEAs like NSGA-II and MO-CMA-ES, in optimizing sunshade designs for office environments. The investigation is centered around a primary research question, supplemented by secondary questions that focus on comparative evaluations and the efficacy of different methodological approaches, as outlined in the sections on motivation (Section 1.1) and methodological frameworks (Sections 3.1, 3.3).

At its core, this research not only conducts a comparative analysis of the exploratory capabilities and solution quality of MO-CMA-ES and NSGA-II, but also evaluates how these algorithms perform relative to traditional manually designed sunshades by examining five closely related objectives. These objectives exhibit varying degrees of correlation—some are inversely related, such as thermal comfort and energy consumption, while some are positively correlated, such as UDI and obstructed view. Detailed in Sections 3.3.1 and 3.3.2, this comparison aims to address secondary questions 2.1 and 2.2 by examining how each algorithm navigates the design space to identify optimal sunshade configurations. The focus is on understanding the dynamics of these algorithms in achieving balanced outcomes across multiple objectives within diverse climate zones.

1. **Primary Research Question:** How do advanced many-objective Evolutionary Optimization Algorithms, specifically Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and many-objective Covariance Matrix Adaptation Evolution Strategy (MO-CMA-ES), enhance the efficiency and effectiveness of sunshade design in office environments by optimizing for thermal comfort, Useful Daylight Illuminance (UDI), energy consumption, cost, and outside view obstruction compared to traditional manually designed sunshades?

2. **Secondary Research Questions:**

   2.1. How do the exploration and exploitation capabilities of many-objective Covariance Matrix Adaptation Evolution Strategy (MO-CMA-ES) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II) compare in identifying high-quality sunshade designs that balance thermal comfort, UDI, energy consumption, cost, and outside view obstruction across different climate zones?

   2.2. In a comparative evaluation of the many-objective Covariance Matrix Adaptation Evolution Strategy (MO-CMA-ES) and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) for sunshade design optimization, which algorithm demonstrates superior performance when assessed using quantitative metrics, including energy savings, cost efficiency, UDI levels, occupant comfort, and aesthetic preferences, as modeled in the evaluation framework?

To tackle the secondary research question 2.1, this study evaluates the effectiveness of MO-CMA-ES and NSGA-II in exploring the design space and exploiting optimal solutions. By implementing these algorithms within four distinct climate zones, the research assesses their ability to generate Pareto-optimal sunshade designs that effectively balance the five key objectives. This analysis provides insights into the strengths and limitations of each algorithm in managing complex, many-objective optimization tasks.

For the secondary research question 2.2, the study conducts a thorough analysis of the solution sets produced by MO-CMA-ES and NSGA-II. This evaluation encompasses both quantitative measures—such as energy savings, cost efficiency, and UDI levels—and qualitative aspects, including occupant comfort and aesthetic integration as in unobstructed outside view of sunshades. By comparing these metrics against traditional manually designed sunshades, the research aims to determine which algorithm offers more effective and comprehensive optimization outcomes.

Together, these secondary questions contribute to answering the primary research question by highlighting how advanced many-objective optimization algorithms can surpass traditional design methods in achieving sustainable, cost-effective, and user-friendly building environments. The comparative analysis not only demonstrates the potential of NSGA-II and MO-CMA-ES in sunshade optimization but also provides a framework for selecting the most suitable algorithm based on specific performance criteria and environmental contexts.

1.3 Contributions

This research makes contributions to the field of architectural optimization, particularly through the application of advanced computational methods. These contributions enhance the practical approaches utilized in designing innovative sunshade systems. The primary contributions are detailed as follows, with the most important listed at the top and the less significant ones following in order:

1. **Comprehensive Comparative Analysis of many-objective Evolutionary Algorithms (MOEAs):**

   This study performs a comparative evaluation of two leading MOEAs, namely the NSGA-II and the MO-CMA-ES (unlike recent studies, which used only NSGA-II) (Naji et al., 2021; Yi, 2019; Zhao & Du, 2020)-by assessing their performance across five essential objectives—thermal comfort,UDI, energy consumption, cost, and outside view obstruction. This research highlights the strengths and weaknesses of each algorithm. The insights gained provide valuable guidance on navigating complex, many-objective design spaces which is essential for designing next-generation sunshade systems.

2. **Incorporation of Diverse Climate Zones for Comprehensive Algorithm Evaluation:**

   Unlike many studies that does not use real world data, this research utilizes real-world weather data from four distinct climate zones—Cape Town (moderate), Nairobi (hot), Colombo (hot-humid), and Oslo (cold) (Abdou et al., 2021; Al-Tamimi, 2022; Elsheikh et al., 2023; Zhao & Du, 2020), which represents both the northern and southern hemispheres, as well as regions above and below the equator. This broad climatic representation ensures that the optimized sunshade designs are tested across a wide range of environmental conditions.

3. **Integration of Real-World Weather Data to Enhance Design Relevance:**

   An important aspect of this research is the incorporation of real-world weather data into the optimization process. Over the course of a year, weather data across four distinct climate zones has been simulated. This study ensures that the resulting sunshade designs are practical and resilient under diverse environmental conditions. This data-driven methodology enhances the accuracy, reliability, adaptability, and effectiveness of optimization outcomes in real-world settings. This ensures the sustainability and long-term performance of the sunshade designs.

4. **Empirical Validation of Superior Performance Over Traditional Designs:**

   By benchmarking the algorithmically optimized sunshades against traditionally manually designed alternatives, this research empirically demonstrates the superiority of advanced MOEAs. The optimized sunshades show marked improvements in energy consumption, cost efficiency, and occupant comfort while effectively managing natural light and preserving external views. This comparative analysis underscores the potential of computational methods to revolutionize sunshade design, offering more sustainable, cost-effective, and user-centric solutions compared to conventional manual approaches.

5. **Development of a Robust Optimization Framework for Architectural Design:**

   This study establishes a comprehensive framework for applying many-objective optimization in architectural design, specifically targeting sunshade systems. By integrating multiple performance metrics and utilizing sophisticated algorithms, the research provides a replicable methodology that can be extended to other aspects of building design and environmental control systems. This framework not only advances theoretical knowledge in optimization techniques but also offers practical tools for architects and engineers to implement sustainable and efficient design solutions in various building contexts.

6. **Advancing Sustainable Building Practices:**

   The optimized sunshade designs contribute to broader sustainability objectives by reducing energy consumption and lowering the carbon footprint of office buildings. By effectively managing solar radiation and natural light, the sunshades help maintain optimal indoor temperatures and lighting conditions, thereby decreasing reliance on artificial heating, cooling, and lighting systems. This enhancement not only promotes environmental sustainability but also results in economic benefits through reduced energy bills and operational costs, making sustainable building practices more accessible and financially viable.

Overall, the contributions of this research advance both the theoretical understanding and practical application of MOEAs in architectural design. By addressing existing research gaps and demonstrating the tangible benefits of advanced computational methods, this study paves the way for future innovations in sustainable building design and energy-efficient architectural solutions. These contributions collectively improve architects' and engineers' abilities to create building environments that are environmentally responsible, economically viable, and conducive to occupant well-being.

1.4 Overview

This thesis is structured into five primary chapters. Following the Introduction (Chapter 1), which presents the central research questions and motivation, the content is organized as follows:

Chapter 2 – Literature Review, this chapter establishes the current research within the broader context of computational design, sunshade innovation, and architectural optimization. It begins by tracing the evolution of computer-aided methods in architecture and their impact on generative design. The discussion then focuses on the role of sunshades in building performance, highlighting traditional shading strategies and the progression toward more dynamic, adaptive systems. Key concepts in MOO, EAs, and the significance of balancing conflicting objectives—such as energy, daylighting, occupant comfort, cost, and external views—are also examined. The chapter concludes by identifying the research gap addressed in this thesis: the need for a robust, multi-criteria optimization framework that can handle five interrelated performance measures simultaneously.

Chapter 3 – Methodology, the third chapter details the methodological framework used to explore and optimize sunshade designs. It begins by defining the office room geometry, material assumptions, and the parametric sunshade parameters. The integration of two specialized simulation engines—EnergyPlus for thermal and energy modeling and Radiance for daylighting metrics—through the Honeybee toolset is then described. The chapter outlines the five objectives (thermal comfort, UDI, energy consumption, cost, and outside view obstruction) and explains how they are computed. Subsequently, the chapter introduces the two MOEAs (MO-CMA-ES and NSGA-II) employed, describing their search processes, population initialization, selection, and crossover or mutation approaches. Finally, it discusses the experiment setup for all four locations for climate and how performance data were collected, including statistical tests and result visualization techniques.

Chapter 4 - Experiment Setup, this chapter establishes the experimental framework used to evaluate and compare sunshade designs. It begins by presenting a set of traditional sunshade configurations that serve as baseline references, each exemplifying a distinct approach to mitigating solar heat gain and glare. The discussion then describes the unified simulation environment—detailing the office room geometry, window dimensions, and diverse climatic conditions—to ensure that both traditional and evolved designs are assessed under consistent and realistic conditions. Key simulation tools, such as

EnergyPlus and Radiance integrated via the Honeybee toolset, are introduced to capture critical performance metrics including energy consumption, thermal comfort, useful daylight illuminance, cost, and the preservation of external views. Finally, the chapter outlines the many-objective optimization strategies, employing NSGA-II and MO-CMA-ES, alongside the statistical and visualization methods used to analyze the outcomes. In doing so, it provides a comprehensive framework for addressing the challenge of balancing five interrelated performance measures in sunshade design.

Chapter 5 – Results and Discussion, in this chapter the outcomes from the optimization experiments are presented and interpreted. Separate sections examine each geographic location (Cape Town, Nairobi, Colombo, and Oslo), explaining how the evolved sunshade designs address local climatic conditions. The chapter contrasts the algorithmically generated non-dominated solutions with five traditional sunshade configurations, providing a quantitative basis for performance comparisons. Box plots, Pareto fronts, and 3D visualizations of representative sunshades illustrate the trade-offs among the five objectives. The discussion integrates statistical findings, highlighting cases in which the evolutionary algorithms outperform traditional methods and illuminating the distinct strengths of NSGA-II and MO-CMA-ES in exploring or converging on optimal solutions.

Chapter 6 – Conclusion and Future Work is the final chapter which synthesizes the key insights gained from the research, directly addressing the research questions posed in the introduction. It reiterates how MOEAs can advance sunshade design by offering superior performance across a range of conflicting objectives. Limitations are acknowledged, including the single-zone office model, simplified occupant assumptions, and the static nature of the shading devices studied. The chapter then proposes directions for future work, suggesting how dynamic sunshades, more detailed cost and occupant models, or real-time controls could further refine the optimization process. Ultimately, the chapter underscores the broader importance of computational methods in creating energy-efficient, cost-effective, and comfortable architectural environments.

By organizing the thesis in this manner, the reader can trace the progression from established knowledge and identified gaps (Chapter 2), through the systematic approach to address them (Chapter 3), then understand the experiment setup (Chapter 4), to a thorough evaluation of the results (Chapter 5), and finally toward broader reflections and prospective improvements (Chapter 6).

Chapter 2

Literature Review

The Literature Review chapter has been arranged into five key sections. which build a comprehensive background for the study. The following summaries outline each section briefly:

1. Section 2.1 traces the historical and technological advancements—from early Computer-Aided Design and Building Information Modeling to parametric and generative design—that have revolutionized architectural practice.

2. Section 2.2 reviews the progression from traditional sunshade methods (like overhangs and mashrabiyas) to modern dynamic sunshade systems enabled by advanced materials and technology.

3. Section 2.3 discusses how sunshade systems are optimized to balance thermal comfort, energy efficiency, daylight quality, view preservation, and cost-effectiveness.

4. Section 2.4 examines computational strategies—including evolutionary algorithms, many-objective methods, and machine learning approaches—applied to optimize sunshade design.

5. Section 2.5 highlights the limitations in current studies, such as the narrow focus on objectives, limited algorithm comparisons, and a lack of diverse climatic evaluations, motivating this research.

2.1 The Evolution of Computational Design in Architecture

The integration of computers in architectural design has revolutionized the field. Architects can explore more complex forms, enhance precision, and streamline the design process. Since the 1950s, the evolution of Computer-Aided Design (CAD) began and an increasing number of computer applications have been developed to support various tasks and processes throughout the building lifecycle (Eastman, 1999). One of the earliest significant developments was the Sketchpad system, created by Ivan Sutherland in 1963, which introduced the concept of interacting with a graphical interface using a light pen, laying the groundwork for modern CAD software (Sutherland, 1964).

The introduction Building Information Modeling (BIM) in the late 1990s further advanced the use of computers in architecture. BIM systems allowed for the creation of highly detailed 3D models that integrate information on various aspects of a building's lifecycle, including structural, mechanical, and electrical systems. BIM has become a cornerstone of contemporary architectural practice, facilitating collaboration and improving the accuracy of construction planning and cost estimation (Smith & Tardif, 2009).

The use of advanced computational design techniques, such as parametric modeling and generative design, has pushed the boundaries of what is possible in architecture. These methods allow architects to explore a vast array of design possibilities through algorithmic processes, enabling the creation of complex and innovative forms that were previously impossible. Moreover, the use of computers has provided architects with immersive tools for presenting designs, enhancing the decision-making process and client engagement (Burry & Burry, 2016). Even though computer tools now help shape many parts of a building's design, the use of these methods specifically for sunshades has been relatively overlooked (Bushra, 2022).

2.2 Evolution of Sunshade

Sunshade has been an integral component of architectural design throughout history. It enhances indoor comfort, reduces energy consumption, and protects building interiors from excessive solar radiation. The evolution from traditional to modern sunshade techniques reflect advancements in materials and technology and a deeper understanding of environmental sustainability.

This section examines the historical evolution of sunshade systems and their contribution to energy-efficient building design. Section 2.2.1 reviews the transition from traditional passive sunshade devices to modern dynamic systems enabled by advanced materials and computational tools. Section 2.2.2 explores how sunshades reduce solar heat gain and optimize natural lighting to enhance indoor comfort and lower energy consumption.

2.2.1 From Traditional to Modern Sunshade Techniques

Overhangs and colonnades are among the earliest forms of passive sunshades. Overhangs are horizontal extensions that project beyond a building's façade, effectively blocking high-angle summer sun while allowing low-angle winter sun to penetrate interiors (Olgyay, 2015). Colonnades, consisting of a series of columns supporting a roof, create shaded walkways and buffer zones that reduce solar heat gain on building exteriors (Meir et al., 1995)

The "mashrabiya" (Figure: 2.1) is a traditional architectural element prevalent in Middle Eastern and North African regions. These intricate wooden lattice screens cover windows and balconies, providing shade, enhancing privacy, and facilitating natural ventilation (Karban & Watt, 2021). Mashrabiyas allow for airflow and diffuse daylight while preventing direct solar radiation, thus cooling interior spaces through passive means.

Traditional sunshade systems are typically static and cannot adjust to changing environmental conditions or occupant needs. This rigidity can result in suboptimal performance during different times of the day or year, as the fixed structures may either block too much sunlight or allow excessive solar gain (Tzempelikos & Shen, 2013). Incorporating traditional sunshade elements into contemporary designs can pose aesthetic challenges. Modern architectural trends often favor minimalist and transparent facades, which may not harmonize with the ornate and opaque characteristics of traditional sunshade devices like mashrabiyas (Cheng et al., 2005).

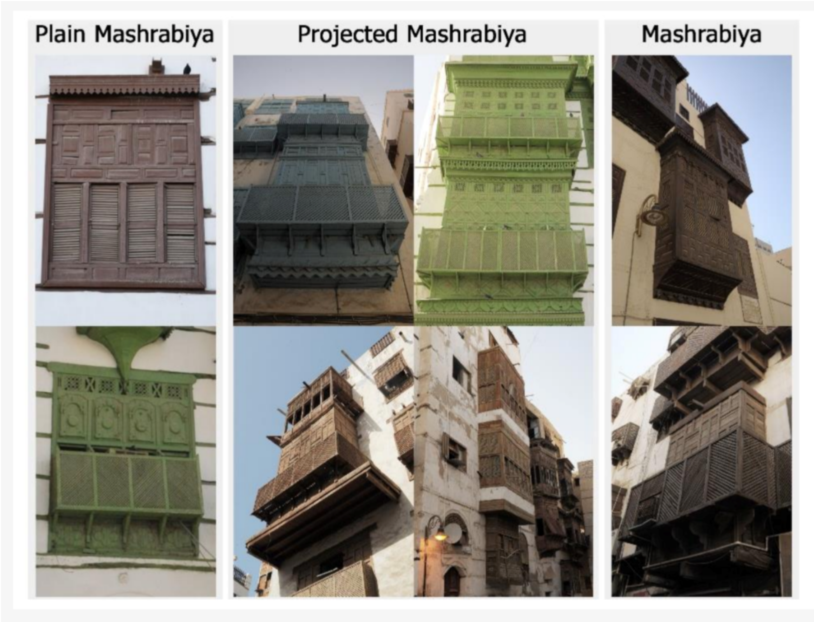

Figure 2.1: Various Forms of Mashrabiya in Historic Jeddah (Bagasi et al., 2021).

While traditional methods are effective in moderate climates, they may not provide sufficient protection in extreme conditions. In regions with intense solar radiation, traditional sunshades might not prevent overheating, leading to increased reliance on air conditioning and higher energy consumption (Al-Tamimi & Fadzil, 2011).

The Industrial Revolution introduced new building materials such as steel and glass. Which enabled architects to design larger windows and transparent façades. This shift required innovative sunshade solutions to manage increased solar heat gain (Banham, 1984). The use of lightweight materials allowed for more flexible and varied sunshade designs.

The Modernist movement emphasized functionality, simplicity, and the rejection of ornamentation. Architects like Le Corbusier introduced the concept of brise-soleil—permanent sunshade structures integrated into the building façade (Frampton, 2024). These devices projected from the exterior, sunshade windows and reducing glare without compromising the building's minimalist aesthetic.

Advancements in computer technology have revolutionized building and sunshade design. Software tools enable architects to simulate solar paths, analyze sunshade performance, and optimize designs for energy efficiency and occupant comfort (Tzempelikos & Athienitis, 2007). Computational modeling facilitates the integration of sunshade systems with other building components, enhancing overall performance.

One of the modern sunshade techniques is dynamic sunshade systems that adjust in response to environmental conditions. Examples include automated louvers, blinds, and electrochromic glass, which can change opacity when an electrical voltage is applied (Lee et al., 2006). These systems optimize daylighting and thermal comfort by modulating solar gain throughout the day. Modern sunshade devices are often integrated with Building Management Systems (BMS), allowing for automated control based on sensor data such as light intensity, temperature, and occupancy (Shen & Tzempelikos, 2013). This integration enhances energy efficiency, reducing the load on Heating, Ventilation, and Air Conditioning (HVAC) systems.

Modern sunshade techniques significantly reduce energy consumption by minimizing reliance on artificial lighting and HVAC systems. By controlling solar gain and glare, these systems maintain comfortable indoor temperatures and lighting levels. Adjustable sunshade devices allow for precise control over daylight penetration, reducing glare and enhancing visual comfort for occupants. This flexibility supports occupant well-being and productivity, particularly in office environments (Wienold & Christoffersen, 2006).

The evolution of sunshade techniques from traditional methods like mashrabiyas and overhangs to modern dynamic systems reflects significant advancements in both material science and architectural design. Traditional methods, while effective in specific climates, often lacked the flexibility required for modern buildings and environments.

2.2.2 The Role of SunShade in Energy-efficient Building Design

Sunshades are very important in minimizing unwanted solar heat gain in buildings, especially in hot climates. By blocking direct sunlight, particularly during peak hours, they reduce the amount of heat entering the building. This significantly lowers the cooling load on HVAC systems, leading to reduced energy consumption. A study found that external sunshade devices can reduce cooling energy needs by up to 30%, depending on the building orientation and local climate conditions (Tzempelikos & Athienitis, 2010).

Sunshades can optimize the amount of natural light entering a building. This controlled natural lighting reduces the need for artificial lighting, which in turn decreases energy consumption. Studies have shown that well-designed sunshade systems can reduce artificial lighting needs by 40-50% in commercial buildings (Ochoa et al., 2012). Proper daylighting not only leads to energy savings but also enhances occupant comfort by providing more consistent light levels throughout the day.

Sunshades reduce glare, a common issue in spaces with large windows, by diffusing direct sunlight. This improves visual comfort, which is critical for work environments, as excessive glare can strain the eyes and reduce productivity (Al-Tamimi, 2022). Additionally, by controlling solar heat gain, shades contribute to thermal comfort by preventing overheating, making indoor environments more pleasant without relying heavily on air conditioning.

Sunshades work Interdependently with building systems like HVAC and lighting, enhancing their efficiency. By reducing heat gain, they lower the demand on Air Conditioning (AC) systems, enabling HVAC systems to operate more efficiently. It is an essential component of passive design strategies, improving the building's overall efficiency and occupant's well-being without the need for active intervention (Al-Tamimi & Fadzil, 2011).

2.3 Sunshade Design: Performance Objectives and Their Impact

This section provides an overview of the performance objectives and their relationship with sunshade design in relation to any kind of building even offices. Section 2.3.1 discusses strategies for increasing Thermal Comfort through sunshade design by reducing heat gain and improving indoor thermal conditions. Section 2.3.2 evaluates strategies for Decreasing Energy Consumption through sunshade design by optimizing sunshade to minimize cooling and lighting energy demand. Section 2.3.3 explores methods for Maximizing UDI through sunshade design, ensuring sufficient daylight without glare. Section 2.3.4 addresses the importance of Decreasing View Obstruction through sunshade design while balancing functional and aesthetic requirements. Section 2.3.5 examines the role of Cost Efficiency in sunshade design, focusing on the economic viability and long-term benefits of sunshade systems.

2.3.1 Enhancing Thermal Comfort through Sunshade Design

Thermal comfort is the state of satisfaction individuals feel with their thermal environment. It is influenced by various factors, including air temperature, humidity, air movement, and the thermal properties of a building's envelope. These factors interact with building design elements to shape the indoor thermal environment (Wu et al., 2016). Notably, The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) guidelines, such as those outlined in ASHRAE Standard 55, provide comprehensive criteria for evaluating thermal comfort, thereby serving as an industry benchmark for ensuring occupant satisfaction (Edition et al., 2010). Thermal comfort is important when evaluating building performance, as it reflects the ability of a space to meet the needs of its occupants. Approaches like the adaptive comfort model also account for occupants' ability to adapt to environmental changes, particularly in naturally ventilated spaces. Ensuring thermal comfort during the preliminary design stage is essential for aligning building performance with the goals of energy efficiency and user satisfaction (Acar et al., 2021).

Calculating thermal comfort provides a deeper understanding of how building designs affect indoor conditions and occupant satisfaction. Metrics such as the hours of discomfort or indices like Thermal Discomfort Percentage (TDP) allow designers to ensure acceptable comfort standards while optimizing energy use. Moreover, thermal comfort calculations can be integrated into larger optimization processes, such as balancing occupant needs with Life Cycle Costs (LCC). This approach is particularly valuable when designing naturally ventilated systems, as it ensures that improved comfort does not come at the expense of energy efficiency. By refining design choices—such as window-to-wall ratios, sunshade systems, and ventilation strategies—discomfort can be reduced without the need for additional cooling systems, contributing to both environmental and economic sustainability (Grygierek & Ferdyn-Grygierek, 2018).

Optimizing thermal comfort in offices is especially critical because these spaces significantly impact occupant productivity and well-being. According to (Nazari et al., 2023), poor thermal conditions in offices can lead to discomfort, decreased focus, and even health issues, all of which reduce employee efficiency. By designing for optimal thermal comfort alongside energy efficiency, operational costs can be lowered, and sustainable building practices can be promoted. Achieving this balance ensures that indoor environments remain comfortable while also reducing energy consumption and meeting regulatory standards. This is particularly important as offices often serve as the setting for prolonged periods of activity, necessitating environments that support concentration and productivity.

One of the most effective strategies to enhance thermal comfort and energy efficiency in office settings is the use of sunshades. As demonstrated in (Wu & Zhang, 2022), horizontal louvers with a depth of 0.7 to 0.8 meters are particularly effective in reducing overheating during hot seasons while maintaining adequate daylight levels. Sunshades limit excessive solar radiation, minimizing cooling loads and reducing thermal discomfort during transition seasons. By creating a more stable indoor environment, these sunshade devices not only enhance occupant comfort but also contribute to energy savings. This dual benefit of thermal comfort and energy efficiency makes sunshade design an integral component of sustainable building practices. The strategic application of sunshades can ensure that buildings are both comfortable and environmentally responsible. Without Façade people use air conditioners to keep the thermal condition comfortable and that consumes a lot of energy.

Optimizing thermal comfort and energy efficiency in buildings or offices is interconnected: achieving thermal comfort with better insulation, airtightness, and passive designs reduces energy demand for heating and cooling. This synergy ensures sustainable energy use while maintaining occupant comfort (Wang et al., 2020).

2.3.2 Decreasing Energy Consumption Through Sunshade Design

Energy consumption refers to the total energy required by buildings for thermal comfort and operational needs such as heating, cooling, and running AC systems. It is significantly influenced by factors like the building envelope (insulation, walls, plaster, etc.), material properties, and climatic conditions. According to Himmetoğlu et al., 2022, energy includes heating and cooling needs calculated via simulations like EnergyPlus, which account for material, design, and environmental factors. Abdou et al., 2021 expands this by incorporating renewable energy systems (e.g., solar and wind) to supplement or replace traditional energy sources, facilitating a nearly zero-Energy Building (nZEB). Meanwhile, Lin et al., 2021 introduces performance metrics such as Envelope Energy Load (ENVLOAD) and Performance of Air Conditioning Systems (PACS), emphasizing their role in energy conservation. Torres-Rivas et al., 2018 highlights bio-based insulation materials like hemp and cellulose, which influence energy efficiency by reducing operational energy demands. Finally, Ascione et al., 2019 focuses on Primary Energy Consumption (PEC) measured in kWh/m^2/year, targeting its reduction through optimization using advanced simulations and algorithms.

Decreasing energy consumption yields significant environmental and financial benefits, including lower operational costs, reduced CO2 emissions, and improved sustainability. himmetouglu2022green emphasizes that reduced energy consumption mitigates environmental impacts and supports global policies like the Paris Agreement. It also lowers LCC by minimizing both construction and operational expenses. Similarly, Abdou et al., 2021 demonstrates that efficient design strategies can reduce thermal loads by up to 65% and save 21% of total energy, making retrofitting more economical. Lin et al., 2021quantifies the impact of optimization, showing that CO2 emissions can be reduced by 58.3% with only a 5.3% increase in construction costs. Torres-Rivas et al., 2018 focuses on bio-based materials that achieve energy savings while lowering environmental burdens and life cycle costs. Lastly, Ascione et al., 2019 provides an example of optimized building envelopes in Italian climatic zones, where energy demand was reduced to 62.0–91.9 kWh/m^2/year, meeting strict sustainability targets. In summary, decreasing energy consumption aligns with climate goals, reduces economic burdens, and supports sustainable development.

Optimizing energy consumption is essential for achieving environmental sustainability, cost efficiency, and occupant comfort. According to Himmetoğlu et al., 2022, energy-efficient building envelopes designed for specific climatic zones reduce environmental pollution, comply with local regulations, and enhance indoor comfort. Belhous et al., 2021 stresses the importance of integrating passive measures and renewable energy systems to achieve nZEB, ensuring energy demands are met sustainably. Lin et al., 2021 highlights that optimized designs not only meet green building standards but also provide long-term cost savings and ecological benefits. Torres-Rivas et al., 2018 underscores the role of bio-based materials and many-objective optimization methods in selecting cost-effective solutions that minimize environmental impacts and condensation risks. Lastly, Ascione et al., 2019 emphasizes compliance with nearly zero-energy building standards, showing how optimization helps reduce energy poverty, combat climate change, and maintain economic feasibility.

Reducing energy consumption in office buildings is crucial for minimizing operational costs, lowering greenhouse gas emissions, and improving energy efficiency. As noted in (Kang et al., 2018), office buildings have significant heating and cooling loads due to factors such as envelope design, insulation levels, and window-to-wall ratios. Optimizing these elements can substantially reduce energy usage, decrease CO2 emissions, and align with sustainability goals. Additionally, Seghier et al., 2022 emphasizes the importance of green retrofitting strategies, such as enhancing insulation and optimizing window-to-wall ratios, which can significantly reduce cooling loads—a major contributor to energy use in office spaces. Both studies highlight that energy-efficient office buildings not only meet regulatory standards like Overall Thermal Transfer Value (OTTV) and nZEB targets but also enhance thermal comfort for occupants.

Properly designed sunshades can reduce energy consumption in office buildings by controlling solar radiation and mitigating overheating. Nasrollahzadeh, 2021 highlights that well-designed external sunshade devices can block unwanted solar heat gain during summer, significantly reducing cooling loads and enhancing indoor thermal comfort. At the same time, sunshade can minimize glare and improve visual comfort, which contributes to reduced lighting energy use. The study emphasizes that proper sunshade configurations, tailored to building orientation and climatic conditions, optimize thermal performance while balancing energy savings for heating, cooling, and lighting (Zhao & Du, 2020).

2.3.3 Maximizing UDI Through Sunshade Design

UDI is a metric that measures the usability and quality of natural light in indoor spaces by quantifying the percentage of time daylight levels fall within an optimal range, typically between 100 and 2000 lux (Karaman et al., 2017). This range ensures that lighting is sufficient for most visual tasks while avoiding issues such as glare or underlighting that can cause discomfort (Cascone et al., 2018). As a performance indicator, UDI is particularly valuable in assessing how well a space benefits from natural light under varying conditions, ensuring it meets both functional and visual comfort needs (Karaman et al., 2017).

Calculating UDI provides architects and building designers with critical insights into the effectiveness of daylighting in a given space. By analyzing UDI values, they can identify areas with either inadequate or excessive daylight exposure and refine designs by adjusting window placement, orientation, glazing types, or sunshade strategies (Xu et al., 2022). This process ensures better daylight distribution, reduces dependency on artificial lighting, and enhances visual comfort for occupants (Cascone et al., 2018). Additionally, UDI serves as a key metric for evaluating energy efficiency and sustainability, helping designers create spaces that balance natural lighting and energy performance (Cascone et al., 2018; Xu et al., 2022). In this study, daylight simulations were performed using Honeybee Radiance to accurately evaluate UDI under various sunshade configurations, ensuring that the results reflect realistic daylight behavior and inform evidence-based design decisions (Nabil & Mardaljevic, 2006).

Optimizing UDI is critical for achieving energy efficiency, sustainability, and occupant comfort. A well-designed daylighting strategy reduces reliance on artificial lighting, leading to lower energy consumption and operational costs, while also minimizing the building's carbon footprint (Cascone et al., 2018). Furthermore, maintaining optimal daylight levels contributes to the well-being and productivity of occupants by creating visually comfortable environments (Cascone et al., 2018; Xu et al., 2022). This is especially important in settings such as schools, offices, and healthcare facilities, where lighting quality has a direct impact on performance, satisfaction, and functionality (Xu et al., 2022).

In office settings, UDI optimization holds particular importance due to its significant impact on productivity, comfort, and overall work experience. Insufficient daylight can lead to eye strain and fatigue, while excessive light may cause glare and discomfort. By achieving optimal UDI levels, offices can create well-lit environments that promote focus, reduce energy usage, and enhance the overall quality of the workspace (Mashaly et al., 2021).

Sunshades are essential in office buildings to optimize UDI by regulating natural light levels, reducing glare, and preventing overheating while ensuring sufficient illumination for tasks. They balance daylight's benefits with its challenges, such as thermal discomfort and excessive brightness, by filtering and diffusing sunlight to create a consistent and comfortable indoor environment. By reducing the need for artificial lighting and lowering cooling demands, sunshades enhance energy efficiency and sustainability while supporting cost-effective operations. Thoughtfully designed, they align aesthetics with functionality, fostering well-being and productivity in high-performance office spaces (Yi, 2019).

2.3.4 Minimizing View Obstruction Through Sunshade Design

Sunshades must not only reduce heat gain and glare but also preserve occupants' outward views for psychological well-being, productivity, and overall satisfaction (Aries et al., 2015). Numerous studies have highlighted how a clear visual connection to the outdoors, as encompassed by biophilic design principles, can alleviate stress and enhance cognitive function (Kellert, 2011). Consequently, avoiding excessive window coverage while still controlling solar exposure remains a key challenge in high-performance facade design (Wienold & Christoffersen, 2006).

View obstruction is typically quantified by measuring the ratio of window area physically covered or perceived as blocked by sunshade elements (Fung & Lee, 2012). Strategies to mitigate obstruction include optimizing louver spacing and orientation to permit outward visibility, curving or contouring fins to shield critical sun angles but maintain peripheral views (Datta & Chaudhri, 1964). While such measures help retain visual openness, they can clash with goals like limiting heat gain or glare, necessitating a deliberate balance between sunshade effectiveness and transparency (Tzempelikos & Shen, 2013).

Achieving this balance often requires MOO to evaluate trade-offs among occupant comfort, daylight distribution, energy consumption, cost, and outside views. MOEAs can address these conflicting metrics by identifying Pareto-optimal solutions that guide designers toward feasible compromises (Mashaly et al., 2021; Turrin et al., 2011). Such approaches may ensure that building facades deliver both energy-efficient sunshade and a visual connection to the outdoors—key considerations in occupant-centric, sustainable architecture (Dabaj et al., 2022).

2.3.5 Cost Efficiency in Sunshade design

Cost efficiency is a critical measure in building envelope design, defined as the ability to achieve desired outcomes—such as improved thermal comfort, energy efficiency, and environmental sustainability—while minimizing LCC (Naji et al., 2021; Zong et al., 2022). Specifically, it involves reducing both initial construction expenses and long-term operational costs associated with components like wall insulation, glazing, and sunshade systems, all while maintaining Indoor Environmental Quality (IEQ) within acceptable standards (Naji et al., 2021). This balance ensures that financial resources are allocated effectively without compromising the performance and sustainability of the building façade (Zong et al., 2022).

When cost efficiency is calculated, it identifies the most economical configurations of building envelope components that achieve energy savings, indoor comfort, and long-term sustainability without incurring excessive costs (Elsheikh et al., 2023; Zong et al., 2022). This process often involves generating a Pareto front set of solutions through many-objective optimization techniques, such as dynamic energy simulations, genetic algorithms, and many-objective stochastic optimization (MOSO) combined with decision-making frameworks like TOPSIS (Zong et al., 2022). By evaluating the net present value of all costs over a building's lifespan, these calculations provide actionable insights into high-performing, cost-effective design alternatives tailored to specific climate zones (Elsheikh et al., 2023; Naji et al., 2021). For instance, in diverse climate conditions like Egypt, optimizing cost efficiency leads to significant energy savings, improved indoor comfort, and reduced financial burdens, making sustainable design more accessible and practical (Elsheikh et al., 2023).

Optimizing cost efficiency is paramount as it facilitates the development of sustainable and financially viable building designs that meet both environmental goals and occupant comfort standards (Naji et al., 2021; Zong et al., 2022). This optimization ensures effective resource allocation, enhances the feasibility and scalability of sustainable building practices across various climate zones, and supports compliance with energy and environmental regulations (Elsheikh et al., 2023; Zong et al., 2022). Additionally, it fosters innovation by encouraging the exploration of high-performance, low-cost sunshade solutions, and other envelope components, thereby promoting robust and adaptable design solutions that can handle uncertainties in design parameters and external factors (Zong et al., 2022). In regions with resource constraints and high energy demands, such as the Mediterranean and Egypt, optimizing cost efficiency is essential for reducing LCC while maintaining high energy performance and occupant comfort, ultimately supporting the transition to sustainable construction practices on a larger scale (Elsheikh et al., 2023; Naji et al., 2021)

Minimizing the cost of sunshade systems is crucial for the nZEB, especially in cost-sensitive projects (Wu et al., 2016). Sunshade systems are essential for managing daylight distribution and controlling solar heat gain, which significantly enhances the energy performance of building envelopes by reducing cooling loads during summer and maintaining heat retention in winter. This improvement in energy efficiency not only ensures occupant comfort but also supports economic feasibility by preventing over-engineering and the use of expensive materials that could hinder the scalability and accessibility of nZEB principles (Ciardiello et al., 2020; Wu et al., 2016). By optimizing the cost of sunshade systems, designers can incorporate effective solutions without imposing excessive financial burdens, making energy-efficient building practices more accessible and economically viable (Chatzikonstantinou et al., 2015).

Furthermore, cost minimization is integral to MOO processes that balance the expenses of sunshade systems with their contributions to daylighting performance, structural stability, and environmental impacts (Chatzikonstantinou et al., 2015; Ciardiello et al., 2020). Techniques such as dynamic energy simulations and Genetic Algorithms (GAs) enable designers to identify sunshade configurations that are both effective in reducing energy demands and cost-efficient over the building's life cycle (Ciardiello et al., 2020). This approach not only supports budget compliance and resource efficiency but also fosters innovation by encouraging the exploration of high-performance, low-cost sunshade solutions (Chatzikonstantinou et al., 2015). In climates like the Mediterranean, where solar heat gain is a critical factor, cost-effective sunshade strategies are particularly important for optimizing building energy performance (Wu et al., 2016). Ultimately, these cost-effective sunshade systems enhance the feasibility and scalability of energy-efficient office buildings, promoting the transition to broader sustainable construction practices and making advanced sustainable practices more accessible on a larger scale (Wu et al., 2016)

2.4 Optimization Techniques

This section provides an overview of the optimization techniques employed in sunshade design. Section 2.4.1 discusses EAs in Optimization, highlighting their ability to handle complex, multi-variable design spaces. Section 2.4.2 explores MOO methods, emphasizing the balance between conflicting objectives such as energy efficiency and occupant comfort. Section 2.4.3 delves into MOEAs, detailing their role in identifying Pareto-optimal solutions for sunshade design. Section 2.4.4 examines the NSGA-II, focusing on its effectiveness in solving many-objective optimization problems within architectural contexts. Section 2.4.5 evaluates the many-objective MO-CMA-ES, highlighting its adaptability and efficiency in complex optimization scenarios. Finally, Section 2.4.6 reviews other contemporary approaches in sunshade optimization, including machine learning techniques and hybrid methodologies.

2.4.1 Evolutionary Algorithms in Optimization

EAs are computational optimization techniques inspired by the biological principles of natural selection, reproduction, and mutation (Turrin et al., 2011). They operate on a population of candidate solutions, iteratively refining them based on a user-defined fitness function until a near-optimal or optimal solution is found (Machairas et al., 2014). This population-based, stochastic search makes EAs particularly suitable for architectural and building performance applications, where numerous design variables—such as façade geometry, insulation materials, or sunshade systems—must be simultaneously evaluated. Furthermore, EAs do not require gradient or derivative information, which is advantageous for complex simulation models integrating energy, daylighting, and structural analyses.

Among EAs, GAs are among the most frequently adopted methods in architecture. They have demonstrated high effectiveness in addressing multiple conflicting objectives—e.g., minimizing energy consumption, maximizing daylighting, and ensuring occupant comfort—especially when large, non-linear design spaces are involved. For instance, (Narangerel et al., 2017) employed an EAs–based MOO of a 3D faceted façade in office buildings. The study's objectives were to minimize thermal load, maximize daylight penetration, and increase on-site photovoltaic electricity generation. To achieve these goals, the researchers integrated several parametric design tools—namely, Grasshopper (Sadeghipour Roudsari et al., 2013), Ladybug (Goharian et al., 2022), Honeybee (Goharian et al., 2022), Radiance (Nabil & Mardaljevic, 2006), and EnergyPlus (Crawley et al., 2001)—with their optimization workflow. The GAs-driven approach subsequently uncovered façade configurations that not only reduced energy loads but also enhanced photovoltaic output (Sadeghipour Roudsari et al., 2013). Similarly, (Chang et al., 2020) leveraged EAs for building envelope retrofits under uncertain conditions, coupling the algorithm with Bayesian modeling and IoT data to identify cost-effective yet low-emission retrofit packages. In Paper Albatayneh, 2021, EAs were used to optimize window-to-wall ratio, glazing type, sunshade devices, and insulation in a cool Saharan Mediterranean climate, achieving an 88% reduction in total energy consumption and highlighting how EAs-based methods can navigate trade-offs among energy costs, occupant comfort, and environmental impact.

many-objective formulations often call for specialized EAs like the Strength Pareto Evolutionary Algorithm 2 (SPEA-2). SPEA-2 introduces an external archive of non-dominated solutions (i.e., the Pareto front) and a strength-based fitness assignment to encourage a balanced exploration of competing objectives (Zitzler et al., 2001). (Wu & Zhang, 2022), for example, implemented SPEA-2 to optimize sunshade depth, window-to-wall ratio, and solar heat gain coefficient for reduced Energy Use Intensity (EUI), improved UDI, and minimized TDP. Deeper louvers proved beneficial for cooling and glare control but revealed trade-offs in winter solar gains, demonstrating SPEA-2's capacity to uncover nuanced design compromises. Likewise, (Wu & Zhang, 2022) used SPEA-2 to optimize transparent envelope parameters in rural Chinese residences, revealing that increasing south-facing window sizes boosted daylighting but demanded carefully balanced heating and cooling measures. The resulting Pareto-optimal solutions cut heating and cooling loads by 23% and simultaneously improved daylight metrics, underscoring the effectiveness of SPEA-2 in resolving many-objective building design problems.

In summary, EAs—encompassing both standard GAs and advanced variants like SPEA-2—offer a powerful toolkit for architectural design and building performance optimization. By exploiting the parallel and adaptive nature of these algorithms, researchers and practitioners can systematically explore vast parametric spaces, illuminate trade-offs among conflicting objectives, and ultimately develop innovative, high-performing building solutions.

2.4.2 Many-objective Optimization

MOO is an approach to finding solutions that simultaneously satisfy multiple, often conflicting objectives (Deb, 2001). Unlike single-objective optimization, which seeks a unique best solution, MOO attempts to find a set of "Pareto-optimal" solutions where improving performance in one objective may compromise another (Coello Coello, 2000) For example, reducing a building's energy consumption could negatively affect occupant comfort or increase construction costs. By considering these trade-offs collectively rather than in isolation, MOO techniques support more holistic and balanced decision-making across diverse domains, including engineering, economics, and architectural design (Zitzler et al., 2001).

Unlike single-objective methods that produce a solitary "best" solution, MOO identifies a Pareto frontier—a suite of equally optimal solutions offering different balances among competing objectives (Deb, 2001). Each point on this frontier represents a unique trade-off: improving performance for one objective (e.g., lowering cooling energy) may necessitate sacrificing another (e.g., daylight levels or views). In the context of sunshade design, MOO solutions might include varying louver geometries that reduce glare yet maintain acceptable daylight, or sunshade configurations that curb cooling loads without excessively blocking passive winter solar gains (Tzempelikos & Athienitis, 2007; Wu & Zhang, 2022). Additionally, some Pareto-optimal solutions may feature integrated photovoltaics for on-site power generation, balancing both energy reduction and energy production (Ascione et al., 2015). By presenting multiple high-quality design options, MOO empowers architects, engineers, and stakeholders to choose the most appropriate configuration based on project-specific priorities—be they environmental impact, occupant comfort, or cost constraints.

Architectural design frequently involves a complex interplay of aesthetics, functionality, energy efficiency, and occupant well-being. Since different performance goals can conflict with each other—e.g., maximizing daylight while minimizing cooling loads—a many-objective perspective is essential for achieving a balanced outcome (Evins, 2013; Machairas et al., 2014; Turrin et al., 2011). By applying MOO methods to parametric building models, architects and engineers can systematically explore vast design spaces to uncover solutions that represent the best possible trade-offs among various objectives, such as reducing energy use, enhancing indoor environmental quality, and lowering life-cycle costs (Asadi et al., 2012).

Sunshade systems are critical for regulating solar heat gains, controlling glare, and ensuring visual comfort in buildings, yet these factors often conflict with objectives like maximizing daylight or capturing beneficial solar radiation in colder seasons. many-objective optimization provides a framework for balancing these competing requirements, enabling designers to compare sunshade device configurations that reduce cooling loads while maintaining or improving daylight availability and occupant comfort (Evola et al., 2017; Wu & Zhang, 2022). Through MOO, designers can fine-tune parameters such as louver depth, spacing, orientation, and material properties to develop sunshade strategies that minimize energy consumption, enhance indoor environmental quality, and potentially even integrate photovoltaic systems for on-site electricity generation (Ascione et al., 2015).

2.4.3 Many-objective Evolutionary Algorithm

MOEAs extend traditional EAs to handle optimization problems with multiple conflicting objectives. In the case of sunshade systems, these objectives often include minimizing energy consumption (heating, cooling, and lighting), optimizing thermal comfort (maintaining indoor temperatures within acceptable limits), and maximizing daylight availability without causing glare. MOEAs aim to provide a set of optimal trade-off solutions known as the Pareto front, where no solution is strictly better than another with respect to all objectives (Deb et al., 2002).

Sunshade plays a crucial role in passive solar design strategies by modulating solar radiation. However, finding optimal sunshade configurations is challenging due to the nonlinear and dynamic interactions between energy, comfort, and daylighting metrics. By applying MOEAs, designers can efficiently explore a wide range of sunshade configurations and identify solutions that balance these competing objectives. Several studies have demonstrated the efficacy of MOEAs in optimizing sun sunshade systems, often achieving energy savings while simultaneously improving indoor environmental quality (Attia et al., 2013; Machairas et al., 2014).

The primary advantage of evolutionary algorithms, particularly MOEAs, is their ability to handle multiple conflicting objectives simultaneously. For sunshade design, this means finding a balance between reducing energy consumption, improving occupant comfort, and increasing natural daylight. Unlike traditional optimization methods that focus on a single objective or combine multiple objectives into a single weighted function, MOEAs maintain a diverse population of solutions that reflect different trade-offs, offering flexibility in the decision-making process (Machairas et al., 2014)

Exploring diverse sunshade configurations efficiently, EAs are particularly well-suited for exploring large and complex solution spaces, which are common in sunshade design due to the wide range of possible configurations (e.g. various geometries). Their population-based search enables them to explore diverse design solutions, ensuring that the algorithm does not converge prematurely to suboptimal designs. This diversity in exploration makes it possible to discover novel sunshade solutions that might not be considered using conventional optimization approaches (Evins, 2013; Tuhus-Dubrow & Krarti, 2010; Wright & Mourshed, 2009)

2.4.4 Non-dominated Sorting Genetic Algorithm II

The NSGA-II is an evolutionary algorithm designed specifically for solving many-objective optimization problems (Deb et al., 2002). It improves upon its predecessor, Non-dominated Sorting Genetic Algorithm (NSGA), by addressing three key shortcomings: high computational complexity, the absence of elitism, and reliance on a user-defined sharing parameter for maintaining diversity among solutions (Deb, 2001). NSGA-II incorporates advanced mechanisms for nondominated sorting, diversity preservation, and elitism, making it more efficient and effective in solving complex many-objective optimization problems.

NSGA-II significantly reduces computational complexity from $\mathcal{O}(MN^3)$ to $\mathcal{O}(MN^2)$ by employing a more efficient non-dominated sorting method, making it scalable for large problems. Further, it incorporates an elitism mechanism by combining parent and offspring populations and selecting the best solutions based on non-domination rank and a crowding distance measure. This ensures that high-quality solutions are preserved across generations. In addition to that, NSGA-II eliminates the need for a user-defined diversity-maintaining parameter by introducing a crowding distance-based selection, which estimates solution density to maintain a well-distributed Pareto front. These features enable NSGA-II to converge closely to the true Pareto-optimal front while achieving a diverse spread of solutions, outperforming other algorithms like Strength Pareto Evolutionary Algorithm (SPEA) and Pareto Archived Evolution Strategy (PAES) in both convergence and diversity on benchmark problems (Wang et al., 2023b).

The paper Shan and Junghans, 2023 highlights the so many applications of the NSGA-II in optimizing building façade design parameters, including windows, sunshade systems, walls, glazing, and air tightness. Its primary focus is on addressing many-objective Building Façade Optimization (BFO) challenges. From the reviewed studies, spanning

2015 to 2025, NSGA-II has been used a lot, making it the most widely adopted heuristic algorithm for this purpose. Studies have shown its use in diverse scenarios, including optimizing energy efficiency, daylighting, thermal comfort, and environmental impact. NSGA-II's popularity stems from its ability to handle complex, MOO problems effectively and produce Pareto-optimal solutions with high diversity, which is essential in architectural design where aesthetic and functional considerations often conflict.

2.4.5 Many-objective Covariance Matrix Adaptation Evolution Strategy

The MO-CMA-ES is an extension of the CMA-ES, tailored to address many-objective optimization problems. CMA-ES, originally developed by (Hansen, 2016), is renowned for its robust performance in continuous single-objective optimization by adapting the covariance matrix of the search distribution to navigate complex fitness landscapes effectively. MO-CMA-ES extends this framework to handle multiple conflicting objectives simultaneously, aiming to approximate the Pareto front—a set of non-dominated solutions representing optimal trade-offs between objectives (Igel et al., 2007). This adaptation involves mechanisms to maintain diversity among solutions and balance the exploration and exploitation processes across different objectives, ensuring a comprehensive search of the solution space.

MO-CMA-ES is employed in optimization problems due to its ability to efficiently explore and exploit complex, multi-dimensional search spaces while simultaneously optimizing multiple conflicting objectives. Traditional optimization algorithms often struggle with maintaining diversity among solutions and converging towards the Pareto front, especially in high-dimensional spaces with intricate dependencies between variables. MO-CMA-ES addresses these challenges by dynamically adapting the covariance matrix, which captures the dependencies between variables, thereby enhancing the search process's adaptability and efficiency (Hansen, 2016). Additionally, its evolutionary strategy framework allows for robust performance in noisy or dynamic environments, making it suitable for a wide range of real-world applications where multiple objectives must be balanced. The algorithm's inherent parallelism and scalability further contribute to its effectiveness in tackling large-scale optimization problems, where computational resources and time are critical considerations (Ascia et al., 2011).

MO-CMA-ES has been successfully applied to various optimization domains beyond its initial development, demonstrating its versatility and robustness. In engineering design optimization, for instance, it has been utilized to simultaneously minimize weight and maximize structural integrity in aerospace component design, effectively navigating the trade-offs between different performance criteria (Marescaux, 2022). In machine learning, MO-CMA-ES has been employed to optimize hyperparameters of complex models, balancing objectives such as accuracy, computational cost, and model complexity to achieve optimal performance (Rodrigues et al., 2014). Additionally, it has been applied in the field of robotics for many-objective trajectory planning, where it optimizes for criteria like energy efficiency, time, and safety simultaneously (Ascia et al., 2011). These applications underscore MO-CMA-ES's capacity to handle diverse and complex optimization challenges, making it a valuable tool in both academic research and practical engineering solutions.

2.4.6 Other approaches in Sunshade optimization

Machine learning (ML) approaches have been increasingly applied in recent years to optimize building Façade systems. These models have shown potential in predicting sunshade performance by analyzing complex, non-linear relationships between design variables and outcomes like energy savings, daylight availability, and thermal comfort.

In façade design, ML techniques such as Artificial Neural Networks (ANNs) are used to predict performance metrics (e.g., energy efficiency and thermal comfort), accelerate optimization, and balance conflicting variables like material properties and occupant comfort. ML techniques, such as ANNs, are utilized to predict daylight performance and optimize sunshade parameters, including slat dimensions, rotation angles, and extensions, to improve daylight autonomy and reduce glare. Particularly in Sunshade design, ML-driven approaches optimize sunshade parameters, such as slat dimensions and rotation angles, to enhance daylight autonomy and reduce glare. Deep Reinforcement Learning (DRL) is also applied to develop dynamic sunshade systems that adapt in real-time to environmental changes, simultaneously optimizing daylight and heat gain for improved energy efficiency and occupant comfort(Bianchi et al., 2024).

Another ML technique used for sunshade design is Random Forests. This method has been noted for its robustness to over-fitting and its ability to handle both categorical and continuous input data, making it suitable for evaluating the impact of sunshade on multiple performance indicators (Tian et al., 2020).

One of the commonly used models is ANNs and they are effective in capturing non-linearities in the system and can be used for real-time decision-making once trained. One of the studies shows ANNs to predict energy savings from sunshade devices in different climatic regions, achieving significant accuracy compared to traditional simulation tools (Tuhus-Dubrow & Krarti, 2010).

Support Vector Machines (SVMs) have also been used in sunshade performance prediction, particularly for classification tasks, such as determining whether a particular sunshade design will meet certain energy efficiency or daylighting criteria. By mapping input variables to a higher-dimensional space, SVMs create decision boundaries that can effectively separate high-performing sunshade designs from low-performing ones (Wang et al., 2019).

Limitations of Traditional ML in many-objective sunshade design despite the successes of machine learning ML in predicting sunshade performance. Traditional ML models face significant limitations when applied to many-objective sunshade design. One of the primary challenges is their difficulty in handling multiple, often conflicting objectives simultaneously, such as minimizing energy consumption while maximizing daylight quality. Most ML models are designed for single-objective optimization and lack the capability to provide a set of trade-off solutions that balance multiple objectives effectively.

Another limitation is the lack of adaptability in real-time decision-making for dynamic environmental conditions. Sunshade systems often need to respond to changes in sunlight, temperature, and user preferences, which traditional ML models are not designed to handle efficiently.

2.5 Identification of Research Gap

Sunshades play an important role in shaping the environmental performance, occupant comfort, and visual quality of interior spaces, especially in offices where working conditions directly influence productivity and well-being (Kim & Clayton, 2020). The optimization of sunshades has progressed substantially—transitioning from manual heuristics to advanced many-objective algorithms— but shortcomings are present in current research (Li et al., 2024).

One of the most prominent limitations in sunshade research is the tendency to optimize only two or three objectives at once—such as daylight availability, energy consumption, or thermal comfort—while omitting other important factors such as cost, occupant well-being, and the preservation of exterior views (Wu & Zhang, 2022). Ignoring any one of these dimensions can lead to suboptimal results; for instance, a solution might deliver exceptional daylight but compromise cost or user satisfaction. Over the last five years, only a handful of studies have been conducted that consider more than three objectives (Shan & Junghans, 2023). This limited scope fails to capture the multifaceted complexity of real-world projects and conflicting objectives.

Another research gap concerns the use of algorithms. While MOEAs have proven effective for building design problems, most studies rely on just the NSGA-II(Naji et al., 2021). NSGA-II performs well in balancing multiple criteria and producing a diverse set of Pareto-optimal solutions. However, the literature shows far less experimentation with other MOEAs, particularly MO-CMA-ES has not been used at all (Shan & Junghans, 2023). MO-CMA-ES, in its many-objective form, is well-regarded for self-adaptation and effective handling of complex problems (Igel et al., 2007). Yet, this algorithm has not been used in building façade or sunshade optimization. Hence, its ability to outperform or complement NSGA-II is not well understood.

Beyond the choice of a single algorithm, there is also little discussion on algorithmic comparisons in the face of different climatic conditions. Most existing studies present a single optimization approach and test it on a single site or climate. What remains unexplored is how distinct algorithms might cope differently across multiple, vastly dissimilar weather contexts. A method that excels in a tropical climate, for instance, might not perform as effectively in a cold, northern environment, and vice versa.

Furthermore, the limited focus on a single location or climatic zone is another gap in overall building design (Abdou et al., 2021; Belhous et al., 2021; Elsheikh et al., 2023;

Semahi et al., 2021; Wu & Zhang, 2022; Zhao & Du, 2020). Sunshade performance is highly sensitive to local weather patterns, solar angles, and humidity levels, yet the existing research analyzes just one region. This overlooks the diversity of conditions in which office buildings must operate worldwide. In contrast, this thesis study examines four distinct climates across four different cities—Cape Town in South Africa, Colombo in Sri Lanka, Nairobi in Kenya, and Oslo in Norway. These locations were strategically chosen to represent a broad climatic range, from hot and humid to cold and temperate environments. By spanning different hemispheres and latitudes, the research captures different sun angles, seasonal fluctuations, and humidity levels. This diversity offers a more rigorous basis for understanding whether a particular optimization algorithm excels universally or only under certain environmental parameters.

Finally, very few optimization initiatives in the last five years have targeted office buildings specifically (Shan & Junghans, 2023). Most recent published work focuses on residential, tourism, educational, or mixed-use structures, each of which has distinct internal load patterns and occupant behaviors (Wang et al., 2023a). Offices, in particular, have high internal heat gains from electronic equipment and lighting, as well as consistent occupancy schedules (Mashaly et al., 2021). These characteristics differentiate offices from residential or institutional buildings, influencing how sunshades should be sized or oriented. Yet, in the past five years, research dedicated to office sunshades has been notably less, with fewer than two studies addressing sunshade optimization. Furthermore, these studies do not exclusively concentrate on sunshade design. Rather, most research simultaneously considers additional design parameters, like- Walls, Air-tightness, Glazing, and Windows altogether including sunshades (Chen et al., 2018; Nazari et al., 2023).

Chapter 3

Methodology

This chapter outlines the systematic approach to optimizing sunshade designs by integrating parametric modeling, simulation-based objective evaluation, and many-objective evolutionary algorithms. The chapter is organized into four main sections, each summarized as follows:

1. Section 3.1 describes the creation of a parametric digital office model with adjustable sunshade fins using the Honeybee toolset.
2. Section 3.2 details the simulation framework that evaluates thermal comfort, energy consumption, daylight performance (UDI), view obstruction, and cost.
3. Section 3.3 explains the implementation of two MOEAs, NSGA-II and MO-CMA-ES, to optimize the shading configurations.
4. Section 3.4 summarizes the overall workflow and key outcomes of the methodology.

3.1 Model Creation and Setup

This section outlines the process of creating and setting up the sunshade model. Section 3.1.1 details the Baseline Office Geometry, defining the fundamental spatial parameters. Section 3.1.2 describes the Digital Modeling in Honeybee, focusing on the integration of simulation tools. Section 3.1.3 discusses the Materials and Constructions, specifying the material properties and construction details used in the model.

3.1.1 Baseline Office Geometry

The initial phase involves defining a simplified yet representative office space. The selected room dimensions are 3 meters in width, 4 meters in height, and 3 meters in length, striking a balance between computational efficiency and relevance to typical small to medium-sized office environments. The front facade, which houses the primary window, features a single rectangular glazing aperture measuring 1.3 meters in width, 1.7 meters in height, and 0.2 meters in depth, centrally positioned on the north wall. Sunshades are critical for regulating solar gain, glare, and daylight in buildings, thereby reducing energy consumption and aligning with ASHRAE guidelines (Edition et al., 2010).

To facilitate parametric variations of shading elements, the front facade is enhanced with fin structures. These fins are designed to allow systematic manipulation of their configurations—such as the number of fins, fin angles, depth, offset, and contour angle—during simulation runs. This parameterization is critical for exploring a wide array of design possibilities and identifying optimal shading solutions.

3.1.2 Digital Modeling in Honeybee

Digital modeling is executed using the Honeybee libraries, which define building surfaces including walls, floors, ceilings, and glazed elements. The parametric nature of the model ensures consistent geometric modifications without the need for manual remodeling when adjusting shading fins or other design elements.

Honeybee Core (Waibel et al., 2021) manages the geometric and semantic relationships between building components, ensuring that all elements interact correctly within the model. Honeybee Radiance (Nabil & Mardaljevic, 2006) integrates radiance objects such as light sensors into the model and interfaces with the Radiance engine to evaluate daylighting metrics, specifically UDI. Meanwhile, Honeybee Energy incorporates energy-consuming objects like air conditioning systems and connects with EnergyPlus (Crawley et al., 2001) to perform thermal and energy simulations. By leveraging these libraries, boundary conditions (indoor and outdoor environments), material properties, operational schedules, and additional systems (e.g., air conditioning) are precisely defined and integrated into the model.

3.1.3 Materials and Constructions

Each building component—walls, windows, and shading devices—is assigned specific material constructions to accurately reflect their thermal and visual properties. Interior walls include an insulation layer appropriate for typical office applications, while exterior walls are assigned a moderate thermal resistance value to mirror average construction standards. The window features a double-glazed system to balance indoor comfort and daylight penetration. The fins are constructed from lightweight materials, such as metal or composites, which minimally impact the overall thermal resistance of the building envelope but play a crucial role in controlling solar gains and daylight distribution. For optimization purposes, each construction is parameterized to represent common practices in office building design, allowing for realistic yet flexible adjustments during the optimization process.

3.2 Simulation Framework and Objective Calculations

This section outlines the simulation framework and the methodologies used to calculate key performance objectives for sunshade design. Section 3.2.1 discusses the assessment of thermal comfort and energy consumption using EnergyPlus simulations. Section 3.2.2 explains the process of energy calculations, focusing on HVAC energy usage. Section 3.2.3 details the daylighting analysis utilizing UDI metrics. Section 3.2.4 covers the outside view calculations, evaluating view obstruction caused by shading fins. Section 3.2.5 examines the cost assessment, analyzing the economic aspects of different sunshade configurations. Finally, Section 3.2.6 describes the implementation of objectives, integrating simulation results into the optimization workflow.

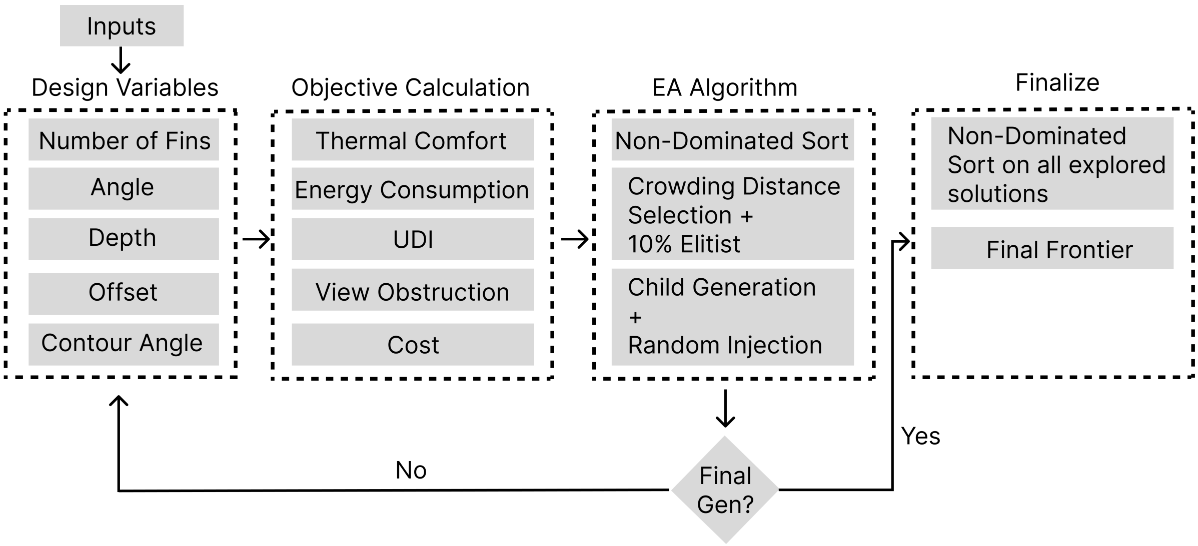

Figure 3.1: This figure depicts the overall workflow for sunshade optimization. On the left, design variables (number of fins, angle, depth, offset, contour angle) are defined. These feed into objective calculations for thermal comfort, energy consumption, daylight (UDI), view obstruction, and cost. Next, MOEAs applies non-dominated sorting, crowding distance selection, and elitist strategies to evolve improved solutions. Finally, a global non-dominated sort identifies the Pareto frontier of optimal designs, with a feedback loop enabling iterative refinement of the sunshade parameters.

3.2.1 Thermal Comfort Calculation

To assess thermal comfort and energy consumption, Honeybee Energy interfaces with the EnergyPlus engine. This integration utilizes EnergyPlus Weather (EPW) files for four distinct locations: South Africa: Cape Town, Sri Lanka: Colombo, Kenya: Nairobi, and Norway: Oslo (Sadeghipour Roudsari et al., 2013). These files ensure that local climatic conditions—such as solar radiation, ambient temperature, humidity, and wind speed—are accurately represented in the simulations. Typical office occupancy profiles, including operating hours (e.g., 9:00 to 17:00), lighting usage patterns, and air conditioning schedules, are modeled to reflect realistic usage scenarios. An AC system is incorporated to maintain occupant comfort, directly influencing energy consumption metrics.

Thermal comfort is evaluated through simulated indoor conditions, including air temperature, mean radiant temperature, relative humidity, and air speed. Metrics Predicted Mean Vote (PMV), Predicted Percentage Dissatisfied (PPD), and operative temperature are utilized to quantify comfort levels. The objective is to maximize thermal comfort, represented by minimizing discomfort hours or maximizing the percentage of hours within a defined comfort band.

3.2.2 Energy Calculations

Energy consumption is determined through the following process: the building model, including shading geometry, material definitions, and operational schedules, is processed by EnergyPlus. The energy usage of the air conditioning system for cooling (and heating, if applicable) is extracted and expressed in kilowatt-hours per year (kWh/year). Shading fins play a significant role in reducing solar heat gain during warm seasons, thereby lowering cooling demands. When strategically designed, these fins can also reflect sunlight into the building during colder months, enhancing passive heating and reducing the need for additional heating. The primary objective is to minimize the total HVAC energy use over the year.

3.2.3 Daylighting Analysis (UDI)

Daylighting performance is evaluated using Radiance through Honeybee Radiance. This process involves placing daylight sensors at 1-meter intervals at desk height to measure daylight distribution across the workspace. Radiance calculates illuminance levels under various sky conditions (e.g., clear, cloudy, intermediate) using local climate data. The fraction of time each sensor's illuminance falls within the 100–2,000 lux range is calculated to produce a UDI score, with the goal of maximizing UDI to ensure sufficient natural light without causing glare or under-lighting.

3.2.4 View Calculations

View obstruction is assessed by measuring the portion of the window obscured by the shading fins. This involves quantifying the projected area of shading devices on the glazing from an occupant's viewpoint to determine the obstructed area. The objective is to minimize the obstructed area to maximize outward visibility while maintaining the shading system's functional benefits.

3.2.5 Cost Assessment

Cost efficiency is analyzed based on shading device specifications. The total volume of fins—determined by parameters such as number and depth—is directly proportional to the overall cost. The aim is to minimize cost while ensuring effective shading performance, balancing initial construction expenses with long-term operational savings through energy reductions. Sunshades contribute to cost savings by lowering energy bills through reduced cooling demands and minimizing maintenance needs, aligning with sustainable and cost-effective building practices.

3.2.6 Implementation of Objectives

Algorithm 1 Model Creation and Objective Computation (Condensed)

Create Honeybee Model:
    Define room dimensions and corner points.
    Build *Floor, Ceiling, Walls* with FACE3D geometry.
    Create an *Aperture* (window) and add sunshade fins
    Assign materials, constructions, AC, and schedules to the model.
Run Energy Simulation:
    Serialize model to IDF (EnergyPlus).
    Invoke the EnergyPlus run with the specified weather file.
    Collect EUI, thermal comfort results.
Compute Daylight Metric (UDI):
    Create a *SensorGrid* above the floor.
    Generate and run *Radiance/Annual Daylight* simulation.
    Parse simulation output for UDI and compute average or normalized metric.
Calculate Additional Objectives (Cost, Obstruction):
    Cost = weighted sum of fin count, angle, depth, etc.
    Obstruction = approximate shaded area ratio on the window.
Return All Objective Values (UDI, Thermal Comfort, Cost, Obstruction, EUI).

Algorithm 1 presents the workflow for developing a mode, conducting energy and daylight simulations, and evaluating various performance metrics essential for optimizing sunshade design. The process begins with the creation of a Honeybee model, a tool widely used for energy and daylight analysis in architectural design. This initial step involves defining the room's dimensions and specifying the coordinates of its corner points to establish the basic geometry. Once the room's shape is established, the algorithm proceeds to construct the primary structural elements—Floor, Ceiling, and Walls—using the Face3D geometry, ensuring accurate three-dimensional representations of these components.

To incorporate natural light into the model, an aperture, such as a window, is created.

This aperture is enhanced with adjustable fins that allow for customization of their number, angle, and depth, enabling precise control over sunlight penetration, glare reduction, and thermal comfort. Once the structural setup is established, the algorithm assigns appropriate materials and constructions to various building elements, ensuring an accurate representation of their thermal and structural properties. Additionally, the model includes AC systems and operational schedules that define heating and cooling conditions, ensuring realistic behavior under different usage scenarios.

With the model fully defined, the next phase involves running an energy simulation to assess the building's energy performance. The model is serialized into an Input Data File (IDF) format, which is compatible with EnergyPlus, a leading energy simulation engine. The algorithm then invokes EnergyPlus, supplying it with a specified weather file that contains climatic data pertinent to the building's location. EnergyPlus conducts the simulation, analyzing factors such as heating and cooling loads, energy consumption, and thermal comfort levels within the space. Upon completion, key results are extracted, including the EUI, which measures energy consumption per unit area, and thermal comfort metrics that indicate how well the office room maintains comfortable temperature and humidity levels for occupants.

Beyond energy performance, the algorithm evaluates the building's daylighting effectiveness using the UDI metric. This involves creating a sensor grid positioned 0.8m above the floor level, which acts as a network of virtual sensors to monitor daylight levels throughout the space. A annual daylight simulation is then generated and executed using Radiance, a suite of tools designed for lighting simulation. This simulation models the interaction of natural light with the building's interior over an entire year. The output from the simulation is parsed to extract UDI values, which quantify the percentage of time that daylight levels remain within a range considered useful for occupants. The algorithm computes an average or normalized UDI metric, providing insights into the effectiveness of daylight distribution and its potential to reduce reliance on artificial lighting.

In addition to energy and daylight metrics, the algorithm calculates other objectives related to the sunshade design and functionality. Cost is assessed as a weighted sum of various factors, including the fin count, angle, depth, and other relevant parameters. This comprehensive cost evaluation ensures that design choices balance performance benefits with financial feasibility. Obstruction refers to the extent of shading or blockage caused by architectural elements like fins or external structures. The algorithm approximates the shaded area ratio on the window, offering a measure of how much natural view is obstructed by these elements. This metric is vital for understanding the impact of shading devices on obstruction of the outside view.

Finally, the algorithm compiles and returns all the calculated objective values, which include UDI, thermal comfort, cost, obstruction, and EUI. These metrics provide a holistic view of the sunshade's performance. By integrating geometric modeling, energy, cost, and daylight simulations, and the evaluation of various design objectives, this algorithm ensures that the resulting metrics are both accurate and actionable, thereby enhancing sunshade design and sustainability.

3.3 Implementation of MOEAs

This section explains the implementation of two prominent MOEAs used in our sunshade optimization research: NSGA-II and MO-CMA-ES. Section 3.3.1 details the implementation of the NSGA-II, outlining its procedural steps and functionalities. Section 3.3.2 discusses the implementation of the MO-CMA-ES, highlighting its adaptability and efficiency in handling complex optimization scenarios.

3.3.1 Implementation of NSGA-II

Algorithm 2 provides a structured approach to optimizing shading configurations using the NSGA-II. The process begins with the initialization phase, where key parameters such as population size (N), number of generations (G), and mutation rate (α) are defined. An initial population P_0 of size N is then generated with random discrete parameters representing various shading fin configurations and angles.

As the algorithm iterates through each generation from 0 to $G - 1$, it first evaluates the current population P_g. For every individual shading configuration within the population, the parameters are decoded to determine specific attributes like fin angles and counts. If the results for a particular configuration are not already cached, a simulation is executed to obtain the objective values, which include UDI, Thermal Comfort (TC), Cost, Obstruction (Obs), and Energy Use Intensity (Eng). These objective values are then cached to avoid redundant computations in future evaluations.

Following evaluation, the algorithm proceeds to the crossover and mutation phase to generate offspring. An empty offspring population O_g is initialized, and parents are selected randomly from the current population P_g. The crossover function combines the genetic information of two parents to produce offspring, which are then subjected to mutation with a probability of α. Each offspring is assigned a generation number and a unique identifier before being added to the offspring population. This process continues until the offspring population reaches the desired size N.

In the combine and select stage, the parent and offspring populations are merged into a combined population R_g. This combined population is evaluated, leveraging the cached objective values to streamline the process. A fast non-dominated sort is applied to rank the individuals based on their dominance across multiple objectives. Within each non-dominated front, a crowding distance metric is calculated to maintain diversity among the solutions. The next generation P_{g+1} is then selected from R_g by prioritizing individuals based on their rank and crowding distance, ensuring a balanced and diverse population for subsequent generations.

Algorithm 2 NSGA-II for many-objective Shading Optimization

Initialize:
  Population size N, number of generations G, mutation rate α.
  Create an initial population P_0 of size N by random discrete parameters.
  (Optional) Load any existing checkpoint if continuing a prior run.
for $g = 0 \to G - 1$ **do**
  Evaluate P_g:
  for each individual $x \in P_g$ **do**
    Decode parameters (sunshade fins, angles, etc.).
    If results not cached **then** run simulation to obtain objectives.
    Cache objective values $\big(\mathrm{UDI}, \mathrm{TC}, \mathrm{Cost}, \mathrm{Obs}, \mathrm{Eng}\big)$.
  end for
  Crossover and Mutation:
  Initialize empty offspring population O_g.
  while $|O_g| < N$ **do**
    Select two parents at random from P_g.
    Offspring $\leftarrow$ *advanced_crossover*(parent1, parent2).
    Mutate offspring with probability α.
    Assign offspring Gen $= g + 1$, unique ID.
    $O_g \leftarrow O_g \cup \{\text{offspring}\}$.
  end while
  Combine and Select:
  $R_g \leftarrow P_g \cup O_g$ (union of parents and offspring).
  Evaluate R_g (with caching).
  Sort R_g by non-dominated fronts (fast non-dominated sort).
  Apply *crowding distance* within each front.
  Select the next generation P_{g+1} of size N from R_g by rank and crowding distance.
  (Optional) Random Injection:
  Inject a few random individuals if desired, ensuring $|P_{g+1}| = N$.
  Save Checkpoint $(P_{g+1}, \text{cache}, g + 1)$.
end for
Final Sorting:
Perform non-dominated sort on the final population P_G to retrieve solution fronts.
Output: Final Pareto-optimal fronts of shading configurations.

In summary, this NSGA-II-based algorithm systematically evolves a population of shading configurations through selection, crossover, and mutation, while continuously evaluating and caching objective metrics. By leveraging non-dominated sorting and crowding distance, it effectively identifies a diverse set of Pareto-optimal solutions, facilitating informed decision-making in shading optimization for building design.

3.3.2 Implementation of MO-CMA-ES

The algorithm includes a random injection step, where a few random individuals are introduced into the population. This injection helps maintain genetic diversity and prevents premature convergence by introducing new genetic material into the population. After these steps, the current state of the population, along with the cache and generation number, is saved as a checkpoint, allowing the optimization process to be resumed if interrupted.

Once all generations have been processed, the algorithm performs a final sorting on the last population P_G to extract the final Pareto-optimal fronts. These fronts represent the set of non-dominated shading configurations that offer the best trade-offs among the multiple objectives considered. The output of the algorithm is the collection of these Pareto-optimal fronts, providing a range of optimal shading solutions that balance factors such as daylight availability, thermal comfort, cost, obstruction, and energy efficiency.

MO-CMA-ES (Algorithm 3) initiates by setting up the essential parameters for the optimization process. It defines a five-dimensional search space, which corresponds to key design variables of a sunshade such as fin count, angle, depth, offset, and contour angle. The algorithm specifies the population size (λ) and the parent size (μ), along with the maximum number of generations (G) to control the optimization duration. It initializes the mean vector ($\mathbf{m}$) to represent the current best estimate of the optimal solution and sets the covariance matrix (C) to the identity matrix to start with no prior assumptions about variable dependencies. The global step size (σ) governs the exploration scale, while the evolution paths ($\mathbf{p}_c$ and $\mathbf{p}_s$) are initialized to zero, serving to adapt the search direction and step size dynamically. Additionally, the algorithm maintains an evaluation cache to store previously assessed solutions, preventing redundant evaluations, and an archive to retain elite solutions that exemplify optimal trade-offs among objectives.

Algorithm 3 many-objective CMA-ES (MO-CMA-ES)

Initialize:
  Dimension $d = 5$, population size λ, parent size μ, maximum generations G.
  Mean vector $\mathbf{m}$, covariance matrix $C = I$, global step size σ, and evolution paths $\mathbf{p}_c, \mathbf{p}_s \leftarrow \mathbf{0}$.
  Set generation counter $g \leftarrow 0$ and initialize empty *evaluation cache* and *archive*.
while $g < G$ **do**
  Sample Offspring:
  for $i \leftarrow 1$ to λ **do**
    Draw $\mathbf{z}_i \sim \mathcal{N}(0, I)$, then $\mathbf{x}_i \leftarrow \mathbf{m} \; + \; \sigma \sqrt{C}\, \mathbf{z}_i$.
    Decode $\mathbf{x}_i$ into discrete shading parameters (e.g., fin count, angle, depth).
    Evaluate objectives and cache results to avoid duplicates.
  end for
  Merge new offspring with any archived *elite* solutions.
  Non-Dominated Sorting:
  Perform a fast non-dominated sort on all solutions.
  Assign crowding distances within each front.
  Selection:
  Select the top μ individuals based on rank and crowding distance.
  CMA-ES Update:
  Recompute weighted mean of the selected solutions in the $(\mathbf{z}_i)$-space.
  Update evolution paths $\mathbf{p}_c$, $\mathbf{p}_s$.
  Update $\mathbf{m}$, C, and σ via rank-μ CMA-ES formulas:

$$\mathbf{m}_{\text{new}} \leftarrow \mathbf{m} + \sigma \cdot (\sqrt{C}\, \bar{\mathbf{z}}), \quad C_{\text{new}} \leftarrow (1 - c_1 - c_\mu)\, C + \cdots, \quad \sigma_{\text{new}} \leftarrow \sigma \cdot \exp\Big(\tfrac{c_s}{d_{\text{amps}}}\left(\|\mathbf{p}_s\| - \text{const}\right)\Big).$$

  Archive Update: Keep a fraction of the top non-dominated solutions as *elites*.
  Checkpoint: Save the current state to resume if needed.
  $g \leftarrow g + 1$
end while
Output: Final non-dominated set (Pareto front) from all evaluated solutions.

The core of the MO-CMA-ES operates within a loop that iterates until the maximum number of generations (G) is reached. In each generation, the algorithm generates λ offspring by sampling from a multivariate normal distribution defined by the current mean vector and covariance matrix, scaled by the global step size. These continuous candidate solutions ($\mathbf{x}_i$) are then decoded into discrete shading parameters relevant to sunshade design, such as the number of fins, their angles, depths, etc. Each decoded solution is evaluated against multiple objectives—such as minimizing glare and maximizing shade coverage—and the results are cached to enhance computational efficiency.

After generating the offspring, the algorithm integrates them with any elite solutions stored in the archive to preserve high-quality designs and maintain diversity within the population. It then performs a non-dominated sort to categorize all solutions into Pareto fronts based on dominance relationships, ensuring that no solution in a higher front is dominated by those in lower fronts. Within each Pareto front, crowding distances are assigned to promote diversity by favoring solutions in less densely populated regions of the objective space. The top μ individuals are selected based on their Pareto rank and crowding distance, forming the parent population for the next generation.

Subsequently, the CMA-ES update mechanism recalculates the weighted mean of the selected parents in the transformed ($\mathbf{z}_i$)-space, updating the mean vector ($\mathbf{m}$) to guide the search towards more promising regions. The covariance matrix (C) is adapted to capture the distribution and dependencies of the selected solutions, while the global step size (σ) is adjusted based on the evolution path $\mathbf{p}_s$, balancing exploration and exploitation. These updates are governed by rank-μ CMA-ES formulas, ensuring efficient and adaptive search behavior.

To maintain the integrity of the optimization process, the algorithm updates the archive by retaining a fraction of the top non-dominated solutions as elites, safeguarding the best trade-offs discovered thus far. Upon reaching the maximum number of generations, the algorithm outputs the final set of non-dominated solutions, representing the Pareto front of optimal sunshade designs that balance the competing objectives effectively.

3.4 Summary

The chapter methodology provides a guideline for optimizing sunshade designs in office buildings. Figure 3.1 briefly illustrates the key highlights of the methodology. First, a parametric digital model was created in Honeybee (see Section 3.1). A baseline office with defined dimensions and a centrally located glazing aperture was enhanced with adjustable fin structures parameterized by number, angle, depth, offset, and contour angle. Leveraging Honeybee's Core, Radiance, and EnergyPlus libraries ensures seamless integration of building geometry, daylighting analyses, and thermal simulations.

Second, a simulation framework was established to evaluate multiple performance objectives (Section 3.2). Key metrics include thermal comfort and HVAC energy use (simulated via EnergyPlus) and daylighting performance (UDI via Radiance). Additionally, view obstruction and cost implications of varying fin configurations were quantified. Together, these metrics offer a holistic perspective on sunshade effectiveness, occupant well-being, and economic viability.

Third, two MOEAs—NSGA-II and MO-CMA-ES—were implemented to navigate the trade-offs among the multiple objectives (Section 3.3). NSGA-II utilizes non-dominated sorting and crowding distance to evolve a diverse set of solutions, while MO-CMA-ES adaptively updates its mean vector and covariance matrix to efficiently explore complex search spaces. Both algorithms incorporate caching to avoid duplicate simulations and produce Pareto-optimal fronts for informed decision-making.

By coupling parametric modeling, comprehensive performance simulations, and sophisticated optimization techniques, this methodology delivers robust insights into sunshade performance. The resulting workflow highlights optimal fin configurations that balance occupant comfort, energy efficiency, cost considerations, and outdoor visibility, ultimately guiding the design of sustainable and adaptable building envelopes across diverse climatic contexts.

Chapter 4

Experiment Setup

This chapter outlines the experimental process used to compare traditional sunshade configurations with designs obtained through multi-objective evolutionary algorithms. The complete code for this work is available at the following GitHub repository: https://github.com/farzana-haque-toma/MSc_Thesis_codes

This chapter is organized into four main sections, each summarized as follows:

1. Section 4.1 describes the simulation framework including room geometry, climatic variations, and material properties for a consistent testing environment.
2. Section 4.2 details the configuration and operation of two multi-objective evolutionary algorithms (NSGA-II and MO-CMA-ES) used to evolve sunshade designs.
3. Section 4.3 outlines the performance metrics and statistical methods employed to compare the traditional and evolved sunshades.
4. Section 4.4 recaps the experimental framework and sets the stage for the presentation and discussion of the simulation results in subsequent chapters.

4.1 Traditional Sunshade as Baselines

Figure 4.1 depicts five widely referenced sunshades (O'Conner et al., 1997), each reflecting a distinct approach to reducing heat gain and glare. A basic horizontal overhang (A) extends above the window to shield midday sun but offers limited coverage during morning or evening hours. A slight variation adds multiple horizontal louvers (B) below the overhang; these layers create small gaps for daylight to enter while blocking strong direct beams. By contrast, a 15° sloped overhang with multiple downward-angled fins (C) intercepts sunrays aggressively, thus minimizing glare and cooling demands, yet it may reduce natural lighting too significantly in certain climates. An even steeper sloped overhang (D) offers enhanced sun-blocking for high solar angles, favoring hot regions but potentially limiting winter heat gains. Finally, a vertical louver system (E) arranges fins alongside the window to shield low sun angles—particularly useful for east or west orientations—although it may reduce outward views if not carefully spaced. Taken together, these five designs represent standard practices that have seen broad adoption. They are modeled under identical simulation conditions to ensure reliable and consistent comparisons with newly evolved solutions.

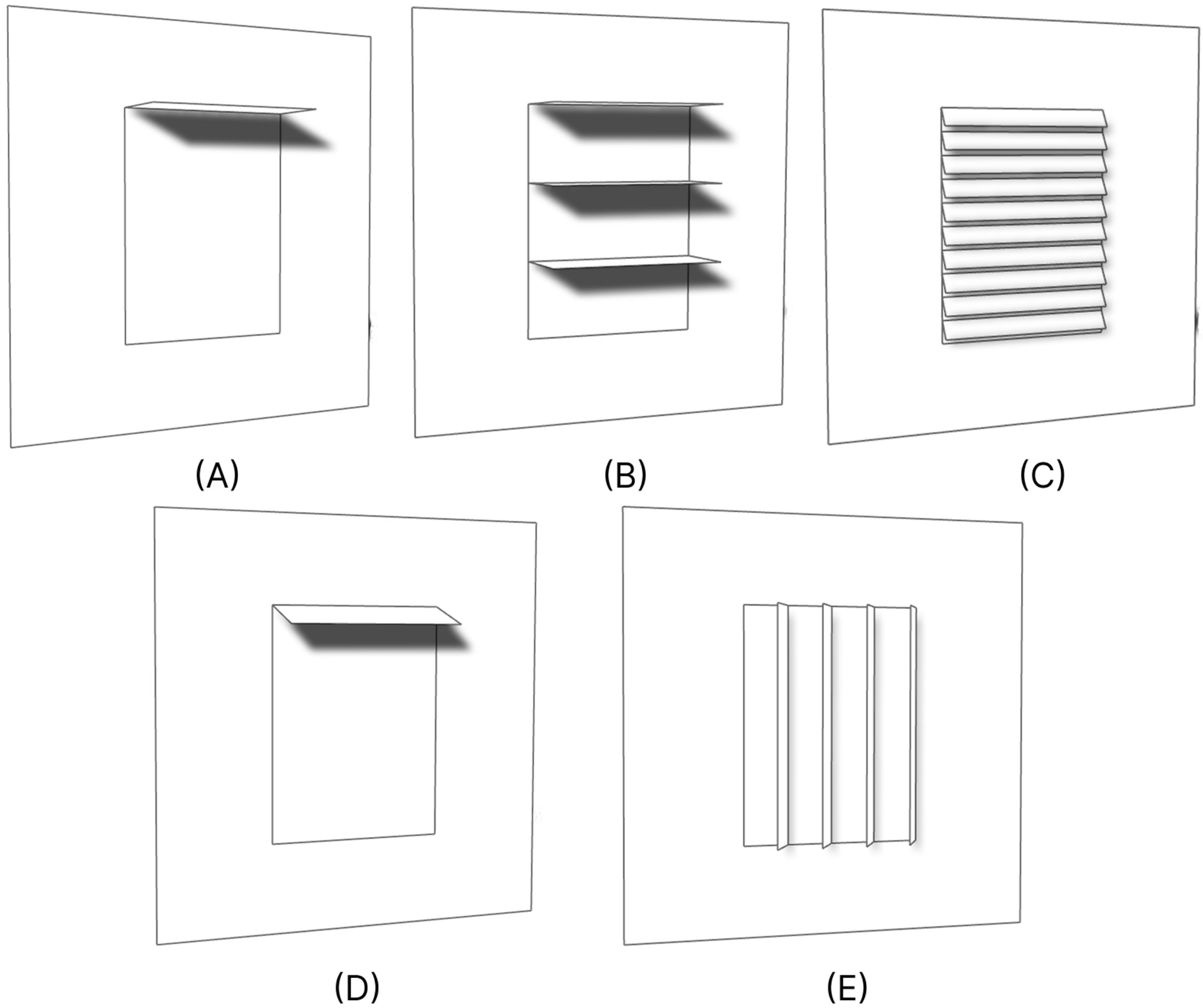

Figure 4.1: Five traditional sunshade designs (O'Conner et al., 1997): (A) a basic horizontal overhang, (B) a horizontal overhang with three louvers, (C) a sloped overhang with ten downward-angled fins, (D) a steeper sloped overhang, (E) a vertical louver with four fins.

4.2 Simulation Environment and Parameters

In order to compare these traditional baselines with algorithmically evolved designs, all simulations are conducted within a single parametric framework. A ($3\,\mathrm{m} \times 4\,\mathrm{m} \times 3\,\mathrm{m}$) office room is chosen, featuring a rectangular window ($1.3\,\mathrm{m} \times 1.7\,\mathrm{m} \times 0.2\,\mathrm{m}$) with a sunshade and a set of material properties typical of small office construction. Four different climates—Cape Town (South Africa), Colombo (Sri Lanka), Nairobi (Kenya), and Oslo (Norway)—provide a wide range of weather conditions, from hot and humid to cold or moderate. Year-long simulation data from each city's *EPW* file ensure that variations in solar altitude, ambient temperature, and humidity are captured.

Sunshade fins, whether traditional or evolved, are analyzed in *Honeybee* using the *EnergyPlus* and *Radiance* tools. This approach provides a quantitative account of energy use, thermal comfort, natural lighting, cost, and outside visibility. Table 4.1 summarizes key experimental parameters, including population sizes for the optimizations and the range of fin numbers, angles, lengths, offsets and contour angles used to define sunshade configuration. A year-long simulation period is applied, and each test is repeated 10 times to account for variability in algorithmic runs.

Table 4.1: Simulation and Experiment Parameters

Parameter	**Value**
Simulation Environment	
Locations	South Africa: Cape Town, Sri Lanka: Colombo, Kenya: Nairobi, Norway: Oslo
Office room dimensions	Width: 3m, Height: 4m, Length: 3m
Facade window dimensions	Width: 1.3m, Height: 1.7m, Depth: 0.2m
Weather data span	1 year
Number of runs	10
Facade Properties	
Number of fins on facade	1 to 10
Angle	0 to 90 (5 increments)
Length	0.05m to 0.5m (0.05m increments)
Depth	0.05m to 0.5m (0.05m increments)
Offset	0.01m to 0.1m (0.01m increments)
Contour Angle	0 to 360 (5 increments)
Optimization Algorithms	
Algorithms	NSGA-II, MO-CMA-ES
Generations	100
Population size	100
Offspring Generation	Random Injection + Algorithm specific offspring generation
Mutation rate	10%
Selection rule	Elitist + Crowding Distance
Performance Metrics	
Energy consumption	Total energy required for heating and cooling
Thermal comfort	Thermal comfort of the occupants in the room.
Useful daylight illuminance (UDI)	Aggregated UDI measurements
Outside view preservation	Unobstructed window area
Cost	Manufacturing cost

4.2.1 Algorithmic Optimization Setup

Two Many-Objective Evolutionary Algorithms (MaOEAs), NSGA-II and MO-CMA-ES, are used to generate sunshades that attempt to balance these five objectives simultaneously. The search space for the parameters used in the sunshade optimization consists of predefined discrete sets of numerical values. Following an analysis of preliminary experimental results, we determined that these hyperparameters were the most suitable for further experimentation. Each algorithm runs for 100 generations with a population size of 100 individuals. Within each generation, new configurations are formed by sampling or recombining the design parameters, after which the shading systems are simulated to gather performance metrics. The elitist selection procedures in both algorithms preserve the most promising individuals in subsequent generations, and a 10% mutation rate helps maintain enough genetic diversity to avoid premature convergence. After the final generation, each run should yield a set of high-performing designs that reflect different trade-offs among energy savings, occupant comfort, daylight availability, cost, and outside views.

4.3 Algorithm Evaluation Approach

Five quantitative metrics underpin the evaluation. *Energy consumption* measures annual heating and cooling loads, while *thermal comfort* indicates the indoor conditions for building occupants. *UDI* quantifies how often daylight levels remain within a comfortable illumination range. *Outside view preservation* checks the percentage of the window area left unobstructed by fins, and *cost* is gauged by approximating each design's volume and complexity. By examining how well each design balances all five, we aim to identify shading solutions that outperform traditional fixed designs.

Once simulations are complete, the outcomes for each design—traditional and evolved—are collected to allow both statistical and graphical comparisons. Because multi-objective data often deviate from normality, a Kruskal–Wallis H test will be used to compare performance across three key groups: (i) traditional sunshades, (ii) NSGA-II results, and (iii) MO-CMA-ES results. Each of the five objectives (energy, comfort, UDI, view, and cost) will be tested at a significance level of $p < 0.05$. Where significant differences arise, pairwise contrasts with Bonferroni corrections will clarify if evolved sunshades outperform the traditional sunshades and for which objectives.

To visualize the solution spaces, the final Pareto frontiers are examined using boxplots. These charts will depict the range and median of each group's performance values while highlighting outliers. By overlaying the five traditional designs as reference points, it becomes clear how much room for improvement each algorithmic approach provides. Outlying configurations may indicate unusual or extreme designs that excel in one objective but underperform in others, prompting closer examination of their feasibility.

In conjunction with numerical data, 3D renderings of selected evolved sunshades will help assess whether the proposed geometries are practically realizable. Observing features such as spacing, angles, and overall shading coverage in a three-dimensional view can reveal potential fabrication challenges or aesthetic concerns. This qualitative check, while not replacing the objective metrics, offers an extra layer of confidence that the evolved solutions are not only mathematically optimal but also suitable for real-world implementation.

4.4 Summary

This experiment setup ensures that all sunshades—traditional or evolved—are tested under consistent conditions, allowing for unbiased comparisons in four distinct climate contexts. Over 100 generations of NSGA-II and MO-CMA-ES runs, thousands of candidate designs are examined, each evaluated on five critical performance objectives. The subsequent chapters will present and interpret the resulting data, focusing on whether algorithmically generated sunshades can substantially improve upon conventional designs and how trade-offs among energy usage, comfort, daylight, view, and cost are managed.

Chapter 5

Results and Discussion

This chapter presents a comparative evaluation of two EAs (MO-CMA-ES and NSGA-II) and five traditional sunshade configurations across four distinct climates: Cape Town, Nairobi, Colombo, and Oslo. The goal is to examine how effectively each algorithm balances the five primary objectives—thermal comfort, energy consumption, UDI, cost, and outside view obstruction—under varying environmental conditions. Each of the following sections details a specific location, highlighting climate-specific trade-offs, algorithmic performance, and illustrative sunshade designs from the Pareto frontiers. The chapter concludes with a synthesis of the findings, including observations on algorithmic behaviors and practical implications for sunshade optimization.

To ensure a fair comparison between MO-CMA-ES and NSGA-II, both algorithms were forced to run for 100 generations, enhanced by random injection of offspring to maintain diversity. These experiments were conducted on an AMD Ryzen 9 7950X processor, with each run taking approximately six days to complete. Although the code was not explicitly parallelized at the algorithmic level—particularly due to Radiance's reliance on temporary files—Radiance itself utilized the system's 32 cores in parallel for ray-tracing calculations. Potential future improvements include GPU acceleration and modifications to Radiance to support parallel file handling and graphics processing.

Each algorithm underwent ten independent runs to enable statistical analyses. The Kruskal–Wallis H test with Bonferroni correction ($p < 0.05$) was employed to evaluate differences between the algorithms' non-dominated sets and the traditional sunshades for each of the five objectives. Despite running each experiment ten times, a single representative run was used to generate the box plots. This approach allows for both rigorous statistical comparisons and clear visual demonstrations of algorithmic performance.

This chapter structure is organized into six main sections, each summarized as follows:

1. Cape Town (Section 5.1) examines sunshades under a relatively mild, comfortable climate. Shows how both MO-CMA-ES and NSGA-II outperform traditional designs in energy and thermal metrics and daylight quality.
2. Nairobi (Section 5.2) discusses the challenges of a warmer setting, where excessive solar heat is a primary concern. Highlights the need for stronger sun blocking and the trade-offs in daylight control.
3. Colombo (Section 5.3) focuses on the challenges of a hot-humid climate, where shading alone cannot mitigate high humidity levels. Emphasizes that both algorithms still reduce discomfort and energy consumption, though less dramatically.
4. Oslo (Section 5.4) details strategies for capitalizing on solar heat gains in a colder climate. Demonstrates how minimized fin coverage can aid passive heating.
5. Final Remarks (Section 5.5) summarizes algorithmic tendencies—MO-CMA-ES's wider exploration vs. NSGA-II's tighter distribution—alongside the overall outperformance of evolved sunshades over traditional options. Highlights extreme frontier designs optimized for single objectives (e.g., minimal cost or near-complete sun blocking) and underscores the importance of multi-objective consideration to select balanced, real-world solutions.
6. Important Takeaways (Section 5.6) highlights that, across four climates, both MO-CMA-ES and NSGA-II evolved sunshades significantly outperformed traditional designs in thermal comfort, energy consumption, and UDI, with modest gains in cost and view preservation, and minimal differences between the two algorithms.

5.1 Results and Discussion: South Africa, Cape Town

In this section, the performance of evolved sunshades obtained through the MO-CMA-ES and NSGA-II algorithms is compared with five traditional sunshade designs under Cape Town's climatic conditions. Cape Town experiences moderate temperatures over much of the year, which influences both the thermal comfort metric and energy requirements. The analyses focus on all five 5objectives. All reported findings are supported by non-dominated frontiers produced by each algorithm, along with statistical tests to assess significant differences from traditional sunshades.

Both algorithms generated sizable Pareto frontiers, indicating that Cape Town's moderate climate allows for a broad spectrum of sunshade configurations balancing the five objectives. On average, MO-CMA-ES produced a frontier size of 264 solutions, whereas NSGA-II produced a frontier size of 421 solutions. While NSGA-II demonstrated a slightly larger set of non-dominated solutions, both approaches revealed multiple designs capable of outperforming the traditional sunshades.

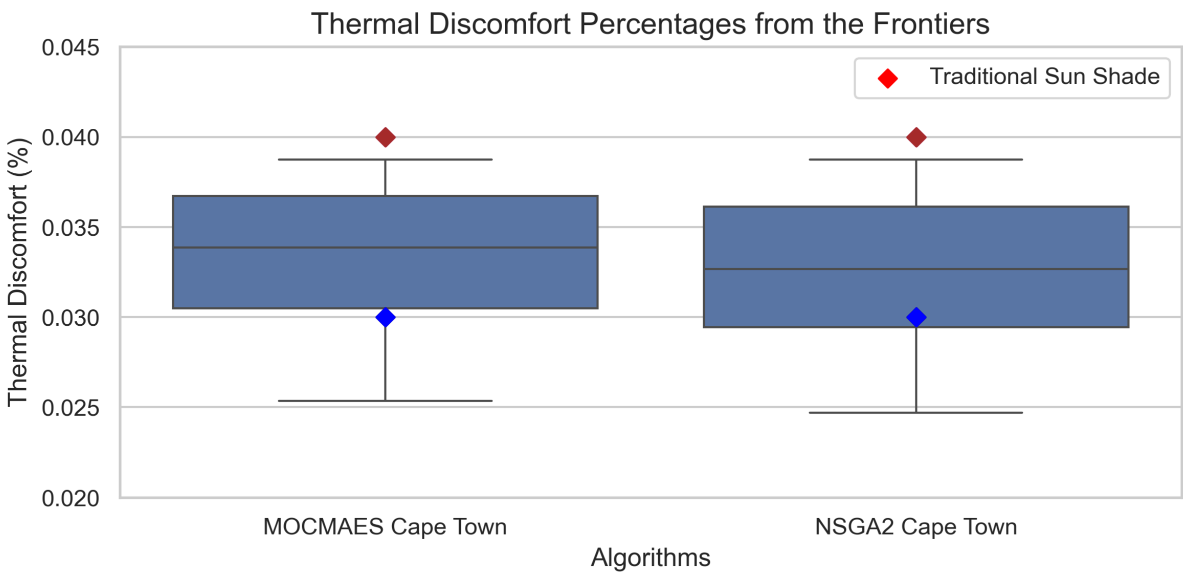

Figure 5.1: Box plots of the normalized thermal discomfort percentage frontier for Cape Town. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). Some overlaps made all five points not fully visible. The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

Thermal discomfort was measured as the percentage of office operating hours in which the indoor environment fell outside acceptable comfort ranges. The box plot in Figure 5.1 illustrates that both EAs consistently achieved lower thermal discomfort values compared to traditional sunshades. However, the absolute values of discomfort remained relatively low overall, reflecting Cape Town's temperate climate. A Kruskal–Wallis H test with Bonferroni correction ($p < 0.05$) indicated statistically significant differences between each evolutionary algorithm's solutions and the traditional sunshade set, but no statistically significant difference was found between MO-CMA-ES and NSGA-II. In other words, both algorithms achieved superior thermal comfort levels to those obtained from conventional manual methods, and neither algorithm dominated the other for this metric.

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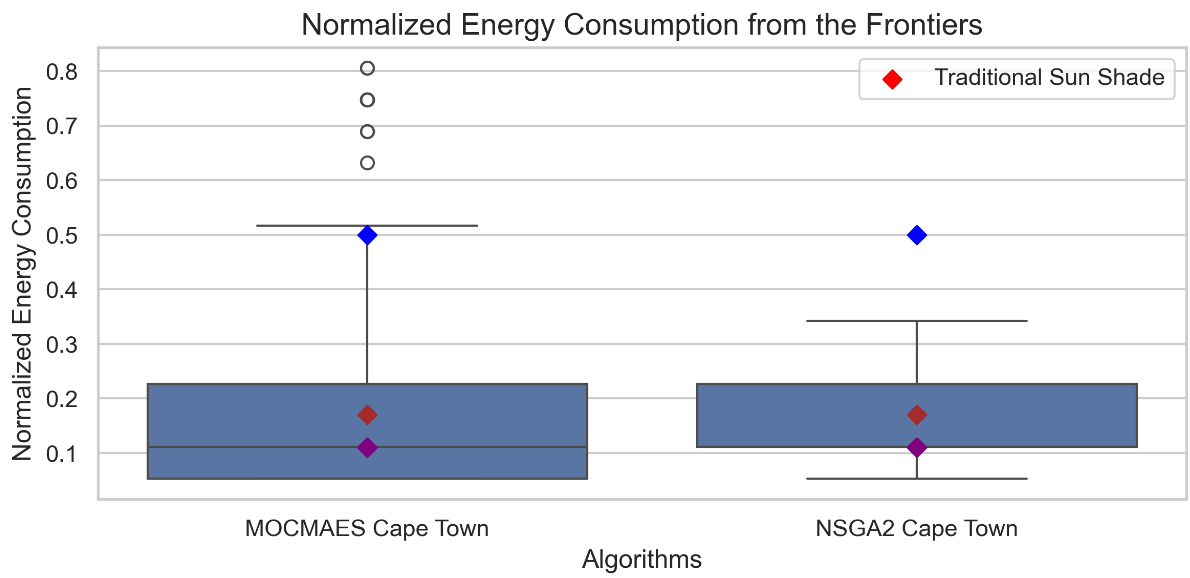

Figure 5.2: Box plots of the normalized energy consumption frontier for Cape Town. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). Some overlap made all five points not fully visible. The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

Figure 5.2 presents the normalized energy consumption for the generated Pareto frontiers. Normalization was performed relative to the maximum and minimum energy consumption values observed across all designs. Both algorithms outperformed the traditional sunshades by producing designs that effectively reduced annual cooling and heating loads. Similar to thermal discomfort, the Kruskal–Wallis H test ($p < 0.05$) showed a significant reduction in energy consumption for the evolved sunshades compared to the traditional ones, but no distinguishable difference emerged between MO-CMA-ES and NSGA-II. The overall reduction is primarily attributed to Cape Town's moderate temperatures, where optimized sunshades can either admit solar heat during cooler periods or block excessive heat during warmer days.

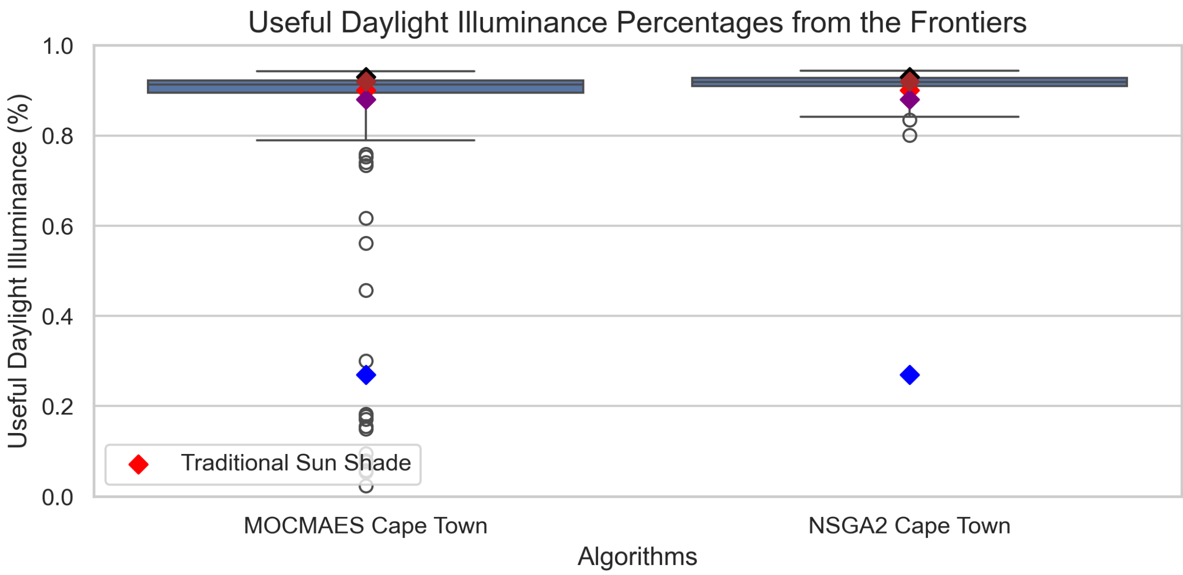

Figure 5.3: Box plots of the normalized UDI percentage frontier for Cape Town. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Higher values indicate improved performance.

The UDI results, displayed in Figure 5.3, demonstrate that both EAs produced shading configurations with higher percentages of useful daylight than the traditional designs. In Cape Town's climate, moderate external conditions and ample daylight hours allow for shading layouts that admit sufficient natural light without causing excessive glare or overheating. Notably, three of the five baseline sunshades already employed relatively open or minimal shading strategies, yet some optimized configurations improved upon them by strategically reflecting more sunlight indoors. This approach helped in raising overall daylight availability while also supporting adequate indoor temperatures. According to the Kruskal–Wallis H test ($p < 0.05$), both MO-CMA-ES and NSGA-II solutions significantly outperform the traditional sunshades in UDI, with no statistically significant difference between the two algorithms.

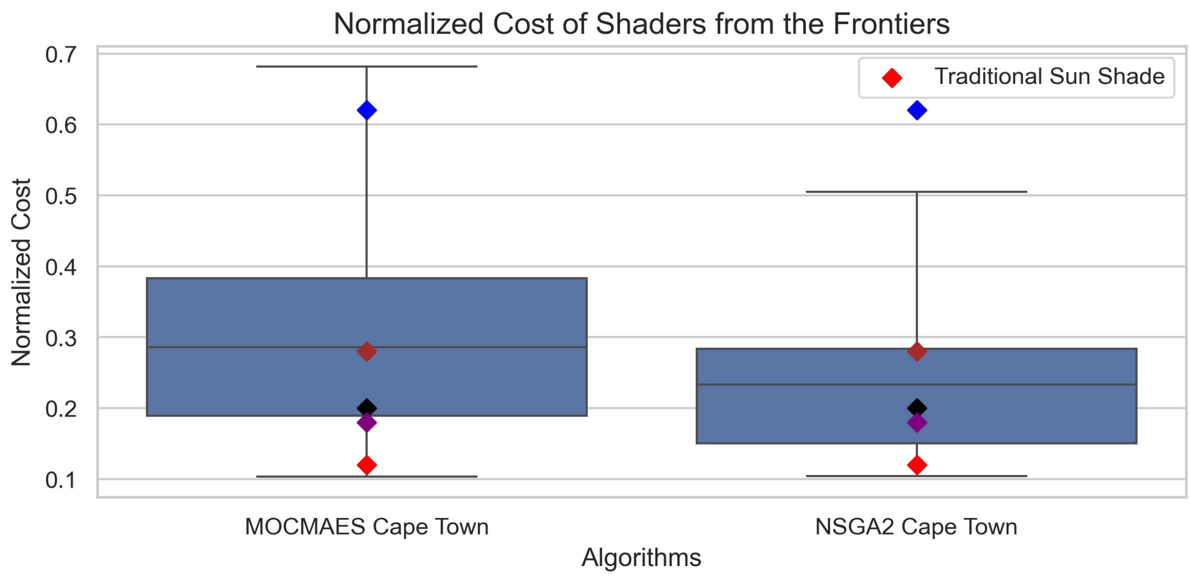

Figure 5.4: Box plots of the normalized cost frontier for Cape Town. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

Figure 5.4 shows normalized costs for all evaluated solutions. The normalization references a lower bound (no sunshade) and an upper bound set by a realistically large sunshade system (excluding impractical designs). Evolved sunshades exhibited lower or at least comparable costs to traditional sunshades, though the statistical test revealed no significant difference ($p < 0.05$) among any of the design groups, including the two evolutionary algorithms and the traditional designs. Because Cape Town's climate already provides comfortable conditions, extensive sunshade structures offering only marginal benefits in energy or comfort may not justify much higher costs, thereby favoring relatively inexpensive configurations across both algorithms and traditional methods.

Figure 5.5 displays the percentage of the window area covered by sunshade structures. Although both algorithms produced solutions with less obstructed views compared to some of the bulkier traditional designs, the Kruskal–Wallis H test ($p < 0.05$) once again indicated no significant differences among any of the groups. This outcome suggests that both evolutionary algorithms and manual designs can be tuned to preserve adequate views in Cape Town's setting, especially given that less shading mass is often required for thermal or daylight benefits in moderate climates.

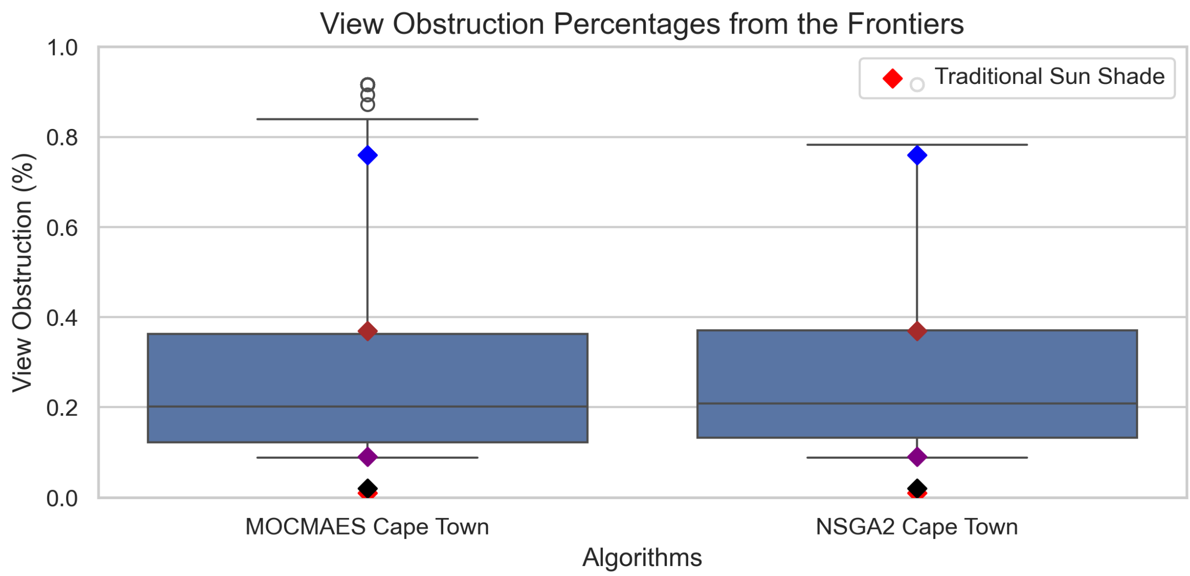

Figure 5.5: Box plots of the normalized window obstruction percentage frontier for Cape Town. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

Visual inspection of selected solutions confirms that the algorithms favored fin angles that admit or even reflect light into the room (Figure 5.6). In cooler months, such angles capitalize on desirable solar gains. MO-CMA-ES Example (Figure 5.6, left) attains above-average thermal comfort and UDI, while reducing energy demands to below-average levels. Cost and outside view obstruction lie near the population averages. The fins are angled and spaced to optimize daytime daylight inflow and moderate warming. NSGA-II Example (Figure 5.6, right) targets very high UDI and simultaneously achieves minimal thermal discomfort and energy consumption. Though it maintains average cost and moderate view obstruction, the fin geometry is more pronounced, reflecting a design that carefully balances solar heat gain against view preservation.

Overall, Cape Town's mild climate reduces the pressure on sunshades to block or admit extreme solar radiation. Nonetheless, both MO-CMA-ES and NSGA-II deliver quantitatively superior performance compared to traditional sunshades for thermal comfort, energy efficiency, and daylighting metrics. Statistically, the evolved solutions differ significantly from the traditional methods across most objectives, yet no strong evidence suggests that one algorithm systematically outperforms the other. The balance of cost and view obstruction objectives remains relatively stable, indicating that moderate climates allow designers greater flexibility to optimize shading designs without incurring substantial expenses or obscuring views.

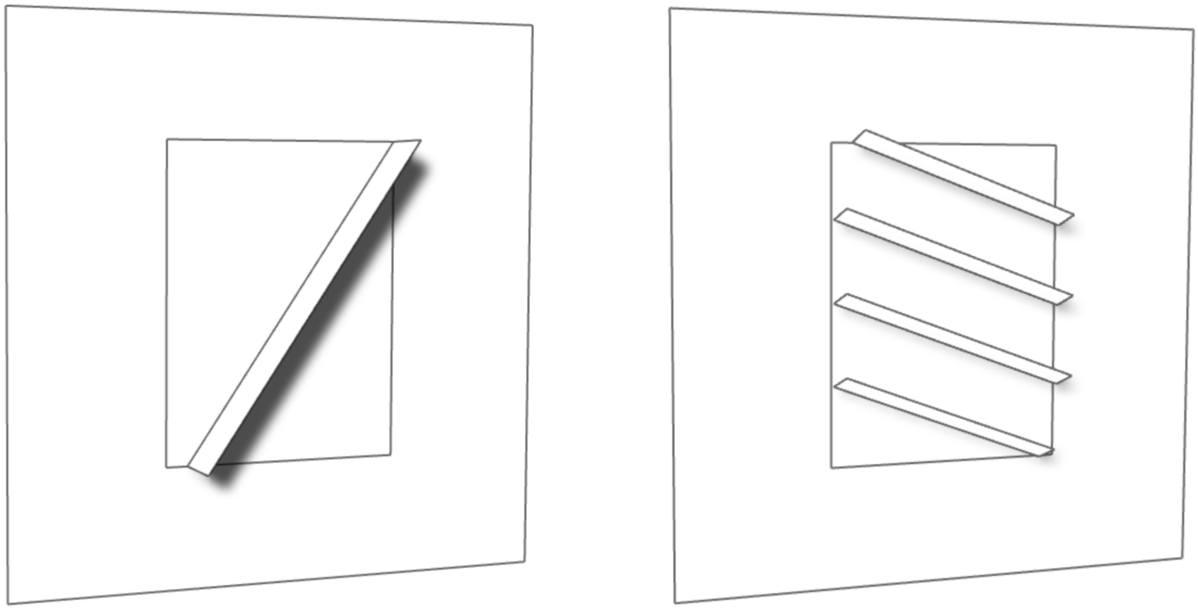

Figure 5.6: Three-dimensional models of the two selected, evolved sunshade designs for Cape Town. The left model is derived from MO-CMA-ES, and the right model is derived from NSGA-II.

5.2 Results and Discussion: Kenya, Nairobi

Compared to Cape Town's conditions, Nairobi's warmer climate has a tangible effect on both the optimization processes and the final sunshade configurations. This section highlights key findings for all five objectives while also noting how the resulting designs differ from those observed in Cape Town. For this Nairobi experiment MO-CMA-ES generated an average of 199 Pareto-optimal solutions, whereas NSGA-II produced an average of 329. Although the overall quantity of non-dominated solutions is lower than in Cape Town, both algorithms still revealed many ways to negotiate the trade-offs among sunlight control, comfort, and other performance goals.

Figure 5.7 indicates that the main challenge in Nairobi is mitigating heat during the hotter parts of the year, as reflected by higher thermal discomfort percentages are mostly from hotter days. Nonetheless, the EAs outperformed traditional sunshades, maintaining lower discomfort values (Kruskal–Wallis with Bonferroni correction, $p < 0.05$). A similar pattern emerged in the energy usage plots (Figure 5.8), where both MO-CMA-ES and NSGA-II configurations reduced the normalized energy consumption compared to the baselines. Statistical analysis confirmed no significant difference between the two EAs.

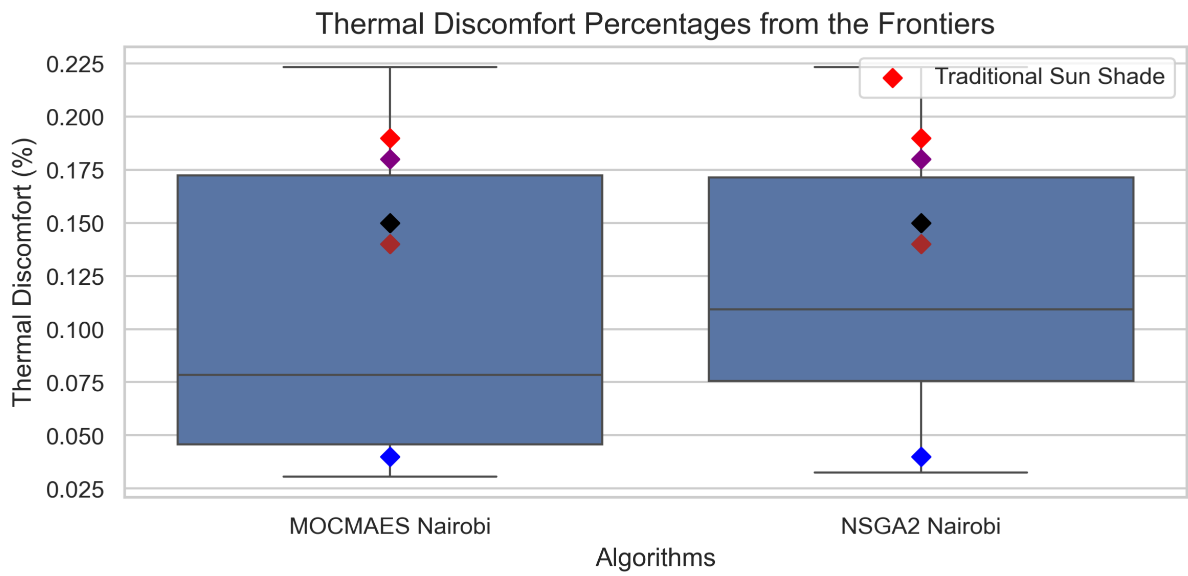

Figure 5.7: Box plots of the normalized thermal discomfort percentage frontier for Nairobi. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

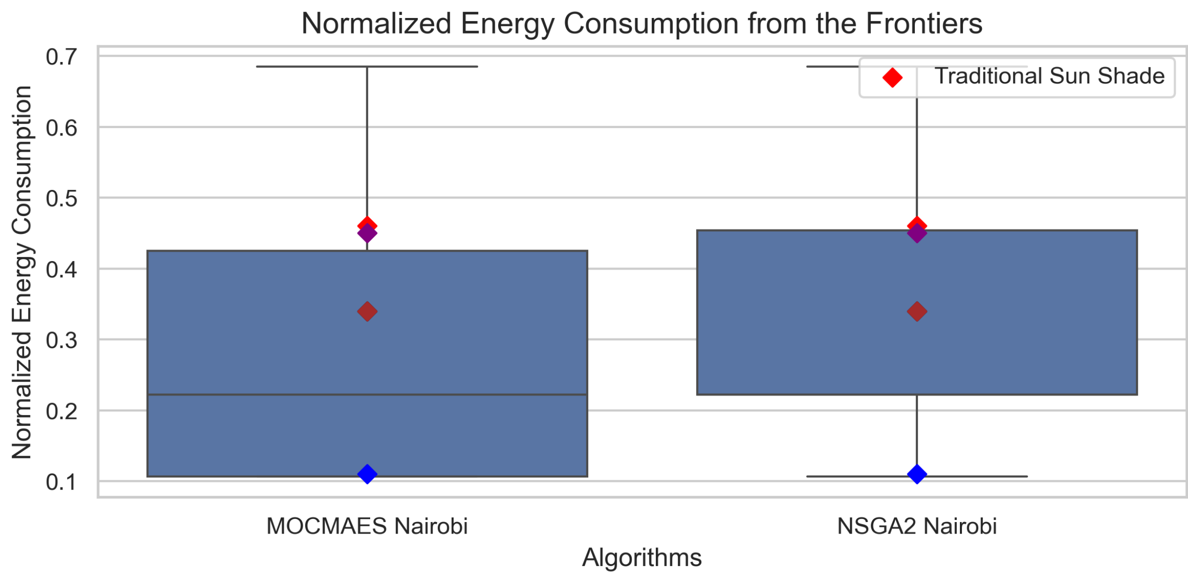

Figure 5.8: Box plots of the normalized energy consumption frontier for Nairobi. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

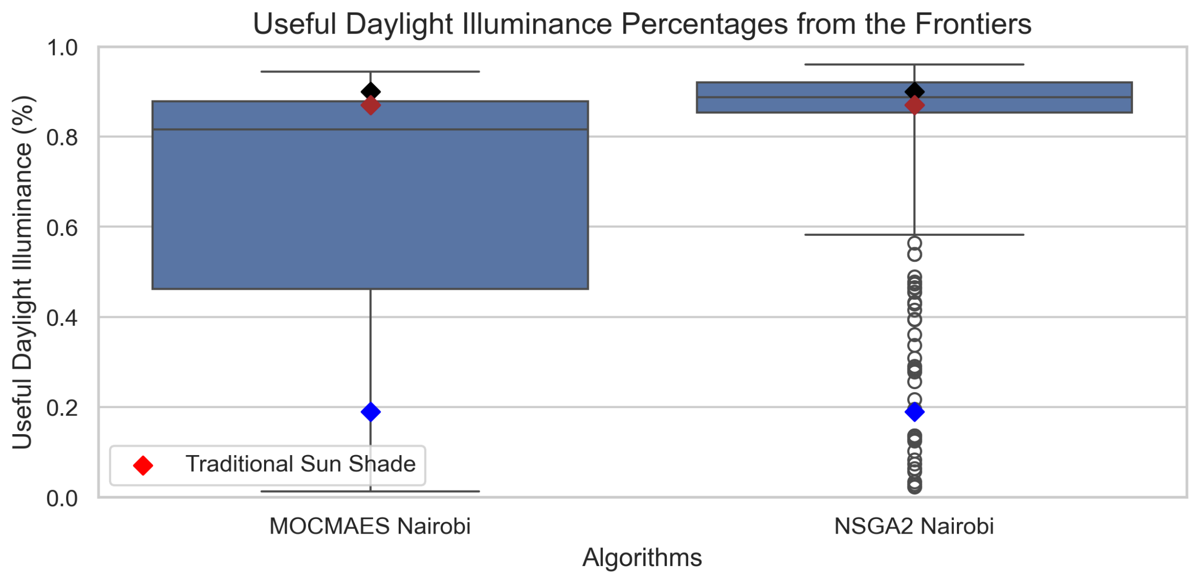

Figure 5.9: Box plots of the normalized UDI percentage frontier for Nairobi. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). Some overlap made all five points not fully visible. The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Higher values indicate improved performance.

Although limiting excessive heat gain is a priority in this climate, the evolved configurations also preserved (and in some cases improved) UDI (Figure 5.9). Traditional sunshades that blocked a large fraction of the direct sun yielded lower discomfort and energy demands but simultaneously reduced daylight quality. By contrast, the algorithmic solutions managed to strike a balance, achieving relatively high UDI while maintaining comfortable indoor temperatures. Once again, neither EAs had a significant difference over the other according to the Kruskal–Wallis results but both showed significant differences over traditional sunshade designs.

In Figure 5.10 (applied to Nairobi's designs under the same normalization approach), both algorithms produced moderately higher-cost structures than in Cape Town, primarily because the fins or overhangs needed to be deeper or more numerous to block strong solar radiation. However, there were no statistically significant differences among the evolved and traditional designs in terms of cost. Equally, the range of window coverage (Figure 5.11) stayed broadly similar across both sets of sunshades. The large fins and angled elements effectively reduced heat gain and some did not necessarily obscure more of the outward view—again reflecting no significant differences ($p < 0.05$).

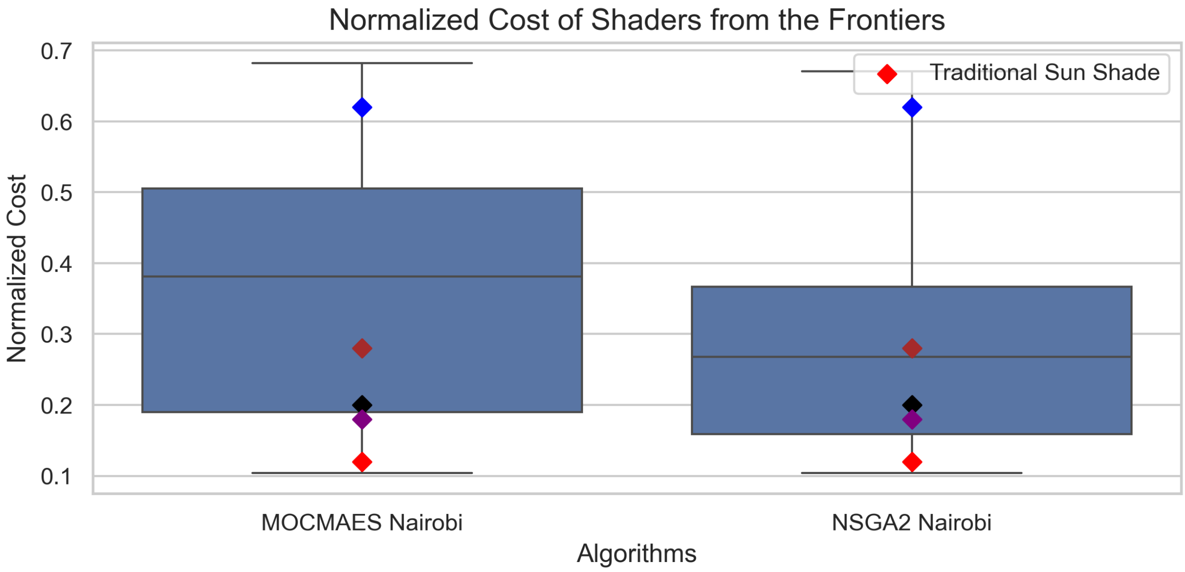

Figure 5.10: Box plots of the normalized cost frontier for Nairobi. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

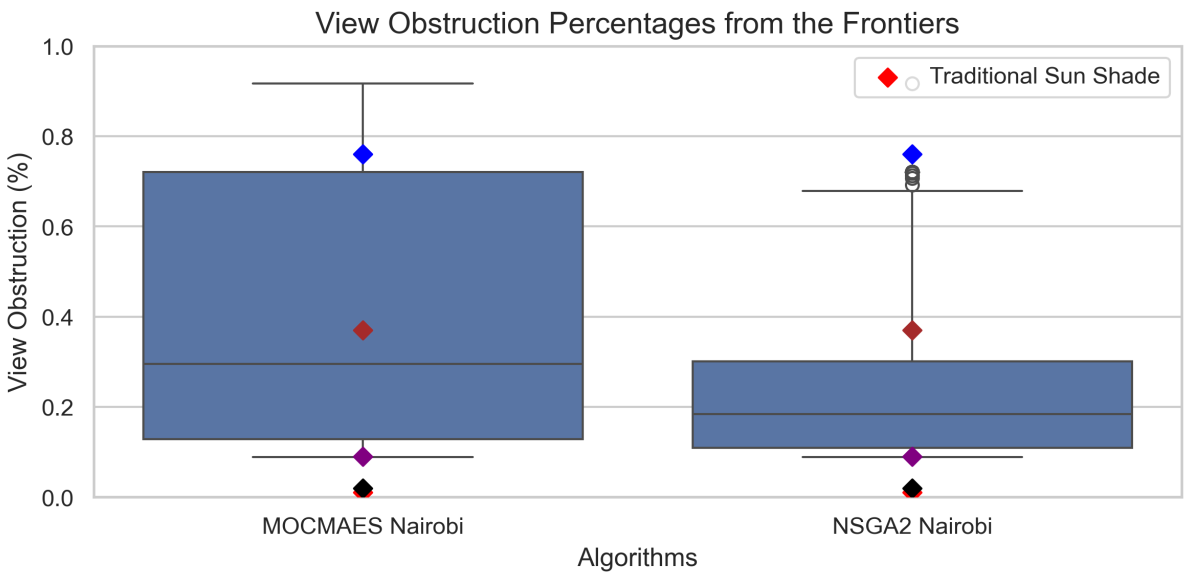

Figure 5.11: Box plots of the normalized window obstruction percentage frontier for Nairobi. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

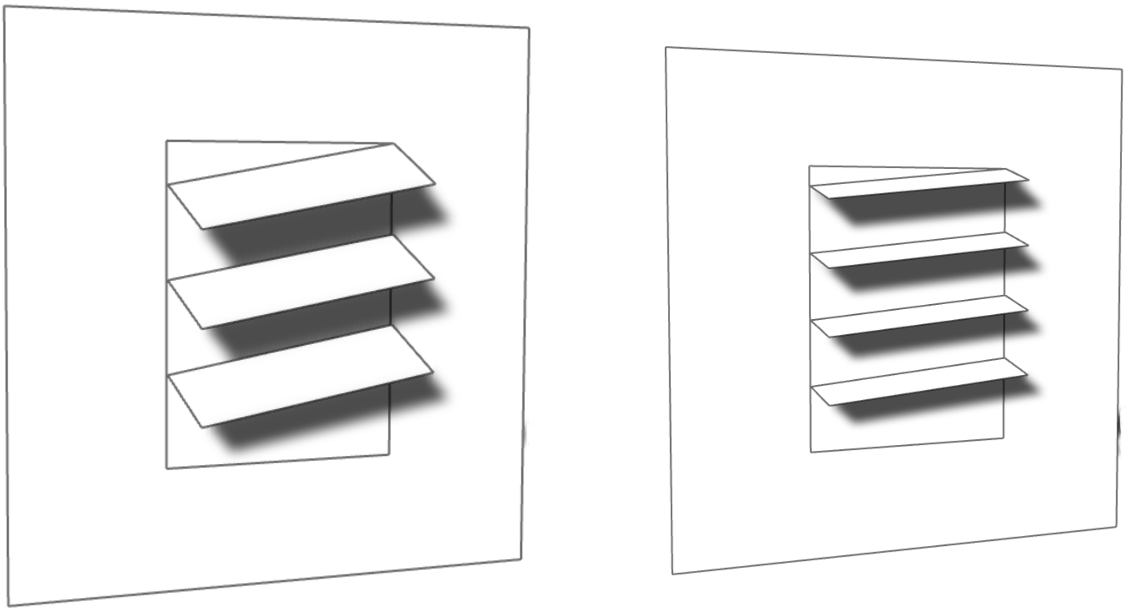

Figure 5.12: Three-dimensional models of the two selected, evolved sunshade designs for Nairobi. The left model is derived from MO-CMA-ES, and the right model is derived from NSGA-II.

Visual inspection of representative solutions (Figure 5.12) underscores a key difference from Cape Town: in Nairobi, fins are angled to repel sunlight during the hottest periods, avoiding overheating. This geometry arises naturally from both MO-CMA-ES and NSGA-II in an effort to minimize thermal discomfort and cooling demand. Notably, the precise angle and depth of fins vary based on the window orientation (North, South, etc.) (This was seen from extra experiments done) and small adjustments in fin angle can affect internal temperatures given the higher ambient heat.

Overall, the algorithms adapt to the hotter environment in Nairobi by proposing sunshades that aggressively limit solar penetration during peak sun hours, unlike Cape Town designs that admitted more sunlight to warm cooler seasons. This targeted blocking of sunrays still allows for adequate daylight, demonstrating that MOO can deliver higher UDI even in climates where solar gains pose a risk of overheating. Statistically, both evolutionary approaches again outperform traditional sunshades but do not differ significantly from each other in terms of thermal, energy, and daylight.

5.3 Results and Discussion: Sri Lanka, Colombo

In contrast to the more moderate climates of Cape Town and Nairobi, Colombo's consistently hot and humid conditions present an added challenge for achieving indoor thermal comfort. This section summarizes how MO-CMA-ES and NSGA-II compare to the traditional sunshades under these tropical conditions.

The hotter, more humid environment of Colombo resulted in relatively smaller non-dominated sets than those of Cape Town but was on par with Nairobi. On average, MO-CMA-ES yielded 192 non-dominated solutions, while NSGA-II produced 325. Despite this reduced range, both algorithms still uncovered a broad array of design trade-offs, especially regarding heat mitigation and daylight management.

Figure 5.13 shows that both EAs reduce thermal discomfort compared to the traditional sunshades. However, Colombo's high humidity diminishes the overall effect of shading, as solar control alone cannot reduce moisture levels. Statistical tests (Kruskal–Wallis with Bonferroni correction, $p < 0.05$) confirmed that MO-CMA-ES and NSGA-II outperform traditional methods but do not differ significantly from each other.

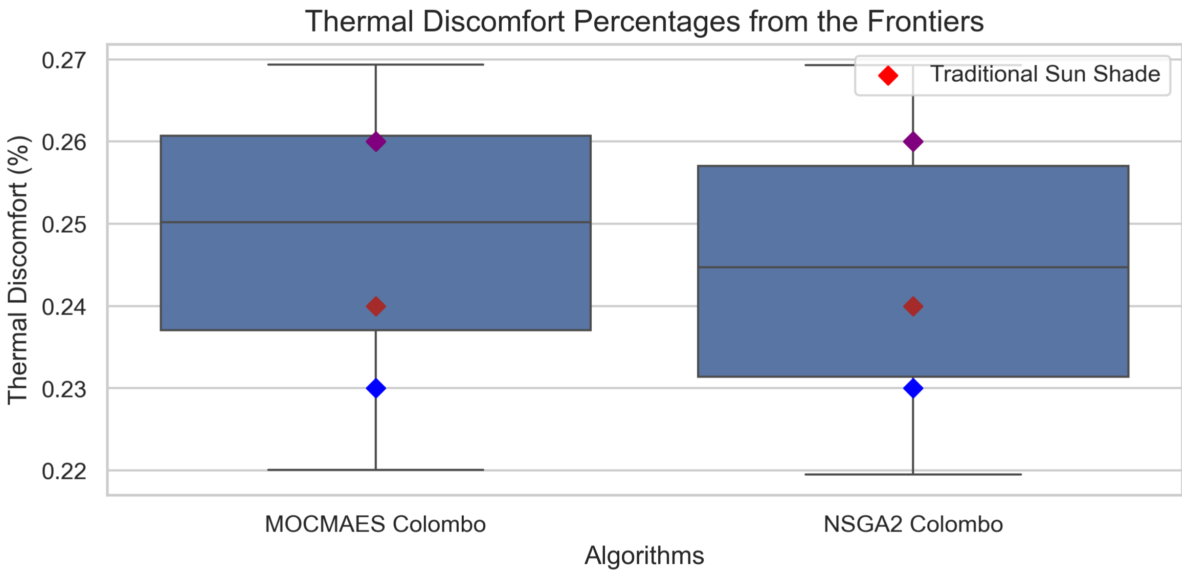

Figure 5.13: Box plots of the normalized thermal discomfort percentage frontier for Colombo. Diamond shapes portray the performance of traditional sunshades (A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). Some overlap made all five points not fully visible. The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

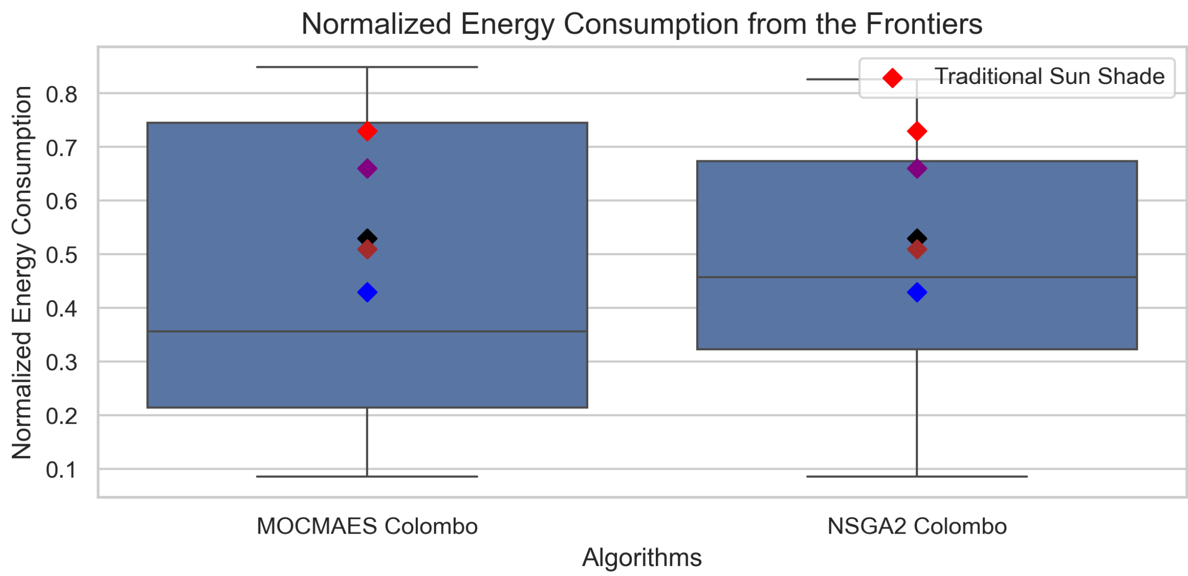

Figure 5.14: Box plots of the normalized energy consumption frontier for Colombo. Diamond shapes portray the performance of traditional sunshades (A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

In Figure 5.14, normalized energy consumption for the evolved solutions shows modest improvement over traditional sunshades; however, these gains did not reach statistical significance. The driving factor remains the year-round heat and humidity, where mechanical cooling is almost always required, and shading alone cannot drastically reduce overall HVAC loads. Still, the results suggest that carefully angled fins help lessen peak cooling demand without inflating energy use in other periods.

Similar to Nairobi, successful designs in Colombo frequently prioritized sun-blocking features to counteract continuous high temperatures. Figure 5.15 indicates that evolutionary approaches maintained or improved UDI while limiting solar gains, a trade-off often overlooked in the best-performing traditional baselines (which tended to sacrifice daylight for lower cooling loads). Once more, both MO-CMA-ES and NSGA-II produced comparable outcomes that were significantly better than the baselines for UDI ($p < 0.05$).

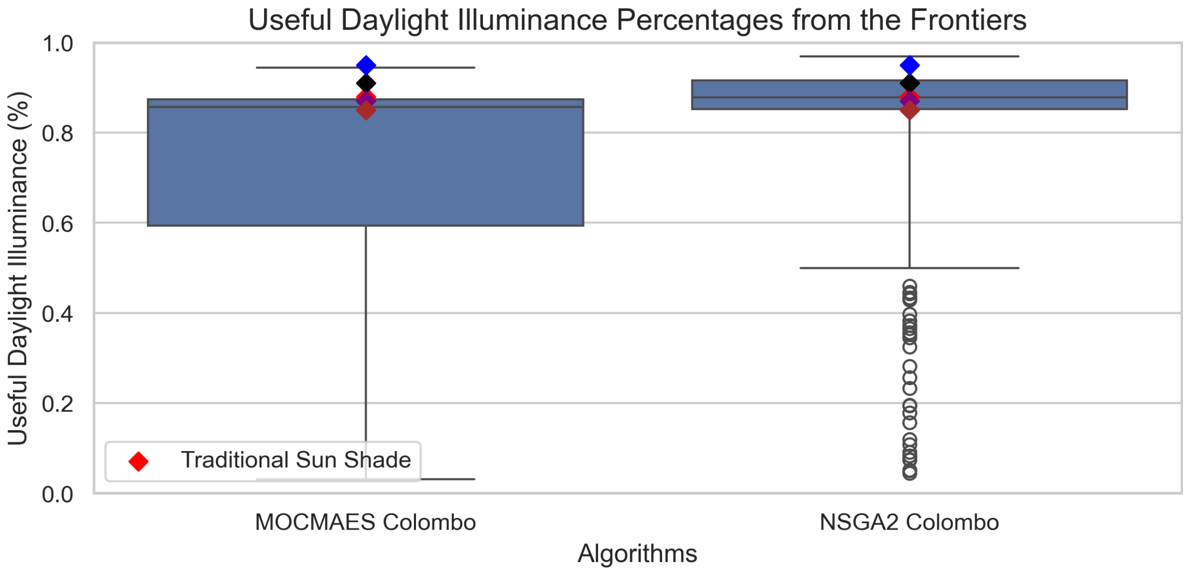

Figure 5.15: Box plots of the normalized UDI percentage frontier for Colombo. Diamond shapes portray the performance of traditional sunshades (A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Higher values indicate improved performance.

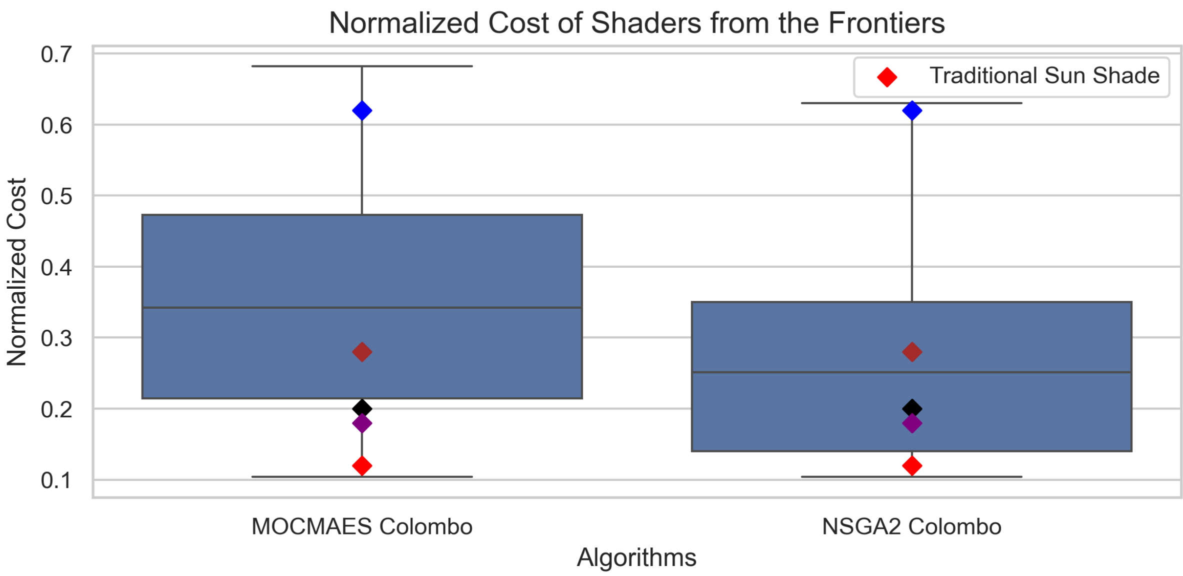

Figure 5.16: Box plots of the normalized cost frontier for Colombo. Diamond shapes portray the performance of traditional sunshades (A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

Costs remained on par with Nairobi's results, reflecting the need for deeper or more numerous fins. Even so, Figure 5.16 shows no significant difference in cost distributions, implying that neither the evolved nor the traditional sunshades incur evidently higher expenses. A similar conclusion applies to outside view obstruction (Figure 5.17); most designs used angled or partially overlapping fins that minimize glare without heavily encroaching upon outward views. No statistically meaningful differences ($p < 0.05$) emerged in this regard.

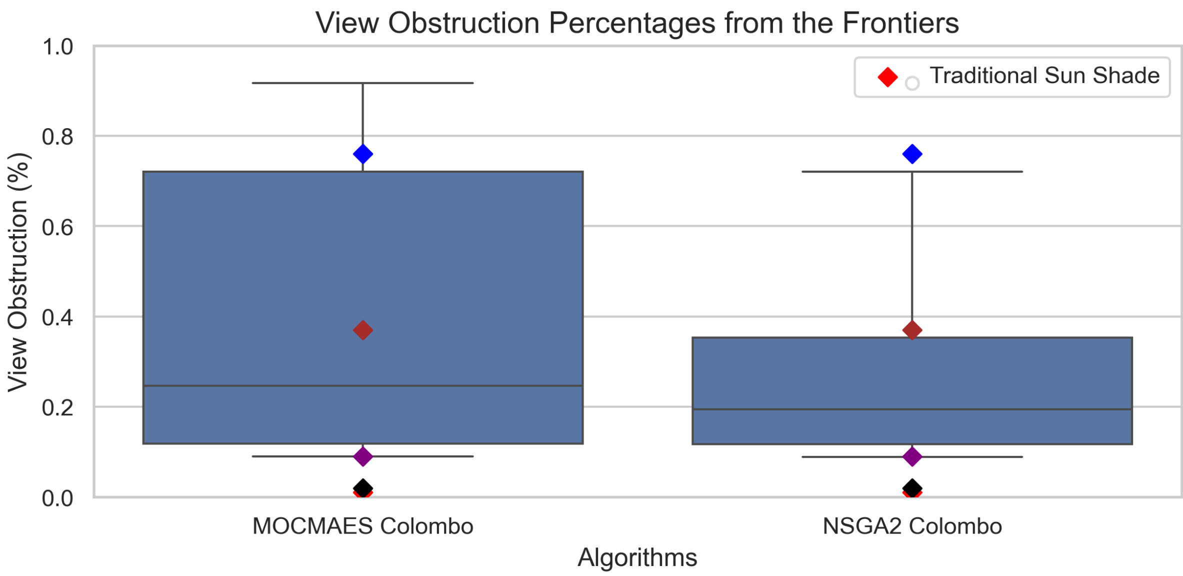

Figure 5.17: Box plots of the normalized window obstruction percentage frontier for Colombo. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

Representative solutions in Figure 5.18 highlight the design adaptations to Colombo's climate. Figure 5.18 left (MO-CMA-ES), a configuration that prioritizes minimal cost and low view obstruction while still achieving high UDI. Although its thermal comfort and energy savings are "average", they might suffice in this tropical setting where shading alone cannot overcome high humidity if low cost needs to be achieved. Figure 5.18 right NSGA-II, a design that aggressively blocks the strongest sun rays during peak heat periods while retaining acceptable daylight levels. It balances thermal comfort and UDI, suggesting that angled fins can be tuned to limit direct radiation without severely restricting visibility or inflating cost.

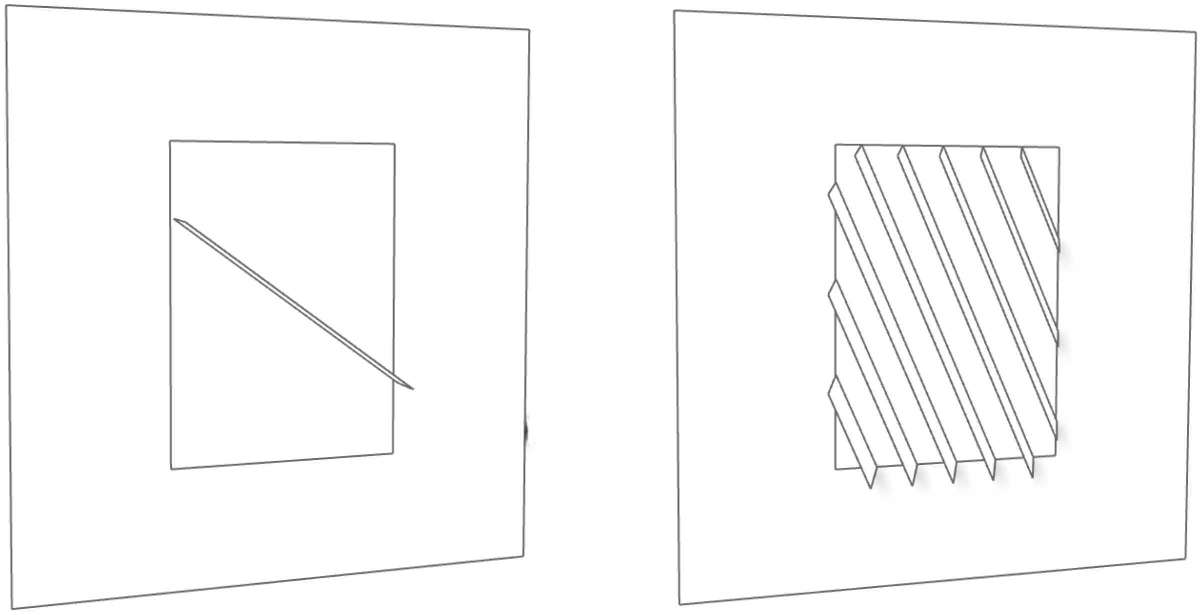

Figure 5.18: Three-dimensional models of the two selected, evolved sunshade designs for Colombo. The left model is derived from MO-CMA-ES, and the right model is derived from NSGA-II.

Overall, both MO-CMA-ES and NSGA-II again surpass traditional sunshades in core performance measures such as discomfort reduction and daylight quality. However, their impact on energy consumption is more modest, consistent with the notion that high humidity necessitates mechanical cooling regardless of shading strategies. Additionally, costs and view obstruction remain similar between the evolved and traditional sunshades, as well as between the two evolutionary methods themselves. These findings underscore that, in hot-humid environments like Colombo, advanced shading can be beneficial but is only one element among many (e.g., HVAC efficiency, ventilation, dehumidification) required to optimize indoor comfort and energy use comprehensively.

5.4 Results and Discussion: Norway, Oslo

In contrast to the hotter climates examined previously, Oslo's colder environment shifts the role of sunshades toward maximizing passive solar heating while still maintaining acceptable daylight and view. This section summarizes how MO-CMA-ES and NSGA-II responded to these conditions compared to traditional sunshades.

The two EAs exhibited differing capacities for generating non-dominated solutions in Oslo's climate: MO-CMA-ES found 155 configurations on average, while NSGA-II produced approximately four times as many (618) on average. Although NSGA-II's larger frontier indicates higher solution diversity, both algorithms effectively discovered improved designs over the traditional sunshades.

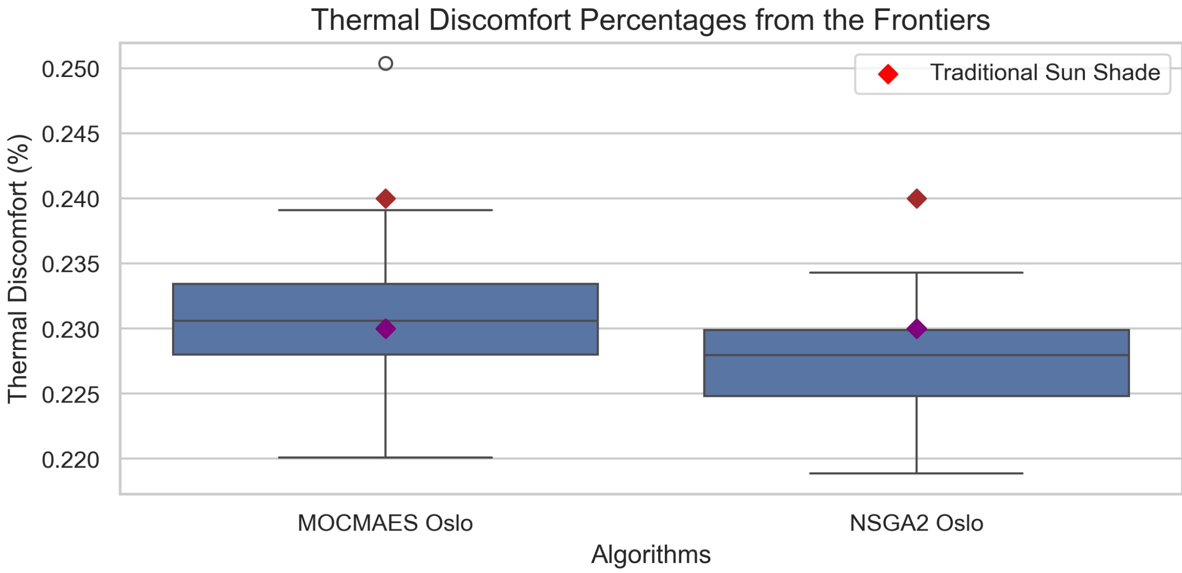

Figure 5.19: Box plots of the normalized thermal discomfort percentage frontier for Oslo. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1), Some overlap made all five points not fully visible. The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

Figure 5.19 demonstrates that evolved sunshades generally lower the percentage of uncomfortable hours compared to the baselines. However, Oslo's cold weather inherently raises discomfort rates if solar gains are insufficient. Statistical tests (Kruskal–Wallis with Bonferroni correction, $p < 0.05$) reveal that both EAs perform significantly better than traditional sunshades. As with other locations, no meaningful difference emerged between MO-CMA-ES and NSGA-II.

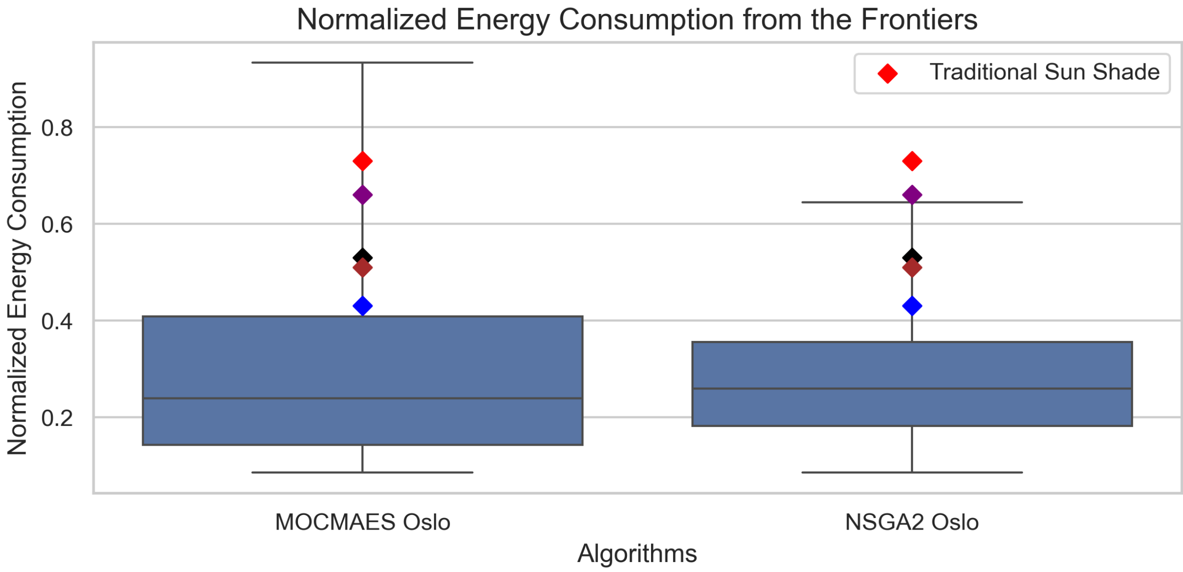

Figure 5.20: Box plots of the normalized energy consumption frontier for Oslo. Diamond shapes portray the performance of traditional sunshades (4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

As shown in Figure 5.20, low shading coverage leads to reduced heating energy—a key difference from hot climates, where the goal is to minimize cooling loads. Again, both MO-CMA-ES and NSGA-II achieved lower normalized energy use than traditional baselines ($p < 0.05$). The results confirm that well-chosen sunshade geometry can exploit solar heat gain to offset heating demands, thereby reducing total HVAC usage.

Many of the evolved solutions managed to improve daylight levels over the traditional sunshades (Figure 5.21). As in Cape Town, designs that reflect or admit sunlight (e.g., upward-angled fins) help warm the interior and enhance natural illumination simultaneously. But the Kruskal–Wallis analysis again supports that the EAs outperform the baseline in UDI, with no significant difference between them.

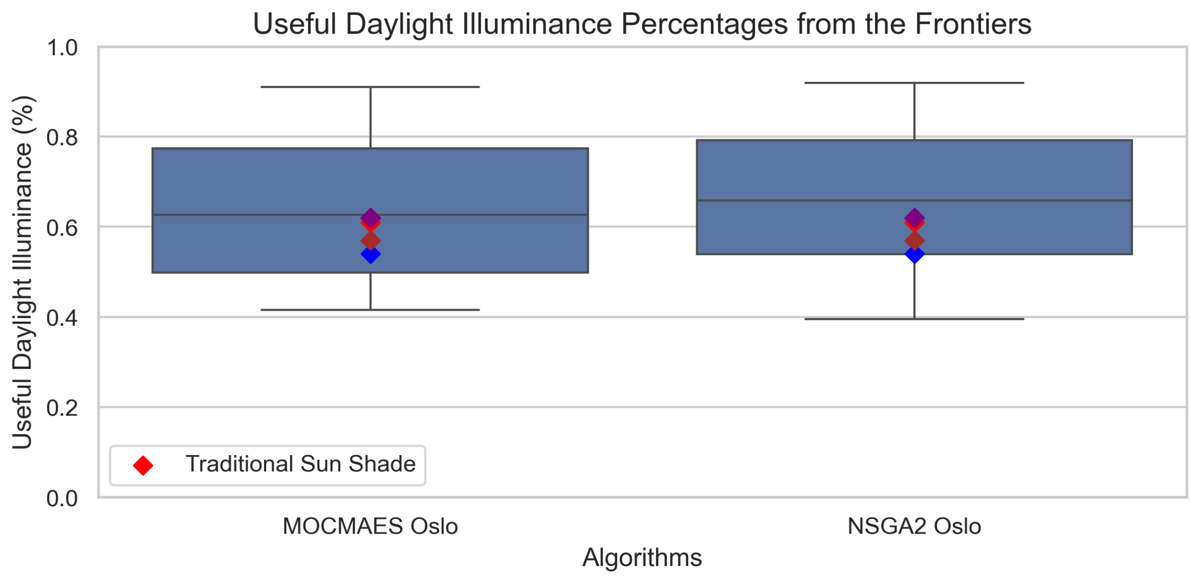

Figure 5.21: Box plots of the normalized UDI percentage frontier for Oslo. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Higher values indicate improved performance.

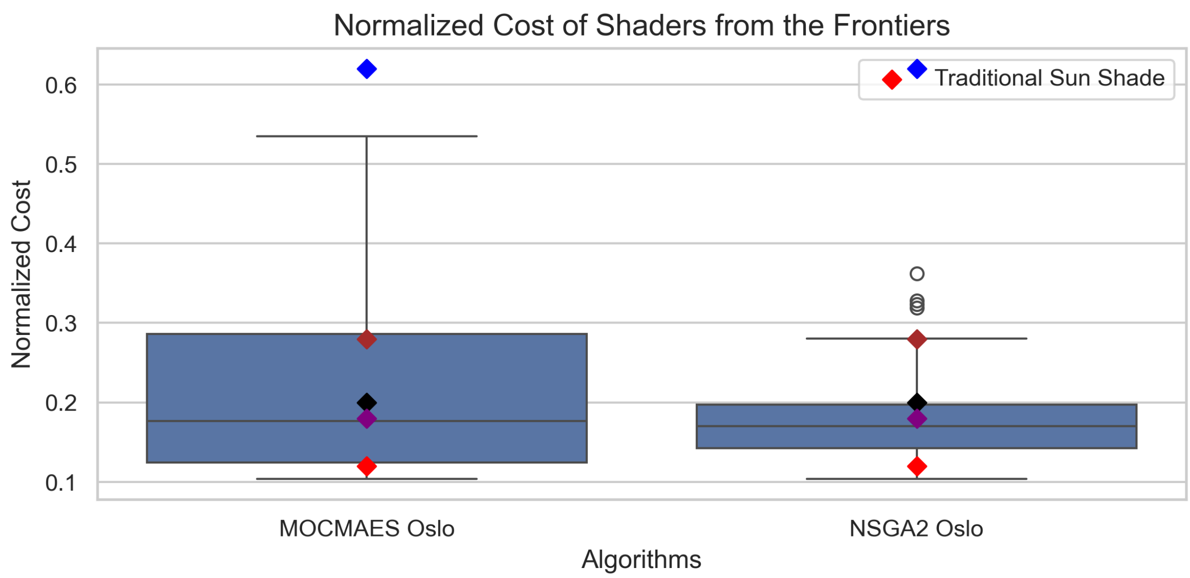

Figure 5.22: Box plots of the normalized cost frontier for Oslo. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

In Figure 5.22, normalized cost remains low across the evolved frontiers. With minimal or even partial shading sufficient for capturing useful winter sun, there is little incentive to invest in more elaborate or expensive designs.

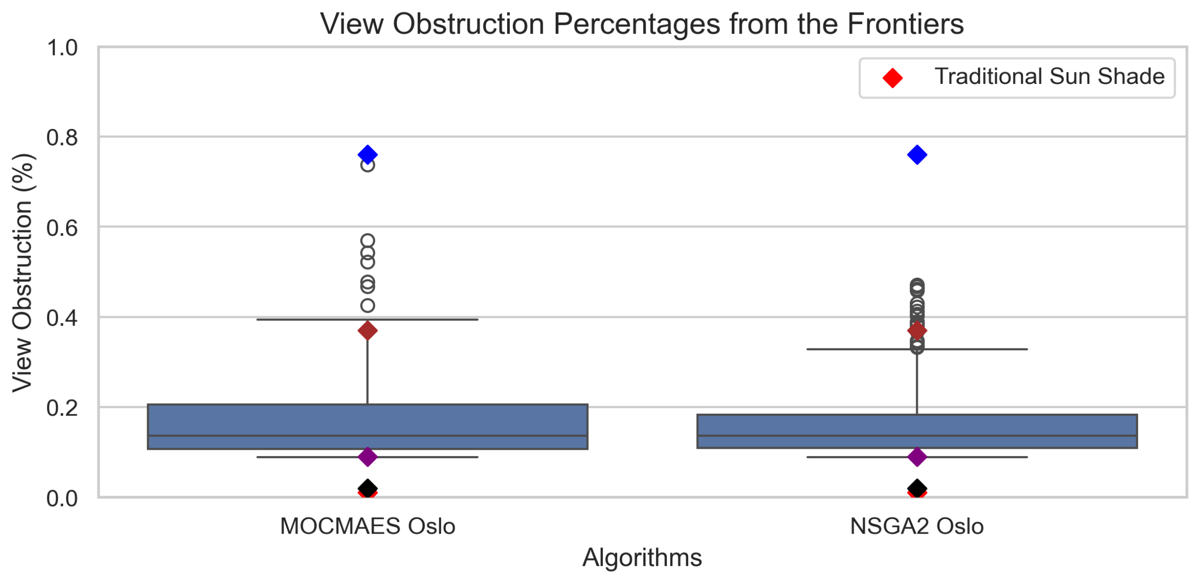

Figure 5.23: Box plots of the normalized window obstruction percentage frontier for Oslo. Diamond shapes portray the performance of traditional sunshades(A, B, C, D, and E represent red, black, blue, purple, and brown, respectively 4.1). The left and right distributions correspond to MO-CMA-ES and NSGA-II results, respectively. Lower values indicate improved performance.

Similarly, outside view obstruction (Figure 5.23) stays limited, as large shading structures are counterproductive in an environment needing solar heat. Statistical tests indicated no notable cost or view-coverage differences among the EAs and the baselines.

Figure 5.24 highlights two representative frontier designs. Figure 5.24 Left (MO-CMA-ES), a configuration with sparse, upward-oriented fins allowing increased solar penetration for heating while preserving outward views and holding costs in check. Figure 5.24 Right (NSGA-II), a similarly open approach emphasizing daylighting and minimal coverage of the window. This design trades off thermal discomfort for cost and outside view obstruction.

Oslo's cold climate necessitates sunshade strategies that favor solar admission rather than aggressive blocking. Both evolutionary algorithms focus on partial or angled shading to reduce glare while still capturing winter sun, leading to moderate gains in comfort, daylight, and cost savings over traditional sunshades. As seen in other locations, NSGA-II and MO-CMA-ES achieve statistically indistinguishable results on most metrics, reinforcing that either method can effectively handle even the challenging goal of boosting indoor comfort in a predominantly cold setting.

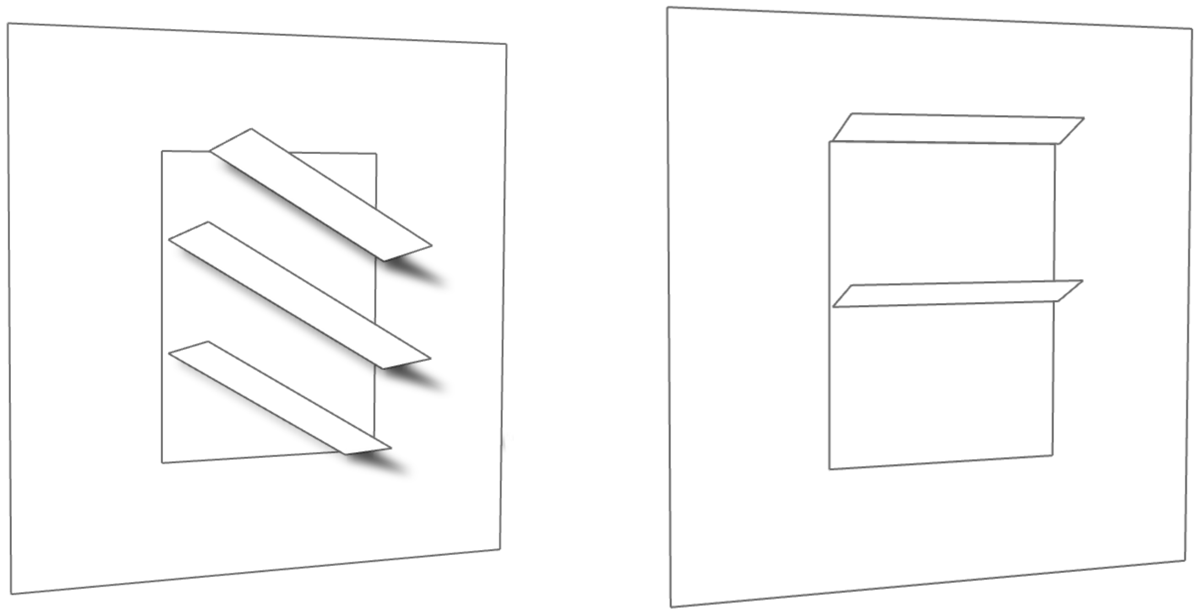

Figure 5.24: Three-dimensional models of the two selected, evolved sunshade designs for Oslo. The left model is derived from MO-CMA-ES, and the right model is derived from NSGA-II.

5.5 Final Overview of Multi-Location Findings

Taken together, the experiments across Cape Town, Nairobi, Colombo, and Oslo confirm that both NSGA-II and MO-CMA-ES exceed the performance of traditional sunshades for critical objectives, notably daylight utilization (UDI), thermal comfort, and energy consumption. In contrast, improvements in cost and outside view obstruction remain modest, reflecting inherent trade-offs in sunshade design.

A notable distinction between the two algorithms emerged in the shape of their non-dominated solutions:

1. MO-CMA-ES often exhibited a more explorative behavior, generating a wider spread of objective values—evidenced by larger boxplot ranges and more outliers.

2. NSGA-II tended to be more elitist, producing fewer extreme outlier values and generally forming tighter distributions near high-performing solutions. Paradoxically, it often yielded a larger overall frontier size, reflecting its strategy of preserving diverse Pareto-optimal designs across generations.

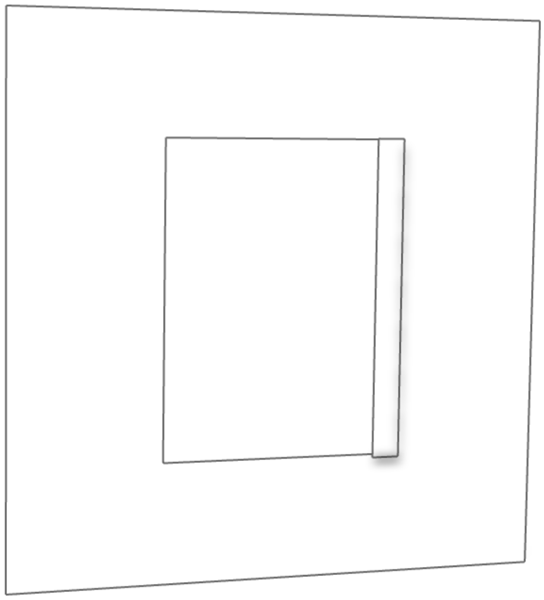

Figure 5.25: Norway MOCMAES Extremes

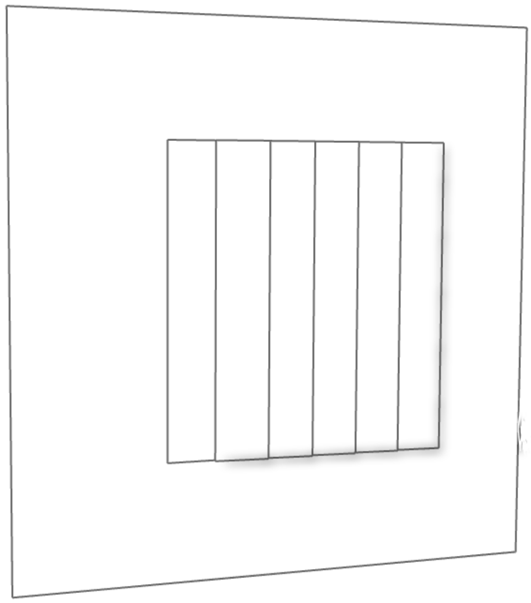

Figure 5.26: Nairobi NSGA Extremes

While both EAs found ways to improve cost-effectiveness and reduce window coverage to a certain degree, neither dramatically surpassed the simpler traditional configurations, such as the single overhang (Figure 4.1 A). That baseline design inherently features low cost and minimal view obstruction, albeit at the expense of poorer thermal comfort and higher energy usage. The presence of cost and view obstruction as explicit objectives within the algorithms ensures that at least some evolved solutions aim to remain lightweight and visually unobtrusive—though other solutions choose heavier shading to optimize thermal or lighting goals.

Another recurring insight from all four locations is the presence of “extreme” solutions at the ends of the Pareto frontier. These represent the best performance in one or two objectives but notably weaker results elsewhere:

1. Figure 5.25 (MO-CMA-ES, Oslo): A design prioritizing minimal cost and window coverage, suitable for those valuing an unencumbered view and reduced expenses. However, it underperforms energy and thermal comfort, emphasizing the need for mechanical heating in Oslo’s climate.

2. Figure 5.26 (NSGA-II, Nairobi): A nearly fully covered window aimed at maximum overheating reduction, thus significantly improving thermal comfort. Yet, the solution admits far less daylight, negatively affecting UDI and also far less occupant view satisfaction.

These outliers highlight that decision-makers should carefully consider the trade-offs: a single high-performing metric does not necessarily imply a globally optimal choice for all objectives.

Overall, the MOEAs excel in adapting to diverse climates and occupant needs, surpassing traditional sunshades on core performance measures while also factoring in cost and view. The findings underscore the importance of evaluating a range of Pareto-optimal solutions rather than focusing on a singular “best” design; building owners or designers can thus select the configuration that most closely aligns with their priorities for cost, comfort, daylighting, and aesthetics.

5.6 Summary and Contributions

Across all four climates—Cape Town, Nairobi, Colombo, and Oslo—both MO-CMA-ES and NSGA-II consistently outperformed the five traditional sunshade configurations in the core objectives of thermal comfort, energy consumption, and UDI. The evolved sunshades were able to admit or block solar gains more strategically than conventional designs, resulting in lower overheating in warm climates and better passive heating in cold climates. Cost and outside view obstruction exhibited comparatively smaller improvements, as many existing baseline solutions were already inexpensive and minimally visible. Statistical analysis confirmed that, while both algorithms significantly improved upon traditional sunshades in most cases, there were few consistent performance differences between MO-CMA-ES and NSGA-II themselves. Each algorithm's Pareto front showed a variety of 'extreme' and 'balanced' solutions, that fit specific goals, such as cutting costs, preserving views, or maximizing comfort or energy or UDI.

Chapter 6

Conclusions and Future Work

This thesis investigated the application of two MOEAs (MO-CMA-ES and NSGA-II) to optimize sunshades in office environments. In contrast to the common practice of focusing on two or three objectives, this work incorporated five interconnected objectives—thermal comfort, UDI, energy consumption, cost, and outside-view obstruction—into a single optimization framework. Analyses of four distinct climatic contexts (Cape Town, Nairobi, Colombo, and Oslo) captured a wide array of temperature ranges, solar paths, and humidity levels. This broad scope offers a deeper understanding of how each algorithm adapts sunshade geometries to meet competing design targets under different environments.

The simulation results showed that MO-CMA-ES and NSGA-II both generated sunshade designs outperforming five traditional baseline configurations. Reductions in thermal discomfort and total energy consumption were particularly notable, accompanied by increases in UDI across all climates. In hot regions (e.g., Nairobi, Colombo), evolved sunshades minimized indoor overheating by effectively blocking excessive solar radiation, yet still allowed adequate natural lighting. In cooler settings, Oslo, optimized solutions showed beneficial solar gains, thus lowering heating demands and maintaining comfortable daylight. In moderate conditions, Cape Town, these methods strategically balanced moderate solar control with enhanced indoor illumination through angled or offset fins.

Although both algorithms significantly improved upon traditional sunshades in thermal and lighting objectives, advances in cost and outside-view obstruction were moderate. This outcome is attributed to certain basic baselines—such as a single overhang—which were already low-cost and only minimally disrupted outward views. Nevertheless, including cost and outside-view obstruction as explicit objectives in the optimization ensured that some solutions either matched or exceeded these baselines in those metrics.

Comparisons between MO-CMA-ES and NSGA-II revealed no systematic performance advantage for any single approach. MO-CMA-ES often explored a broader range of values in each objective, whereas NSGA-II produced somewhat larger Pareto fronts with more tightly clustered, high-performing solutions. Despite these differences in exploration strategies, both algorithms converged on high-quality, site-specific sunshades without exhibiting statistically significant differences in final objective values.

In addressing research question 1., the results demonstrated that both evolutionary algorithms provided substantial improvements over manually designed sunshades regarding indoor comfort, daylight distribution, and reduced energy usage. Although neither algorithm radically surpassed basic sunshades in cost or outward visibility, the many-objective framework nonetheless delivered several well-rounded designs suitable for diverse design goals.

Regarding research question 2.1, MO-CMA-ES displayed a broader exploration of trade-offs, producing solutions spanning a wide spectrum of cost, obstruction, and energy performance. Meanwhile, NSGA-II generally yielded larger Pareto fronts that clustered around strong overall performance. Across all four climates, however, both approaches consistently identified solutions that balanced multiple and sometimes conflicting objectives without evidence that one algorithm was fundamentally better.

Finally, about research question 2.2, neither MO-CMA-ES nor NSGA-II showed absolute superiority when evaluated against quantitative criteria (including energy, cost, and UDI) and qualitative considerations (occupant comfort, aesthetics). Each method uncovered a range of Pareto-optimal sunshades to suit project-specific performance targets, reinforcing the conclusion that algorithm choice can be guided by practical considerations—such as ease of integration with other design processes or computational resource requirements—rather than a clear technical advantage.

Overall, this thesis demonstrates the effectiveness of many-objective evolutionary optimization in addressing complex design challenges, exemplified by the development of static sunshades that optimize five key performance metrics. Examining dissimilar climates in both hemispheres highlights how computational approaches can flexibly generate robust designs that mitigate overheating in hot regions, capture solar gains in cold contexts, and reconcile cost and visual priorities. Importantly, while this study did not find one algorithm inherently superior, it did establish that incorporating multiple, potentially conflicting objectives within an optimization framework gives sunshade designs that more comprehensively satisfy occupant comfort and environmental goals than traditional baselines.

6.1 Future Work

Looking ahead, future research could explore the use of multiple MOEAs in tackling even more complex design problems, allowing for the simultaneous optimization of a broader range of performance objectives and enabling more robust and adaptable solutions. Also, prospective research could extend the single-zone office model to multi-zone building layouts with more realistic internal partitions and occupant schedules, thereby enabling the analysis of large-scale energy and comfort interactions. An additional avenue involves dynamic or sensor-driven shading systems, in which fins or louvers adjust continuously to varying solar angles, temperature fluctuations, and occupant presence; this approach could offer further reductions in cooling loads and enhanced daylight control. On the computational side, improved parallelization—both within the evolutionary algorithms themselves and in the Radiance engine—would reduce total run times and expand the feasible design space, potentially accommodating more complex geometries or additional performance objectives such as embodied carbon. Future work could revisit NSGA-III and SPEA-2 once computational resources permit larger sample sizes or when the objective list expands beyond five, cases where those algorithms are expected to outperform NSGA-II. Lastly, integrating life-cycle assessments, occupant health outcomes, and more detailed aesthetic considerations into the optimization framework may yield even more holistic design solutions that align with emerging sustainability standards and occupant wellness targets.

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