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Review

The Road to Developing Economically Feasible Plans for Green, Comfortable and Energy Efficient Buildings

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Abstract: Owing to the current challenges in energy and environmental crises, improving buildings, as one of the biggest concerns and contributors to these issues, is increasingly receiving attention from the world. Due to a variety of choices and situations for improving buildings, it is important to review the building performance optimization studies to find the proper solution. In this paper, these studies are reviewed by analyzing all the different key parameters involved in the optimization process, including the considered decision variables, objective functions, constraints, and case studies, along with the software programs and optimization algorithms employed. As the core literature, 44 investigations recently published are considered and compared. The current investigation provides sufficient information for all the experts in the building sector, such as architects and mechanical engineers. It is noticed that EnergyPlus and MATLAB have been employed more than other software for building simulation and optimization, respectively. In addition, among the nine different aspects that have been optimized in the literature, energy consumption, thermal comfort, and economic benefits are the first, second, and third most optimized, having shares of 38.6%, 22.7%, and 17%, respectively.

Keywords: daylighting; economic benefits; environmental impact; multi-objective simulation-based optimization; retrofitting building energy consumption; thermal-visual comfort

Citation: Mousavi Motlagh, S.F.; Sohani, A.; Djavad Saghafi, M.; Sayyaadi, H.; Nastasi, B. The Road to Developing Economically Feasible Plans for Green, Comfortable and Energy Efficient Buildings. *Energies* **2021**, *14*, 636. https://doi.org/10.3390/en14030636

Academic Editor: Jae-Weon Jeong
Received: 4 January 2021
Accepted: 24 January 2021
Published: 27 January 2021

1. Introduction

During recent years, the standard of living has raised increasingly [1–4]. Moreover, the issues such as energy and environmental crises have led to growing concerns about the future of human-beings on the planet [5–8]. Since there are a lot of buildings in different applications all around the world, any improvement in the building sector, in which all the previously mentioned parameters are involved, is greatly appreciated by the entire world [9–11]. Different experts, including architects, energy engineers, mechanical engineers, etc., with different points of view, corporate in the design process [12]. This means that acquiring a desirable condition is a really challenging matter [13–16]. As a solution, optimization approaches, which are systematic ways to deal with such problems, have been increasingly applied [17].

Depending on the project goal and expected requirements, single-objective optimization (SOO) or multi-objective optimization (MOO) can be employed. In SOO, only one objective is minimized or maximized, whereas in MOO two or more than two objective functions are enhanced, simultaneously.

Optimization problems can be categorized in different ways, for example, based on the optimized objective functions, considered decision variables or constraints, and so on.

In order to perform further studies, being well informed about the investigations done in the past is of great importance. The more comprehensive information provided from the literature, the higher quality the future studies will be.

Investigating the review studies in the field of building performance optimization (BPO) clarified that, despite providing valuable information, these studies also have some drawbacks. The main drawbacks of the review articles done recently are collected in Table 1.

Table 1. List of the recent review studies in the field of building performance optimization (BPO).

Study	Year	The Main Drawbacks
Wong and Zhou [18]	2015	• The research aimed to provide an overview of the ways to improve buildings environmental sustainability in their life cycle. The studies that optimized other objectives were not investigated.
Carlucci et al. [19]	2015	• Visual comfort definitions, and its constraints and indicators were well defined; however, details about other building aspects, decision variables, employed algorithms, and software were not reported.
Shi et al. [20]	2016	• This paper discussed the literature from the architectural perspective. Other perspectives were not taken into account. • The investigation did not classify different optimization approaches. • The constraints imposed to the optimization problems were not mentioned. • Studies which employed both MOO and SOO were not compared to the ones which conducted either MOO or SOO.
Bonyadi and Michalewicz [21]	2017	• Only a brief description about the previous review studies was presented. It means that the research papers were not taken into account. • The review was limited to the particle swarm algorithm; other algorithms were not taken into account. • MOO problems were not studied. • The information about decision variables, constraints, and other key parameters in an optimization problem were not presented.
Kumar et al. [22]	2017	• Methods and software programs were the only investigated parameters.
Tian et al. [23]	2018	• The review merely covered passive design buildings. • There is the lack of reviewing decision variables, objective functions, constraints, software, and so on. • The review was written from the architectural point of view and there is no sufficient information for the other experts.
Ekici et al. [24]	2019	• Among all the key parameters, only the building aspects which were considered as the objectives were discussed. • Among evolutionary, juts swarm algorithms were investigated. • The consideration of decision variables was restricted to form-finding ones.
Alothaimeen and Arditi [25]	2019	• SOO studies were not reviewed. • The investigated MOO publications were in the range of 2012–2016, which is not up to date. • Explanations about some important parameters of an optimization problem, such as the considered decision variables and employed software programs were not given.
Joench et al. [26]	2019	• The paper was dedicated to review the optimization methods; there was no explanation about other involved aspects including the considered objective functions, decision variables, constraints, etc.

Considering the mentioned gap of study, which can be identified from Table 1, in this paper, the investigations done in the field of BPO are discussed from different viewpoints:

- The optimization problems are classified to SOO and MOO, and they are compared to each other. In addition, the studies that evaluated both SOO and MOO are also taken into account.
- All the key parameters in an optimization problem are considered and the investigations are analyzed based on each of them, separately. The key parameters include objective functions, decision variables, and constraints. There have been nine different aspects from which objective functions have been selected so far. The review investigates all the nine aspects completely and in detail.
- The studies are also categorized and investigated based on other criteria, such as optimization algorithms and software programs. Moreover, software programs are divided into building simulation-based and optimization tools.
- The review is written in a way that it provides information for not only architects but also other experts in the building sector.

Therefore, this study serves as a reference to acquire brief but detailed information for researchers in the future to achieve better results in their further studies. Having the information about the previously done investigations reported in this review will help the researchers who are going to conduct BPO studies to select the key parameters in a more efficient and comprehensive way. Moreover, they will not forget some points which make the optimization results unfavorable from some aspects.

This paper has the following structure. After this part, i.e., the introduction, the core literature is introduced. Then, it is analyzed from different aspects, including the considered objective functions, decision variables, constraints, and the case study. Next, the algorithms employed for optimization and the software used are reviewed, and after that, conclusions are presented.

2. Paper Searching Methodology

This review concentrates on investigations within the building performance optimization (BPO) framework found from Scopus and Science Direct databases. Since the optimization algorithms and computer infrastructure have been significantly enhanced during these years, the studies done in the years before 2015 were usually simple, and for that reason, only recent studies that were published in the period of 2015 to 2019 were taken into account. Moreover, some keywords, such as "multi-objective optimization", "single-objective optimization", "simulation-based optimization", "zero-energy buildings", "energy consumption", "thermal comfort", "daylighting", "visual comfort", and "life cycle cost" were used to select the relevant studies. This search method resulted in collecting 44 studies that were considered as the core literature.

3. Overview of the Studies Selected

Here, a general classification of the core literature is presented based on the year and the optimization approach. As is seen in Table 2, two different approaches have been followed in the optimization processes of these studies, including single-objective optimization (SOO) and multi-objective optimization (MOO). Moreover, in some of the reviewed studies, the results of these two approaches have been compared with each other. Such investigations are presented in the category of "single-objective versus multi-objective approach" in Section 3.3.

Table 2. The core literature.

Study	Year	Optimization Approach	
		SOO	MOO
Abdallah and El-Rayes [27]	2015	√	
Mangkuto et al. [28]	2016	√	
Ferdyn-Grygierek and Grygierek [29]	2017	√	
Baglivo et al. [30]	2017	√	
Bamdad et al. [31]	2017	√	
Zhou et al. [32]	2018	√	
Li et al. [33]	2018	√	
Sghiouri et al. [34]	2018	√	
Xue et al. [35]	2019	√	
Echenagucia et al. [36]	2015		√
Yu et al. [37]	2015		√
Carlucci et al. [38]	2015		√
Ascione et al. [39]	2015		√
Zhang et al. [40]	2016		√
Gadelhak and Lang [41]	2016		√
Pan et al. [42]	2016		√
Ascione et al. [43]	2017		√
Bingham et al. [44]	2017		√
Zhang et al. [45]	2017		√
Mostavi et al. [46]	2017		√
Bre and Fachinotti [47]	2017		√
Hamdy and Mauro [48]	2017		√
Wu et al. [49]	2018		√
Lin et al. [50]	2018		√
Grygierek and Ferdyn-Grygierek [51]	2018		√
Schito et al. [52]	2018		√
Gou et al. [53]	2018		√
Harkouss et al. [54]	2018		√
Sohani et al. [55]	2019		√
Zemero et al. [56]	2019		√
Yi [57]	2019		√
Hong et al. [58]	2019		√
Kirimtat et al. [59]	2019		√
Ascione et al. [60]	2019		√
Zhai et al. [61]	2019		√
Si et al. [62]	2019		√
Sharif and Hammad [63]	2019		√
Fang and Cho [64]	2019		√
Sohani et al. [65]	2019		√
Lu et al. [66]	2015	√	√
Delgarm et al. [67]	2016	√	√
Delgarm et al. [68]	2016	√	√
Delgarm et al. [69]	2016	√	√
Xiong et al. [70]	2019	√	√

As is shown in Figure 1, about 30% of the selected studies were done in 2019. This demonstrates that there is a growing interest in the BPO topics among researchers worldwide.

3.1. Single-Objective Optimization (SOO)

In the optimization process, based on the SOO approach, only one aspect is optimized. In order to achieve better results, the researcher may consider other aspects than the constraints which are very likely to have the readers confused with the objective functions (e.g., [27,30,33,35]). It should be noted that Mangkuto et al. [28] claimed the MOO approach was proposed in their paper. In fact, in that paper, in the optimization process minimizing lighting energy demand was subjected to the limitation of five daylight indicators. This means that lighting energy demand was the only objective function, and the five daylight indicators were the constraints of the SOO.

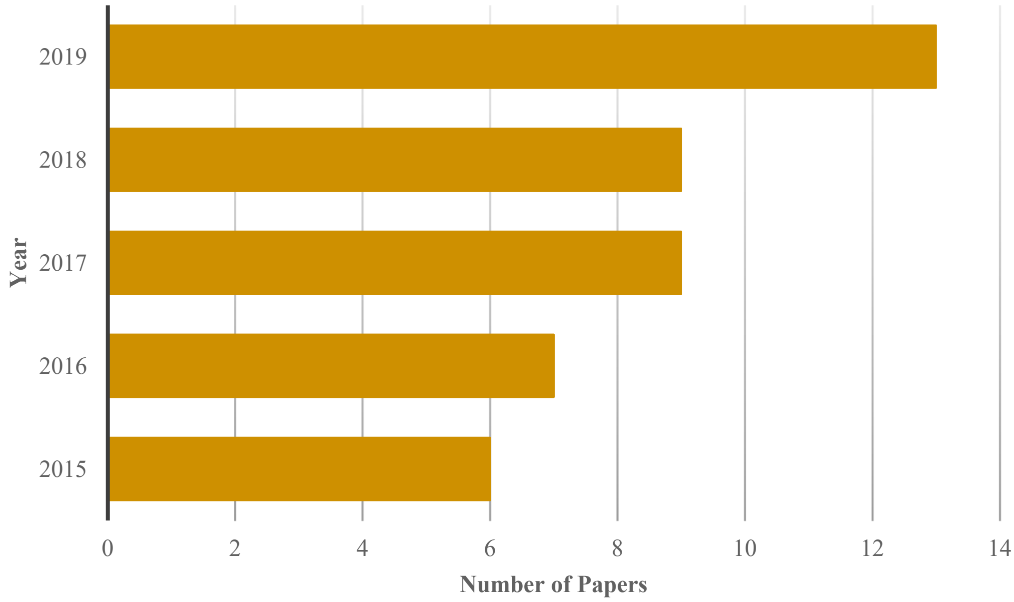

Figure 1. Comparing the number of applicable studies done in each year.

3.2. Multi-Objective Optimization (MOO)

MOO is used to optimize different objectives at the same time. Reviewing the studies belong to this group shows that, in such investigations, two, three, or four objectives were optimized simultaneously. In order to choose the objective functions, three different types of approaches have been employed:

- Type 1: optimizing two or more than two indicators of one aspect (e.g., [36,40]);
- Type 2: optimizing one indicator of two or more than two aspects (e.g., [37,39,41]);
- Type 3: a mixture of both (e.g., [38,55,57]).

Figure 2 represents that the majority of the reviewed studies, with the share of 77%, employed type 2 of MOO.

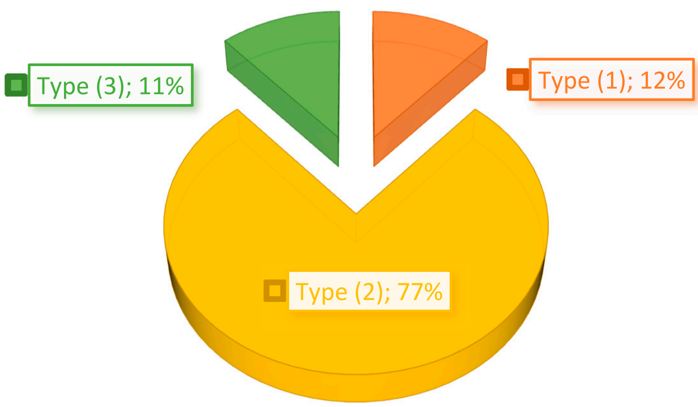

Figure 2. Share of different types of multi-objective optimization (MOO) in the core literature.

3.3. Single-Objective Versus Multi-Objective Optimization

In these studies, different objectives have been optimized independently by SOO. Since different objectives usually behave contrary to each other, the impact of other objectives might be considered as the constraints of SOO (e.g., [70]). On the other hand, MOO has been also conducted, and the results of SOO considering different objective functions are compared to the MOO outcome.

4. Overview of the Selected Studies

In this part, the core literature is analyzed based on three key parameters in an optimization process, namely, objective functions, decision variables, and constraints. As is shown in Figure 3, in the BPO procedure, there is a strong connection among these three parameters.

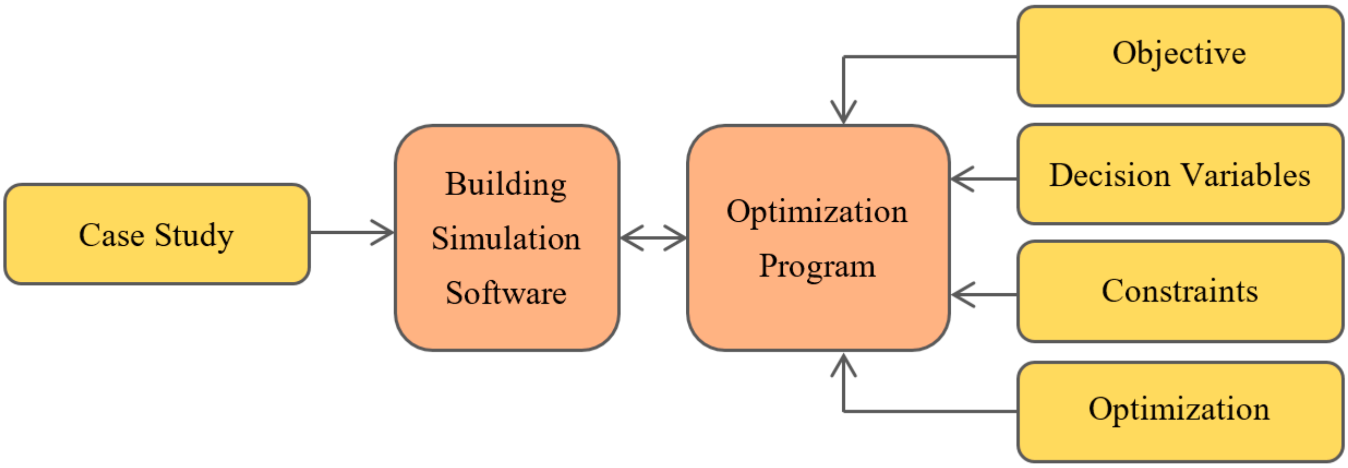

Figure 3. The BPO procedure.

4.1. *Objective Functions*

Reviewing the studies shows that nine different aspects have been considered in the optimization process. Each of these aspects has been assessed with some indicators, and the objective functions have been chosen among them. In the MOO approach, two or more than two indicators were chosen and defined. As it was mentioned in Section 3.2, these indicators might belong to the same aspects or not.

These aspects have been taken into account in the reviewed studies:

- Energy consumption (E.C);
- Thermal comfort (T.C);
- Economic benefit (E.B);
- Visual comfort (V.C);
- Environmental impact (E.I);
- Shape (S.);
- Artwork preservation risk (A.P.R);
- Aesthetical perception (A.P);
- Water consumption (W.C).

As it is shown in Figure 4, energy consumption indicators were the dominant objectives in the reviewed studies, accounting for 38.6%. Thermal comfort and economic benefit indicators, with 22.7% and 17.0%, were the second and third most-optimized objectives, respectively. The aspects and objective functions considered in each study are presented in Table 3.

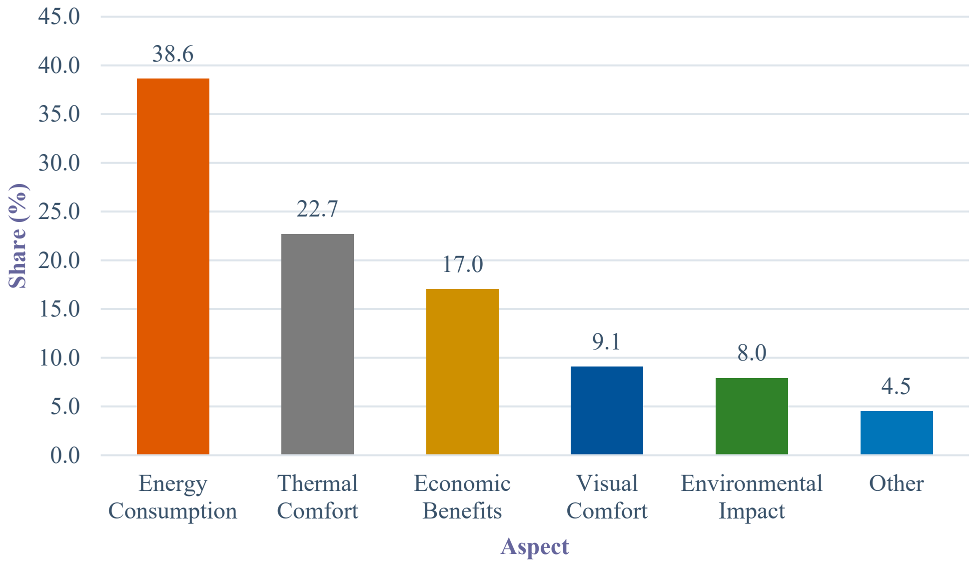

Figure 4. Share of each aspect in the optimization studies.

Table 3. The aspects which have been considered as the optimization objective functions in the core literature.

Study	Considered Aspect									Objective Function
	E.C	T.C	E.B	V.C	E.I	S.	A.P.R	A.P	W.C	
Abdallah and El-Rayes [27]					✓	✓				Min. Building Environmental Impacts Index
Mangkuto et al. [28]	✓									Min. Total Annual Lighting Energy Demand
Ferdyn-Grygierek and Grygierek [29]			✓							Min. Life-Cycle Cost
Baglivo et al. [30]		✓								Opt. The Operative Temperature
Bamdad et al. [31]	✓									Min. Annual End Use Energy Consumption
Zhou et al. [32]	✓									Min. Annual Heating Energy Consumption
Li et al. [33]	✓									Min. Total Energy Consumption (Heating + Cooling + Lighting)
Sghiouri et al. [34]		✓								Min. Discomfort Degree-hours
Xue et al. [35]	✓									Min. Annual Cooling Load
Echenagucia et al. [36]	✓									(1) Min. Heating Energy Need (2) Min. Cooling Energy Need Min. Lighting Energy Need
Yu et al. [37]	✓	✓								(1) Min. Annual Energy Consumption. (2) Max. Percentage of Thermal Comfort Hours throughout the Year

Table 3. *Cont.*

Study	Considered Aspect									Objective Function
	E.C	T.C	E.B	V.C	E.I	S.	A.P.R	A.P	W.C	
Carlucci et al. [38]		✓		✓						(1) Min. Long-term Percentage of Dissatisfied Calculated for Summer (2) Min. Long-term Percentage of Dissatisfied Calculated for Winter (3) Min. Percentage of Time Exceeding the Discomfort Glare Index (4) Max. Useful Daylight Illuminance
Ascione et al. [39]	✓	✓								(1) Min. Annual Primary Energy for Space Conditioning (2) Min. Percentage of Thermal Discomfort Hours
Zhang et al. [40]						✓				(1) Max. Solar Radiation Gain (2) Max. Space Efficiency Min. Shape Coefficient
Gadelhak and Lang [41]	✓	✓		✓						(1) Max. Spatial Daylight Autonomy (2) Min. Annual Energy Use (3) Min. Percentage of Discomfort Hours
Pan et al. [42]	✓	✓								(1) Min. Annual Source Energy Consumption (2) Min. Percent of People Dissatisfied
Ascione et al. [43]	✓	✓								(1) Min. Annual Primary Energy Consumption (2) Min. Annual Percentage of Discomfort Hours (3) Min. Global Cost
Bingham et al. [44]	✓		✓							(1) Min. Total Energy Consumption (2) Min. Life Cycle Cost
Zhang et al. [45]	✓	✓		✓						(1) Min. Heating + Lighting Energy Demand (2) Min. Summer Thermal Discomfort Time (3) Max. Average Useful Daylight Illuminance
Mostavi et al. [46]		✓	✓		✓					(1) Min. Life Cycle Cost (2) Min. Life Cycle Emission (3) Max. Occupants' Thermal Comfort Index
Bre and Fachinotti [47]	✓	✓								(1) Min. Annual Energy Consumption (Heating + Cooling) (2) Min. Heating and Cooling Degree-hours

Table 3. *Cont.*

Study	Considered Aspect									Objective Function
	E.C	T.C	E.B	V.C	E.I	S.	A.P.R	A.P	W.C	
Hamdy and Mauro [48]			✓		✓					(1) Min. Carbon Dioxide Equivalent Emissions (2) Min. Discounted Payback Time
Wu et al. [49]	✓		✓							(1) Min. Life Cycle Energy Consumption (2) Min. Life Cycle Cost
Lin et al. [50]	✓	✓								(1) Min. Annual Cooling and Heating Load (2) Min. Total Number of Discomfort Degree Hours
Grygierek and Ferdyn-Grygierek [51]		✓	✓							(1) Min. Life Cycle Cost (2) Min. Number of Hours with Thermal Discomfort
Schito et al. [52]	✓	✓								(1) Min. Total Energy Needs at The HVAC System (2) Min. Predicted Percentage of Dissatisfied (3) Max. Lifetime Multiplier
Gou et al. [53]	✓	✓								(1) Min. Annual Energy Demands for Heating and Cooling (2) Max. Annual Indoor Thermal Comfort Time Ratio
Harkouss et al. [54]	✓		✓							(1) Min. Electrical Consumption (2) Min. Life Cycle Cost
Sohani et al. [55]	✓		✓							(1) Min. Operating Cost (2) Min. Water Cost (3) Max. Energy Performance
Zemero et al. [56]	✓		✓							(1) Min. Annual Energy Consumption (2) Min. Constructive Cost
Yi [57]				✓				✓		(1) Max. Average Value of Spatial Daylight Autonomy (2) Min. Average Value of Annual Sun Exposure (3) The Preference Look of a Building Skin
Hong et al. [58]	✓	✓	✓		✓					(1) Min. Predicted Mean Vote (2) Min. Initial Investment Cost (3) Min. Thermal Energy consumption + Net Present Value + Global Warming Potential
Kirimtat et al. [59]	✓			✓						(1) Min. Total Energy Consumption (2) Max. Average Value of Useful Daylight Illuminance
Ascione et al. [60]	✓	✓	✓							(1) Min. Primary Energy Consumption (2) Min. Global Cost (3) Min. Discomfort Hours

Table 3. *Cont.*

Study	Considered Aspect									Objective Function
	E.C	T.C	E.B	V.C	E.I	S.	A.P.R	A.P	W.C	
Zhai et al. [61]	✓	✓		✓						(1) Min. Annual Total Energy Consumptions for Heating, Cooling and Lighting (2) Min. Total Number of Discomfort Degree hours (3) Max. Useful Daylight Illuminance
Si et al. [62]	✓	✓								(1) Min. Annual Energy Demand for Cooling and Heating and Artificial Lighting (2) Min. Annual Average Predicted Percentage Dissatisfied
Sharif and Hammad [63]	✓		✓		✓					(1) Min. Global Warming Potential (2) Min. Life Cycle Cost (3) Min. Total Energy Consumption
Fang and Cho [64]	✓			✓						(1) Max. Useful Daylight Illuminance Min. Energy Use Intensity
Sohani et al. [65]	✓		✓		✓				✓	(1) Min. Life Cycle Cost (2) Min. Annual Carbon Dioxide Emission (3) Min. Annual Water Consumption (4) Max. Annual Energy Performance
Lu et al. [66]	✓		✓		✓					(1) Min. Total Cost (2) Min. Carbon Dioxide Emissions (3) Min. Grid Interaction Index
Delgarm et al. [67]	✓									(1) Min. Annual Heating Electricity Consumption (2) Min. Annual Cooling Electricity Consumption (3) Min. Annual Lighting Electricity Consumption
Delgarm et al. [68]	✓	✓								(1) Min. Total Energy Consumption. (2) Min. Predicted Percentage Dissatisfied
Delgarm et al. [69]	✓									(1) Min. Annual Cooling Energy Consumption. (2) Min. Annual Lighting Energy Consumption
Xiong et al. [70]	✓			✓						(1) Max. Satisfaction Utility (2) Max. Energy Saving

4.1.1. Energy Consumption

To the best of our knowledge, researchers have used 13 indicators to minimize energy consumption in buildings. These indicators are shown in Figure 5. In some studies (e.g., [42,61,62]), the three most used indicators, heating, cooling, and lighting energy consumption, have been optimized as one objective function, named the total energy demand. That is usually done to simplify the computational difficulties of the optimization process caused by the increase in the number of objective functions. In addition, for more simplification, the combination of two of these three indicators might be taken into account, depending on the parameters such as location and function of the case study. As an example to clarify the impact of climate on choosing the energy related objective functions, Zhang et al. [45], studied the performances of school buildings in the cold climate of China by investigating heating and lighting energy demands as one objective to describe the energy performance for thermal and visual comfort indicators. In that work, due to the climatic conditions, the energy demand for cooling was not considered.

Moreover, the function of the case study can also help to simplify the optimization process in temporarily occupied buildings, such as office buildings. This means that if the building is only occupied during the day, the main concerns are about cooling and lighting energy consumption. It should be pointed out that reviewing some other studies (e.g., [36,67,69]) has made it clear that the best condition is achieved while the energy demands for heating, cooling, and lighting are optimized together and independently. However, Mangkuto et al. [28], Zhou et al. [32], and Xue et al. [35], have optimized lighting, heating, and cooling energy demands using the SOO approach, respectively.

4.1.2. Thermal Comfort

Figure 6 shows the eight different indicators that have been taken into account in the reviewed studies to investigate thermal comfort. These indicators can also be assessed for different seasons, independently. In the work published by Carlucci et al. [38], the percentages of dissatisfied people in summer and winter were optimized as two independent objectives, using the MOO approach. In another study [30], the operative air temperature was considered as the thermal comfort-describing objective function. Based on the definition, the operative air temperature is dependent on the season. It means that in the cooling and heating periods, it should be minimized and maximized, respectively.

4.1.3. Economic Benefit

In the reviewed studies, the optimum solution for this aspect has been achieved by optimizing nine different indicators imposed on both SOO and MOO. Among all these indicators mentioned in Figure 7, life cycle cost has been the most optimized. In the process of evaluating the life cycle cost, the significance of minor costs such as water cost might be disregarded. To avoid that, Sohani et al. [55] considered operating costs and water costs separately.

4.1.4. Visual Comfort

Despite the importance of visual comfort to both occupants' behavior and energy use, only five indicators describing this aspect have been considered in the reviewed studies. These indicators are introduced in Figure 8. In the research done by Mangkuto et al. [28], other metrics such as daylight factor, uniformity, and daylight glare probability have been taken into account as the constraints imposed on the SOO.

4.1.5. Environmental Impact

The growing concern for the environmental impacts of buildings has built a strong urge in researchers to consider this aspect in the optimization studies. Figure 9 shows the four indicators used in the studies we reviewed. It should be noted that there is a huge difference between carbon dioxide emissions and the equivalent carbon dioxide emissions, as two of the four indicators that describe the environmental impact. In the equivalent carbon dioxide emissions, unlike carbon dioxide emissions, other types of emissions besides carbon dioxide have been also taken into account.

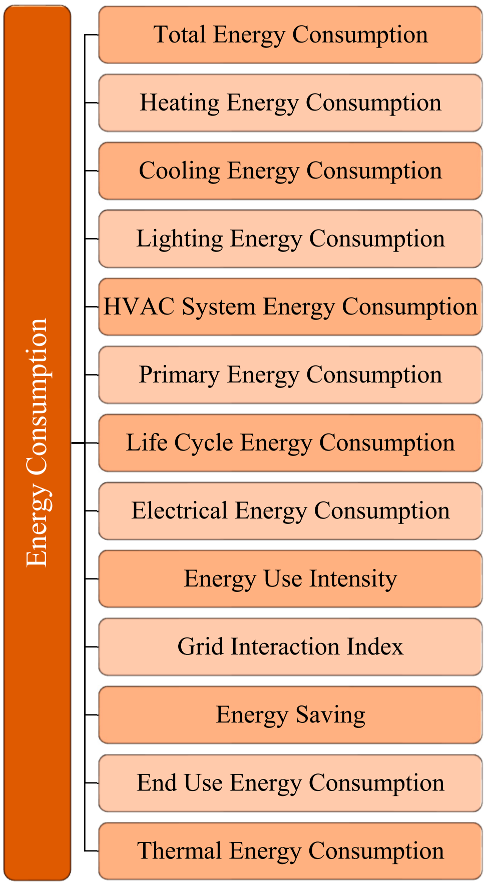

Figure 5. Energy consumption indicators.

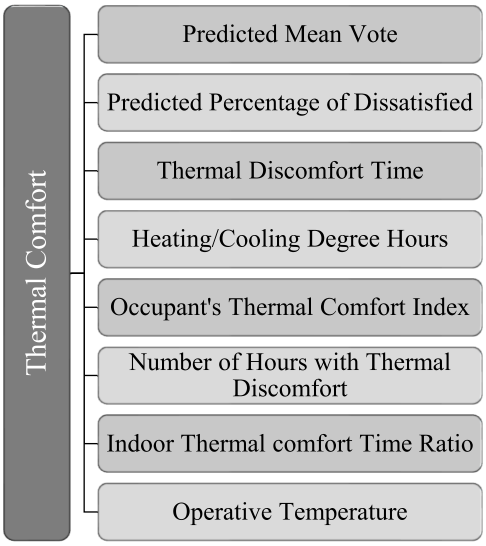

Figure 6. Thermal comfort indicators.

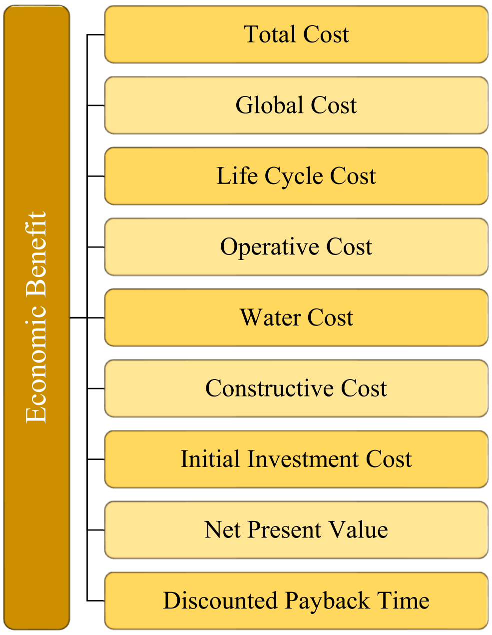

Figure 7. Economic indicators.

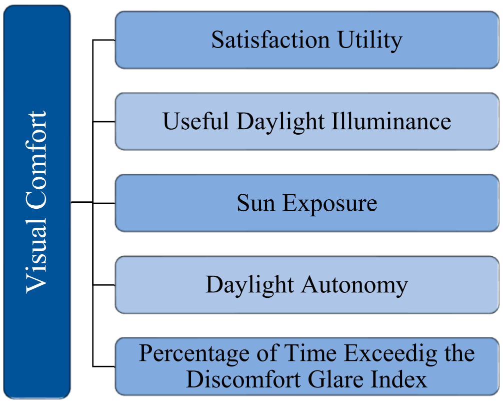

Figure 8. Visual comfort indicators.

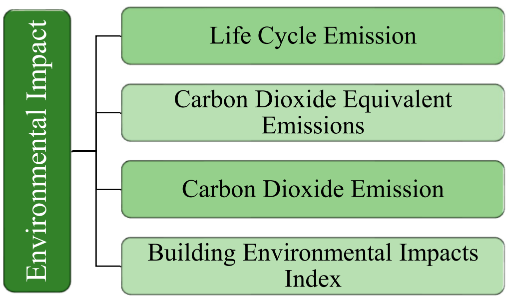

Figure 9. Environmental indicators.

4.1.6. Others

Here are the four other aspects that have been rarely studied in the reviewed investigations:

- Shape;
- Artwork preservation risk;

- Aesthetic perception;
- Water consumption.

The indicators that have been used to optimize these aspects are introduced in Figure 10. Shape, artwork preservation risk, and aesthetic perception are well defined aspects in architecture; however, water consumption is popularly used in energy engineering. Zhang et al. [40] presented a three-objective optimization method to enhance the shape of a free-form building by maximizing solar radiation gain and shape efficiency and simultaneously minimizing the shape coefficient.

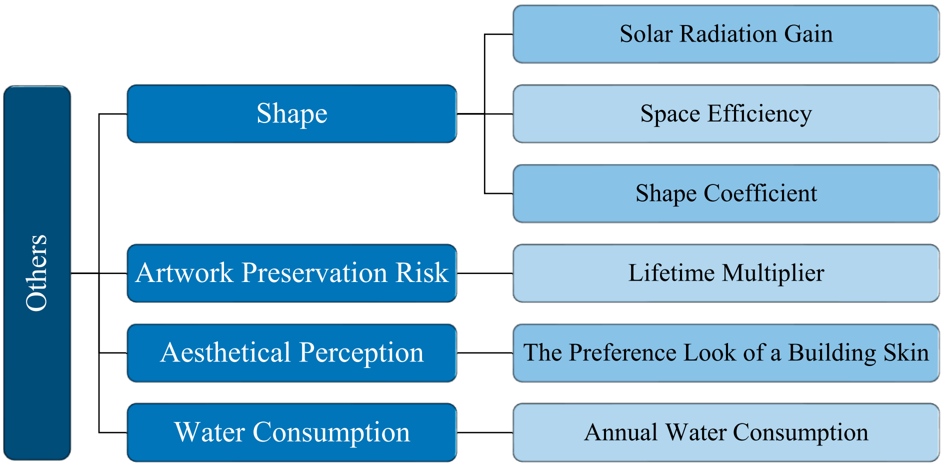

Figure 10. Other indicators.

Moreover, artwork perseveration risk is an important aspect that should be considered where the damage to sensitive objects is needed to be decreased [71]. Light, for example, can cause damage to artifacts, but it is critical for displaying them in museums; thus, an optimal solution should be presented [71]. In the study done by Schito et al. [52], artwork preservation risk was promoted by evaluating a lifetime multiplier to avoid artwork degradation; and an Italian museum was simulated as the case study where assessing artwork preservation risk is more effective.

Furthermore, reviewing a very recent study [57] that considered aesthetic perception as a qualitative aspect and changed it into a measurable goal has opened up a new perspective for future investigations. Additionally, Sohani et al. [72] optimized the water consumed during a year in a residential building.

4.1.7. Summary Report

Based on the review conducted, these different ranges of improvements have been achieved for each building aspect:

- E.C has been reduced in the range of 1.6% [67] to 60.1% [65] with an average of 26.13%.
- T.C has been improved in the rage of 1.5% [37] to 60.0% [52] with an average of 25.61%.
- E.B has been enhanced in the range of 4.6–39.56% [54] with an average of 24.0%.
- V.C has been increased in the range of 15.0–63.0% [45] with an average of 35.0%.
- The three indicators of the shape aspect, including solar radiation gain, shape coefficient, and space efficiency have been enhanced by 30–53%, 15–20%, and less than 10% [40], respectively.
- A.P.R and W.C have been improved less than 10% [52] and 153.2–390.0% [65], respectively.

It should be underlined that these wide ranges were attributed to case study factors (function and location), optimization approaches, and key parameters considered (decision variables, objective function, and constraints), which are all investigated in different parts of this review. Moreover, since A.P is a qualitative aspect, it was not possible to report its enhancement in a numerical format.

4.2. Decision Variables

In the simulation-based optimization, achieving the best solution is done by adjusting decision variables [73–75]. The decision variables are chosen among a group of parameters that affect the value of each objective function; they are called effective parameters [76]. In general, the decision variables reported in Table 4 are classified into two groups: architectural and mechanical. It should be noted that, in order to find the highest possible performance enhancement in the optimization, the decision variables from both groups should be taken into account.

4.3. Constraints

According to the limitations that come from technical or economic issues, some constraints are usually imposed on the optimization problem [77–79]. Constraints have been considered in 50% of the core literature. Technically, constraints are sorted out into two groups, equality and inequality [80–82]. Equality constraints are those that bind the optimization to satisfy the equations. In contrast, inequality constraints are not enforced to be at their limits [83–85]. Due to the computational difficulties caused by employing equality constraints, the constraints are usually considered in the form of inequality.

In some studies, several aspects that are mentioned in Section 4.1 have been taken into account as the constraints. As it was described before, this usually happens to reduce the number of objective functions and subsequently simplify the optimization process. For instance, Ascione et al. [60], Gadelhak and Lang [41], and Li et al. [33], have imposed thermal comfort, visual comfort, and energy consumption constraints, respectively. It should be underlined that the range of the decision variables (called as bound) has not been considered among the constraints, which are reported in Table 5.

4.4. The Considered Case Studies

In order to show the application of the proposed multi-objective optimization procedure, a case study has been usually considered in each investigation. The case study is a parameter which has substantial impacts on the values of objective functions and decision variables in the optimal condition, and it also might lead to adding or removing a number of objective functions, decision variables, and constraints.

Table 4. Decision variables which have been considered in the core literature.

Study	Decision Variables
Abdallah and El-Rayes [27]	• All energy and water consuming building equipment and fixtures • Energy-saving measures • Parameters related to solid waste management plans
Mangkuto et al. [28]	• Window to wall ratio • Wall reflectance • Window orientation
Ferdyn-Grygierek and Grygierek [29]	• Window type • Window area • Building orientation • Insulation of external wall, roof and ground floor • Infiltration
Baglivo et al. [30]	• Thermal characteristics affect the building load

Table 4. *Cont.*

Study	Decision Variables
Bamdad et al. [31]	• Roof emissivity • Roof and wall solar absorptance • Wall insulation • Window height • Overhang depth • Heating and cooling set-point • Building orientation
Zhou et al. [32]	• Window opening for ventilation • Indoor air temperature
Li et al. [33]	• Story number • Dimensional characteristics • Plan ratios • Window to wall ratio • Thermal characteristics of the building • Solar heat gain through the transparent areas
Sghiouri et al. [34]	• Overhanging projection in rooms
Xue et al. [35]	• Window to wall ratio
Echenagucia et al. [36]	• Wall thickness • Windows shape, placement and number • Glazing characteristics
Yu et al. [37]	• Floor area. • Building story • Orientation • Shape coefficient • Heat transfer coefficient of wall, roof and window • Thermal inertia index of wall and roof • Window to wall ratio
Carlucci et al. [38]	• Glazing optical properties • Windows orientation and extension • Shading devices operation and typology • Thermo-physical properties of external walls, roof, and floor
Ascione et al. [39]	• Solar absorptance and infrared emittance of the external plastering • The thermal insulant thickness • Brick thickness and density • Windows thermal transmittance
Zhang et al. [40]	• The curve and the surface control-point coordinates. Each of them is made up of X, Y and Z coordinates.
Gadelhak and Lang [41]	• Window to wall ratio • Insulation thickness • Glazing system • Shading systems • Daylight systems

Table 4. *Cont.*

Study	Decision Variables
Pan et al. [42]	• Building azimuth • Window to wall ratio • Heat transfer coefficient of window • Solar gain coefficient of window • Insulation thickness
Ascione et al. [43]	• Roof and external walls solar absorptance • Roof and external walls insulation thickness • Window type • Shading system • Free cooling system • Set-point temperature of heating and cooling • Boiler and chiller type • Photovoltaic roof coverage
Bingham et al. [44]	• Construction of roof and exterior wall • Insulation type of exterior and interior wall and roof • Glazing type • Insulation thickness of wall and roof • Lighting type.
Zhang et al. [45]	• Orientation • Room and corridor depth • Window to wall ratio • Glazing material • Shading type
Mostavi et al. [46]	• Construction materials in different building components
Bre and Fachinotti [47]	• Building azimuth • Shading size • External walls solar absorptance • Infiltration rate • Area fraction of window for natural ventilation • Window width • Roof, wall, window and floor (the first floor) types
Hamdy and Mauro [48]	• Walls, roof and floor insulation • Window and shading type • Tightness level of building • Heat recovery, primary energy system and HVAC system type
Wu et al. [49]	• Wall material thickness • Window and outside door heat transfer coefficient • Area of photovoltaic
Lin et al. [50]	• Concrete thickness • Insulation thickness • Solar radiation absorptance • Window to wall ratio

Table 4. *Cont.*

Study	Decision Variables
Grygierek and Ferdyn-Grygierek [51]	• Glazing type • Windows area • Building orientation • External wall, ground floor and roof insulation • Infiltration
Schito et al. [52]	• Set-point values of temperature • Set-point values of relative humidity
Gou et al. [53]	• Building orientation • Window to wall ratio • Window U-value • Window SHGC • Airtightness of window and door • Control type of window opening • External shading • Solar absorptance of building surface • Thickness of XPS board • Type of exterior wall
Harkouss et al. [54]	• Thickness of roof and external walls insulation • Glazing type • Cooling/heating set point • Solar collectors Number • Photovoltaic array • Windows width
Sohani et al. [55]	• The specification of the HVAC system
Zemero et al. [56]	• Building shape • Materials of interior and exterior wall • Materials of roof and floor • Window materials • Shadings • Building orientation
Yi [57]	• Building skin's geometry elements: amplitude and period of the waves, openings size
Hong et al. [58]	• Window type • Heating and cooling set-point • Type of ventilation and window opening
Kirimtat et al. [59]	• Shading parameters
Ascione et al. [60]	• Heating and cooling set-point • Roof and external walls solar absorptance • Insulation layer position • Vertical walls, floor and roof insulation thickness • Thickness, thermal conductivity and density of the construction materials • Windows type • Building orientation

Table 4. *Cont.*

Study	Decision Variables
Zhai et al. [61]	• WWR • Orientation • Glazing material
Si et al. [62]	• Roofs and opaque walls thermal properties • Window types • Eaves shape • Thermostat set-points
Sharif and Hammad [63]	• External walls, window frame, façade and roof types • Glazing template • Window to wall ratio • HVAC and lighting systems • Operation schedules of heating and cooling • Open percentage of external window • Mechanical Ventilation Rate • Airtightness
Fang and Cho [64]	• Building depth • Location of roof ridge • Skylight width, length, location and orientation • Width of south and north window • Louver length
Sohani et al. [65]	• The specification of the HVAC system
Lu et al. [66]	• Photovoltaic power generation capacity • Wind turbine power generation capacity • Bio-diesel generator capacity
Delgarm et al. [67]	• Orientation. • Shading overhang characteristics • Window size • Glazing and wall material properties
Delgarm et al. [68]	• Orientation • Window size • Air-conditioning system set-point temperature • Glazing and wall material properties
Delgarm et al. [69]	• Orientation • Window size • Characteristics of overhangs
Xiong et al. [70]	• The shading position

In each optimization project, two factors about the case study have to be defined, including its function and location. As it is shown in Table 6, 13 different functions and a variety of locations have been taken into account in the core literature. These different functions and the number of papers in which each one has been studied are presented in Figure 11.

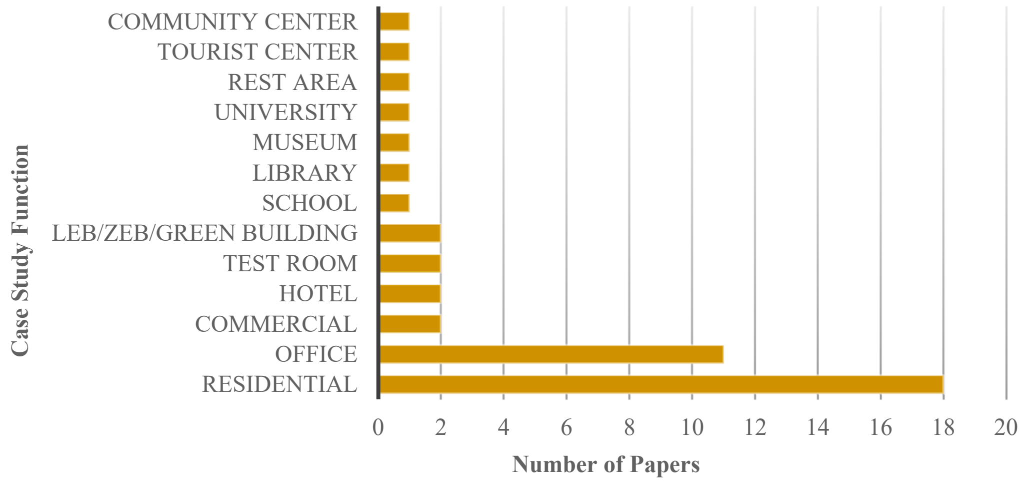

Figure 11. Different functions which have been considered as the case studies in the core literature in addition to the number of papers in which each one has been studied.

As two examples of the mentioned point about the impacts of the function and location of the case study on the selection of the objective functions, the investigations done by Schito et al. [52] and Zhang et al. [45] are considered, respectively. Schito et al. [52] chose a museum as the case study, which resulted in adding artwork preservation risk as one of the objective functions. In addition, considering the case study in Tianjin in China, Zhang et al. [45] eliminated the energy consumption for cooling because of its small portion of the total energy demand in the cold climate of China compared to the heating and lighting energy demands.

In order to provide more extensive insights, the graphical representation of the frequency of objective functions is given in the tree map format in Figure 12. The branches in this figure demonstrate a hierarchy view of the considered building functions in different colors. Moreover, the frequency of the building aspects in each of these functions is illustrated in the form of sub-branches.

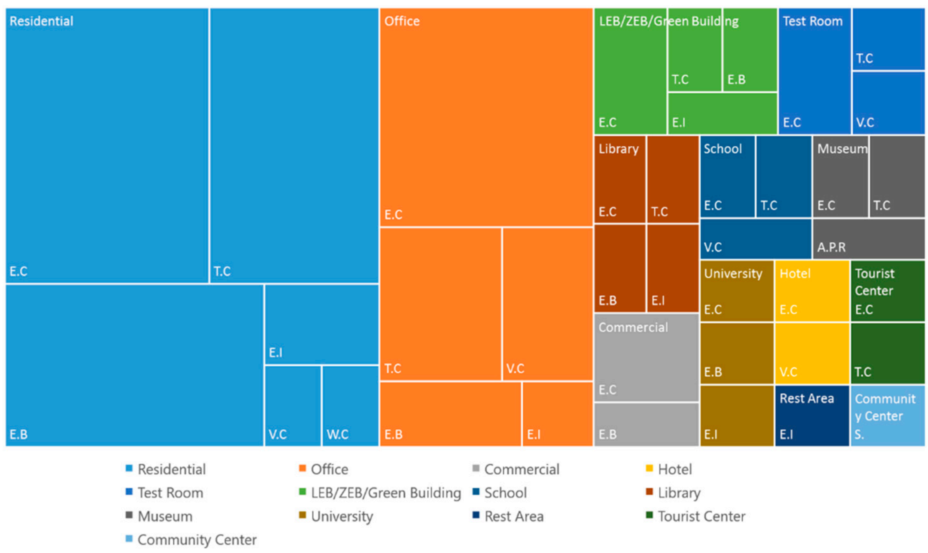

Figure 12. The frequency of the objective functions from different aspects for various applications in the tree map format.

Table 5. Constraints which have been considered in the core literature.

Study	Constraints
Abdallah and El-Rayes [27]	• Budget • Operational performance
Mangkuto et al. [28]	• Daylight metrics
Ferdyn-Grygierek and Grygierek [29]	• The cost of insulation
Baglivo et al. [30]	• Thermal comfort condition
Bamdad et al. [31]	• N.M.
Zhou et al. [32]	• Different energy efficiency standards.
Li et al. [33]	• The energy consumption constraint
Sghiouri et al. [34]	• N.A.
Xue et al. [35]	• Daylighting performance
Echenagucia et al. [36]	• N.A.
Yu et al. [37]	• N.A.
Carlucci et al. [38]	• Minimum air change rate
Ascione et al. [39]	• N.M.
Zhang et al. [40]	• The functional requirements
Gadelhak and Lang [41]	• Annual Sunlight Exposure
Pan et al. [42]	• N.A.
Ascione et al. [43]	• The investment cost
Bingham et al. [44]	• Percentage of Persons Dissatisfied
Zhang et al. [45]	• N.M.
Mostavi et al. [46]	• N.M.
Bre and Fachinotti [47]	• N.A.
Hamdy and Mauro [48]	• Overheating in summer
Wu et al. [49]	• Heat transfer coefficient constraint
Lin et al. [50]	• N.A.
Grygierek and Ferdyn-Grygierek [51]	• Infiltration-related constraint
Schito et al. [52]	• N.M.
Gou et al. [53]	• N.A.
Harkouss et al. [54]	• The average predicted mean vote
Sohani et al. [86]	• Supply air constraint • Thermal comfort
Zemero et al. [56]	• N.A.
Yi [57]	• N.M.
Hong et al. [58]	• Indoor environmental quality • Budget
Kirimtat et al. [59]	• N.A.
Ascione et al. [60]	• The maximum number of discomfort hours
Zhai et al. [61]	• N.A.
Si et al. [62]	• N.A.
Sharif and Hammad [63]	• N.A.
Fang and Cho [64]	• N.A.
Sohani et al. [65]	• Supply air constraint • Thermal comfort • Geometrical limitation for channels' height
Lu et al. [66]	• Zero annual energy balance
Delgarm et al. [67]	• N.A.
Delgarm et al. [68]	• N.A.
Delgarm et al. [69]	• N.A.
Xiong et al. [70]	• Satisfaction utility (Only in SOO)

Table 6. Considered case studies in the core literature.

Study	Building Function	Location
Abdallah and El-Rayes [27]	Rest Area	N.M.
Mangkuto et al. [28]	Office	Bandung in Indonesia
Ferdyn-Grygierek and Grygierek [29]	Residential	Katowice in Poland
Baglivo et al. [30]	Residential	Southern Italy
Bamdad et al. [31]	Commercial	Brisbane, Darwin, Hobart and Melbourne, in Australia
Zhou et al. [32]	Residential	Tianjin in China
Li et al. [33]	Office	Beijing, Shanghai and Guangzhou, in China
Sghiouri et al. [34]	Residential	Marrakech, Casablanca and Oujda, in Morocco
Xue et al. [35]	Hotel	Shanghai, Qionghai and Fuzhou, in China
Echenagucia et al. [36]	Office	Palermo, Torino, Frankfurt and Oslo
Yu et al. [37]	Residential	Chongqing in China
Carlucci et al. [38]	Residential	Mascalucia (CT) in Southern Italy
Ascione et al. [39]	Residential	Naples in Italy and Istanbul in Turkey
Zhang et al. [40]	Community Center	Shenyang in China
Gadelhak and Lang [41]	Office	Cairo in Egypt and Munich in Germany
Pan et al. [42]	Residential	Nanjing in China
Ascione et al. [43]	Office	Naples in South Italy
Bingham et al. [44]	Residential	Bahamas
Zhang et al. [45]	School	Tianjin in China
Mostavi et al. [46]	Office	Pennsylvania in The USA
Bre and Fachinotti [47]	Residential	Paraná in Argentine
Hamdy and Mauro [48]	Residential	Helsinki in Finland
Wu et al. [49]	Residential	Tianjin in China
Lin et al. [50]	A two-star green building	Wuhan in China.
Grygierek and Ferdyn-Grygierek [51]	Residential	Poland
Schito et al. [52]	Museum	Pisa in Italy
Gou et al. [53]	Residential	Shanghai in China
Harkouss et al. [54]	Residential	Beirut, Qartaba, Zahle and Cedars in Lebanon, Embrun, La Rochelle, Nice, Nancy and Limoges in France
Sohani et al. [86]	Residential	Riyadh in Saudi Arabia, Ahmedabad in India, Windsor in Canada, London in the UK
Zemero et al. [56]	Commercial	Curitiba, Florianópolis, Campo Grande and Belém in Brazil
Yi [57]	Hotel	Barcelona in Spain
Hong et al. [58]	Library	Seoul in South Korea
Kirimtat et al. [59]	Office	Izmir in Turkey
Ascione et al. [60]	Residential	Palermo, Naples, Milan and Florence, In Italy
Zhai et al. [61]	Test room	Xi’an in China

Table 6. *Cont.*

Study	Building Function	Location
Si et al. [62]	Tourist center	Nanjing in China
Sharif and Hammad [63]	University	Montreal in Canada
Fang and Cho [64]	Office	Miami, Atlanta, Chicago in the USA
Sohani et al. [65]	Residential	Riyadh in Saudi Arabia, Ahmedabad in India, Windsor in Canada, London in the UK
Lu et al. [66]	Two types of buildings (LEB and ZEB)	Hong Kong in China
Delgarm et al. [67]	A single thermal zone test case room.	Tabriz, Tehran, Kerman and Bandar Abbas, in Iran
Delgarm et al. [68]	Office	Tabriz, Tehran, Kerman and Bandar Abbas, in Iran
Delgarm et al. [69]	Office	Tabriz, Tehran, Kerman and Bandar Abbas, in Iran
Xiong et al. [70]	Office	West Lafayette in Indiana

4.5. Optimization Algorithm and Simulation Software

Based on the type of optimization approach, i.e., either SOO or MOO, different algorithms have been used to acquire the optimum solution. The optimization algorithm and the software which have been used in each study are shown in Table 7. For SOO, the genetic algorithm is the most dominant method, whereas the non-dominated sorting genetic algorithm II (NSGA-II) has been the mostly-used in the MOO. Both SOO and MOO have been usually done using MATLAB.

Table 7. The optimization algorithms and the software which have been used in the core literature.

Study	Optimization Algorithm	Software	
		Simulation	Optimization
Abdallah and El-Rayes [27]	Genetic Algorithm	eQUEST	N.M.
Mangkuto et al. [28]	Graphical Optimisation Method	Radiance, Daysim	N.M.
Ferdyn-Grygierek and Grygierek [29]	Genetic Algorithm	EnergyPlus	MATLAB
Baglivo et al. [30]	Sequential Search Technique	TRNSYS	TRNSYS
Bamdad et al. [31]	Ant Colony Optimisation for continuous domain	EnergyPlus	GenOpt, MATALB
Zhou et al. [32]	Measurement	N.A.	N.A.
Li et al. [33]	Genetic Algorithm	DesignBuilder, Radiance	MATLAB
Sghiouri et al. [34]	NSGA-II	TRNSYS	jEPlus + EA
Xue et al. [35]	N.M.	Radiance, EnergyPlus	N.M.
Echenagucia et al. [36]	NSGA-II	EnergyPlus	Python
Yu et al. [37]	NSGA-II	EnergyPlus	MATLAB
Carlucci et al. [38]	NSGA-II	EnergyPlus	GenOpt, Java Genetic Algorithms Package
Ascione et al. [39]	NSGA-II	EnergyPlus	MATLAB
Zhang et al. [40]	Multi-objective Genetic Algorithm	Rhinoceros and its plug-ins Grasshopper, Ladybug,	Octopus

Table 7. *Cont.*

Study	Optimization Algorithm	Software	
		Simulation	Optimization
Gadelhak and Lang [41]	Multi-Objective SPEA-2 Optimization Algorithm	Rhinoceros's plug-ins Diva, Grasshopper, Ladybug and Honeybee	Octopus
Pan et al. [42]	NSGA-II	EnergyPlus	MATLAB
Ascione et al. [43]	Multi-objective Genetic Algorithm	EnergyPlus	MATLAB
Bingham et al. [44]	NSGA-II	EnergyPlus	jEPlus + EA
Zhang et al. [45]	Multi-Objective SPEA-2 Optimization Algorithm	Rhinoceros and its plug-ins Grasshopper, Ladybug, Honeybee	Octopus
Mostavi et al. [46]	A Harmony Search Based Algorithm	EnergyPlus	C#
Bre and Fachinotti [47]	NSGA-II	EnergyPlus	Python
Hamdy and Mauro [48]	The optimization algorithm PR_GA_RF	IDA ICE	MATLAB
Wu et al. [49]	NSGA-II	DesignBuilder	MATLAB
Lin et al. [50]	Multi-objective Genetic Algorithm	DesignBuilder	MATLAB
Grygierek and Ferdyn-Grygierek [51]	NSGA-II	EnergyPlus	MATLAB
Schito et al. [52]	N.M.	TRNSYS	MATLAB
Gou et al. [53]	NSGA-II coupled with the Artificial Neural Network	EnergyPlus	MATLAB, jE-Plus
Harkouss et al. [54]	NSGA-II	TRNSYS	MOBO
Sohani et al. [86]	NSGA-II	Carrier Hourly Analysis Program	MATLAB
Zemero et al. [56]	PAES multi-objective optimization algorithm	EnergyPlus	Python
Yi [57]	NSGA-II	Rhinoceros and its plug-ins DIVA, Grasshopper and Human UI	MATLAB
Hong et al. [58]	NSGA-II	EnergyPlus	Python
Kirimtat et al. [59]	Non-dominated Sorting Genetic Algorithm and Self-adaptive Continuous Genetic Algorithm with Differential Evolution	Radiance, EnergyPlus	N.M.
Ascione et al. [60]	NSGA-II	EnergyPlus	MATLAB
Zhai et al. [61]	NSGA-II	EnergyPlus	MATLAB
Si et al. [62]	NSGA-II	EnergyPlus	MATLAB, modeFrontier
Sharif and Hammad [63]	NSGA-II	DesignBuilder	ATHENA
Fang and Cho [64]	Multi-objective Genetic Algorithm	Rhinoceros and its plug-ins Grasshopper, Ladybug, Honeybee	Octopus

Table 7. *Cont.*

Study	Optimization Algorithm	Software	
		Simulation	Optimization
Sohani et al. [65]	NSGA-II	Carrier Hourly Analysis Program	MATLAB
Lu et al. [66]	NSGA-II	TRNSYS	MATLAB
Delgarm et al. [67]	Multi-Objective Particle Swarm Optimization Algorithm	EnergyPlus	MATLAB
Delgarm et al. [68]	Multi-Objective Artificial Bee Colony Optimization Algorithm	EnergyPlus	MATLAB
Delgarm et al. [69]	NSGA-II	EnergyPlus	MATLAB, jE-Plus
Xiong et al. [70]	N.M.	N.M.	MATLAB

For the simulation of the building, EnergyPlus has been the favorite software in the reviewed investigations. EnergyPlus and OpenStudio, which is used as its graphical user interface, are both open-source software programs, and that is a big advantage of them. Moreover, EnergyPlus has the potential of being easily coupled with MATLAB. In addition to EnergyPlus, Rhino has been increasingly used in recent studies. In fact, its user-friendly environment accounted for its popularity among researchers, although it is not open-source. Furthermore, among all the software programs that have been used in the literature, eQuest, Radiance, and some of Rhino's plugins, including Ladybug and Honeybee, are free to use.

Software programs in the future could be promoted by taking the following items into account to become more helpful:

- Using artificial intelligence tools to provide predictions from changes in occupants' behavior and climate change in the future years of building life.
- Adding more powerful economic databases for better evaluation of the building from this point of view.
- Providing "tagging" possibility for each project done by an individual in a way that if wanted, could enable the tags to be shared on an online database with other people. In this way, researchers will have better interactions together.
- Applying the virtual reality to get the chance of understanding the graphical issues related to works in a much more perfect way.

5. Conclusions

In order to provide a new perspective into the literature, the studies that have been conducted to optimize the building performance were reviewed from different viewpoints. The core literature consists of 44 recent studies that were investigated in detail and all the key parameters involved in the optimization procedure were described individually. The review showed that there is a strong connection among these parameters. Moreover, selection of such parameters in the optimization should be done based on the function and location of the case study, and the requirements of the experts who are involved in the project practically. In addition, it is found that EnergyPlus and MATLAB have been the most-used software programs for building simulation and optimization, respectively. Among the nine various aspects that have been considered in the reviewed studies, energy consumption has been taken into account as the objective function more than others, accounting for 38.6%. Thermal comfort and economic benefits with shares of 22.7% and 17% are the second and third mostly optimized aspects, respectively. Figure 13 demonstrates a graphical view of the conclusion.

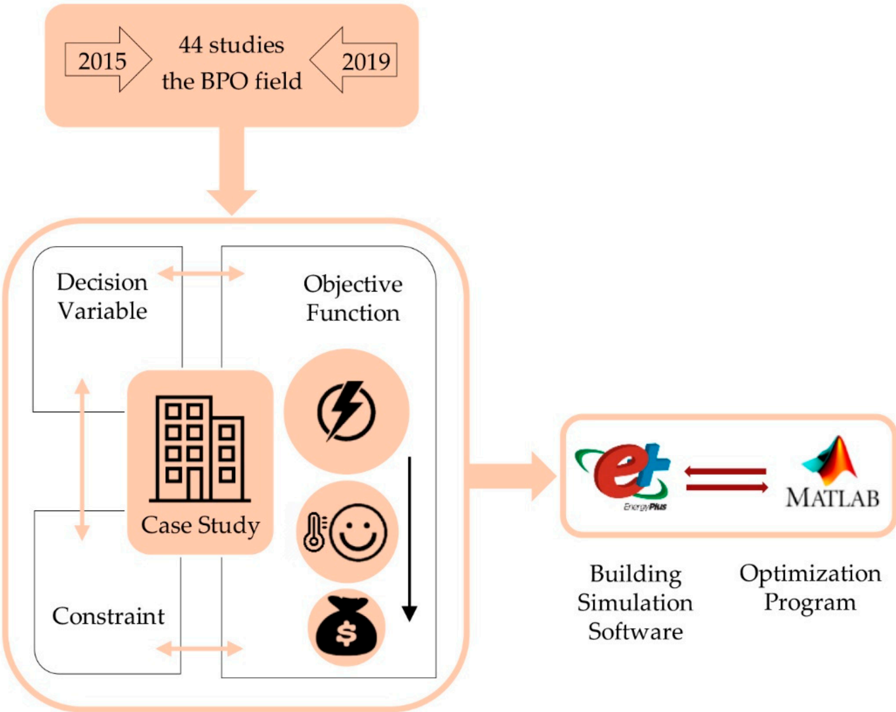

Figure 13. The graphical description of the work.

In addition, based on the conducted review, a number of open questions could be identified, which are:

- How could the policy makers help to put the results of BPO into practice for a town, a city, or a country?
- How could changing the occupants' behavior could affect the optimum values of decision variables and objective functions?
- Could some dimensionless numbers be defined as the decision variables and objective functions to reach a general BPO method and provide the possibility of better comparisons for various buildings?
- Would it be possible to find an updated procedure for BPO in which different buildings are optimized altogether? How much further improvement will be achieved under that condition?
- Could the current BPO procedure be modified to provide plans for adding renewable energy resources?
- How many changes will be made to the results of BPO by the future changes in the climate, buildings design techniques, and the employed masonry materials?

Moreover, as observed, in a large number of the studies, objective functions, decision variables, and constraints have not been selected comprehensively. For instance, the researchers who have a background in architecture have not considered the objective functions, decision variables, or constraints from energy or mechanical sides and vice versa. The reported information of this review will help the future researchers to avoid such issues.

Furthermore, the following items can be suggested based on the conducted literature review for future investigations:

- Conducting multi-objective optimization in which more aspects from different sides are taken into account;
- Performing multi-objective optimization by considering the objective functions based on the application and the climatic zone;
- Combining the efficient software programs and algorithms to have more effective and faster calculations;

- Selecting the case studies in which the multi-objective optimization has been done less often, and taking the advantage of BPO for them;
- Identifying the aspects which have not been usually optimized in each application and considering them;
- Studying the impacts of different strategies for giving incentives to implement the results of BPO;
- Taking advantage of new optimization techniques like dynamic multi-objective optimization to provide a better outcome.

Funding: This research received no external funding.

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

Abbreviations

SOO	single-objective optimization
MOO	multi-objective optimization
BPO	building performance optimization
E.C	energy consumption
T.C	thermal comfort
E.B	economic benefit
V.C	visual comfort
E.I	environmental impact
S.	shape
A.P.R	artwork preservation risk
A.P	aesthetical perception
W.C	water consumption
NSGA-II	non-dominated sorting genetic algorithm II

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