Performance Optimization Studies on Heating, Cooling and Lighting Energy Systems of Buildings during the Design Stage: A Review

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Abstract: Optimizing the building performance at the early design stage is justified as a promising approach to achieve many sustainable design goals in buildings; in particular, it opens a new era of attractive energy-efficient design for designers and architects to create new building constructions with high-energy efficiency and better overall performance. Accordingly, this study aims to provide a comprehensive review of performance optimization studies on heating, cooling, and lighting energy systems of buildings during the design stages, conducting a systematical review covering various aspects ranging from the building type, optimization inputs, the approach used, and the main conclusion. Furthermore, the benefits and limitations of early optimizations in the energy-efficient design performance of buildings and future research directions are identified and discussed. The review results show that previous research efforts of optimizing energy-efficient design performance in buildings have addressed a wide variety of early stage design optimization issues, including orientation and multi-objective building function-related conflicts, such as cooling and lighting. However, significant research issues related to investigations of design envelope materials, proper energy-efficient design form, and other passive parameters, such as solar photovoltaic systems, are still lacking. Therefore, future research should be directed towards improving existing optimization approach frameworks in the context of appropriate energy-efficient design features; integrating sensitivity and uncertainty analyses in the performance optimization framework of buildings to provide a more balanced assessment of influential design envelope properties and extending optimal design envelope investigations of buildings to include other passive parameters and lifecycle assessment under long-term weather conditions.

Keywords: building designs; design parameters; design stages; optimization algorithms; energy simulation tools; lighting simulation tools

1. Introduction

Buildings are the only sector with the highest potential and lowest cost to reduce greenhouse gas emissions, nevertheless, as societies evolved, energy uses in buildings have increased due to higher comfort requirements and relativity low energy prices from non-renewable resources, until it became clear that such high energy use of buildings has a negative impact on the economy and environment, and therefore it should start looking for more energy efficient building solutions [1,2]. Several regulatory incentives and certifications, including LEED assessments, European Energy Performance of Buildings Directive, national building regulations, and local proactive planning policies, have been introduced to make buildings more sustainable [3]. This coincides with several optimization techniques that have been developed to optimize the building envelope performance in the design stages by considering all influential factors related to construction components, thermo-physical properties, building geometry, building shape, control strategies, occu-
pancy, and climate [4,5]. Nonetheless, the design of sustainable buildings is slowly moving forward. The evidence for this is that the performance of the newly built buildings is very poor during the operational phase because 40% of overall energy usages for the lighting, cooling, and heating [5,6], and 39% of the global greenhouse gas emissions still come from buildings [7]. As per the two-degrees scenario, the building sector should reduce its total carbon footprint by more than 60% by 2050 to prevent the global temperature rise by 2 °C [8].

Accordingly, the concept of optimizing building performance at the early design stage is a major research topic for reducing environmental concerns associated with energy-related emissions in buildings, as a result of the high standards of living required in the indoor environments of buildings by their occupants. In particular, the early stage of designing buildings represents the most appropriate opportunity, as the most building design optimization decisions can be made, and there is the greatest, most appropriate potential to obtain high-performance buildings in terms of energy efficiency and reduced carbon-related emissions [9]. For instance, the design possibilities in the early stages of a building can be examined and improve its performance through dealing with many design problems, using optimization techniques, such as optimization algorithms and simulation tools, which enable exploring a wide variety of ideal design solutions with high efficiency, and evaluating and determining high-influential variables. Furthermore, several other design issues/problems, including indoor thermal comfort, façade design, daylighting, structural design analysis, cost, and energy, can be completely addressed [10] to reach optimum values for a building’s performance function. In particular, with the development of optimization techniques in conjunction with simulation tools of building performance in the past two decades, the transformation process of building design problems into the mathematical domain became possible [11].

Consequently, studying building performance optimization in the early design stages has become an automated process by combining a “simulation engine” (e.g., EnergyPlus, DOE-2, TRNSYS, ESP-r, Radiance, Dialux, etc.) with an “optimization engine” (e.g., genetic algorithm, GPS Hooke-Jeeves algorithm, etc.) consisting of one or more optimization strategies [12,13], or through only simulation engines. These optimization techniques are usually classified into two main groups, which are techniques that integrate simulation software packages into generic optimization platforms and techniques that integrate simulation software packages into specific purpose optimization platforms. Therefore, different aspects of the building design performance that contradict with each other are dealt with. A typical example of this paradox is natural lighting versus solar shading [4]. Significantly, in the design optimization process, building geometry and input variables that should be optimized such as physical properties of envelope materials, shape, orientation, and settings of building systems are the most interesting topics regarding interdisciplinary design [14,15]. In particular, building geometry characteristics are a major component of the building envelope structure and represent a large part of their budget. The influence of these characteristics will not be limited to the aesthetic value, but will comprise the other functions of a building lifecycle, including lighting, heating, cooling, ventilation, cost, etc.

In response, optimizing the energy-efficient design performance in buildings gained a lot of attention during recent years. Several previous studies have focused on optimizing the performance of heating, cooling, and lighting energy systems of buildings during the early design stages. Since, they are a quantifiable performance index, which can be used as key indicators to determine the values of design parameters that have a significant impact on building performance, including the design shape and other envelope components. This is in addition to other influencing factors, such as occupancy and weather conditions, which were considered. The simulation-based performance optimization approach has become an effective measure to achieve many stringent requirements of high-performance buildings, such as passive sustainable-buildings, nearly/zero energy buildings, green buildings, low-energy buildings, etc. In addition, a wide variety of building problems in the design stages were considered, together with many design parameters and other relevant parameters
(e.g., occupancy and climate) that have been addressed, with the aim of reaching high-performance buildings in terms of energy efficiency and comfortable indoor environments. In this context, Chokwitthaya et al. [16] recommended that optimizing building designs should be able to correctly describe human-building interactions for buildings to contribute to the development of satisfactory building models and the performance discrepancy between predictions and real buildings. Menezes et al. [17] demonstrated that building occupancy is a significant influential factor in the use of building electrical energy and is able to predict the use of electrical energy with an accuracy of ±3% by applying occupancy patterns in simulations. Singh et al. [18] found, through sensitivity analysis to identify the most influential factors on the energy performance of a building under different climate conditions, that building envelope measures, such as thermal mass and heat transmission, could be used to reduce the energy demand of buildings.

In contrast, a number of review papers [3,13,19,20] have been published on this topic, despite the significance of building performance optimization-related review studies, however, there is still a great need for a review study on optimizing the performance of heating, cooling, and lighting energy systems of buildings at the early design stages, because; (1) previously published review studies [3,13,19,20] do not summarize the current state-of-the-art applications of heating, cooling, and lighting performance optimizations of building energy systems in the early design stages; (2) previously published review papers paid more attention to relevant aspects of simulation-based optimization methodologies for buildings [3,13,19], in general and passive design strategies [20]; and (3) no extensive review study on the inputs and outputs of the energy-efficient design optimization process. To fill this gap, this study searches for the most research papers in the field of energy-efficient design performance optimization in buildings including the older research papers dating back to the 2000s and state-of-the-art ones in recent years, and then provides a comprehensive review for all research works related to heating, cooling, and lighting energy optimization applications of buildings during the early design stages from a more multivariate perspective. With a special focus on the relevant aspects of design parameters, optimization inputs, optimization technique used, optimization outputs, and major conclusions, to gain a deeper understanding of the state-of-the-art applications of optimizing the heating, cooling, and lighting energy systems and future research and development opportunities on energy-efficient design performance optimizations of buildings. This is in addition to analyzing and discussing all relevant aspects of the benefits, and limitations of optimizing energy-efficient design performance of buildings in the early stages.

The contributions of this review study are; (1) to reveal the most frequently used optimization techniques and relevant optimized variables considered when optimizing the building performance in the design stages, (2) to highlight the most prominent limitations relevant to energy-efficient design performance optimization in the early stages; and (3) to refine a few key future tasks, which should be considered in the field of energy-efficient design performance optimization in the early stage buildings. The rest of this paper is organized into six key sections: Section 2 defines the scope of the review and various relevant terms, including design stage, building performance, optimization techniques, early evaluation, design parameters, building geometry, and climatic factor. Section 3 reviews and analyzes existing building energy-efficient design performance optimizations and sensitivity analysis of building design performance optimization. Section 4 presents the benefits of building performance optimization and discusses the most prominent limitations related to building performance optimization in the design stages. Section 5 discusses the future research directions relevant to building performance optimization in the design stages, and Section 6 draws salient conclusions.

2. Methodology

This study is conducted based on gathering and analyzing all relevant previous research works in the field of energy-efficient building optimization at the early design stages, specifically, those efforts related to lighting, heating, and cooling optimizations in
buildings, according to the research question, which is, “Does early design optimization positively affect building performance?” All of those efforts have been categorized as lighting optimization applications and heating and cooling optimization applications in buildings, also referred to as the “core literature”. Four criteria were, therefore, proposed to facilitate a reliable understanding of the core literature in this study.

- The literature must indicate that the research work deals directly with building performance in the design stages, specifically, applications of heating, cooling, and lighting; and uses one/multiple optimization techniques related to simulation tools, algorithms, or both. If an article discusses the cooling/heating or lighting performance in buildings at another stage, such as the renovation stage of the building lifecycle, it is excluded.
- The research work must distinctly define the optimization technique used, and the objective to optimize the building performance, i.e., building energy efficiency whether heating, cooling, or lighting. The article that studies building design performance optimization without using any optimization techniques to push the design optimization process is excluded.
- The research work must clearly address the characteristics and components of a building design, such as the shape, envelope materials, and other design parameters. The article that only studied mechanical or existing energy systems is excluded. For example, papers that discussed the design optimization process of the ground heat-pump systems in buildings were not included.
- Researches published before 2000 were excluded, as the amount of literature in the area of energy-efficient design optimization in buildings is not significant. Therefore, this study focused on reviewing all research efforts related to energy-efficient building performance optimization in the design stages that were published from 2000 to 2021.

Based on the mentioned-criteria, and as shown in Figure 1, the keyword-based search was performed utilizing Google Scholar, Scopus and ScienceDirect. Keywords, such as multi-objective building design performance optimizations, energy performance optimization of early stage building designs, energy performance investigations for early building design stages, energy and lighting predictions at design stages of buildings, lighting assessment in building design stages, and building lighting performance optimization in the early design stage, were used. All articles were screened using the above selection criteria, and then were classified as lighting optimization articles; and heating and cooling optimization articles. The articles that were cited by the article that passed the selection criteria were determined as additional candidate research work. All articles that were selected using these two previous steps were systematically reviewed by defining building type, input and output variables, optimization techniques used, and the main conclusion. The review results were analyzed to determine the benefits and limitations of building performance optimization in the early design stages. Finally, future research directions were discussed and identified. A majority of those work researches were papers in scientific journals.
Terminology

In this study, the concept of “design stage” was used as a general concept for performance optimization of energy efficient buildings, ranging from the preliminary-design stages to the developed-design stage, to obtain new buildings with high performance in terms of lighting, cooling, and heating. “Building performance” was used to express the ability of a building to perform its functions during the operational phase, where lighting, heating, ventilation, and cooling aspects are encompassed in a balanced way. The term “optimization technique” describes the optimization algorithm and simulation tool used (i.e., white box, black box, and grey box optimization techniques) to optimize and evaluate the building design performance in the early stages. The “early evaluation” refers to the early stages of building designs in which the performance of the building design is simulated/predicted using optimization techniques within certain climatic conditions. The term “optimization” was used to describe a certain procedure that makes the building design perfect and functional. The “design parameters” describe all variables related to building components, including shape, materials, floor area, total floors, total rooms, design length, design width, design height, footprint, wall height, floor height, shading, glazing, WWR (i.e., the ratio of the window-to-wall), WFR (i.e., the ratio of the window-to-floor), etc. The term “building geometry” was used to refer to the representative design of building components, which is subjected to optimization during the early design stages for buildings. “Occupancy” describes user activities, which is expressed in heating, ventilation, and air conditioning schedules; and lighting schedules in the early design stages of the building. The “climate file” refers to variables of outdoor weather, e.g., temperature, humidity, wind, and solar radiation, which are utilized as test inputs on design performance during the optimization process.

3. Energy-Efficient Design Optimizations

Building performance assessment in the design stages is defined as the replication of building performance aspects using a computer-based model, mathematical model created based on fundamental physical principles and engineering practices. This process is often aimed to identify different aspects of the design performance of buildings related
to heating, cooling, ventilation, and lighting. Three main types of optimization techniques, classified as black-box based optimization approach (i.e., machine learning and artificial intelligence algorithms), White box-based optimization techniques (e.g., EnergyPlus, ESP-r, TRNSYS, Modelica, IDA ICE, Ecotect, Radiance, etc.), and grey box-based optimization techniques (e.g., integrating genetic algorithm with archetype model, integrating genetic algorithm, artificial neural network algorithm with archetype model, etc.), are usually employed for this purpose. The building geometric model represents the target building in the design stages and comprises all components, including design parameters, changes, modifications, and manipulations implemented by the model optimizer/operators, such as an architect, designer, and engineer.

To optimize the building performance (specifically energy systems) in the early design stages, performance optimization-models are usually built based on a dataset consisting of detailed-physical-information (i.e., design parameters) for building components, along with the dataset of occupancy and outdoor weather to investigate from the performance and efficiency of building energy systems. The model outputs are employed as a criterion to justify the building energy efficient design performance under different conditions of operating and weather. All parameters of the proposed model are carefully selected and adjusted through systematic comparisons between model inputs and outputs, and when the output error falls within the required threshold, corresponding models (i.e., optimized designs) are considered eligible for practical applications. The following subsections summarize how previous research efforts dealt with the issues of optimizing the energy efficient design performance of buildings, specifically, those efforts related to lighting, cooling, and heating optimizations.

3.1. Heating and Cooling Optimization Models

Originally, many previous studies regarding building energy performance optimization in the design stages were published, particularly regarding the demand for cooling and heating energy loads. The reason is due to the increased in the energy usage intensity and related environmental concerns, as the shape, orientation, space, and envelope components of a building, represent fundamental features for the building design that must be considered in the energy efficiency optimization studies of buildings at the design stages. These features have a key impact on the energy efficiency in buildings, in particular, the determination of both cooling and heating energy loads. For this reason, significant efforts were made in the field of energy efficiency optimization for buildings to develop initial designs and test their performance via the different optimization techniques to compute the energy demand-or-other energy-related-factors. The energy assessment results are then compared against the design-targets. If the design targets were achieved, the design optimization process will be terminated and identified as the optimal design. If not, the design optimization process will be iterated. Tables 1 and 2 present results of previous research efforts related to heating and cooling optimizations in buildings during the design stages, which are not summarized in the subsequent text.

Based on the reviewed literature, two main directions of previous efforts in the field of energy-efficient design performance optimization of buildings during the early stages have been followed. The first direction focused on identifying the most variables that would affect energy-efficient design performance (i.e., the most influential input variables on the energy efficiency that increase the demand for cooling and heating loads) and proposed suitable modifications to improve the design performance and reduce energy loads, as summarized in Table 1. While the second direction is to explore the most appropriate optimization approaches or propose a specific approach or tools, as summarized in Table 2. Regarding the first direction, five categories of building designs were considered, including residential, commercial, office, educational, and other unspecified buildings (NA). Each category has different energy requirements based on the building’s function. In this regard, many researchers paid more attention to energy-efficient design envelope configurations, that is, design parameters to increase high-performance designs and thus reduce cool-
ing and heating energy requirements in the subsequent stages of a building’s lifecycle using different optimization techniques. For example, Echenagucia et al. [4] integrated multi-objective genetic algorithms with the EnergyPlus simulation engine to get detailed information on energy-saving envelope components for an open space office building located in four different climatic zones, i.e., Torino, Palermo, Oslo, and Frankfurt. They found that the window position and window to wall ratio (i.e., window surfaces) have a fundamental role in heating and cooling energy efficiency in buildings. Gercek and Arsan [21] used EnergyPlus to examine the relationship between design envelope parameters (e.g., floors, shading, exterior walls, and thickness of insulation materials) and annual heating, cooling and CO$_2$ emissions under future climate conditions, for present, 2050 and 2080. They observed that the most influential parameters on energy demands of cooling and heating loads under present and future hot-humid climate conditions are associated with transparent surfaces of building envelopes.

Furthermore, Vullo et al. [22] adopted the façade configuration of building design as the main criterion to assess the overall performance of the building. Several performance predictions of building design were made based on different façade systems, and the overall performance score of each façade design system was computed. They found that the overhangs reduced glare and the cooling demand. However, it increased heating demands and reduced independence of daylight. Elbeltagi et al. [23] proposed the visualized strategy for predicting heating and cooling consumptions in the early stages of residential building design. This method integrated design parameters with energy simulation tools (Rhino, Grasshopper, EnergyPlus, DIVA) in order to assist architects in identifying design parameters that can lead to high performance designs before modeling the entire building, as well as find out integrated solutions, and examine the alternative designs. Koo et al. [24] used the finite element method to study the effects of different envelope design elements on cooling and heating energy loads of a residential building, as a predictive model is developed for this purpose. They found a nonlinear relationship between heating and cooling loads with the orientation and ratio of window-to-walls, and concluded that the development of predictive models can be a useful tool for assessing design alternatives in the early stage of building design. Granadeiro et al. [25] integrated the flexible design system with energy simulations to evaluate building envelope shape implications on energy efficiency in the early design stages. They concluded that finding a combination of variable values that lead to optimal solutions for energy performance was the most appropriate step to define the most efficient shape of a building envelope with the required architectural qualities. Likewise, Al-Saggaf et al. [26] evaluated the effect of seven main parameters of building design (i.e., orientation, envelope, window and glazing, shape, floor area, storeys and height, and building space) on cooling loads under hot climate conditions. Ihm and Krarti [27] studied the effect of design parameters (e.g., location of the window, glazing type, window size, etc.) on the residential building energy efficiency. Sim and Sim [28] evaluated the impact of exterior walls on energy consumption. Lapisa et al. [29] studied the influence of design parameters, such as roof thermal insulation, on energy efficiency of building design. They all concluded that determining the impact of design variables sheds light on the fundamental aspect of design issues and increases the potential opportunities to improve building design performance.
Table 1. Results of optimizing the energy-efficient design performance of buildings in the early stages by considering the most influential variables (the first direction).

| Reference          | Building Type | Inputs                                                                 | Outputs                           | Method                                                                 | Major Conclusion                                                                 |
|--------------------|---------------|------------------------------------------------------------------------|----------------------------------|------------------------------------------------------------------------|---------------------------------------------------------------------------------|
| Fang and Cho [11]  | Office building | Depth of building; roof-ridge-location; width, length, location, and orientation of the skylights; window width on the south and north facade; the length of the louver; weather | Heating and cooling loads        | Integrating genetic algorithms with EnergyPlus                          | In hot climatic zones, the design requires large windows on both south and north facades, large-aspect ratio, a long-louver, and high-horizontal skylights, whereas in the cold climatic zone needs small north–south windows, short-louver, and high-vertical skylight |
| Azari et al. [14]  | Office building | Insulation materials; type of windows; materials of window frame; thermal resistance of the walls; WWR on the south and north facades | Energy consumption              | Using eQuest to evaluate the operational energy use; Hybrid ANN and GA as optimization techniques | The optimal design scenario incorporated a fiberglass triple-glazed window, approximately 60% south side WWR, 10% north side WWR, and R-17 insulation |
| Ihm and Krarti [27]| Residential    | Orientation, window position, size and type of glazing, insulation of wall and roof, lighting fixtures, appliance, HVAC efficiency, weather | Annual energy savings            | Relying on performance-based design optimization by using simulation tool and sequential search optimization technique | Design optimization measures could effectively reduce approximately 50% of the cost of annual energy use in houses |
| Sim and Sim [28]   | Residential    | Location, floor area, structure, envelope, height, width and length of building, floors above ground, wall u-value, WWR | Heating, cooling and total energy | Using DesignBuilder with EnergyPlus simulation tool to optimize building walls | A traditional building with small windows showed better energy consumption performance |
| Reference      | Building Type | Inputs                                                                 | Outputs                                  | Method                                                                 | Major Conclusion                                                                 |
|---------------|---------------|------------------------------------------------------------------------|------------------------------------------|----------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Lapisa et al. | Commercial    | Design parameters including surface area of skylights, Orientation,    | Heating, cooling demand                 | Relying on the NSGA-II algorithm and TRNSYS simulation engine         | In northern France, the ideal design is consisted of a well-insulated envelope, small skylights' area, and standard roof with high solar absorption, whereas in southern France, non-insulated ground slab and reflective cool roof are used |
|               |               | thermal insulation of both ground, roof, and the vertical walls, passive-cooling-techniques |                                           |                                                                      |                                                                                 |
| Catalina et al.| Residential   | Shape; envelope U-value; WWR; time constant of a building; climate     | Monthly heating energy demand            | Multiple regression and dynamic simulation (TRNSYS)                    | Developed models can predict the heating demand of buildings in more complex scenarios with 3.2% errors |
|               |               |                                                                        |                                           |                                                                      |                                                                                 |
| Bambrook et al.| Residential   | Floor area; wall insulation thickness; roof insulation thickness; U-value; | Annual cooling and heating loads        | Using building simulation program “IDA, ICE” to evaluate the performance of building designs | Space cooling and heating requirements were reduced by up to 94% in a new building in Sydney compared to that with BASIX requirements |
|               |               | type of the window; size, orientation, and shading; mechanical          |                                           |                                                                      |                                                                                 |
|               |               | ventilation; weather                                                   |                                           |                                                                      |                                                                                 |
| Fesanghary et al.| Residential | Design variables; roof, ceiling, walls, floor materials, type of       | Energy consumption                      | Using the harmony-search algorithms and EnergyPlus to find the optimal building envelope | Future work should be directed toward finding ideal building envelope designs for various conditions of weather in the USA, and involved studying the effect of different HVAC systems |
|               |               | glazing, weather                                                        |                                           |                                                                      |                                                                                 |
| Reference       | Building Type | Inputs                                                                 | Outputs                              | Method                                      | Major Conclusion                                                                 |
|-----------------|---------------|------------------------------------------------------------------------|--------------------------------------|--------------------------------------------|----------------------------------------------------------------------------------|
| Magurean [33]   | Residential   | Building envelope materials including wall, windows, exterior slabs, glazing, etc. | Heating energy consumption           | Using the finite element method and THERM simulation program to $\psi$-values   | Optimizing design energy efficiency should be associated with renewable systems and HVAC solutions |
| Attia et al. [34]| Residential   | Weather, orientation, zone dimensions, width and type of north and south window, shading, wall type, type and thickness of insulation of walls and roof | Energy consumption                  | Using ZEBO and DesignBuilder simulation engines including EnergyPlus             | Building performance simulation programs and sensitivity analysis techniques are useful tools for designers to improve the new design performance |
| Attia et al. [35]| Residential   | Weather, design parameters; including orientation, shape, height of the floor, floors, roof and floor U-values, WWR, area of windows, glazing | Annual energy consumption            | Using ZEBO and DesignBuilder simulation engines including EnergyPlus             | Incorporating energy simulation tools into the early design stages facilitates evaluating the performance of design alternatives |
| Gou et al. [36]  | Residential   | Orientation, window external shading, WWR, exterior wall type, window-U-value, window-SHGC, window/door-airtightness, thickness, window-opening-control | Annual energy demand                 | Combining a genetic algorithm with an artificial neural network and using EnergyPlus to create a baseline state building model | The difference in both actual climatic conditions and building shapes plays a major role in the passive design of residential buildings |
| Futrell et al. [37]| Educational building | Ceiling height, window light transmittance, window solar transmittance, window width, window transmittance for daylighting, length of external shade, length of the lightshelf, view window for light, view window for solar, weather | Hourly heating and cooling loads     | Using GenOpt and a hybrid GPS Hooke Jeeves integrated with the Epsilon Constraint Method, as well as EnergyPlus and Radiance simulation tools | The thermal performance contrasts with the daylighting performance strongly in the north orientation, while the conflict appears somewhat in the south, west and east orientations |
| Reference          | Building Type | Inputs                                                                 | Outputs            | Method                                                                 | Major Conclusion                                                                                                                                 |
|--------------------|---------------|------------------------------------------------------------------------|--------------------|------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------|
| Shiel et al. [38]  | Commercial    | Nine groups: geometry-materials; glazing; HVAC; lighting; equipment; occupancy; adjacencies; weather | Energy usages      | Use of modeling software packages including Autodesk Revit, Trimble SketchUp, OpenStudio, Legacy OpenStudio Plugin and EnergyPlus | The study provides relevant guidance for the energy modeler regarding potential accurate for his model depending on the data used to create the model |
| Chen et al. [39]   | Residential    | Orientation, external-obstruction-angle, thermal-resistance of external walls, specific-heat, window-U-value, solar heat gain coefficient, window-to-ground ratio, overhang, infiltration-air-mass-flowrate coefficient, transmittance of the window, weather | Cooling energy     | Using Non-dominated sorting-genetic algorithms integrated with EnergyPlus (simulation-based optimization approach) | Based on optimization results, the transmittance for windows and levels of the external-obstruction showed significant effects on cooling energy demand, so it should be considered in the building designs and evaluation guidelines |
| Rodrigues et al. [40] | Commercial    | Design parameters, climate                                             | Heating, cooling, and total energy | Relying on a performance-based generative design using dynamic simulations and EPSAP algorithm | The precise models are necessary to increase the credibility of the results |
| Si et al. [41]     | NA            | Design parameters including thermal insulation of walls, thermal insulation of roof, type of windows, edge shape of roof, thermostat-setpoints, location | Energy use         | Using the integrated ANN with EnergyPlus and genetic optimization algorithms | By integrating ANN modeling with the appropriate optimization algorithm, will work effectively for complex problems of building design, as well as optimizing different design goals |
| Reference        | Building Type | Inputs                                                                 | Outputs                        | Method                                                                 | Major Conclusion                                                                                                                                 |
|------------------|---------------|------------------------------------------------------------------------|--------------------------------|----------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------|
| Hester et al. [42] | Residential   | Leaving area, orientation, stories, bedrooms, aspect ratio, ext. wall u-value, attic u-value, foundation conductance, foundation ceiling u-value, WWR, window distribution, window u-value x SHGC, roof type, roof pitch, overhang length, duct u-value, duct leakage, percent CFL usage, water heater-efficiency, boiler-efficiency, AC-rating | Energy usage                   | Using multi-regression-based energy metamodel and Monte Carlo technique | By identifying the most influential factors on building design performance, the variance in expected energy consumption can be decreased by about 90%. A great discrepancy between building design alternatives can be observed in the case of limited information for many aspects of the building design |
| Romani et al. [43] | Residential   | Location; thermal transmission coefficient for exterior wall, roof, and floor; thermal bridges, air change rate, glazing, shading coefficient of windows facing south, east and west; roof solar radiation absorption coefficient | Cooling and heating needs     | Using regression approach and dynamic simulation (TRNSYS)             | The interaction between design parameters increases significantly the accuracy of developed models. Optimization of the design envelope is a starting point to optimize low energy buildings |
| Hopfe and Hensen [44] | Office building | Design parameters including; glazing, material properties of wall, floor, ceiling, and roof | Annual heating and cooling    | Simulation-based design performance optimization by using dynamic simulations and multiple regression analyzes | The input to a design problem is a significant consideration in the meaning of building design process |
| Reference                              | Building Type | Inputs                                                                 | Outputs                                                                 | Method                                                                 | Major Conclusion                                                                 |
|---------------------------------------|---------------|------------------------------------------------------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Panagiotidou and Aye [45]             | Residential   | Weather, insulation thickness of the exterior walls and floor, insulationthickness of the basement floor, insulationthickness of the exterior roof, glazing, type of the replacement window | Annual electricity consumptions for cooling and heating                 | Coupling multi-objective genetic algorithm optimization and design analysis Kit with TRNSYS simulation tool | Based on the comparison, advanced programming knowledge is required to deal with design optimization issues |
| Zhu et al. [46]                       | Commercial    | Building shape, WWR, orientation of facade                             | Energy                                                                 | Using Rhino-Grasshopper and algorithm optimization                     | Shape and WWR are significant parameters                                        |
| Al-Saadi and Al-Jabri [47]            | Residential   | Envelope characteristics: insulation of roof and walls, area of windows, glazing type, shading of windows | Energy                                                                 | Using EnergyPlus and genetic-algorithm-technique                        | Windows’ shading is an important thermal and economic indicator across different climates |
| Foroughi et al. [48]                  | Commercial    | Window characteristics, including WWR, position                        | Heating and cooling                                                   | Using EnergyPlus and genetic-algorithm-technique                        | Location and dimensions of windows reduce 2% to 15 of energy use in cold and hot climates |
| Giouria et al. [49]                   | Office building | Building characteristics, including WWR and glazing type              | Cooling and total energy                                              | EnergyPlus; Rhino; Grasshopper                                          | Saving 33% of final building energy demand                                        |
| Jin and Jeong [50]                    | NA            | Shape characteristics of building                                      | Energy                                                                 | Using genetic-algorithm-technique; Grasshopper                          | Thermal load properties are affected by the shape of building                    |
| Li et al. [51]                        | Commercial    | Wall thickness, glass type, WWR, orientation, exterior shading         | Energy                                                                 | Using holistic method with jEPlus and EnergyPlus                       | Solar wall absorption has a great impact on winter comfort                         |
| Heydari et al. [52]                   | NA            | Window characteristics: WWR, glazing type, position, thickness of glazing | Heating and cooling                                                   | Using DesignBuilder; EnergyPlus                                         | Thickness of the glaze is closely related to the demand for cooling and heating   |
Table 1. Cont.

| Reference                  | Building Type   | Inputs                                                                 | Outputs            | Method                                  | Major Conclusion                                                                 |
|-----------------------------|-----------------|------------------------------------------------------------------------|--------------------|-----------------------------------------|---------------------------------------------------------------------------------|
| Badeche and Bouchahm [53]   | Office building | Window orientation, window characteristics, including glazing; shading | Heating and cooling| The orthogonal method of Genichi Taguchi| Window orientation in semi-arid climate is a prominent parameter; as well as glazing in the Mediterranean climate; whereas low glazing ratio is the most efficient in all climates |

With respect to the second research direction of optimizing the heating and cooling system of buildings, it focused on the optimization technique used (i.e., optimization algorithms and simulation tools), with the aim of improving existing techniques or proposing new techniques to overcome optimization problems and optimize energy-efficient design performance of buildings, as summarized in Table 2. These efforts are categorized into four main groups. The first group, called group (a) [5,54–64], focuses on developing a certain model or a method to evaluate the energy-efficient design performance and design alternatives in the early stages in terms of economic and environmental criteria. For instance, Wang et al. [5] developed a multi-objective-optimization model utilizing multi-objective-genetic-algorithms to assist architects in detecting optimum or near optimum design alternatives of green buildings for specific conditions. Feng et al. [54] presented a quantitative approach utilizing parametric design-technology that connected design parameters with integrated FC-ELM (Fuzzy-C-means-clustering and extreme-learning-machine) to assess the indoor environmental performance in the early design stages, with considering the uncertainties related to design parameters. The results demonstrated that the proposed method is an alternative approach to evaluate environmental uncertainties in the early design stages for buildings. Hygh et al. [55] developed a MLR (multiple linear regression) model using 27 parameters, including building size, location, and other building factors related to early design stages to obtain a suitable evaluation tool that provides quick-feedbacks based on changes in design parameters. They concluded that the MLR model can be utilized as the basis for an effective design decision support tool instead of the energy simulation model in the design stages. Moreover, Pulido-Arcas et al. [56] and Asadi et al. [57] presented a predictive regression model to evaluate and identify building energy usages at the early design stages. They concluded that such models could be an assistant tool in adopting appropriate solutions/strategies of designs, which would promote the energy efficiency in buildings during operational stages. Singaravel et al. [58] introduced a component-based approach combining deep-learning architectures, transfer learning and multitask learning to find the appropriate approach that can provide rapid feedback information to support the early stages of building-design. Kumar et al. [59] presented a new method based on external learning machine and its variants online sequential to forecast cooling and heating loads of designs. Based on the accuracy, computational performance and activation functions, 24 models were developed and compared. They found that these developed models are very fast compared to those mentioned in the literature and provided predictions in less than 0.5 s.

As for the second group (b) [12,65–83], more attention was given to introducing and proving the efficiency of new optimization techniques to support the building energy efficient design optimization. In this regard, Bustamante et al. [12] demonstrated the use of mkSchedule as a useful tool in the supporting process of design optimization to increase the energy efficiency in office buildings. Ochoa and Capeluto [65] presented the idea of intelligent facades known as “NewFacades” that is based on energy and visual comfort...
strategy abstracted from the “prescriptive-energy-codes of hot-climates” to suggest a set of good and appropriate solutions. Likewise, Li et al. [66] introduced bidirectional workflow as a new approach to providing real-time-performance feedback from building design, and allowing to search optimum solutions utilizing a genetic algorithm. Robic et al. [67] introduced a Big Bang–Big Crunch optimization algorithm to use in the passive design of buildings to evaluate the number of annual hours that lead to uncomfortable thermal conditions in indoor environments of buildings based on EN 15251. They found that the proposed approach achieves more than 90% of the computational savings during the design performance simulations. Gervasio et al. [68] proposed an approach to address the deficiency of input data at the early stages of building-design through a macro-component approach that provided precise estimations of building performance over its lifecycle based on simplified shapes and assumptions. Petersen and Svendsen [69] presented a simplified and transparent economic optimization approach that used the concept of energy frame to express restrictions of the optimization problem and then solved the problem by decreasing the energy conservation costs at all individual energy saving measures. They concluded the potential benefit of this method is introduced economic optimization in the early stages of building-design and illustrated the efficiency of the economic and service building elements that identify the potential product development. Meanwhile, Rezaee et al. [70] proposed a data-driven linear inverse modeling method that creates reasonable values for design variables and meet energy targets during the early design stages. Forde et al. [71] introduced a novel method that coupled “a genetic multi-objective optimization algorithm” with “Passive-House-Planning Package software” to obtain the cost of optimal design that perfectly meet the “Passivhaus standard”. Homaei and Hamdy [72] presented a robustness-based decision-making approach, which integrated robustness evaluation and steps of decision-making. They found that this approach could choose building designs with high energy performance compared to design targets without the need for additional analysis efforts.

The third group “(c)” [84–90] was directed to test hybrid approaches to obtain optimal solutions for multi-objective-optimization-problems, for instance a comfortable indoor environment and lighting. In this context, Ekici and Aksoy [84] presented an adaptive network based an interface system model that integrated with ANN (artificial neural network) to forecast household cooling and heating loads of buildings located in cold climatic conditions. They found that the “ANFIS” is a powerful tool that provided 83.8% and 96.5% of cooling and heating load predictions, respectively, in the early stages of building energy-efficient design. Bre et al. [85] proposed coupling a “multi-objective non-dominated sorting-genetic-algorithm-II” (NSGA-II) with ANN metamodels that are previously trained using EnergyPlus data to solve the multi-goal building design performance issues/problems. Twelve of discrete and categorical design parameters, including roof type, internal and external wall types, window size, and types of windows, were involved. The results demonstrated that the proposed method, can reduce up to (75%) of the building energy simulation iterations to find a suitable Pareto front for actual multi objective building performance optimization problems while maintaining good precision results. Geyer and Singaravel [86] presented a new approach based on design components and ML (Machine Learning) models (i.e., the artificial neural networks) at two levels of decomposition, i.e., construction-level-components (e.g., walls, windows, floors, etc.) and zone-level components, to predict building design performance and reduce computation time. The results showed high prediction quality for building design performance with errors of (3.7%) in case of cooling energy and (3.9%) in case of heating energy. Furthermore, Ramallo-Gonzalez and Coley [87] suggested a multiple evaluation approach, which combined modern optimization techniques with various evaluation methods of the energy demand of building design instead of a single evaluation method to assess solution quality. This approach included a “covariance-matrix-adaptation-evolutionary-strategy” (CMA-ES) and a “building-dynamic-simulator based on the lumped-parameter-model”. They observed that this approach could achieve the same optimized design with much less computational
time compared with those optimization approaches in the literature. Oh et al. [88] also integrated the EnergyPlus simulation tool and genetic algorithm (GA) with Pareto optimality to solve the multi-criteria-optimal-residential design problem of building information modeling-based energy performance-simulation-model. Hamdy et al. [89] coupled the building performance simulation engine (IDA ICE) with a GA to design low-energy and carbon emission buildings, whereas Yu et al. [90] integrated an improved-multi-objective-genetic-algorithm, simulation-based-improved back-propagation neural network, and Pareto solution in order to get a multi-objective-design-performance-optimization-model. They concluded that the optimized design models can be employed as an assistant tool in optimizing the performance of energy efficient buildings at the design stages.

The fourth group “(d)” [91–97] focused on evaluating the current methodologies used to find the most appropriate way to optimize the energy efficient design of buildings. Carlos and Nepomuceno [91] compared EN 832 (a standard calculation method) with RC-CTC (Portuguese regulation methodology), SOLACALC (computer simulation program), Yannas (calculation worksheet method), and HERC to evaluate the heating demand of building designs during winter. Picco et al. [92] compared the simplified and detailed simulation models for commercial buildings by considering simulation results of the heating and cooling loads and found a difference between the simulation models equivalent to 14.6% and 15.6% for cooling and heating loads, respectively. Qstergard et al. [93] compared different methods, including the heuristic and Monte Carlo approaches, to explore their ability in optimizing the office room performance regarding the energy demand and indoor microclimate. Leskovar and Premrov [94] presented an architectural design approach to identify the optimum ratio of glazing areas with regard to the energy efficiency of prefabricated wooden frame buildings with a specific focus on glass surfaces facing south. They compared difference glazing systems and found that the increase of glass surfaces facing south in the single panel-wall elements with higher wall U-value has positive influences on the total annual cooling and heating energy demands. Despite the efforts presented in this subsection, each effort has benefits and limitations in terms of optimization techniques or relevant dataset, which may affect the energy efficient building optimization process in the early design stages. All of these will be discussed in Section 4.

Table 2. Results of optimizing the energy efficient design performance in buildings by considering the optimization technique used based on the reviewed literature (the second direction).

| Reference (a)          | Building Type | Inputs                                                                 | Outputs                              | Method                               | Major Conclusion                                                                 |
|------------------------|---------------|------------------------------------------------------------------------|--------------------------------------|--------------------------------------|----------------------------------------------------------------------------------|
| Bustamante et al. [12] (b) | Office building | Location, glazed façade orientation, office space, opaque surfaces, window, HVAC system, lighting schedule, weather | Cooling and heating loads            | Using mkSchedule with the help of both EnergyPlus and Radiance                   | MkSchedule is a powerful tool for identifying the performance of different complex fenestration systems in the early design stages, and used for setting key parameters of control algorithms |
| Reference (a) | Building Type | Inputs                                                                 | Outputs                                      | Method                                                                 | Major Conclusion                                                                                      |
|--------------|---------------|------------------------------------------------------------------------|----------------------------------------------|----------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|
| Hygh et al. [55] (a) | Office building | Building area, orientation, no. of floors, depth, aspect ratio, roof R-value, roof color, roof emissivity, window U-value, window SHGC, wall U-value, shading projection factor, WWR | Heating, cooling, total energy consumption  | EnergyPlus within a Monte Carlo framework to develop a multiple regression model based on 27 design parameters | The linear regression-model is a basic tool to support effective decision-making instead of energy simulation models in the early stage of building designs |
| Pulido-Arcas et al. [56] (a) | Office building | No. of floors, floor area, shape ratio, WWR, performance coefficient, energy-efficient ratio, heating and heat-emission variables | Heating, cooling, total energy consumption | Multiple regression analysis to predict the building performance in the design stages | Predictive models achieved a high-performance between 91.81% and 98.05% for consumptions of energy and between 96.83% and 99.56% for CO₂ emissions |
| Asadi et al. [57] (a) | Commercial   | Building materials; material thickness; shape; schedule of occupants | Annual total energy consumption | DOE-2 and eQuest to simulate individual building configuration; the simulation dataset to develop the regression prediction model | The developed model can be employed to forecast the overall energy use in the early stage of the building design when different building schemes and design concepts are considered |
| Singaravel et al. [58] (a) | NA            | Length and width of building, WWR, orientation, U-values of windows, floors and walls, roof U-value, window g-value, air change rate, floor heat storage capacity, height of ground thermal zone from ground in stories, weather | Monthly heating and cooling demand | EnergyPlus was used to generate monthly heating and cooling energy; deep learning to evaluate building design performance | Deep learning models can achieve highly accurate predictions in 0.9 s for design space explorations |
Table 2. Cont.

| Reference (a) | Building Type | Inputs | Outputs | Method | Major Conclusion |
|---------------|---------------|--------|---------|--------|-----------------|
| Catalina et al. [60] (a) | Residential | Heat loss coefficient of building envelope, south surfaces, variance in the internal setpoint temperature and the external temperatures | Heating energy demand | Use of simulation database to develop a multiple regression prediction model, which was validated by an actual dataset for 17 flats. | The proposed model is distinguished by simplicity, high applicability, good match with the simulation and with energy certification calculations, human-behavior correction |
| Ngo [61] (a) | Office building | Floors, WWR, building-plan aspect-ratio, outdoor-air rate, floor area, glass U-factor, occupants, equipment, indoor thermal setpoint, height of floors, depth of shading | Cooling loads | Machine learning algorithms (ANN, CART, LR and SVM) and simulation tool | The ML model showed a high performance with R between 0.98 and 0.99, as well as error between 6.17 and 12.93% compared with the observed cooling load values |
| Li et al. [62] (a) | NA | U-values of walls and windows, SHGC, building length, WWR, storey height, no. of storey, no. of rooms, heating and cooling temperatures, heating and cooling periods | Heating, cooling; total energy consumption | Artificial neural network algorithms | The ANN model is characterized by its high accuracy, high speed and good response to complex relations; the relative deviation of heating and cooling energy usage is within ±10% and 10% for the total energy usages |
| Santos et al. [63] (a) | Residential | Weather, envelope properties (roof floor, interior floor, ground floor, exterior wall, interior wall, glazing area) | Monthly heating and cooling energy | Integration of energy calculation algorithm and lifecycle environment impacts of building configurations | Good results are achieved, an error was not more than 10% compared to the performance of EnergyPlus dynamic simulation |
| Reference | Building Type | Inputs | Outputs | Method | Major Conclusion |
|-----------|---------------|--------|---------|--------|------------------|
| Rezaee et al. [70] (b) | Office building | All design parameters including weekdays cooling setpoint, occupancy load, air leakage, weather | Energy use | Linear inverse modeling that generates values for design parameters | Applying the proposed method can help designers make informed decision regarding the building energy performance in the design stages |
| Forde et al. [71] (b) | Residential | Insulation of floor, external wall, and roof, glazing, window jamb, window sill, window and floor area, ceiling height, air change rate, MVHR | Annual heating | The method coupled constrained genetic algorithm to passive house-planning-program | This method enables us to make better-decisions regarding the cost-optimal trade-offs between achieving performance and house developments |
| Homaei and Hamdy [72] (b) | Residential | Weather, overall u-value, WWR, heating and ventilation systems, lighting, KPIS | Total energy consumption | The method proposed multi-target-robustness-based decision-making approach using genetic algorithms with design simulation | The proposed method showed high efficiency in selecting a high-performance and design concurrently with less analysis effort and high reliable rate |
| Zhang et al. [73] (b) | Residential | Depth of bedroom, living room, kitchen and equipment balcony, floor height, WWR, window size, u-value of wall and window | Energy load | Ladybug and Honeybee tools to obtain energy use feedback and then use a genetic algorithm in Rhino and Grasshopper software to optimize the design | The proposed parametric method showed a high ability to optimize the building design performance and energy use reduction |
| Jakubiec and Reinhar [74] (b) | Office space | Design parameters; floor, ceiling, walls, exterior ground, glazing, weather | Heating and cooling loads | Integration of daylighting using Radiance and thermal load using EnergyPlus; additionally DIVA/DAYSIM was used | DIVA allows coupling and visualizing of daylighting and energy consequences from within the architectural modeling tool, Rhinoceros 3D |
| Reference (a) | Building Type | Inputs | Outputs | Method | Major Conclusion |
|--------------|---------------|--------|---------|--------|------------------|
| Petersen and Svendsen [75] (b) | Office building | Design parameters, including windows, window area, wall, roof, floor, g-value, u-value | Energy consumption | iDbuild that consisting of daylight and thermal simulation tools | The proposed method provides economic optimization and the express representation of building element efficiency |
| Granadeiro et al. [76] (b) | Residential | 60 variables including envelope shape | Annual heating, cooling; total energy consumption | Integration of shape grammar-based parametric design with energy simulation | The proposed approach transformed the grammar into parametric design systems |
| Bernett and Dogan [77] (b) | Office building | Exterior wall, roof R-value, glazing, structure, WWR, shading, floorplate shape, weather | Heating and cooling energy | EnergyPlus-based early design-making framework | The framework can assist architects in developing and refining preliminary designs based on project and budget constraints |
| Oh et al. [88] (c) | Educational building | Weather, design parameters including exterior wall, roof, ceiling, floor, WWR, form, glazing, occupancy density | Heating and cooling energy use | Integration of EnergyPlus, genetic algorithm, and Pareto optimality | Significant information can be provided depending on process-driven interoperability utilizing BIM and genetic algorithm with Pareto optimality |
| Hamdy et al. [89] (c) | Residential | Energy source, ventilation heat recovery type, building tightness, type of window, shading, external wall, thickness of roof and floor | Heating and cooling | Combination of modified-multi-objective genetic algorithm and IDA ICE | Early assessment assists in understanding the influence of design variables on emissions, cost, and thermal comfort |
| Yu et al. [90] (c) | Residential | Layout plan, orientation, shape, floor area, stories, WWR, heat transfer of roof, wall, and window | Annual energy consumption | Pareto solution, integrated with multi-objective genetic algorithm and ANN, EnergyPlus as well | Design multi-objective optimization model is a significant tool for optimizing the building designs |
Table 2. Cont.

| Reference (x)       | Building Type | Inputs                                                                 | Outputs                        | Method                                                                 | Major Conclusion                                                                 |
|---------------------|---------------|------------------------------------------------------------------------|--------------------------------|------------------------------------------------------------------------|---------------------------------------------------------------------------------|
| Carlos and Nepomuceno [91] (d) | Residential | External wall, ground floor, window and door, ceiling, roof-unheated attic, sunspace vertical envelope, sunspace horizontal envelope, weather | Hourly heating load            | Ecotect simulation program to simulate heating demand with assumption of stable external and internal conditions | The proposed spreadsheet is a useful methodology that can be used without complicated simulation software |
| Picco et al. [92] (d) | Commercial   | Weather, floor area, floor height, face length, number of floors, transparent surfaces | Heating and cooling energy demand | Using EnergyPlus and Openstudio software to evaluate design performance of the building | The proposed methodology can help to reduce the simulation time to only 2–4 h instead of several days |
| Qstergard et al. [93] (d) | Room office  | Internal load, room depth, WWR, solar heat gain coefficient, overhand, shading factor, ventilation, cooling | Energy consumption             | Five different methods were used to explore the optimal design space of the building including Monte Carlo method | Monte Carlo method easily addresses many design parameters, which can be provided a great potential to help designers making a perfect design with high performance |
| Leskovar and Premrov [94] (d) | Residential | Exterior wall, window glazing, glazing size, orientation, shading, weather | Heating and cooling demand     | Architectural design approach with help of a PHPP simulation tool       | Linear interpolation is a good approach to forecast energy demand according to glazing-to-wall area ratio and wall u-values |
| Schlueter and Thesseling [95] (d) | NA           | Floor area, floors to ground, wall to room, u-value wall, u-value window, g-value window, orientation, WWR | Total energy use                | Development of a geometrical model using Revit Architecture and simulation by DPV | Using BIM to achieve a rapid energy performance assessment opens up an integrated look at the building industry during early design stages |

Note: (x) is used to refer to the classification of previous research efforts, which have been classified into a, b, c, and d groups.

3.2. Lighting Optimization Models

Optimizing the lighting system of buildings during the early design stages is an essential step for moving towards high-performance buildings. Different methods of building lighting simulations, including lighting energy, daylight and daylight factor, have been applied. Several research works have also been published in this field, and concluded that the lighting efficiency/performance in the early stages of building designs can be optimized by implementing parametric studies for various windows, dimensions, orientation, shading devices, etc., using different techniques, including optimization algorithms and lighting simulation tools. Computer simulation software packages, including building lighting
simulation tools, were the most effective approach to support building design by finding
and assessing appropriate solutions, such as daylight saving possibilities. Specifically, these
techniques and tools can include a great number of design parameters and then perform the
lighting/daylight performance analysis with more detail that based on potential solution
scenarios [98]. Furthermore, they allow us to conduct a precise comparison within the
empirical uncertainty level, provide practical and computationally effective solutions to
assess energy effectiveness/performance of daylight applications, and enable researchers
focusing on performance optimization of the building designs to obtain better results.

With reference to the previous Section 3.1, optimizing energy-efficient building perfor-
mance in the design stages, research efforts followed two major directions. The first trend
is to determine design variables that are affecting the use of cooling and heating energy
in buildings, whereas the second direction was to find the most appropriate technique
for building design performance optimization. Regarding the lighting optimization of a
building design, many previous research efforts focused on integrating design parameters
and optimization techniques to maximize daylighting and minimize lighting energy con-
sumption in indoor environments, as summarized in Table 3. The other direction sought
to address the conflict in multi-objective optimization (e.g., daylighting versus thermal
performance) while designing buildings, as summarized in Table 4. Concerning the first di-
rection of lighting optimizations, it can be classified into three major groups (i.e., a, b, and c).
Research efforts in group (a) [29,99–103] addressed modification strategies of design param-
ieters and the ability of optimization techniques to deal with that issue. In this regard, Kim
and Chung [99] presented a daylighting simulation model combined with the architectural
design process to obtain high-precision simulations leading to high-performance architec-
tural designs. This work was implemented by changing the optioning size of toplights
and light transmission efficiency using the Radiance simulation program. They concluded
that computer simulation models could accurately represent the interior lighting for build-
ings under clear-sky-conditions. Liu et al. [100] integrated the 3D model and Autodesk
CAD with the ANSYS Fluent simulation tool to take full advantage of natural ventilation
with daylighting performance simulation. The effect of building spaces, orientation, and
size and position of windows were examined. They found that energy-savings through
natural ventilation could reach 40% of the electricity used in Chongqing. Furthermore,
Acosta et al. [102] conducted multiple simulations on room designs using three different
shapes of skylights under overcast-sky conditions by the Lightscape simulation program
to identify the most appropriate shape of lightscoop skylights. Wang et al. [103] adopted a
gradient boosted decision trees-based non-dominated sorting genetic algorithm integrated
with EnergyPlus in the Python environment to address the influence of window ventila-
tion and shading on multi-objective building design optimization process under different
climate conditions. They concluded that with multi-objective optimization strategies, it is
possible to achieve 38.1% of energy savings in severely cold weather and 17.6% of improved
comfort in both summer and winter conditions.

As for group (b) [65,66,77,104–107] of the first direction for the lighting optimization,
various researchers have tried to demonstrate new methodologies to improve daylighting
and lighting in the early design-stages of building projects. Konis et al. [104] introduced
a passive optimization framework (simulation-based parametric modeling framework)
to investigate the daylighting and natural ventilation performance for low-energy design
alternatives in the early stages of building designs. The simulation results were compared
to reference buildings located in four climatic zones. They found that the proposed ap-
proach could achieve 4–17% of energy consumption and improve daylighting performance
by 27–65% depending on the site and weather conditions. Chokwitthaya et al. [105] pre-
sented a computational framework that combined existing building performance modeling
with context-aware design-specific data involving human–building interactions utilizing
artificial neural networks. The results confirmed the ability of the suggested framework
to optimize the prediction precision of the Hunt model, which was assessed against ac-
tual data obtained from an office building. This is along with Krarti et al. [106] and
Vera et al. [107], who presented their methods to optimize the lighting performance in building designs.

The group (c) [46, 47, 62, 108–116] of research efforts varied between the development of new models or systems and test their performance evaluation. For example, Ihm et al. [108] developed and validated a simplified method to calculate the potential annual electrical lighting energy reduction of office buildings using factors related to window size and glazing type. Likewise, Kota et al. [109] offered the development and validation of a typical prototype residential, intending to simulate and analyze the daylighting of a residential building through integrating the Building Information Modeling (Revit) with daylighting simulation software (Radiance and DaySIM). Verso et al. [110] developed two sets of mathematical models to use them to incorporate daylighting strategies in the design stages of buildings. These models were developed depending on the dataset of typical room simulations using DaySIM by changing some design parameters, such as window size, glazing, room depth, and orientation. The two sets of models were meant for daylighting metrics and lighting energy demand. From comparison results, they found that the variation coefficient (CV) was less than 16% for all models except one (30%). Likewise, Mavromatidis et al. [111] developed regression models using Doehlert and Box–Behnken simulation designs for daylight factor predictions during the early stages of building design. Several simulation scenarios were implemented to validate the statistical forecast system. They found that the error caused by simplification was acceptable in most conditions. Hiyama and Wen [112] proposed creating response surfaces to optimize window design by coupling dynamic daylighting simulation (DAYSIM) and energy simulation (EnergyPlus). The results showed that the error resulting from this method was less than 1% compared to the error caused by the daylight simulation algorithm (5%). Andersen et al. [113] and Gage et al. [114] combined a fuzzy rule-based system with a simulation tool (lightsolve) in order to develop an “interactive-expert-system” providing the design guidelines in optimizing daylighting/daylight performance at the early stages of building designs. The results were successful in finding designs with optimized performance for the various initial designs and daylight performance goals.

Table 3. Optimization results of the lighting performance in the early stage designs of buildings based on the reviewed literature (the first direction; design parameters and optimization techniques).

| Reference (a) | Building Type | Inputs | Outputs | Method | Major Conclusion |
|---------------|---------------|--------|---------|--------|------------------|
| Bustamante et al. [12] (a) | Office building | Location, glazed façade orientation, office space, opaque surfaces, window, HVAC system, lighting schedule, weather | Lighting energy consumption | Using mkSchedule in Radiance | MkSchedule is an effective tool for identifying the performance of different complex fenestration systems in early design stages, and setting key parameters of control algorithm |
| Reference (a) | Building Type | Inputs | Outputs | Method | Major Conclusion |
|--------------|---------------|--------|---------|--------|------------------|
| Lapisa et al. [29] (a) | Commercial | Design parameters including; skylight surface areas, thermal insulation of grounds, thermal insulation of roof, thermal insulation of vertical walls, passive-cooling-techniques, orientation | Artificial lighting | NSGA-II algorithm and TRNSYS simulation engine | In northern France, the ideal design consists of small skylight surface areas, standard roof with high solar absorption and insulated-envelope, whereas in southern France includes the non-insulated-ground slab and reflective cool-roof |
| Li et al. [62] (c) | NA | U-values for walls and windows, SHGC, length of building, WWR, height of floors, no. of floors, no. of rooms, heating and cooling temperature, heating and cooling period | Lighting energy consumption | ANN-based building energy-predictions for complex-architectural form | The relative deviation of the lighting energy usages is between ±10% |
| Ochoa and Capeluto [65] (b) | Office building | Climate, design parameters; glazing type, window size, insulation, shade element, shade control, shade type, U value opaque wall | Annually and monthly lighting energy | Using three types of simulation engines, including EnergyPlus | Intelligent facades in hot climates can reduce 20-60% of energy consumption compared to the basecase |
| Li et al. [66] (b) | NA | Building area, building length, number of floors, story height, WWR, u-value of wall, roof and window, SHGC of window, heating and cooling setpoint temperature | Lighting energy consumption | Bidirectional workflow using Genetic Algorithm Toolkit In Matlab and energy simulation engine | For daylight simulations, MOOSAS required more time compared with Radiance and Ecotect, as well as, daylight factor is greatly affected by modifications of WWR |
| Bernett and Dogan [77] (b) | Office building | Exterior wall, roof R-value, glazing, structure, WWR, shading, floorplate shape, weather | Lighting energy | EnergyPlus-based early design-making framework | In Phoenix, the deep static shade had a small advantage over other options only when combined with stacked square floorplate |
Table 3. Cont.

| Reference (a) | Building Type | Inputs | Outputs | Method | Major Conclusion |
|---------------|---------------|--------|---------|--------|------------------|
| Kim and Chung [99] (a) | Commercial | Architectural shape, glass transmittance, glazing shape, indoor reflectance of materials | Daylighting | Integration of architectural design with the daylight simulator using Radiance | Computer-based simulation models could accurately represent the indoor lighting environments for buildings under clear-sky conditions |
| Sun et al. [101] (a) | Educational building | Location, overcast day, outdoor design illuminance, light climate coefficient, glass transparency, reflection coefficient of both floor, wall, ceiling and sunshield, window-floor ratio, floor plan | Lighting/illuminance | Lighting simulation tool “DesignBuilder” and sun-shading design | Based on the simulation result, reasonable sun-shading-design can improve the indoor environments of building |
| Acosta et al. [102] (a) | Commercial | Weather, room shape, height and floor size, skylight shape, different floor plan, height and width of skylight, thickness of roof and wall of skylight, ceiling, floor, wall and roof or room | Daylighting | Lighting simulation program “Lightscape3.2” to calculate luminous distribution | With the height/width ratio of 4/3, the curved shape of lightscoop produced up to 3.5% of daylight factors compared with the rectangular shape under overcast-sky conditions |
| Krarti et al. [106] (b) | Office building | Location, building perimeter, WWR, glazing type, window to floor ratio, glass transmittance | Daylighting | Simulation engine; DOE-2.1E with design parameters | Perimeter area, window area, and window type are key parameters to simulate lighting energy savings |
| Vera et al. [107] (b) | Office building | Weather, building space, materials, longitude and latitude of the location, shading, different dimensions of windows, luminaries matrix | Annual illuminance /lighting | Incorporation of lighting and thermal simulation using EnergyPlus and Radiance software | The proposed method features a short computing time and flexibility. This makes it suitable in the early stages of building designs to deal with complex-fenestration systems and artificial-lighting control strategy |
| Reference                  | Building Type | Inputs                                                     | Outputs       | Method                                      | Major Conclusion                                                                 |
|----------------------------|---------------|------------------------------------------------------------|---------------|---------------------------------------------|----------------------------------------------------------------------------------|
| Ihm et al. [108] (c)       | Office building | Location, building geometry, window size, glazing type, floor, ceiling, opaque walls | Daylighting   | Lighting simulation engine using DOE-2.1    | Based on results, 60% energy savings could be achieved by using lighting dimming control strategies |
| Andersen et al. [113] (c)  | Educational building | Building geometry, location, ceiling, wall, windows, window size overhangs, fins, orientation, footprint, wall height | Daylighting   | Integration of fuzzy logic system with a simulation program, lightsolve | The proposed approach provides designers an opportunity to understand daylighting performance related to design decision and environmental variables. Additionally, it shows how other decisions are influenced at the design stages |
| Gagne et al. [114] (c)     | Educational building | Building geometry, location, ceiling, walls, windows, window size overhangs, fins, orientation, footprint, wall height | Daylighting   | Fuzzy logic system with a simulation program, lightsolve | The proposed approach is an effective tool to find the building designs with optimized performance for various initial geometries and daylight performance objectives |
| Doelling and Nasrollahi [115] (c) | Educational building | Weather, orientation, massing, glazing ratio, fixed shading | Daylight        | Integration of DesignBuilder with DIVA simulations | The heuristic approach and design analysis can be utilized to generate new design seeds that can be used as active design artifacts |
| Yi [116] (c)               | Commercial     | Façade characteristics | Daylight        | Using multi-objective-evolutionary-algorithm, DIVA, and Grasshopper | The proposed approach provides facades that satisfy daylight performance and matches the aesthetic sensitivity with design preferences |

Note: (c) is used to refer to the classification of research efforts, which were categorized into group (a–c).
Concerning the second direction of lighting optimization for energy-efficient designs in buildings, previous research efforts sought to find the best alternative solutions for addressing the conflict in multi-objective optimization (i.e., daylighting against thermal comfort performance), as summarized in Table 4. For instance, Echenagucia et al. [4] used genetic algorithms and multi-objective search optimization integrated, along with EnergyPlus to reduce the demands of lighting, heating, and cooling of buildings in three different regions. They found that the window arrangements on the building façade had a significant influence on energy efficiency, i.e., the strong conflict between lighting and cooling/heating. Fang and Cho [11] also integrated parametric design parameters, daylighting simulation (Radiance), and energy simulation (EnergyPlus) with GAs (genetic-algorithms) to assess energy and daylighting performance in the early design-stages of building to find the optimal design within three different climatic zones. They analyzed the relationship between design parameters and performance measures and found that the width and length of skylight were the most influential variables (i.e., key variables) in each location. However, other design variables differently effected energy and daylighting performance. Futrell et al. [37] combined the hybrid GPS Hooke Jeeves/practical swarm optimization algorithm and epsilon constraint method to maximize the thermal and daylighting performance of a building. The lighting performance was assessed based on the frequency and magnitude at which daylight levels deviated from the lighting range of the desired target. The results showed a low conflict between thermal and daylighting targets for the eastern, western, and southern orientations. Jakubiec and Reinhart [74] integrated the detailed daylighting analysis utilizing Radiance/DAYSIM with the thermal load simulation utilizing EnergyPlus within the DIVA to calculate the annual hourly illuminance and glare values used to identify the status of shading devices. They concluded that the combination of daylight and thermal simulations for simple single-zone models provide designers an assistant tool that can provide quick feedback from existing design models. Similarly, Suga et al. [117] used a multi-objective-genetic algorithm to search optimal outer window format that can enhance the lighting in indoor environments, improve ventilation, and reduce energy consumptions. They concluded that the optimal window format requires consideration of year-round performance and more detailed consideration of objective configurations. Despite these efforts, the conflict issue between lighting and thermal performance of energy efficient designs in buildings, remains a major challenge (Section 4 discusses this issue).

**Table 4.** Results of optimizing the lighting conflict and thermal performance in the early design stages of buildings based on the reviewed literature (the second direction: conflict in multi-objective optimization).

| Reference          | Building Type | Inputs                                      | Outputs         | Method                                                                 | Major Conclusion                                                                 |
|--------------------|---------------|---------------------------------------------|-----------------|------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Echenagucia et al. [4] | Office building | Number, position, shape, and type windows, wall thickness, window to wall ratio, location | Lighting energy | Integrating NSGA-II genetic algorithms with EnergyPlus                  | A significant contrast was observed between cooling and lighting. The window position on building facades plays a fundamental role in energy efficiency |
| Reference          | Building Type     | Inputs                                                                 | Outputs                         | Method                                                                                   | Major Conclusion                                                                                                                                 |
|--------------------|-------------------|------------------------------------------------------------------------|---------------------------------|------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------|
| Fang and Cho [11]  | Office building   | Depth of building, roof-ridge-location; length, width, location, and orientation of skylights, width of windows on north and south facades; louver length, weather | Daylighting                     | Integration of genetic algorithm with Radiance                                            | Length and width of skylight are the most important factors. The skylight to floor ratio is between 0.52 and 2.62% for all cases. With optimization process, the daylight performance metric is raised by 28.8–38.7% |
| Vullo et al. [22]  | Commercial        | Location, infiltration, illumination power, insulation position, insulation resistance, insulation material, fenestration, shading system, ventilated façade cladding, PV technology on façade, PV surface on roof, PV exposure on roof, PV tilt angle on roof | Lighting energy demand          | EnergyPlus simulation engine is used to predict the overall performance of building with different façade designs | The proposed approach can guide architects, engineers, and designers to reconsider the total performance of a facade from the very early design and help in making informed design decisions |
| Futrell et al. [37]| Educational building | Ceiling height, window light transmittance, window solar transmittance, window width, window transmittance for daylighting, length of external shade, length of the lightshelf, view window for light, view window for solar, weather | Daylighting/Lighting demand    | Using GenOpt and a hybrid GPS Hooke Jeeves integrated with the Epsilon Constraint Method, as well as EnergyPlus and Radiance simulation tools | Daylighting targets showed strong conflict with thermal performance in the north orientation while decreasing in eastern, southern, and western orientations |
Table 4. Cont.

| Reference                  | Building Type | Inputs                                                                 | Outputs          | Method                                                                 | Major Conclusion                                                                 |
|----------------------------|---------------|------------------------------------------------------------------------|------------------|------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| Chen et al. [39]           | Residential   | Orientation, external-obstruction angle, thermal-resistance of external walls, specific-heat, window-U-value, soar-heat-gain-coefficient, window-to-ground-ratio, overhang, infiltration-air-mass flowrate coefficient, transmittance of the window, weather | lighting energy  | Non-dominated sorting genetic algorithm integrated with EnergyPlus   | There was a strong disagreement between cooling and lighting energy requirements. The lighting demand varied from 13.30–14.70 kWh/m², while the cooling demand varied from 21.04–77.60 kWh/m². The reason is resulted to the constant light to the solar-gain-ratio and the effects of a window to ground |
| Yi et al. [118]            | Commercial    | Building geometric characteristics, including rooftop/truss structure and glazing | Daylight         | Integrating multi-objective genetic-algorithm and Rhino-Grasshopper (daylight tool simulation) | Future work should combine daylighting, thermal comfort, and natural ventilation |
| Kim and Clayton [119]      | Commercial    | Geometry, location, orientation, WWR, roof, walls, floors, windows, electric-equipment, lighting | Cooling and daylighting | Using parametric behavior map approach and EnergyPlus | Integrating multi-objective optimizations with parametric behavior map contribute to performance-based building design |
| Negendahl and Nielsen [120]| NA            | Design characteristics, including the external façade; window type characteristics, including glazing | Daylight and energy | Using a scripted algorithm with simulations tools, including a Radiance software | The integrated quasi-steady state method with dynamic models is a flexible and fast way to enhance energy-efficient design optimization of buildings |

Note: previous studies, which are not listed in Tables 1–4, are annotated and clarified in the subsection text.

3.3. Sensitivity Analysis Applications

The definition of sensitivity analysis varies according to its applications. Regardless of these definitions, the consensus is that the sensitivity analysis is an important procedure in optimizing energy-efficient design performance of buildings because it is used to identify contributions of each input variable to the overall performance of design solutions, i.e., outputs (to detect the sensitivity of optimization solutions to input parameters). In other words, the sensitivity analysis identifies significant and insignificant design parameters in the building performance optimization model. Therefore, this analysis is usually performed before the design optimization process to find the most influential input pa-
rameters on design performance [121–123], thereby simplifying the optimization problem and reducing the time significantly. Sensitivity analysis includes several key methods, including the correlation and regression methods, screening approach, local approach, global approach, and variance-based method [124–134]. These methodologies vary depending on their characteristics, and scope of application. However, this subsection cannot explain each method separately in detail. According to the review results in the two previous Sections 3.1 and 3.2, a few studies, such as [11,21,23,34,36,37,39,42,44,47,51,55,60,108] conducted sensitivity analysis when optimizing energy-efficient design performance to identify the most influential variables on design performance, as summarized in Table 5. For example, Fang and Cho [11] used the regression method, i.e., sensitivity analysis indicator “standardized regression coefficient (SRC)”, to identify the most influential design variables on daylight and energy performance in an energy-efficient building design. Nine main variables, including depth of the building, roof-ridge location, location, length and width of a skylight, the orientation of skylights, louver-length, and the southern window width were analyzed. They found that the length and width of the skylight were the most influential design variables on useful-daylight illuminance and energy usage intensity. Gercek and Arsan [21] used the correlation coefficient (i.e., sensitivity analysis index) to explore the relationship between annual cooling and heating energy consumption and input variables, including design parameters and climate variables. Investigation results showed that the SHGC values (solar-heat-gain coefficient) of windows on southwest, northeast, southeast, and northwest facades were the most sensitive variables for annual cooling and heating consumption.

Table 5. The most influential input variables on the building performance in the design stages according to the sensitivity analysis in the reviewed literature.

| Reference         | Sensitivity Analysis Index                              | The Most Influencing Input Variable                                                                 |
|-------------------|--------------------------------------------------------|-----------------------------------------------------------------------------------------------------|
| Fang and Cho [11] | Standardized regression coefficient                    | Skylight width, skylight length                                                                  |
| Gercek and Arsan [21] | Partial correlation coefficient                      | Valued of solar heat gain coefficient for windows on the southwest and northeastern façades      |
| Elbeltagi et al. [23] | Standard deviation coefficient                       | Cooling setpoint, length, depth and height of a building, glass SHGC                              |
| Hygh et al. [55]   | Standardized regression coefficient                    | Building area, window to wall ratio                                                              |
| Attia et al. [34]  | Variance coefficient based on simulation              | Wall construction/structure                                                                      |
| Gou et al. [36]    | Standardized rank regression coefficient               | Window-opening factor, WWR, Air-mass-flow coefficient, window SHGC, roof solar absorbance, roof and wall XPS thickness, depth of overhang of a south window |
| Futrell et al. [37] | Radiance daylight coefficient                        | Orientation                                                                                      |
| Chen et al. [39]   | Variance coefficient (ANOVA), regression coefficient   | Window transmittance, exterior obstruction level                                                  |
| Hester et al. [42] | Spearman rank correlation coefficient, variance coefficient | Living area, attic and window U-values, external wall U-value, air leakage                        |
| Hopfe and Hensen [44] | Stepwise regression analysis, standardized rank regression coefficient | Infiltration rate, outside emissivity roof, conductivity floor layer, thickness roof layer, density floor layer, U-value double glass, specific heat capacity roof layer |
| Zhang et al. [60]  | Variation/Spearman correlation coefficient            | Window U-value, wall U-value, height of floor                                                    |
| Ihm et al. [108]   | Correlation coefficient                               | Window dimensions, glazing type                                                                  |

As shown in Table 5, previous studies have been used different indexes for the sensitivity analysis to explore the potential effect of each input variable on energy-efficient design performance optimization. Furthermore, it can also be said that sensitivity analysis is an indicator to justify the optimization process because it reveals the main negative factor
responsible for the poor performance of the building. On this basis, Elbeltagi et al. [23] conducted a sensitivity analysis utilizing simulation results to identify how the optimization outputs can change in response to specific input changes (i.e., how the residential building energy consumption varies in response to changes in the given inputs). The input parameters were orientation, dimensions of a building, cooling and heating set-points, glass properties of windows, wall, roof, etc. They found that the cooling set-point had the largest effect on consumption level, followed by the building dimensions. Gou et al. [36] also used “standardized rank regression coefficient” to explore the most influential parameters of passive-design in terms of the ratio of comfort time and energy demand in buildings, as well as reduce the number of input variables for the optimization procedures. In total, 37 input variables, including orientation, wall type, and the window-to-wall ratio were examined. The sensitivity analysis results showed that the window to wall ratio, SHGC of south and north windows, air-mass-flow-coefficient, the thickness of the roof and north wall, and solar absorbance of the east wall were the top influential input variables. Attia et al. [34], Futrell et al. [37], Chen et al. [39], Hopfe and Hensen [44], Hester et al. [42], Hygh et al. [55], Zhang et al. [60], and Ihm et al. [108] used different indexes for sensitivity analysis to find out the relationship between optimization outputs to the input parameters. Futrell et al. [37] observed that the orientation is the most influential input parameter on daylighting and thermal performance. Chen et al. [39] found that window transmittance properties and levels of external obstructions have a great effect on the energy demands of the building, and thus must be given an increased weighting in the passive design of buildings or evaluation guidelines. Hygh et al. [55] found that the buildings located in Miami, Winston-Salem, Albuquerque, and Minneapolis showed high sensitivity to building area in terms of cooling energy consumption, whereas Zhang et al. [60] observed that building energy use could be significantly reduced by optimizing window and wall heat preservation properties, room depth, and window to wall ratio.

4. Implications and Limitations of Energy-Efficient Design Optimization

4.1. Energy-Efficient Design Optimization Implications

The primary purpose of optimizing the energy-efficient performance of buildings at the early stages using optimization techniques and the subsequent theoretical design models that arise from such studies is to obtain high-performance buildings that provide an adequate level of comfort and lighting for the inhabitants at the lowest possible environmental cost. In particular, the early stage of building design contributes to 85% of the impact on achieving the building’s lifecycle-cost savings. While the construction and operation stages that contribute to approximately 85% of the lifecycle cost of a building, have only (10%) and (5%) of impact on the potential-cost-savings of the building’s lifecycle, respectively [135], as shown in Figure 2. The literature attributes the reason to the fact that the thermal performance of buildings is closely linked to three main elements, namely microclimatic conditions surrounding the building, thermal behavior of the fabric of a building, and required indoor comfort conditions [94,136,137]. Among these elements, the thermal behavior of the building fabric, specifically building envelope components, affect the building performance, including energy use intensity and required comfort level [138–143]. Specifically, the skin of a building, usually consisting of transparent, opaque, or combination of both components, affects cooling, heating, and lighting energy consumption in the building through characteristics, for example; the solar energy transmitted via windows, material conduction, and visual transmittance. Additionally, the building-geometrical configurations, such as orientations, the geometry shape, length-to-width ratio, window-to-wall ratio, and window-to-floor ratio strongly affect the performance of a building in terms of energy loads of cooling and heating.
Al-Saggaf et al. [135] used the hierarchical analytical approach, along with the development of multiple design alternatives to assess the effect of design features/parameters on the building’s lifecycle performance in the early design stage under hot climatic conditions. Seven design parameters, including building orientation, building envelope, shape, number of floors, height of floors, windows, glazing, floor spans and circulation space were identified and their impact on design performance was assessed using four major aspects of the building’s lifecycle, i.e., functional space, construction performance, operational performance, and aesthetic value, as shown in Table 6. From the assessment results, they concluded that the early evaluation decision for building design performance; (1) boosts the ability/potentiality of designers/architects to deeply understand the effects-of-design-parameters on performance of the building’s lifecycle; (2) provides designers/architects a structured and automated decision support system to conduct quantitative valuation and sensitivity analysis; (3) increases the effectiveness of building design during the operation phases; (4) reduces cost, time, and energy emissions; (5) works as an effective tool that can use in architectural-design-competitions to offer cost-effective design alternatives. This corresponds to Bernett and Dogan [77], who developed an EnergyPlus-based early design decision-making framework to simulate the energy performance, carbon footprint and cost concurrently through the early stages of the building-design-process to inform the design of hypothetical eight-story office buildings in Phoenix and Washington, USA.

Table 6. Results of lifecycle performance assessment for five different energy efficient designs of buildings in the early stages [135].

| Design | Space Functionality | Construction Performance | Operational Performance | Aesthetics | Evaluation | Rank |
|--------|---------------------|--------------------------|-------------------------|------------|------------|------|
|        | Accessibility       | Relation                 | Size                    | Cost       | Time       | Energy | Maintenance | Aesthetics |             |      |
| A      | 0.34                | 0.37                     | 0.38                    | 0.20       | 0.12       | 0.03   | 0.32        | 0.07       | 0.26        | 3     |
| B      | 0.02                | 0.00                     | 0.00                    | 0.53       | 0.39       | 0.06   | 0.32        | 0.11       | 0.17        | 4     |
| C      | 0.28                | 0.65                     | 0.15                    | 0.00       | 0.19       | 0.44   | 0.23        | 0.30       | 0.27        | 2     |
| D      | 0.00                | 0.10                     | 0.63                    | 0.01       | 0.24       | 0.67   | 0.00        | 0.29       | 0.33        | 1     |
| E      | 0.03                | 0.25                     | 0.08                    | 0.00       | 0.00       | 0.09   | 0.07        | 0.33       | 0.09        | 5     |
Several studies [144–150] have also acknowledged the importance of optimizing the early design envelope because it can address the most design issues or problems in buildings for a diversity of alternative designs and their associated environmental effects. In this context, various combinations of materials for the building design can be assessed based on the “Building Sustainability Index”, which facilitates designers/architects to select the optimum combination of building envelope materials in terms of economic and environmental sustainability; this is consistent with a conclusion of Baglivo and Congedo [151] in their research regarding the slab efficiency optimization on ground floors for a zero-energy building. Second, exploring the most convenient and efficient designs in terms of material sustainability, shape, orientation, size, function, climatic zone, and available economic potential, in which it allows designers to reveal and know how the early design decision can affect design performance before making any actual design decisions [152,153]. Furthermore, addressing the multi-objective conflict in building functions, such as providing lighting and heating or optimizing daylighting and cooling, saves time and money required to construct a less efficient building. Additionally, detecting design errors in existing buildings, and employing them in proportion to high-performance buildings, along with improving the current techniques/methods used in line with future design issues. Architects/designers can easily merge any group of design options to generate design alternatives based on reliable methodology and thoughtful procedures previously [154].

4.2. Energy-Efficient Design Optimization Limitations

Considering the literature reviewed in Section 3, all previous research efforts have sought to achieve sustainable designs with high performance in terms of energy efficiency and comfortable indoor environments for occupants. However, each effort has its advantages and limitations/disadvantages that may be attributed to either the design itself and the design stage (i.e., the required data, nature of inputs, design target, and the detailed level), or optimization techniques/optimization platform used (i.e., algorithms, simulation tools, and both). The effect of these limitations is not limited to contradicting-and-stricter-requirements, but interoperability, and a discrepancy-between-simulations and realistic-measurements. Accordingly, this subsection discusses the most prominent limitations of optimizing the energy-efficient design performance in buildings from the perspective of the reviewed literature in the previous section (see Table 7).

Table 7. The most prominent limitations and potential future research opportunities in optimizing the energy-efficient design of buildings in the early stages based on the reviewed literature.

| Limitations of the Reviewed Literature                                                                 | Potential Future Research Opportunities                                                                 |
|--------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
| Consideration of a limited number of design parameters and a complete lack of evaluation studies for the characteristics of optimized design envelope materials; thus most previous efforts fail to address multi-objective design functions, such as maximizing daylight and minimizing cooling energy loads, as well. | Modifying the framework of existing hybrid optimization techniques in contexts of multi-objective design performances that respond to the unique requirements of energy-efficient design performance simulations in the early stages of building constructions with a particular focus on a) improving the initialization and mutation operations of the tailored algorithms and other stochastic-based algorithms so that all parts of design search spaces can be effectively explored; and b) developing new sub-processes for the hybrid used as algorithms to define new super-design shapes/variants based on a collection of possible solutions instead of just one solution or include solutions found through voluntary design process simulations that utilize design rules, in addition to allowing the building design to include more disciplines, such as cooling and lighting. |

The used methods are not necessarily suited to the problems addressed in energy-efficient design optimizations of buildings, which need to take into account the nature of design variables (discrete variables, continuous variables, or both), nature of target-design functions, constraints on the objective function, and problem characteristics.
Table 7. Cont.

| Limitations of the Reviewed Literature                                                                 | Potential Future Research Opportunities                                                                                             |
|--------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------|
| Relying only on simulation engines to optimize the building performance in the early design stages would enhance uncertain ideal solutions of building designs. As a result, the optimal solution may not meet the performance requirements of the building design, nor be robust to handle small deviations in both inputs and constraints of the optimization process. | Considering the suitable optimization approach for design problems that enables conducting in-depth investigations on the interactions between the building design envelope optimizations and optimized energy systems under future weather conditions, with a focus on effective design parameters that will significantly contribute to evaluating the lifecycle performance of optimized design envelopes at various levels in terms of cost and efficiency. |
| Investigations on the efficiency and life cycle performance of optimized design envelopes (optimum design envelopes) under future climate conditions, as well as design envelope materials, are often missing. | Enriching the applications of existing hybrid versions to enable investigating ideal solutions to be applicable for building design characterization at different scales and various climate conditions. In addition to assessing the lifecycle performance of an optimized design energy system (optimized design lifecycle performance) and investigating uncertainties in optimum designs. |
| A complete lack of including human-building interactions by considering context-aware design-specific data describing design-specific human–building interactions captured by utilizing immersive virtual environments during the early stages of building designs. | Extending the search scope of optimization algorithms and optimization models with their applications to buildings to include full design parameters, parameters of human-building interactions, and passive parameters, such as renewable energy systems at different large-scale locations and climatic weather conditions. |
| Other parameters, including passive parameters, such as solar photovoltaic energy systems, are not considered during the process of optimizing the energy-efficient design in buildings. |                                                                                                                                 |

4.2.1. Energy-Efficient Design-Related Limitations

Building design envelope parameters and other geometric-configurations are the cornerstone to implement the optimization process in the early stages of building design, which mainly affects the energy performance of buildings. However, many previous studies rarely look at the overall structural optimization of a building, i.e., considering all design parameters and characteristics of the design envelope materials. Moreover, the building design structure is rarely optimized for both daylighting and energy loads together, i.e., multi-objective designs. A few parameters of the building design are usually considered to deal with different design issues, including maximizing daylight and minimizing cooling/heating loads, in addition to the default setting of the unknown detailed design parameters. In such a case, the details of design decisions are often different, because designs with different environmental impacts will be created, as the default setting cannot cover most of the potential variations in the effect [30]. Secondly, without incorporating a different building performance area, a solution in one area would be a problematic solution in another area [118].

Another limitation is the investigation of the lifecycle performance of optimal designs and their envelope efficiency under future climate conditions. Most of the previous studies lacked to address this significant aspect during the early stages of optimizing the energy-efficient design of buildings. For example, many previous research efforts ignored investigating the interactions between the building design envelope optimizations and optimized energy systems under future weather conditions [155]. Besides, a number of those efforts relied solely on simulation tools to perform design performance optimizations, and lifecycle performance assessment of optimal designs using those tools is often missing. Future climate weather data, together with effective design parameters, would significantly contribute to evaluating the lifecycle performance of optimized design envelope scenarios at various levels in terms of cost and efficiency [156]. Furthermore, it has been widely noted that optimization studies of the energy-efficient building design fail to addresses human–building interactions by considering context-aware-design-specific data describing design-specific human–building interactions captured by utilizing immersive virtual environments. The human–building interactions were completely absent from energy-efficient
design performance optimization models. This means that most of the optimized design models may be not able to accurately describe user interactions with buildings. This will contribute to the development of inaccurate building performance models, and their performance varied between predictions and real buildings.

4.2.2. Optimization Technique-Related Limitations

Generally, building performance optimization is performed in the early design stages by coupling the optimization algorithms with a physical model of building design to predict the performance of alternative building designs, which can be based on the physical-based model, a metamodel, a data-driven model, etc., as shown in Figure 3. However, in many of the previous studies, it relied solely on simulation engines in optimizing the building performance during the early design stages. As it is known, in the early stage of optimizing energy-efficient designs in buildings using simulation engines, the analyst has to deal with uncertainties during various optimization process stages, which may result in uncertain ideal solutions. They typically arise from design parameters, building operation, performance evaluation criteria of a building, noise in cost function assessments by computer programs, climate, etc. [13,157–159]. Accordingly, the optimal solution must not only meet the performance requirements of the building design, but also be robust to handle small deviations in both inputs and constraints of the optimization process. This task is referred to as powerful design optimization, which is defined as a “methodology” for optimizing a building design that is unaffected by differentials, such as environments and systems [160]. Figure 4 illustrates this concept, that is, instead of searching for the sensitive global optimum (X1), one must find the local, but the powerful optimum (X2), as the performance of the solution (X2) has a small tolerance for uncertainty. In contrast, lifecycle environmental analysis platforms are rarely connected to building performance simulation engines. The same thing goes for cost evaluations. High performance buildings typically require an effective performance-based design-process that enforces integrating optimization algorithms with building performance simulation software packages. Generic optimization tools such as GenOpt, jEPlus+EA, Matlab toolbox, MOBO, Opt-E-Plus, ParadisEO, modeFRONTIER, ModelCenter, MultiOpt 2, and LionSolver provide acceptable coupling flexibility.

![Figure 3. Example for application of a coupling-loop in a simulation-based-optimization process in design performance optimization studies of buildings.](image-url)
as more discrete variables are added to the problem. Using genetic and evolutionary algorithms, which randomly generate and improve a population of candidate solutions, may satisfy the mixed-integer problem in optimization. However, these algorithms are not able to assure “optimality” of the solution [162]. In real world design optimization issues, architects/designers have to handle with conflicting design-criteria, along with issues related to design variables to achieve high performance designs. Typically, the choice of optimization algorithm depends on some basic considerations, which are represented in [161,163]: (1) nature of design variables, i.e., discrete variables, continuous variables or both; (2) nature of objective/target-functions (i.e., linear or nonlinear, continuous or discontinuous, convex or nonconvex, etc.); (3) constraints on the objective function; (4) algorithm performance; (5) problem characteristics; and (6) availability of first and second degree analytical derivatives for objective/target functions.

Besides previous limitations, there have been shortcomings in a number of the previous studies in aspects related to (a) conducting sensitivity analysis and uncertainty in general while optimizing energy-efficient design and allowing the building design to have nonorthogonal shapes encompassing more disciplines, such as lighting; (b) investigating hybridization schemes, which integrate designed algorithms with building design simulation methods; and (c) investigating the sensitivity of developed hybrid methods to the stochastic nature of designed algorithms, with the aim of applicably modifying
the presented hybridization schemes to reduce the sensitivity of the hybrid method. In general, the sensitivity analysis basically evaluates the behavior of outputs, as a result of contributions of each input variable to the overall performance of design solutions, i.e., outputs. While uncertainty analysis evaluates uncertainties in targeted design outputs that arise from uncertainty in inputs. This contributes to simplifying optimization problems that may arise from the influence of design parameters in multi-objective optimizations [164].

5. Future Research Directions

To effectively discuss research gaps in the current optimization of buildings during the early design stages by using different scenarios and relevant optimization techniques, including energy/lighting simulation tools and optimization algorithms to reach high-performance buildings in terms of thermal comfort and lighting, and reduce emissions related to energy usages. It is noteworthy that optimizing the energy-efficient design performance is a multi-objective and multivariate design task. Thus, the traditional trial-and-error design approach that relies on the experience and knowledge of the designer/architect may be ineffectual when the building design is complex. From the architectural point of view of the authors, traditional architectural design is a procedure or method involving a number of fundamental design principles that depend on function and form. The main driver for this approach/procedure is the rationality and sensibility of the architect and designer [165,166], while the efficiency of the building design depends on the performance. On this basis, the driving force for the generation, development, and evaluation of building designs, should be a quantifiable performance indicator (i.e., quantifiable performance index), such as the total energy consumption for lighting, heating and cooling. Accordingly, incorporating optimization techniques, i.e., optimization algorithms with building energy simulation software packages [167], including lighting simulation tools is a natural procedure to deal with difficulties and challenges of the energy-efficient design performance optimization that the traditional design approach could not overcome, namely a fast and precise computation of the energy performance and the systematically directed research for the ideal solutions in large architectural design spaces. Figure 5 illustrates the primary steps taken in the optimization of the energy-efficient design performance and the implementation of such steps in the early stage of building design. Additionally, below (Figure 6), a simple example of how an optimization framework can be used to implement procedures of multi-objective design optimization of buildings to maximizing daylighting and minimizing cooling/heating loads.

Coincided with the above and as summarized in Table 7, since incorporating optimization techniques are useful and effective means providing profound insights and possible strategic solutions in optimizing the performance of energy-efficient building designs, the hybrid optimization approach has been deemed as suitable means for facilitating in-depth future studies on energy-efficient design performance optimization in buildings. Thus, the first direction of future research is to modify the framework of current hybrid optimization techniques in contexts of multi-objective design performances to achieve high-performance buildings in terms of lighting and energy efficiency while maintaining occupant comfort. Since the hybridization methodology combines more than one optimization platform into a new one in which it inherits its pros/advantages and minimizes its cons/disadvantages. This requires special improvements of the existing hybrid optimization approaches responding to unique requirements of energy-efficient design performance simulations in the early stages of building constructions, with a particular focus on (a) improving the initialization and mutation operations of the tailored algorithms and other stochastic-based algorithms so that all parts of design search spaces (a portfolio of all possible design solutions) can be effectively explored; (b) investigating hybridization schemes, in a case of combining tailored algorithms (e.g., S-Metric-Selection-Evolutionary-Multi-objective-Optimization Algorithms [168–170], etc.) with methods of simulating evolutionary design process (simulation model evaluation function) with the aim of achieving more realistic designs [171]; (c) developing new sub-processes for the hybrid used as algorithms to define
new super-design shapes/variants based on a collection of possible solutions instead of just one solution or include solutions found through voluntary design process simulations that utilize design rules, in addition to allowing the building design to include more disciplines, such as cooling and lighting; and (d) investigating the sensitivity of the hybrid approaches to the stochastic nature of tailored algorithms (including the challenges related to optimization algorithms, which occur when integrated with design performance simulation tools), along with the applicability of modifying hybridization schemes to reduce that sensitivity.

Figure 5. Primary steps of energy-efficient building performance optimization framework at the early design stages.

Figure 6. Simple example of implementing a multi-objective performance optimization for buildings in the early design stages.

Another research direction is to enrich the applications of current hybrid versions, enabling them to be applicable for building design characterization at different scales.
and various climate conditions. All issues related to the optimization of multi-objective design (the structurally optimized building) should be fully addressed. In addition to assessing the lifecycle performance of an optimized design energy system (optimized design lifecycle performance). In the literature, a significant number of research efforts in this trend are limited to single-objective design optimization using a few design parameters/features. Furthermore, the optimization in several research efforts was limited to building energy/lighting simulation tools, which it is not possible to conduct important investigations, such as the lifecycle performance analysis of optimized design envelope, as well as uncertain solutions. Therefore, future research efforts should be placed on multi-objective design optimization, along with the lifecycle performance assessment of an optimized design envelope for a large number of buildings. To be specific, the next generation of optimization techniques, including hybridization approaches, should cover more building design components and human–building interactions (interactions that describe the occupant behavior) under different climatic conditions, and are fit to perform design optimization and evaluation of lifecycle performance at different large scales.

Moreover, it has been widely observed that most efforts of optimizing the energy-efficient design in buildings at the early stages did not offer sensitivity and uncertainty analyses concerning the influential parameters on design performances of buildings in a long time scale; as well as investigating the properties of optimum design envelope materials. Therefore, they fail to develop an optimization system enabling the determination of the prevailing influential parameters and then optimum design envelope for a specific sector of buildings (e.g., such as residential buildings) at large temporal scales, including cities, which represent a large partition of the building sector. Accordingly (and based on the first and second future directions), the future effort should be extended to include full design parameters with their properties and other passive parameters (e.g., solar photovoltaic systems) [172]. Additionally, there should be a strong drive to extend optimization algorithms and optimization models with their applications to buildings of different large-scale locations and climatic conditions. It is expected that optimum energy-efficient designs/optimal envelope designs may vary depending on regulations, standards, and building design properties in each country. However, the specific optimal design envelope of buildings can be compared to assess the differences and similarities concerning studies to be conducted in other countries [173]. The results of reference buildings resented in studies may also be utilized to optimize the next generation of energy-efficient building designs.

Referring to the above-future directions with respect to current optimization techniques and building performance simulation engines, the architects and designers are the end-users, i.e., they are not developers/inventors of building design optimization techniques. Aspects related to overall capacity/ability, user-interface, post-processed, and incorporation with architectural-modeling-tools are the cornerstone of what the designer or architect focuses on and utilizes to assess the efficiency and capacity of optimization techniques of buildings at the design stages. Specifically, this can be another missing piece regarding design optimization techniques of buildings. Therefore, future research should be directed toward developing program packages that most designers are not familiar with. As presented previously (Section 3), public optimization platforms, such as GenOpt, Matlab, PyCharm, RStudio, jEPlus, and modeFrontier can be utilized to incorporate building simulation-programs and establish building performance optimization techniques for design stages. Nonetheless, not all of those optimization platforms have been developed to meet the individual architectural space design needs. Consequently, the user interface and operating style may be slightly unfamiliar for the architects and designers. Furthermore, it cannot be seamlessly linked to architectural modeling software, e.g., SketchUp and Revit. This is an important challenge because designers usually depend on the modeling software to create, test, and adjust their designs in the early building stages. To effectively achieve design optimization, the switch between modeling and optimization environments should not be troublesome and susceptible to mistakes [174,175]. All these will be a significant fac-
tor in the building design optimization process in the early stages that have been changed substantially over the past years. In particular, the computer-aided design has given a significant opportunity to convey/transfer design information to other aided-tools for making the right decision, as well as dealing with the current challenges in the field of buildings.

6. Conclusions

Performance simulation-based design optimization is unquestionably a promising practice and strategy for achieving many sustainable building goals. In particular, it opens a new era of promising energy-efficient designs for both architects and designers to design new buildings, which are characterized by energy efficiency and better performance. Accordingly, this study aimed to provide a comprehensive review of building performance optimization studies in the early design stages, specifically those research efforts related to the heating, cooling, and lighting optimization applications of buildings; and conduct a systematical review covering various aspects ranging from the building type, inputs of the optimization process, the approach used, and the main conclusion. Furthermore, the benefits and limitations of early optimization of energy-efficient building design performance and future research directions are identified and discussed.

As evident from the results, optimization techniques-based energy-efficient building design performance assessment in the early stages has garnered great research interest, so that different aspects of building design performance problems were being addressed. A wide variety of design models have various scopes, were tested on a various dataset, and utilize various design parameters for performance optimization. All of these optimized design models have their advantages and disadvantages; and a different performance under various climatic conditions. Despite, the design optimization objectives in the previous studies are all energy and lighting related, they can take various forms. Along with the design goals are related to energy usages, such as minimizing the cooling, heating, and lighting, implicit energy-related design goals have also been found such as minimizing carbon emissions and reducing lifecycle costs. In the real world, there is no specific-optimum design that fits all conditions, therefore, continuing to address the problems of building design performance optimization is essential by considering all the mentioned-aspects previously (i.e., in Section 5).

Depending on how the design optimization processes are achieved, building performance optimization techniques in the design stages can be classified as techniques incorporating design simulation software packages into generic optimization platform, techniques incorporating design simulation software packages into special purpose optimization platform, and customized-techniques. A wide variety of energy and lighting simulation program packages, such as EnergyPlus, DOE-2, ASHRAE toolkit, Radiance, eQuest, TRNSYS, IDA ICE, DAYSIM, etc., were utilized. EnergyPlus and Radiance were the most used simulation tools in design optimization studies, representing 40% of the literature reviewed. Matlab and GenOpt toolboxes were the most used optimization platforms, while the metaheuristic search algorithms (i.e., POS and genetic algorithms) were the most optimization algorithms applied to building optimization performance simulation. Nonetheless, applications of performance optimization of buildings in the challenges of the real design world remain in the early stages of development. There are a lot of building simulation software packages and optimization techniques, but there are still many barriers/obstacles in pairing strategies, ease of use, pliability, and effectiveness, which are closely related to both of the time and performance of optimization, which partly prevents the propagation of some optimization techniques in the practices of building designs.

In the last two decades, the general trend to optimize and evaluate building performance in the early design stages might have been more encouraging than ever. This rising trend was demonstrated in the number of studies related to performance optimization of buildings during the design stages, where the building research community made a great effort regarding design efficiency. The main motive of this movement is the progress of
computer-sciences and the most stringent performance requirements for building designs, such as the green building codes, zero-energy buildings, passive buildings, etc. However, the challenges and obstacles are still ahead, major research topics need to some major research topics need to be further studied such as: (1) modifying current hybridization optimization approach frameworks in the context of energy-efficient building performance features to more precisely respond specific requirements from building design performance; (2) enriching energy-efficient design optimization applications of buildings to cover different aspects of the performance, design envelope properties, and other passive parameters, such as installing solar photovoltaic systems at various scales under a wide range of climatic conditions; (3) integrating sensitivity and certainty indexes in the large-scale performance optimization framework of buildings to provide a more balanced assessment of influential design parameters; (4) extending optimal design envelope performance investigations of buildings to include lifecycle assessment in long-term weather conditions; and (5) development of design improvement program-packages that better fit into the overall-design workflow and are familiar to designers and architects. Furthermore, design optimization processes should be shared with user activities and validated using climate factor changes and other factors that describe human interactions with buildings.

**Author Contributions:** S.H.C. and A.A.A.G. designed the study; A.A.A.G. collected and analyzed the data and wrote the manuscript; S.H.C. and A.A.A.G. revised and edited the manuscript; C.K. and T.W.K. reviewed the manuscript. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the research fund of Hanyang University (HY-20210000001530).

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** No applicable.

**Conflicts of Interest:** The authors declare no conflict of interest.

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