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An Evaluation of Tools, Parameters, and Objectives in Building Facade Optimization Research

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***Abstract*- This research paper presents an analysis of building facade optimization studies. The shift toward simulation-based design methods empowers architects to conduct detailed environmental performance simulations prior to construction, enabling design adjustments based on simulation outcomes. Various quantitative methods have emerged for assessing environmental factors, including daylight availability, glare mitigation, and improving thermal comfort. Moreover, combining simulation tools with optimization algorithms has enhanced the design process, facilitating the generation of multiple solutions aligned with specific performance criteria. To gain an overall perspective on the present state of building facade optimization, a comprehensive review of related peer-reviewed papers was conducted. This review encompasses an evaluation of building types, geographical locations, design parameters, optimization objectives, as well as the simulation and optimization tools employed in each study. The primary aim is to identify frequently addressed optimization objectives in building performance research and critical parameters within the building facade. The results of this analysis hold significant implications for professionals within the fields of building science and design. By identifying commonly explored optimization objectives, such as maximizing daylighting, controlling glare, and enhancing thermal comfort, this research provides valuable insights for future research endeavors and design methodologies. Furthermore, recognizing pivotal factors within the building facade, such as architectural form, wall composition, insulation materials, glazing specifications, and shading strategies, contributes to a more profound understanding of the key determinants influencing building performance.**

***Keywords*- multi-objective optimization, building facades, objectives, parameters, energy consumption.**

NOMENCLATURE

ADDT	Annual Deficient Daylight Time
AEL	Annual energy lighting requirement
AGI	Annual glaring index
ASE	Annual Sunlight Exposure
BEC	Building Envelope Cost
BED	Building Energy Demand
COS	Cooling Operation Schedule

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COS	Cooling Operation Schedule
CTR	Comfort Time Ratio
DA	Daylight Availability
DF	Daylight Factor
DGP	Daylight Glare Probability
ECo2	Annual Carbon Emissions
Ecooling	cooling energy consumption
Eheating	Heating energy consumption
Elighting	Lighting energy consumption
EUI	Energy Use Intensity
HOS	Heating Operation Schedule
ICF	Insulated Concrete Form
LCA	Life Cycle Assessment
LCC	Life Cycle Costs
LCCO2	Life Cycle CO2 emissions
NPV	Net Present Value
OTTV	Overall Thermal Transfer Value
PDH	Percentage of Discomfort Hours
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
PV	Photovoltaics
Qcool	Cooling Energy Loads
Qheat	Heating Energy Loads
QV	Quality of View
sDA	spatial Daylight Autonomy
SHGC	Solar Heat Coefficient

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I. INTRODUCTION

In the initial stages of building design, architects and engineers historically relied on conventional wisdom and their past experiences (Figure 1a) to choose appropriate facade options based on factors such as building function and location [1]. However, as building facades have evolved to incorporate more intricate designs, diverse materials, and increased flexibility, the process of finding the optimal solution has grown significantly complex. This complexity arises from a wide range of variables, necessitating the use of computational tools for effective analysis. These variables include aspects like building shape, wall composition, insulation, glazing specifications, surface area, the thermal properties of materials, and strategies for shading. Furthermore, the conflicting objectives in facade design, such as balancing daylight availability with minimizing solar heat gain, add an extra layer of challenge when trying to adjust these variables towards a mutually beneficial outcome.

In the realm of building design, an evolving paradigm centers on the quantification of environmental facets to optimize performance. This transformative trajectory steers us toward a design approach rooted in simulation (as shown in Figure 1b). The crux of this approach resides in conducting pre-construction simulations that gauge a building's environmental performance and its intricate interplay with the surrounding milieu. These simulations usher forth opportunities for design refinements and enhancements, capitalizing on data-driven insights. These virtual simulations, grounded in mathematical rigor, necessitate the translation of qualitative parameters into precise quantitative terms. Consequently, researchers and scholars have delved into pioneering studies to introduce numerical methodologies that robustly evaluate an array of environmental considerations within the domain of building design.

For instance, the concept of Daylight Illuminance (UDI), a metric introduced by Nabil and Mardaljevic [2] emerges as a notable benchmark. It measures the annual prevalence of illuminance levels spanning the 100-2000 lux spectrum across the workspace, aligning with occupant preferences, especially within the context of naturally lit office settings. Diving into the realm of glare, the scholarly contribution of Wienold and Christoffersen [3] manifests as the Daylight Glare Probability index (DGP). This intricate index encompasses factors such as vertical eye illuminance, the luminance of the glare source, its geometric solidity, and position index, weaving them into a holistic metric of glare assessment. Likewise, the objective to quantify thermal comfort resonates with practitioners and academics alike. In this pursuit, the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) [4]. materialize as the gold standard. These quantifiable indices, standing as cornerstones of thermal comfort evaluation, provide a numerical scaffold for researchers to rigorously dissect this intricate facet of building performance.

The evolution of architectural thinking in building facade design has progressively embraced the fusion of simulation tools with optimization algorithms. The integration of these two components stands as a pivotal advancement, enabling designers to formulate a multitude of solutions grounded in their prescribed performance metrics. This, in essence, extends to factors encompassing the building's intended function and geographical context (Fig. 1c). In the realm of mathematics, optimization embarks upon the task of identifying the optimal values for a defined set of variables, a pursuit fundamentally aimed at either maximizing or minimizing a given objective function [5]. Within the sphere of building performance optimization, the duo of variable parameters and objective functions emerges as the primary constituents (Fig. 1c). These parameters represent an array of values rigor associated with distinct elements of building design, while the objective functions manifest as quantifiable performance indicators derived through the application of simulation tools [6]. In the intricate landscape of building optimization, especially when confronted with the intricacies of competing optimization objectives, the ascendancy of multi-objective optimization algorithms becomes apparent. These algorithms, distinguished by their capacity to furnish a constellation of non-dominant or Pareto-optimal solutions, become indispensable. They are particularly valuable in addressing complex optimization challenges that involve multiple conflicting objectives. Frequently, stochastic population-based algorithms such as the venerable genetic algorithm and the nimble particle swarm enter the fray within the ambit of building performance optimization [5].

This research paper analyzes seventy peer-reviewed papers on building facade optimization published in the past twenty years, based on an extension and revision of an initial systematic review by Hegazy, Yasufuku, and Abe [7]. This exploration encompasses diverse dimensions, spanning various geographical distributions, design parameters, building typologies, optimization objectives, and the spectrum of simulation and optimization tools applied across various research endeavors. The central objective lies in impartially discerning the optimization objectives that have garnered significant attention within the domain of building performance research. Concurrently, it endeavors to shed light on the crucial parameters that constitute the foundation of building facade optimization.

The implications of this scholarly investigation are providing a valuable resource for building scientists and designers alike. It offers valuable guidance to those working with simulation tools and optimization algorithms, particularly in the context of elevating daylight performance. This analysis objectively unveils not only the optimization objectives most frequently addressed in building performance research but also elucidates

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the fundamental parameters that underpin the optimization of building facades.

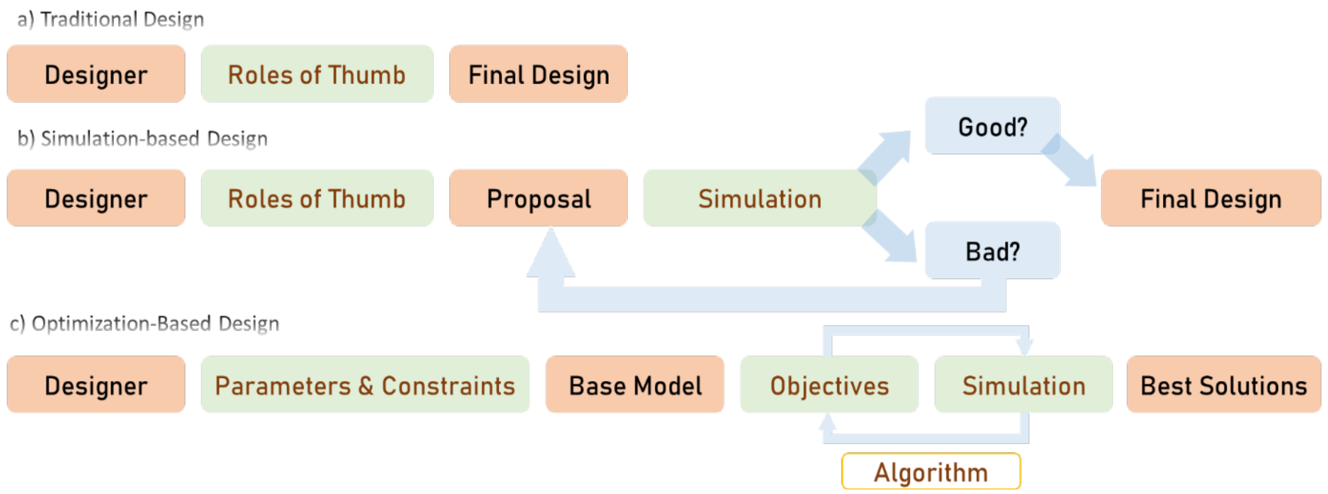

Figure 1. Frameworks for traditional, simulation-based, and optimization-based approaches for building facade design. (by authors)

II. METHODOLOGY

The review study adopted a structured four-phase methodology (Fig. 2) for the purpose of identifying and scrutinizing pertinent literature. In the initial phase, an array of search terms was deployed, encompassing themes pertinent to building simulation, optimization, and facade design. These search terms included keywords such as "evolutionary design," "multi-objective optimization," "façade," "building facade," "building simulation," "parametric design," "window," and "generative design." Notably, terms directly linked to specific optimization objectives like "daylighting," "energy," and "comfort" were deliberately omitted to prevent any bias towards particular objectives. The second phase of this methodological endeavor entailed a comprehensive survey spanning diverse databases. This extensive search was executed by amalgamating the aforementioned selected keywords. Furthermore, databases curated by prominent publishers such as Elsevier, Taylor & Francis, Sage, Springer, and Wiley were systematically explored in pursuit of relevant scholarly works. To uphold the quality and relevance of the reviewed papers, a stringent set of criteria was applied during the screening process. These criteria encompassed the selection of peer-reviewed journal or conference papers, inclusion of case studies, focus on building facade-related variable parameters, utilization of stochastic optimization algorithms, and consideration of publications dated between 2000 and 2022. Following the screening process, a total of seventy papers emerged as fitting the stipulated criteria, forming the basis for subsequent in-depth analysis. This analytical phase involved the extraction of pertinent information, including publication dates, building types, geographic locations, optimization objectives, building parameters, simulation tools employed, and optimization algorithms applied (Table 1 (Appendix)).

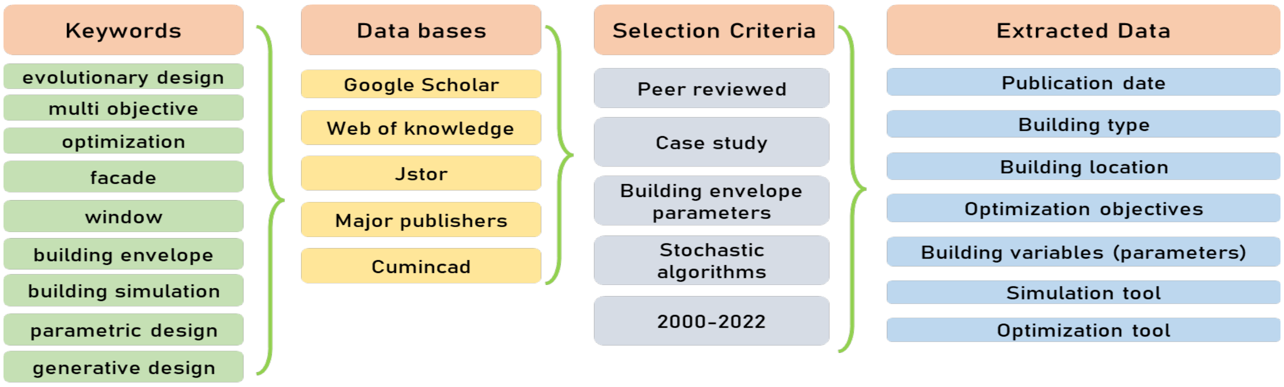

Figure 2. Methodology for the selection and analysis of the relevant work. (by authors)

III. REVIEW RESULTS AND DISCUSSION

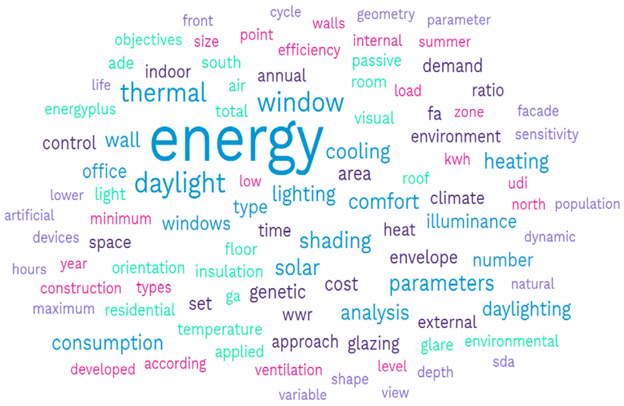

Figure 3. A word cloud visualizing the most frequent 100 keywords in the surveyed studies. (by authors)

To obtain a comprehensive understanding of prevailing methodologies, objectives, and parameters within the reviewed studies, a textual analysis was conducted on the complete texts of all manuscripts, excluding references. An online tool [8] for generating word clouds was employed to visually represent the most frequently occurring keywords across this body of work. Excluding the primary field-related keywords used for initial study selection (Section II), a discernible pattern emerged: the term "energy" held the highest frequency. This observation underscores a prominent focus on optimizing building performance, particularly in relation to energy-related objectives (**Figure 3**). Additionally, keywords like "daylight," "lighting," "shading," and "windows" surfaced prominently, indicating a substantial thematic emphasis on optimizing aspects associated with natural lighting and solar exposure, particularly within the context of building facades.

A deeper exploration of dominant trends within the surveyed studies was facilitated through quantitative analysis of word frequency (**Figure 4**). Concerning objective functions, the most prevalent aim was the minimization of energy consumption, encompassing cooling and heating loads, followed closely by objectives related to "comfort." In terms of parameters, the most frequently addressed building parameter was "windows," followed by "shading devices" and "walls," respectively. Among frequently mentioned building types, "Office" and "residential" featured prominently. In the realm of software tools, "Energyplus" emerged as the primary keyword of significance, reflecting its status as a popular building simulation software upon which many contemporary energy and lighting analysis tools are built [9], [10].

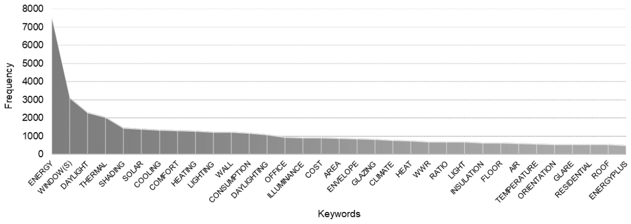

Figure 4. A histogram of keywords by frequency. (by authors)

The historical timeline of selected works was diligently tracked, revealing a diverse temporal distribution. The earliest pertinent work dates back to 2003, authored by Holst [11], who employed a genetic optimization algorithm and energy simulation to achieve a 22% reduction in a building's energy consumption while enhancing daylight availability and thermal comfort levels. Notably, six relevant studies were published in 2022, underscoring the continued relevance of this research domain. For instance, Salem Bahdad et al. [12] optimized passive design strategies for multi-story residential buildings in South Korea, leading to significant enhancements in energy efficiency, environmental impact, and economic feasibility. The majority of selected papers were published between 2016 and 2022, with a peak in 2017 (Fig. 5). This temporal pattern aligns with the findings of Shi et al. [13] , who noted an increasing trend in related papers from 2011 to 2015, attributed to a paradigm shift within the building industry towards heightened energy efficiency and the rapid advancement of simulation tools.

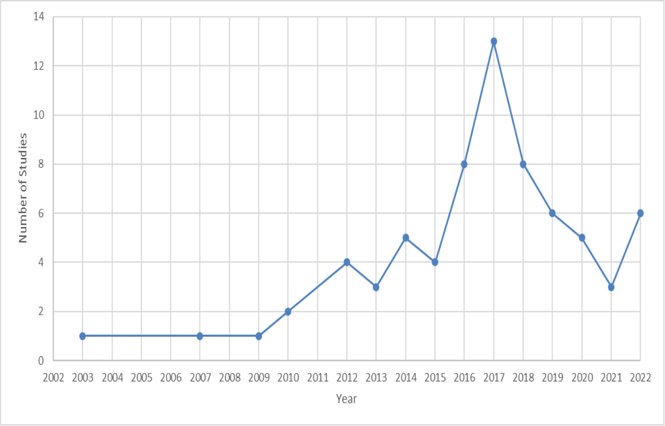

Figure 5. Reviewed studies by publication date. (by authors)

1. *Building types and locations*

The examination of the reviewed studies reveals a pronounced proclivity towards the optimization of office buildings, comprising a substantial 55% of the scrutinized case studies (**Figure 6**). However, it is imperative to note that these office spaces exhibit a remarkable heterogeneity in terms of their specifications and spatial footprints. For instance, Méndez Echenagucia et al. [14] undertook the optimization of an expansive open-plan office encompassing a generous expanse of 280 square meters. The primary impetus behind their endeavor was the minimization of energy consumption, spanning the ambit of heating, cooling, and illumination requirements. In stark juxtaposition, Zhai et al. [15] directed their scholarly attention towards the optimization of window configurations within a more confined office setting, occupying a mere 9 square meters. Their primary thrust was the reduction of energy consumption, while concurrently addressing the intricate challenge of mitigating issues associated with overheating. All the while, they judiciously safeguarded the provision of optimal daylight levels surpassing the threshold of 500 lux.

Residential buildings are another significant focus, encapsulating approximately 26% of the case studies. Within this purview, a tapestry of typologies unfurls, ranging from public housing units [16], to private family residences [17], and dormitory rooms [18]. Expanding beyond the residential sphere, the precincts of educational environments come into sharp focus, manifesting in six curated studies that encompass educational spaces, including classrooms [19], [20] and libraries [21], [22]. Furthermore, healthcare and commercial domains each command a duo of dedicated studies, with the notable inclusion of Menconi et al.'s work [23] , which ventures into the intricacies of optimizing an industrial facility. In this particular context, the focus pivots towards a livestock housing model, navigating the terrain of optimization through the adept application of a genetic algorithm.

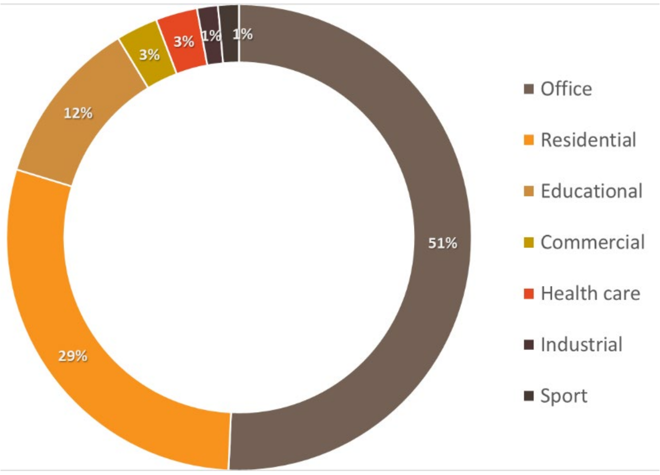

Figure 6. Distribution off Building types in the reviewed case studies. (by authors)

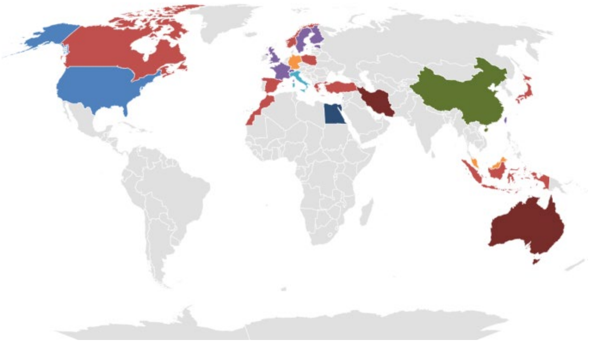

Figure 7. Geographical distribution of case studies included in the reviewed literature. (by authors)

In the realm of building optimization, climate-based simulations occupy a pivotal role, and it is evident that the building's geographical location and climate zone exert substantial influence on the identification of optimization objectives and subsequent outcomes. An analysis of the case studies within the reviewed literature elucidates a remarkably diverse geographical coverage, spanning 27 countries across five continents (**Figure 7**). Approximately 15% of the locations featured within the reviewed literature were situated within the United States (**Figure 8**), reflecting a comprehensive exploration across several distinctive climate zones. For instance, Tuhus-Dubrow and Krarti [24] conducted a comparative analysis, discerning the optimal parameters for minimal energy performance within five distinct climate zones, encompassing locales such as Boulder, Phoenix, Chicago, Miami, and San Francisco.

However, when considering the continental distribution of these studies, European cities emerge as the predominant focal point, comprising 40% of the surveyed locations. Italy stands out as the leading contributor within this European cohort. Notable examples include Rapone and Saro [25] , who undertook optimization analyses concerning louvers and glazing within typical office settings situated in Stockholm, Vienna, London, Rome, and Athens. Their objective was the minimization of annual carbon emissions through optimization. Approximately 34% of the studies were conducted in Asia, with China occupying a prominent position in this landscape. Notably, Japan featured in only one early study authored by Torres and Sakamoto [26] , where a genetic algorithm was employed to optimize daylighting systems within an office room situated in Tokyo. In contrast, Africa is the least represented continent within the surveyed studies, with a mere four cases hailing from Egypt and a solitary instance originating from Morocco [27]. South America remained absent from the purview of the surveyed studies, warranting further exploration in future research endeavors.

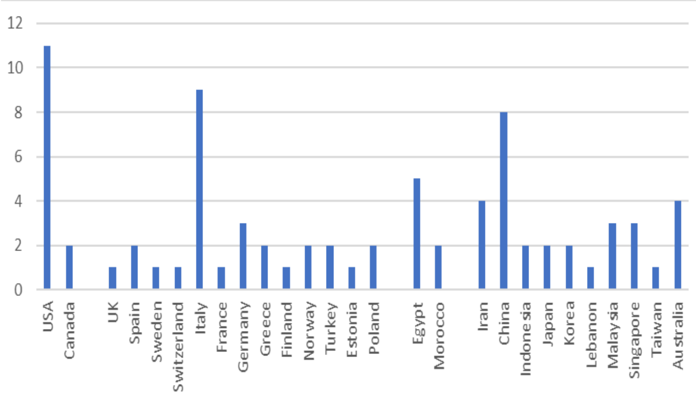

Figure 8. Building locations (X Axis) addressed in case studies and the number of the reviewed studies (Y Axis). (by authors)

2. *Simulation and optimization tools*

Within the domain of multi-objective optimization, the integration of simulation tools serves as a pivotal enabler, furnishing designers with the capacity to orchestrate multiple scenarios and comprehensively assess the performance of diverse building constituents, systems, and technologies. This evaluation extends across an expansive spectrum of objectives, encompassing energy consumption, thermal comfort, indoor air quality, daylighting, and occupant satisfaction [28]. Furthermore, these simulation tools endow designers with a profound understanding of the intricate dynamics governing a building's behavior and the interplay of its various components across diverse operational contexts and meteorological scenarios. This holistic comprehension forms the bedrock upon which the optimization of the building facade, lighting systems, HVAC systems, and other architectural elements is crafted.

In recent years, a rich tapestry of simulation tools has emerged, embracing a diverse array of factors and performance metrics intrinsic to building design. Among this cadre of tools, certain luminaries have risen to prominence. Notably, EnergyPlus commands a preeminent position as a venerable building energy simulation software [29]. Its expanse encompasses a modeling of a building's energy systems, enshrining the intricacies of the building facade, heating, ventilation, and air conditioning (HVAC) systems, lighting systems, and auxiliary equipment. EnergyPlus assumes the mantle of predicting a building's energy performance across manifold operational scenarios and meteorological conditions.

In the realm of building performance analysis, DIVA emerges as a notable software plugin tailored to complement the capabilities of 3D modeling and parametric design tools such as Rhino and Grasshopper [30]. This multifaceted toolset encompasses a comprehensive suite of functionalities spanning daylighting and energy simulations, alongside provisions for acoustic analysis and thermal comfort assessment. DIVA constitutes an indispensable resource for architects and engineers alike, facilitating the evaluation of diverse design alternatives and the optimization of building performance across an expansive spectrum of performance criteria. It empowers these professionals to embark on investigative work, probing the repercussions of each design decision on the building's performance landscape, thereby engendering the identification of the most efficacious design solutions. Conversely, within the purview of daylighting simulation, Daysim assumes a pivotal role as dedicated software [31]. Its primary mandate revolves around the prognostication of a building's daylighting performance, orchestrating a calculation of the influx of natural light into the architectural confines. Furthermore, Daysim predicts the spatial distribution of luminance throughout the architectural expanse, thus furnishing invaluable insights into the interplay of light within the built environment.

A perusal of the surveyed literature unveils a diverse 11 simulation tools that have found favor in conjunction with optimization algorithms, all orchestrated towards the objective of refining building design optimization (**Figure 9**). A predominant choice resonates through the majority of the reviewed literature, with EnergyPlus staking as the preferred simulation tool, wielding its computational prowess in 34% of the cases.

For instance, the work of X. Chen et al. [32] offers an illustration of EnergyPlus. Here, EnergyPlus unfurls as the simulation tool to gauge the combined cooling and lighting energy demands of a typical edifice. In this objective, the authors integrate prescribed mixed-mode ventilation strategies and lighting dimming control algorithms into the EnergyPlus model. This modeling exercise is underpinned by an astute consideration of the pertinent design criteria enshrined within a local green building assessment system, seamlessly combining theoretical insights with pragmatic real-world applications.

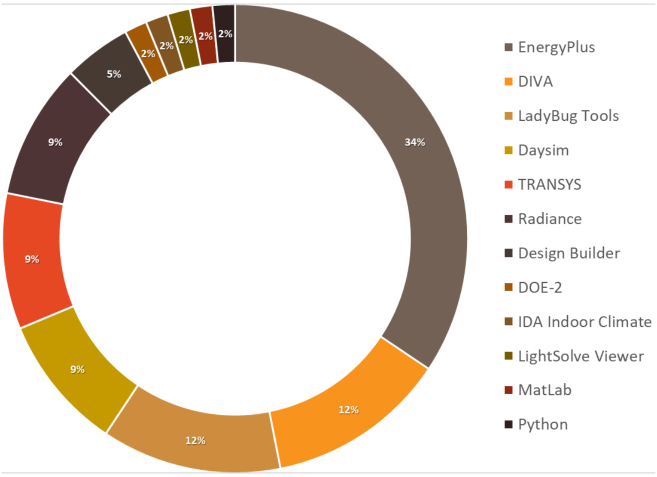

Figure 9. Distribution of the employed simulation tools, ordered clockwise in terms of frequency of utilization among the reviewed studies. (by authors)

Subsequent to EnergyPlus, a trifecta of simulation tools, namely DIVA, Ladybug, and Honeybee, each adorned the landscape of building design optimization in a commendable 12% of the studies. For instance, the discerning work of Camporeale et al. [33], exemplified the utility of DIVA in simulating the cooling and lighting energy demands of a structure. Here, DIVA served as the canvas upon which a tapestry of proposed mixed-mode ventilation strategies and lighting dimming control algorithms were woven into the model's fabric. The attention to detail extended to the incorporation of pertinent design criteria, interwoven within a local green building assessment framework.

Ladybug, a revered tool, graced the academic canvas in the study conducted by [5] In this scholarly odyssey, Ladybug and its symbiotic partner, Honeybee, assumed pivotal roles in the realm of daylighting modeling. Their collective prowess breathed life into the parametric building geometry, interlinked with the materials component nestled within Radiance. Within this intricate ballet, the transparency and reflectance of materials were judiciously defined, forging a path for a detailed simulation. Upon the culmination of this simulation odyssey, the Ladybug plugin imported the resultant trove of simulation data into the digital realm of Grasshopper. Here, it embarked on a voyage of assessment, scrutinizing the metrics of daylight performance, ultimately culminating in the generation of an annual lighting schedule. Additional simulation tools that contributed to the academic discourse included Daysim, Transys, Radiance, and Design Builder, each manifesting their influence in varying degrees, constituting 9%, 9%, 9%, and 5% of the studies, respectively. These versatile tools lent their computational might to diverse facets of the research landscape, enriching the tapestry of building design optimization endeavors.

In tandem with simulation tools, the pursuit of multi-objective optimization invariably beckons the utilization of optimization algorithms, a collective endeavor geared towards unearthing design solutions that harmoniously satisfy a multitude of concurrent objectives. These objectives find their numeric manifestation through the rich troves of simulation results. These optimization algorithms scrutinize a vast gamut of potential design solutions. Through a discerning evaluation process, they select the most promising candidates, their selection criteria rooted firmly in the performance exhibited across multiple objectives. Among the pantheon of optimization algorithms gracing the field of building design, one stands out prominently: the genetic algorithm.

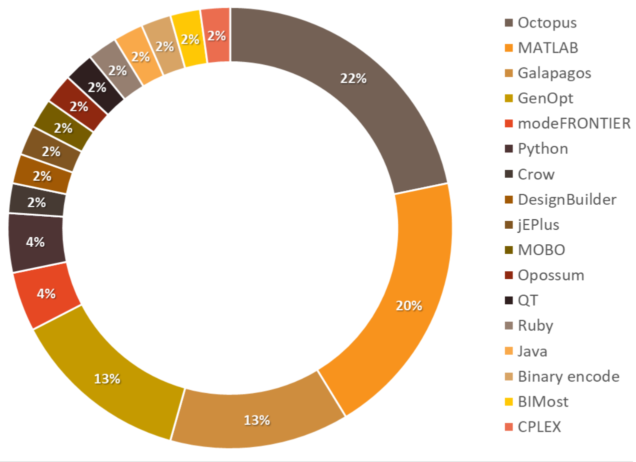

Figure 10. Distribution of the employed optimization tools, ordered clockwise in terms of frequency of utilization among the reviewed studies. (by authors)

The genetic algorithm draws its inspiration from the principles underpinning natural selection and evolution, embarking on its work with a population of potential solutions. Through a judicious interplay of crossover and mutation operations, it begets new design iterations. These fledgling designs, much like saplings reaching for the sun, are then subject to rigorous evaluation, their performance assessed across the spectrum of multiple objectives. Over the course of iterations, this algorithm charts an evolutionary trajectory, culminating in the emergence of a select coterie of optimal solutions, aptly labelled as the Pareto front. This front represents the zenith of design prowess, a realm where the most astute trade-offs between disparate objectives are unveiled, epitomizing the balancing competing interests within the architectural realm.

In the realm of building design optimization, a prominent exemplar of the genetic algorithm lineage is NSGA-II, an acronym denoting "Non-dominated Sorting Genetic Algorithm II" [34]. Its modus operandi revolves around the orchestration of a population of candidate solutions, each imbued with the potential for architectural excellence. These solutions are rigorously evaluated and subjected to a ranking process, predicated upon their non-dominated status. In essence, a solution earns the coveted non-dominated status when it remains unchallenged by any other solution within the population, a testament to its exceptional performance across multiple objectives. With the mantle of non-dominated status, these elite solutions serve as the progenitors for a new generation of architectural ingenuity. Genetic operators, such as selection, crossover, and mutation, are employed to usher in a cadre of offspring solutions. These nascent creations inherit the best traits of their predecessors while also bearing the potential for novel innovations, thus perpetuating the evolutionary approach towards the zenith of architectural optimization.

In building design optimization, some studies developed their own genetic algorithms (using mathematical modelling and programming), however, a variety of platforms and tools are also available to access and utilize various types of genetic algorithms. These tools encompass DesignBuilder, Galapagos for Grasshopper, Octopus for Grasshopper, MATLAB, and GenOpt. MATLAB is a programming environment that offers numerous built-in functions for optimization and machine learning. DesignBuilder is a building performance simulation tool that offers optimization algorithms for building design. Galapagos is a genetic algorithm solver integrated into the Grasshopper parametric modeling software. Octopus is another genetic algorithm plugin for Grasshopper that can be used for multi-objective optimization. GenOpt is a generic optimization program that can work with different simulation tools and offers a range of optimization algorithms.

In the midst of analyzing the amalgam of reviewed studies (Figure 10), a clear landscape begins to take shape, revealing the preferences of researchers in terms of optimization tools. Notably, MATLAB and Octopus emerge as the frontrunners, commanding usage rates of 20% and 22%, respectively. GenOpt and Galapagos for Grasshopper also carve out a substantial presence, each boasting a respectable usage rate of 13%. On a different note, platforms like modeFRONTIER and Python, where studies delve into the realm of algorithm development rather than relying on ready-made tools, exhibit more modest usage rates of 4%. Furthermore, an array of other tools and platforms, including BIMost, CPLEX, Crow, DesignBuilder, jEPlus, MOBO, Opossum, QT, Ruby, Java, and Binary encode, make appearances, each with a 2% usage rate.

In the academic work of Pilechiha et al. [35] the spotlight falls on Octopus optimization software. Here, the researchers embarked on a objective to optimize the intricate energy processes intertwined with window system design within the context of office buildings. The aim was to develop an approach that could quantitatively assess the quality of views in office spaces while reconciling the imperatives of energy efficiency and daylighting. To achieve this, a multi-objective assessment method was employed, featuring a parametrically modeled reference room, infused with real climate data. The study navigated the territory of Pareto Frontier and weighted summation, employing them as compasses in the search for multi-objective optimization solutions that tread the tightrope of design requirements.

In a parallel scholarly narrative spun by Jalali et al. [36], the research endeavor sets their sights on optimizing the energy performance of an office building's facade. The methodology of choice embraced a multi-objective optimization approach, fueled by the Strength Pareto Evolutionary Algorithm (SPEA-2). The aim was to strike a harmonious equilibrium between factors like solar radiation received by the building facade, interior space usability, and design shape coefficients—factors linked to cooling and heating loads, as well as natural lighting provisions.

Looking at the work of Yigit and Ozorhon [16] the backdrop of MATLAB provided ground for their endeavors. Their mission was to craft a software package that could optimize energy consumption while maintaining the precincts of thermal comfort. This package was nurtured into existence through a fusion of a tailor-made thermal simulation software and the versatile toolkit of MATLAB Optimtool. The synergy between energy simulation and optimization, now harmoniously united on a single platform, wielded the twin advantages of eradicating compatibility woes and expediting the objective for optimal designs.

Meanwhile, in the paper by Ferdyn-Grygierek and Grygierek [37], MATLAB was used as the enabler of the genetic algorithm's. Here, the objective was to optimize both energy consumption and life cycle costs (LCC) within the confines of a single-family building situated in temperate climes. A multi-variable optimization approach was used, steering the selection of optimal design parameters, such as window types and sizes, building orientation, insulation of external walls, roofs, and ground floors, and infiltration considerations. This entailed the fusion of the building performance simulation using EnergyPlus with the optimization environment, resulting in simulations across seven distinct optimization scenarios. The effectiveness of this optimization endeavor was rigorously assessed through the prism of two building variants—one equipped with both heating and cooling systems, the other relying solely on a heating system.

3. *Optimization objectives*

The analysis of the seventy scrutinized papers unveiled a tapestry of 132 distinct performance objectives for optimization, categorized into five overarching domains: Visual comfort, Energy consumption, Thermal comfort, Cost, and Emissions (**Figure 11**). Within this complex landscape, energy-related objectives stood as the dominant force, commanding a substantial 48% share. Among these, the pursuit of minimizing cooling energy consumption (Ecooling) held a notable 13% representation, alongside the objective for curbing total energy consumption (ETotal), which also claimed a 13% share. The optimization endeavors further delved into minimizing lighting energy consumption (Elighting) and heating energy (Eheating). Additionally, six studies embarked on the path of optimizing Energy Use Intensity (EUI), defined as the total annual energy consumption of a building divided by its gross floor area—a metric integral to energy benchmarking and urban energy infrastructure planning [38]. In the realm of academic exploration, Pilechiha et al. [35] notably embarked on a multi-objective approach to shape optimized window system designs, thereby striving to minimize the EUI of an office room in Tehran while maximizing daylight performance metrics.

Turning the spotlight to visual comfort and daylighting performance, these objectives occupied a significant 27% share among the optimization endeavors. Here, the beacon of useful daylight illuminance (UDI) shone the brightest, capturing the essence of annual illuminance occurrences within the 100-2000 lux range on the work plane [2]. Various studies also ventured into alternative definitions of daylight availability to encapsulate the essence of visual comfort. For instance, Lartigue et al. [18] introduced the concept of Annual Deficient Daylight Time (ADDT), quantifying those moments when illuminance falls below 300 lux, necessitating the intervention of artificial lighting.

Mahmoud and Elghazi [39] embarked on a work to explore the performance of kinetic façade panels, scrutinizing daylit area percentages across different rotational motion angles on four distinct days of the year, assessed against three thresholds—partially daylit, daylit, and overlit. K. W. Chen et al. [40] charted their course towards optimizing a daylight availability metric, calculated as the ratio of floor area receiving a mean annual illuminance between 300 lux and 2000 lux over the gross floor area. The realm of thermal comfort unfolded in 13% of the optimization objectives, with Predicted Percentage of Dissatisfied (PPD) and Predicted Mean Vote (PMV) emerging as the most embraced metrics. These metrics are intricately tied to human sensations within the thermal environment, serving as predictors of thermal discomfort. Other studies ventured into the realm of physically based metrics, such as Annual Solar Exposure (ASE) and Overall Thermal Transfer Value (OTTV). A distinctive contribution by Gou et al. [50] brought forth a novel metric known as Comfort Time Ratio (CTR), an annual indoor thermal comfort indicator specifically tailored for naturally ventilated environments. The study's mission was to maximize CTR while concurrently minimizing energy demands through the judicious alteration of various facade parameters.

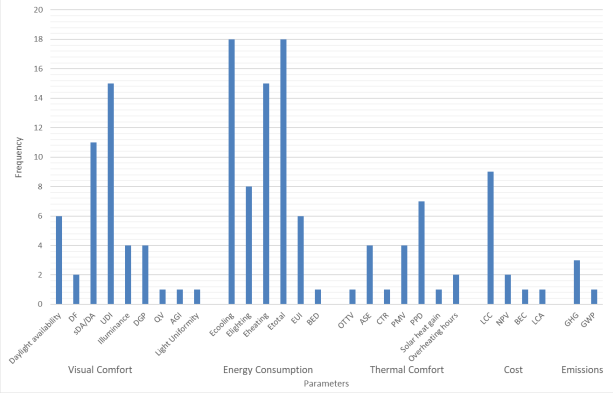

Figure 11. Optimization objectives in the reviewed studies, classified by fields (visual comfort, energy consumption, thermal comfort, cost, and emissions). (by authors)

Minimizing energy consumption stands as a paramount endeavor in the realm of building optimization, heralding a multitude of benefits ranging from the reduction of operational costs to a commendable decrease in greenhouse gas emissions. In the intricate tapestry of research pursuits, several studies have unfurled their sails towards the quantifiable metrics of building cost and emissions optimization.

Ferdyn-Grygierek and Grygierek [37] , for instance, undertook a multifaceted approach to navigate the labyrinth of minimizing Life Cycle Costs (LCC) for a residential edifice nestled in the heart of Poland. In a similar context, Camporeale et al. [33] and Hong et al. [21] charted their course towards the maximization of Net Present Value (NPV) by orchestrating multiple optimization scenarios, tuning the characteristics of windows and glazing types for a social housing block and a library building, respectively. Sun et al. [22] ventured into the realm of Building Envelope Cost (BEC), a fact that found its place within their optimization process as they sought to harmonize the design of a library building in Changchun, China. On the periphery of these optimization endeavors, only a scant few studies, akin to environmental sentinels, extended their gaze to objectives that directly touched upon environmental pollution and emissions. These stalwart endeavors were embodied by the metrics of annual Green House Gas emissions (GHG) [25], [51], [52] and Global Warming Potential (GWP) [21]. As the spotlight shifts to the ensemble of results presented in (**Figure 12**), a salient observation emerges—the optimization of building energy consumption reigns supreme as the central focus of the reviewed studies. Within this arena, the twin objectives of total energy consumption and energy consumption for cooling stand as the most frequently treaded paths, each commanding a prominent 12% share among the reviewed studies. In stark contrast, the optimization objectives entwined with daylight performance, embodied by metrics such as Useful Daylight Illuminance (UDI) and spatial Daylight Autonomy (sDA), occupy a more modest portion of the landscape, with 10% and 7% representation, respectively. This nuanced landscape suggests a prevailing emphasis on building energy consumption optimization within the domain of building facade optimization research, positioning it as a beacon guiding the trajectory of scholarly endeavors, while daylight performance optimization occupies a lesser but still noteworthy niche within this multifaceted field of inquiry.

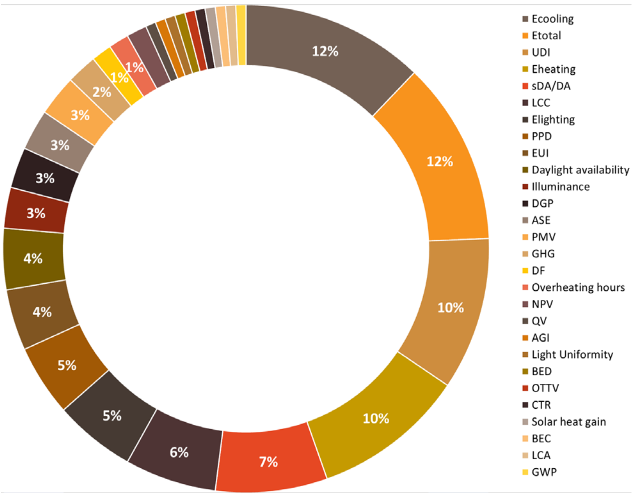

Figure 12. Distribution of Optimization objectives, ordered clockwise in terms of frequency of utilization among the reviewed studies. Unlabeled parts on the pie chart represents values of less than 1%, (by authors)

4. *Building facade parameters*

The intricate web of analysis, as depicted (**Figure 13** , casts a revealing light on the design parameters that serve as the fulcrum for achieving the lofty performance objectives outlined in the reviewed papers. The parameters that emerge as the main item of this scholarly narrative are intrinsically linked to the building's exterior, wielding a pivotal role in the optimization paradigm. In this intricate choreography, the parameter category of "size of building openings" emerges as the leading protagonist, commanding a notable 16% of the spotlight. It is within the size of these openings that the harmonious interplay of light and design finds its expression. Not far behind, "glazing types" take center stage, occupying a significant 15% of the performance arena. The glazing type is a formidable player, shaping the building's response to external forces while lending character to its facade. Moving along this performance stage, we encounter "sunshade parameters," a troupe of variables that includes materials, dimensions, and the window-to-wall ratio (WWR) of sunshades. This ensemble exhibits remarkable versatility, gracing 13% of the scenes in our scholarly performance. Likewise, the "window-to-wall ratio (WWR)" itself, a key facet of building design, secures a notable 12% presence.

However, we find the lesser-utilized parameters, relegated to supporting roles in this performance. The likes of "balcony size," "atrium," and "skylight" appear sparingly in the limelight, each accounting for approximately 1% of the parameters. These understudies, though less frequently employed, contribute their unique essence to the overall composition of building optimization.

As we endeavor to synthesize these diverse parameters, we can discern five overarching categories that encapsulate their essence. The first category, "whole building form," encompasses variables such as building dimensions and orientation. An example of this can be found in the work of Jalali et al. [36] , who optimized the performance of an office building in Tehran by orchestrating building orientation, dimensions, and retreat from the road. The second category, "outer elements," casts a wide net that encompasses ceiling heights, atriums, balconies, courtyards, and skylights. Marzban et al.[53] , for instance, considered the dimensions of balconies and ceiling heights as variables in their objective to optimize the performance of a residential building in New South Wales, Australia. Within the third category, "facade elements," we encounter variables related to glazing types, external walls, and openings such as windows, replete with their window-to-wall ratio (WWR). Gagne and Andersen [44] , for instance, deftly parametrized the number of windows, WWR, window position in the facade, and glazing type to optimize daylight availability while mitigating the menace of glare. The fourth category, "shading elements," introduces a cast of characters including light shelves, overhangs, blinds, sunshades, and louvers. These elements, much like the artists of a stage production, add depth and shading to the building's performance. Sunshades play a prominent role in this category.

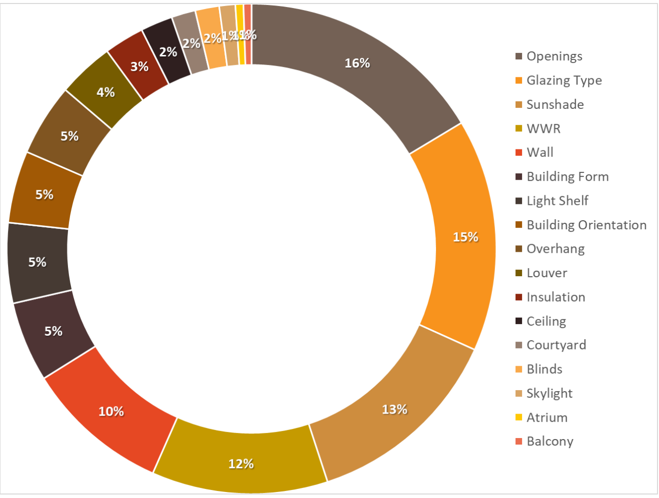

Figure 13. Variable design parameters within the optimization functions ordered clockwise in terms of frequency of utilization among the reviewed studies. (by authors)

The last category, "insulation parameters," encompasses a wide range of building components, including walls, roofs, and floors. These parameters, even though they may not be as conspicuous, are fundamental to the overall performance of the building, ensuring it is energy-efficient and provides thermal comfort. While discussing design factors, the spotlight often falls on facade elements and shading devices, which account for 81% of all the factors considered in the reviewed studies. Among these, factors related to building openings, such as the placement, size, and arrangement of windows, take the forefront, closely followed by considerations like the type of glazing and the window-to-wall ratio (WWR). Among shading elements, sunshades are the most prominent, followed by light shelves, both contributing to the optimization of the building's performance by adding depth and dimension.

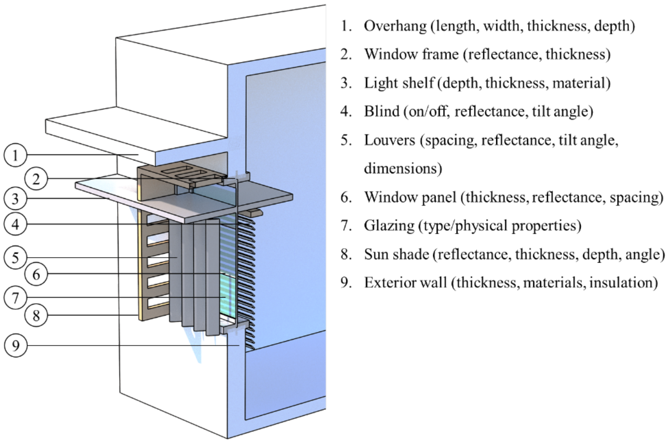

Figure 14. Dominant parametrized elements of building facade in optimization studies (by authors)

Based on the findings, the authors visually depicted the most crucial aspects of optimizing building facades by analyzing various parameters from the studies they reviewed. In (**Figure 14**) , you can see the predominant facade elements, which include factors like the size of the overhangs above windows, the material characteristics of the window frames, the dimensions and materials used for light shelves (horizontal shades integrated into window glazing), the presence and dimensions of window blinds, the properties and sizes of window panels (the vertical bars separating glazing sections), the type and characteristics of glazing, the utilization and dimensions of sunshades, and parameters related to the exterior wall, including its thickness, construction materials, and insulation properties. This visual representation offers a comprehensive overview of the key factors influencing the optimization of building facades.

IV. CONCLUSIONS AND RECOMMENDATIONS

multi-objective optimization algorithms have become invaluable in the face of conflicting optimization goals. These algorithms excel in producing a set of solutions that achieve a win-win outcome when different objectives compete for priority. This study conducted an in-depth analysis of seventy peer-reviewed papers dedicated to the optimization of building facades. The primary goal was to identify the prevailing optimization objectives in building performance research and the critical parameters shaping building facade design. The overarching theme across these papers was the pursuit of improved energy efficiency and enhanced occupant comfort. It is noteworthy that the majority of these studies were published between 2016 and 2022, with the earliest relevant work dating back to 2003. This timeframe witnessed a marked surge in interest in energy-efficient building design, featuring innovative methodologies such as the application of machine learning, including Artificial Neural Networks, to optimize building designs. Among the various building types analyzed in these studies, office buildings took center stage, followed by residential, educational, healthcare, and commercial structures. Geographically, Europe led the way, closely followed by Asia and the United States in terms of research contributions. Widely adopted simulation tools included EnergyPlus, DIVA, and Daysim. When it came to optimization objectives, energy consumption and visual comfort were the key focus areas. Reducing cooling energy consumption and overall energy consumption emerged as the most frequently addressed objectives.

The studies examined a multitude of parameters for optimizing building performance, with special attention given to facade elements and shading devices. Window placement and dimensions, glazing types, and window-to-wall ratios (WWR) were the most frequently parameterized variables. Sunshades were the preferred shading element in the pursuit of optimization. Drawing from the study's findings, the authors put forth a series of recommendations spanning building performance research, simulation, architectural practice, and education. While recognizing the preponderance of research in office buildings, driven by their substantial energy consumption, the authors advocate for diversifying research to encompass other building types, especially educational and commercial structures. This diversification should also extend to objectives related to thermal and visual comfort, given their pivotal role in enhancing the occupant's well-being. Furthermore, the review highlighted a notable absence of research on building optimization in climates typical of developing countries, particularly in Africa. This deficiency suggests a potential lag in the adoption of optimization tools in these regions, a crucial factor in designing high-performance buildings. Thus, the authors call for a more significant emphasis on multi-objective optimization in regions like Africa, the Middle East, and other developing areas, not only in research but also in university curricula and architectural practice. In addition to this, the authors recommend integrating multi-objective optimization into the early stages of the design process, making it a central driver of design decisions. This integration should harmonize with other aspects of digital transformation, such as building information modeling, fostering more efficient and effective design processes that align with the needs of various stakeholders while promoting sustainable building practices.

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APPENDIX

Table 1: Reviewed building optimization studies and their respective objectives and parameters

	Authors, Date, and Title	Objectives of Optimization	Parameters	
1	[14] The Early Design Stage of a Building Envelope: Multi-Objective Search through Heating, Cooling and Lighting Energy Performance Analysis	Heating energy (KWh/m2) Cooling energy (KWh/m2) Lighting energy (KWh/m2)	Wall thickness (0.1-1 m) Windows: Number Shape (8 alternatives) placement	
2	[17] Optimization of Building Envelope Design for NZEBs in Mediterranean Climate: Performance Analysis of Residential Case Study	Cooling loads (KWh) Heating loads (KWh)	WWR (15-80%) Glazing type (7 alternatives) Blind type	
3	[25] Optimisation of Curtain Wall Façades for Office Buildings by Means of PSO Algorithm	Annual Carbon Emissions (ECO2) (Kg/m2yr)	Double glazing (5 alternatives) Percentage of glazed surface Louver depth (0.1-0.8m) Louver spacing (0.3-1.0m)	
4	[54] Optimizing Windows for Enhancing Daylighting Performance and Energy Saving	Thermal heat gain Cooling loads	Glazing type (7 alternatives)	
5	[26] Facade Design Optimization for Daylight With a Simple Genetic Algorithm	Daylight availability (annual total illumination need for all occupants at 500 lux)	window width sill height (0-2.5) window height External light shelf depth (0-0.8) Internal light shelf depth (0-0.8) light shelf height overhang depth low sunshade depth (0-0.5) high sunshade depth (0-0.5) Number of shades / window (2-5) Number of windows (3-7)	Window sill depth (0.1-0.4) wall reflectance external light shelf reflectance. (0.3-0.6) internal light shelf reflectance. (0.3-0.8) window sill reflectance. (0.2-0.7) sunshade reflectance window size factor (1-1.5) shading size factor (0.3-1) window transmittance reflective Light shelf (Yes/No)
6	[35] Multi-Objective Optimisation Framework for Designing Office Windows: Quality of View, Daylight and Energy Efficiency	EUI (kWh/m2) ASE % QV % sDA %	Window Width Height Sill/head height Distance from window to façade edge	
7	[55] A Framework for Performance-Based Facade Design: Approach for Multi-Objective and Automated Simulation and Optimization	Cooling loads Heating loads Lighting loads EUI PMV PPD Energy cost	Wall framing type: Metal (9 alternatives) Insulated Concrete Form (ICF) (2 alternatives) Light wood (3 alternatives) Curtain wall (2 alternatives)	Insulation type WWR Glazing type Overhand Blinds
8	[56] Geometric Optimization of Fenestration	Energy use (KWh)	Window grid distribution	
9	[33] Multi-Objective Optimisation Model: A Housing Block Retrofit in Seville	Cooling load Heat load Net Present Value (NPV)	WWR Glazing type	

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10	[32] Simulation-Based Approach to Optimize Passively Designed Buildings: A Case Study on a Typical Architectural Form in Hot and Humid Climates	Lighting energy (kWh/m2) Cooling energy (kWh/m2)	building orientation External obstruction angle external wall thermal resistance (WTR) Wall Specific Heat (WSH)	Window U-Value (WU) Solar Heat Coefficient (SHGC) window to ground ratio. overhang projection ratio
11	[40] Multi-Objective Optimisation of Building Form, Envelope and Cooling System for Improved Building Energy Performance	Cooling loads Daylight performance (ratio of floor area covered by useful illuminance)	glazing materials (2) shading strategy (2) WWR courtyard size floor shape (4 points)	
12	[57] Multi-Variable Optimization of Building Thermal Design Using Genetic Algorithms	Life Cycle Costs (LCC) Thermal comfort	Orientation Window area Glazing type (4) External insulation (6)	
13	[5] Design Optimization of Building Geometry and Fenestration for Daylighting and Energy Performance	UDI EUI	Building depth roof ridge location skylight width skylight length skylight location	south window width louver length north window width skylight orientation
14	[44] A Generative Facade Design Method Based on Daylighting Performance Goals	Illuminance DGP	WWR Number of windows Window Aspect ratio Window Vertical location Window Horizontal location Window distributions	Overhang (Yes/No) Fins (Yes/No) Length of shading devices Total glass transmissivity (%) Percent specular transmission (%)
15	[50] Passive Design Optimization of Newly-Built Residential Buildings in Shanghai for Improving Indoor Thermal Comfort While Reducing Building Energy Demand	Building Energy Demand (BED) kWh/m2 Comfort Time Ratio (CTR) %	building orientation Window to Wall Ratio (WWR) window U −value window SHGC window/door airtightness	window opening control type. window external shading building surface solar absorptance XPS board thickness exterior wall type
16	[58] Multi-Objective Optimization Methodology for Net Zero Energy Buildings	Heater and pump energy consumption Cooling and heating thermal demands Loads by PV LCC (cost)	Walls Insulation thickness Roof insulation thickness Type of glazing	Number of solar panels Windows width
17	[21] A Multi-Objective Optimization Model for Determining the Building Design and Occupant Behaviors Based on Energy, Economic, and Environmental Performance	Thermal Energy Consumption (TEC) Predicted mean vote (PMV) Net present value Global Warming Potential (GWP)	window type (31 alternatives) heating/cooling system set point ventilation/window opening type	
18	[36] Design and Optimization of Form and Facade of an Office Building Using the Genetic Algorithm	UDI % Cooling load (kWh /m2) Heating load (kWh /m2)	Rotation Width Length Height	X position Y position Retreat distance from road
19	[59] Passive Performance and Building Form: An Optimization Framework for Early-Stage Design Support	UDI % EUI	Courtyard (Yes/No) Number of floors Plan aspect ratio WWR	Shading device (Yes/No) Wall type Window type
20	[18] Multi-Objective Optimization of Building Envelope for Energy Consumption and Daylight	Qheat Qcool ADDT (Annual Deficient Daylight Time)	WWR (10% to 60%) Window type (13 alternatives)	
21	[39] Parametric-Based Designs for Kinetic Facades to Optimize Daylight Performance: Comparing Rotation	Daylight availability	Panel rotation Panel translation	

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	and Translation Kinetic Motion for Hexagonal Facade Patterns			
22	[48] Daylighting 'Energy and Comfort' Performance in Office Buildings: Sensitivity Analysis, Metamodel and Pareto Front	Annual glaring index (AGI) Annual energy requirement for lighting (AEL)	Plan aspect ratio Orientation Overhang Depth	WWR Window sill position Glazing transmittance
23	[60] Optimization of Office Building Façade to Enhance Daylighting, Thermal Comfort and Energy Use Intensity	sDA PDH (Percentage of Discomfort Hours) EUI	WWR (10 to 80%) Insulation thickness Glazing type	Shading system (4 alternatives) Light Shelves (4 alternatives)
24	[27] Shading Devices Optimization to Enhance Thermal Comfort and Energy Performance of a Residential Building in Morocco	Cooling energy demand (KWh) Heating energy demand Discomfort degree hours (%)	Overhang projection	
25	[61] Optimization of Office Building Facades in a Warm Summer Continental Climate	Cooling energy demand (KWh) Heating energy demand	Wall type WWR	
26	[62] Simulation-Based Multi-Objective Optimization of Institutional Building Renovation Considering Energy Consumption, Life-Cycle Cost and Life-Cycle Assessment	Total Energy Consumption (MWh) LCC LCA (10^6Kg CO2)	Roof types (R) External Wall types (EW) Façade Types (FT) Glazing template (G) Window frame types (W)	WWR HVAC systems (HVAC) Cooling and Heating Operation schedules (COS, HOS) Lighting systems (Li)
27	[63] Modelling Zero Energy Buildings: Parametric Study for the Technical Optimization	Total annual energy	Insulation thickness window type solar protection dimension	
28	[24] Genetic-Algorithm Based Approach to Optimize Building Envelope Design for Residential Buildings	Total annual energy LCC	WWR, Glazing type aspect ratio wall type	air infiltration shading solar radiation
29	[64] Building Simulation and Evolutionary Optimization in the Conceptual Design of a High-Performance Office Building	Annual heating loads Annual cooling loads	Atrium width Envelope vertical angle	Envelope chamfer angle Building width
30	[65] Multi-Objective Optimization of Cellular Fenestration by an Evolutionary Algorithm	Annual energy use Capital cost	Cell distribution Overhang (Yes/No)	
31	[52] Multiobjective Optimisation of Energy Systems and Building Envelope Retrofit in a Residential Community	Green House Gas emissions (kg CO2-eq/m2/a)	Building area Façade area WWR	Building height Roof slope Roof type
32	[66] Computational Design and Parametric Optimization Approach with Genetic Algorithms of an Innovative Concrete Shading Device System	Total energy use	Incision depth Upper and lower angle rotation Thickness	
33	[15] A Multi-Objective Optimization Methodology for Window Design Considering Energy Consumption, Thermal Environment and Visual Performance	Total annual energy consumption indoor thermal environment performance (hrs) illuminance at control point	WWR Orientation Glazing type	
34	[20] Optimization of Thermal and Daylight Performance of School Buildings Based on a Multi-Objective Genetic Algorithm in the Cold Climate of China	annual energy use summer discomfort hours UDI	Orientation Class depth Corridor depth	WWR Glazing Type Shading type

35	[67] Envelope Design Optimization by Thermal Modelling of a Building in a Warm Climate	PMV PPD	Wall type Floor type	Glazing type Windows distribution
36	[37] Multi-Variable Optimization of Building Thermal Design Using Genetic Algorithms	LCC	Window types Window size	Orientation Insulation type
37	[68] The Effect of Geometry Factors on Fenestration Energy Performance and Energy Savings in Office Buildings	Annual energy consumption	Building shape WWR Window orientation	
38	[46] Optimization of an External Perforated Screen for Improved Daylighting and Thermal Performance of an Office Space	UDI DGP	Perforation opening spacing (X-Y)	
39	[69] Optimization for Heating, Cooling and Lighting Load in Building Façade Design	Annual Energy cost Annual heating loads Annual cooling loads Annual lighting loads	Shading Depth Shading Depth Shading Height	
40	[70] Daylighting In Hospital Patient Rooms: Parametric Workflow and Genetic Algorithms for An Optimum Façade Design	Daylight Availability	Horizontal wall divisions Vertical wall divisions Number of solid cells	
41	[42] Feasibility Study on Parametric Optimization of Daylighting in Building Shading Design	Daylight Factor	Louver angle Louver Number Louver depth Window panel count in X direction	Window panel count in Y direction WWR (Voronoi) Seed (Voronoi)
42	[11] Using Whole Building Simulation Models And Optimizing Procedures To Optimize Building Envelope Design With Respect To Energy Consumption And Indoor Environment	PMV E total Q heat Q cool Q light	Window area Glazing type Wall insulation thickness Roof insulation thickness	Floor insulation thickness Shading transmission Night setback temperature
43	[41] Design optimisation for window size, orientation, and wall reflectance with regard to various daylight metrics and lighting energy demand: A case study of buildings in the tropics	E lighting DGP DF DA UDI Light Uniformity	Window orientation WWR	
44	[19] Bi-Objective Optimization of Building Enclosure Design for Thermal and Lighting Performance	Q heat Q cool Daylight availability	Ceiling Height Clerestory Window Light Transmittance Clerestory Window Solar Transmittance Clerestory Window Width	Daylight Window Light Transmittance Daylight Window Solar Transmittance Exterior Shade Length Lightshelf Length
45	[71] Multi-Objective Optimization for Energy Consumption, Daylighting and Thermal Comfort Performance of Rural Tourism Buildings in North China	UDI PPD	WWR Form dimensions (court)	
46	[72] Optimization of Daylight Performance Based on Controllable Light-Shelf Parameters Using Genetic Algorithms in the Tropical Climate of Malaysia	UDI	Position height of light-shelf External depth ratio of light-shelf Internal depth ratio of light-shelf	External part angle of light-shelf Internal part angle of light-shelf
47	[22] Many-Objective Optimization Design of a Public Building for Energy, Daylighting and Cost Performance	UDI EUI sDA	floor height skylight width window width	wall type glazing type

	Improvement	BEC		
48	[51] Daylight Design of Office Buildings: Optimisation of External Solar Shadings by Using Combined Simulation Methods	Total CO2 emissions	Shading number Shading angle Shading depth	
49	[73] Multi-Objective Energy and Daylight Optimization of Amorphous Shading Devices in Buildings	UDI - TEC (total energy consumption)	Shade spacing Shade angle	
50	[43] Optimisation of Daylight Admission Based on Modifications of Light Shelf Design Parameters	sDA ASE	Shelf internal width Shelf external width Ext tilt angle Specularity	
51	[45] A Daylight Optimized Simulation-Based Shading Controller for Venetian Blinds	Vertical illuminance Average horizontal illuminance	Blind tilt angle	
52	[74] FAST Energy and Daylight Optimization of an Office with Fixed and Movable Shading Devices	Hours with blinds at 45 degrees Annual total energy	Shade width Shade tilt	
53	[75] A Pareto-Based Multi-Objective Optimization Algorithm to Design Energy-Efficient Shading Devices	Hours above 26 °C (Overheating) Change in annual energy demand Area of shading device Shape acceptance	Shades width (6 segments)	
54	[76] Genetic Optimization of External Fixed Shading Devices	Annual energy consumption	Shade width Shade tilt	
55	[77] A Novel Approach for the Simulation-Based Optimization of the Buildings Energy Consumption Using NSGA-II: Case Study in Iran	Annual cooling energy Annual lighting energy	Building orientation Window length (m) Window width (m)	Overhang tilt angle Overhang depth (m)
56	[16] A Simulation-Based Optimization Method for Designing Energy Efficient Buildings	Total energy consumption	Wall type Window dimensions Glazing type	
57	[53] An Evolutionary Approach to Single-Sided Ventilated Façade Design	Cooling energy Heating energy UDI Air change rate index	Number of windows Window placement Window dimension	Balcony dimensions Ceiling height Shading (Yes/No)
58	[23] Implementation of a Genetic Algorithm for Energy Design Optimization of Livestock Housing Using a Dynamic Thermal Simulator	Site Energy Consumption	WWR Glazing type Wall type Roof type	
59	[78] Optimization of Green Building Design to Achieve Green Building Index (GBI) Using Genetic Algorithm (GA)	OTTV	Wall type Glazing type	
60	[47] Model-Based Optimization for Architectural Design: Optimizing Daylight and Glare in Grasshopper	UDI DGP	Louver tilt angle	
61	[79] Multi-objective optimization of the multi-story	BED LCA	Air mass flow Envelope U-Value	Window SHGC wall capacity ratio (Thermal Inertia)

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	residential building with passive design strategy in South Korea	LCC	Roof solar absorptance Window U-value	WWR Number of occupants
62	[80] Using Parametric Design to Optimize Building's Façade Skin to Improve Indoor Daylighting Performance	sDA DA ASE DGP	Vertical subdivisions (1-3) Openings Size (0-6) Skin depth D (0.2-0.7)	
63	[81] Multi-objective optimization of building design for life cycle cost and CO2 emissions: A case study of a low-energy residential building in a severe cold climate	Life cycle CO2 (LCCO2) emissions LCC	Wall insulation thickness (mm) Roof insulation thickness (mm) External window type South WWR (%)	North WWR (%) West/east WWR (%) Overhang depth (m) Orientation (°)
64	[82] Applying a parametric design approach for optimizing daylighting and visual comfort in office buildings	ASE sDA	Screen depth Perforation percentage Gap width	
65	[83] Multi-objective optimization of daylight performance and thermal comfort in classrooms with light-shelves: Case studies in Tehran and Sari, Iran	UDI sDA	Light Shelf Length of the exterior part Height Length of the inner part Angle of the inner part	
66	[84] Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms	Annual thermal energy demand Annual weighted average of discomfort degree-hours	Transmission coefficient of the exterior walls Transmission coefficient of the Roof Transmission coefficient of the Floor Absorption coefficient of the exterior walls Absorption coefficient of the Roof Linear coefficient of thermal bridges	Air change per hour Shading coefficient for north-facing windows Shading coefficient for south-facing windows Shading coefficient for east-facing windows Glazing
67	[85] A multi-objective optimization design method for gymnasium facade shading ratio integrating energy load and daylight comfort	Illuminance intensity Solar radiation value DGP	Envelope materials Reflectance Transmittance Roughness Specularity	
68	[86] Investigation into the daylight performance of expanded-metal shading through parametric design and multi-objective optimisation in Japan	ASE UDI sDA	Expanded metal parameters Bond Strand	Length Height Angle
69	[87] Multi-Objective Building Design Optimisation Using Acoustics and Daylighting	DA Floor area Speech Clarity (at 500 Hz)	Building geometry vertex positioning	
70	[12] Balancing daylight in office spaces with respect to the indoor thermal environment through optimization of light shelves design parameters in the tropics	UDI Operative air temperature (Tio) (set point 26°C) Indoor air temperature (Tia) (set point 26°C) Mean radiant temperature (Mrt) (set point 26°C)	Light Shelf Height External depth ratios	Internal depth ratios External angles rotation internal angles rotation