sustainability

Review

Sustainability and Optimization: From Conceptual Fundamentals to Applications

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Abstract: In recent years, both sustainability and optimization concepts have become inseparable developing topics with diverse concepts, elements, and aspects. The principal goal of optimization is to improve the overall sustainability including the environmental sustainability, social sustainability, economic sustainability, and energy resources sustainability through satisfying the objective functions. Therefore, applying optimization algorithms and methods to achieve the sustainable development have significant importance. This paper represents a considerable review on the employed optimization methodologies to sustainability and the sustainable development including sustainable energy, sustainable buildings, and sustainable environment. Since energy optimization is one of the major necessities of sustainability, sustainable development is investigated from the energy perspective. In addition, the concept, definitions, and elements of the sustainability and optimization have been presented, and the review of the optimization metaheuristic algorithms used in recent published articles related to sustainability and sustainable development was carried out. Thus, it is believed that this paper can be appropriate, beneficial, and practical for students, academic researchers, engineers, and other professionals.

Keywords: metaheuristics; optimization algorithms; sustainable development; sustainable energy resources; sustainable buildings

1. Introduction

With the publication of the Brundtland Report "Our Common Future," the concept of sustainable development has spread since 1987 [1]. The definition of the United Nations Brundtland Commission on sustainability has become more dynamic than others. We call sustainability the technology that meets today's needs without jeopardizing the future generations' ability to meet their own needs. Therefore, sustainability is a multidisciplinary concept, based on this understanding that covers different aspects of life. Clearly, sustainability is a concept in the core of the planet that focuses on the condition and depletion of the biophysical environment of Earth [2,3]. In 2015, the General Assembly adopted the 2030 Agenda for sustainable development. They adopted the Agenda for its action to combat poverty, protect the planet, and enhance everybody's lives and opportunities. This paper focuses on reviewing trends and recent research papers in sustainability and energy efficiency (i.e., Goals 7 and 12) and sustainable building design (i.e., Goals 11 and 15) problems out of 17 sustainable development goals.

Optimization is one of the most important tools for achieving sustainability. Optimization is a search process for a specific problem according to special conditions of that problem. In fact, optimization refers to finding processes of optimal values for a given network parameter, using all feasible values for the minimization or maximization of network output. The goal of optimization is to discover the best feasible response with the consideration of the problem constraints. The presence of complex scientific and engineering problems calls for using optimization methods to solve the desired problem. Due to the time consuming and complexity of exact methods, utilizing intelligent optimization algorithms has crucial importance.

Optimization of many complex scientific problems which require solutions with accurate computations and appropriate time cannot use classical methodologies. In this regard, nature can be considered as a rich source which, like a powerful mechanism, provides principles and concepts in order to design artificial computational methods for solving complex optimization problems.

Metaheuristic optimization algorithms, which are also called smart and modern optimization algorithms, are categorized as stochastic optimization algorithms employed for finding optimal solutions. The word "metaheuristic" was first adopted by Glover [4] when introducing TS as a novel heuristic method. Heuristic optimization methods are a set of algorithms for optimization of problems which search solution space to find optimal response randomly but purposeful and simple [4]. The metaheuristic optimization algorithms have outsourced approaches from local optimum and are capable of finding optimum solutions in wide ranges of optimization problems [5,6].

Metaheuristic optimizers are methods which are inspired by studying the natural phenomena. Due to their potential and strength, the optimization algorithms have been used in many and various subjects related to sustainability and sustainable development including environmental sustainability, social sustainability, economic sustainability, sustainable energy resources, sustainable buildings, sustainable environment, and more. A variety of articles based on optimization techniques have been published in different international journals. Excellent exploitation and exploration strategies of metaheuristic optimization algorithms have made these algorithms a good alternative for solving optimization problems.

In recent decades, researchers have developed various types of metaheuristic optimization algorithms [7]. These methods have been expanded by mimicry of some well-known processes, primarily in biology, physics, chemistry, math, society, and nature [8]. There are different categorizations of metaheuristic optimization algorithms proposed in the literature [9,10]. Generally, algorithms inspired by nature can be divided into four main categories including EA, SI, PCMB algorithms, and finally the HB algorithm.

GSO [11,12], GAs [13], PSO [14], TLBO [15], HS [16], TS [4] and WCA [17] are the some of the well-known algorithms that are used in order to optimize different problems. A large number of writers in literature have addressed sustainability optimization. In [18], for energy systems, a new and comprehensive model for the evaluation of durability was introduced. This model follows a holistic approach which impacts sustainability. It addresses various disciplines, including energy, exergy, environment, society, technology education, and the energy system's dimension.

A multi-objective model of optimization, which offers a comprehensive method of maximizing sustainability through all three pillars, was introduced in [19]. This article provides a strategy for optimizing the supply chain networks that includes economic, environmental, and social sustainability as three pillars of sustainability. This provides a comprehensive overview of measures and indicators for evaluating the three pillars and links each indicator to a supply chain network portion. A multi-target optimizing model was modified to cover three cost goals as a part of the supply chain network: economic, environmental, and social sustainability.

In [20], a petrochemical network was planned for Kuwait by developing an optimization model where some sustainability indicators were used as objectives. In [21], in order to determine the configuration of industrial metal-fabrication systems, with the greatest sustainable efficiency in three sectors and six facilities, a methodology combined with Monte Carlo simulation was suggested. In [22], multi-objective optimizing the repair choice for infrastructures exposed to natural hazards with the greatest sustainable contribution was suggested.

In [23], in order to identify the most sustainable electricity generation planning scenario in Indonesia for 2050, a multi-target optimization model was presented. In [24], a method was designed to optimize sustainability of a combined heat and power generation system integrated wastewater treatment plant. In [25], sustainability optimization was also pointed out in the nuclear industry.

In [26], optimization models for the optimum implementation of selected sustainability activities called sustainability programs were designed to maximize the efficiency of the manufacturing industry in line with established budgetary and minimum threshold constraints on technological, social, and socio-economic parameters. In addition to modeling shown in this paper [26], a random process is proposed for searching the ANNs for the optimal durability system, the importance of the sample problem is described. Sensitivity analysis is performed to understand the model's behavior. It is noted that the performance of sustainability depends on constraints such as budget restrictions and performance criterion threshold values.

In [27], as a new optimization technique for the sustainable growth of supply chains, the TTS optimization concept was implemented. The TTS approach seeks to replace existing methods of optimization. Its main focus is on the timeframe to achieve a sustainable and stable condition of the system under consideration.

A decision-making issue with the quality-based product recovery was explored in [28] with multiple optimization goals, including economic, environmental, and societal performance of sustainability. In this article, MOEA was utilized for solving the MOOP problem and finding an optimal solution.

A principal contribution of this paper is its summary of a significant research review of all applicable optimization methods to sustainable building design and energy efficiency problems. A description of the popular heuristic optimization algorithms covering direct search, processes, and other bio-inspired algorithms is available. Because green energy resources, systems, and technologies are the major elements of sustainable development, optimization approaches used for sustainable energy resources, sustainable buildings in the literature are investigated and evaluated in details in the current paper.

The remainder of this paper is organized as follows. Section 2 presents sustainability. Section 3 identifies optimization, its concept, definition, objectives, and methodologies related to metaheuristic optimizers as well. Section 4 addresses optimization and sustainable development in the literature, given with concise explanations of its applications and contributions. Section 5 further addresses studies in this paper. Section 6 concludes the findings and purpose of this review paper.

2. Sustainability

2.1. Concept of Sustainability

It is obvious that sustainability is at the heart of this concept, focusing on the condition of the biophysical environment of the earth, particularly with regard to the use and depletion of natural resources. It is more a matter of finding a sort of permanent state to support the people of the earth or a part of it, without endangering the health of human beings, animals, and plants.

In this regard, other attempts have also been made for providing foundations, ideas, and concepts related to sustainability. The general concept of sustainability compared and contrasted by Brown et al. in [29] with different definitions and roots in order to move toward a common understanding (see Table 1). Brown et al. [29] concentrated on definitions including "sustainable biological resources use," "sustainable agriculture," "carrying capacity," "sustainable energy," "sustainable society and sustainable economy," and "sustainable development". Each one of them emphasized different subjects. In this context, roots of sustainability in accordance with the sustainability definitions consist of "ecological/carrying capacity," "resource/environment," "biosphere," and "critique of technology," "no growth–slow growth," and "ecodevelopment". In their view, these six meanings converge around two major aspects of results with focus on ecology and the economy [29].

Table 1. A summary of the sustainability definitions and concepts.

Roots of Sustainability	Points of Emphasis	Definitions of Sustainability	Points of Emphasis
Ecological/carrying capacity	Maintenance of natural systems so that they can support human life and well-being	Carrying capacity	Optimum and maximum ability of Earth's systems to support human life and well-being
Resource/environment	Promoting economic growth only to the extent and in ways that do not cause deterioration of natural systems	Sustainable use of biological resources	Maximum sustainable yield from natural systems, such as forests and fisheries
Biosphere	Concern with the impacts of humans on the health of the Earth and its ability to support human populations	Sustainable agriculture	Maintaining productivity of farming during and after disturbances such as floods and droughts
Critique of technology	Rejection of the notion that science and technology, by themselves, will protect and save the Earth	Sustainable energy	Renewable alternatives to fossil fuel reliance to produce heat energy
No growth–slow growth	Limits to the ability of the Earth to support the health and well-being of ever growing populations	Sustainable society and economy	Maintaining human systems to support economic and human well-being
Ecodevelopment	Adapting business and economic development activities to realities of natural resource and environmental limits	Sustainable development	Promoting economic growth only to the extent and in ways that do not cause deterioration of natural systems

Sustainability is a concept widely understood and discussed. In fact, it is subject to vast partiality and subjectivity. Therefore, sustainability is a multi-disciplinary concept, based on an understanding covering various aspects of life. The principle areas that impact sustainability are highlighted in Figure 1. In addition, the areas are in various ways intertwined. The social sphere affects the cultural realm, for example, while the economic sphere influences public policy.

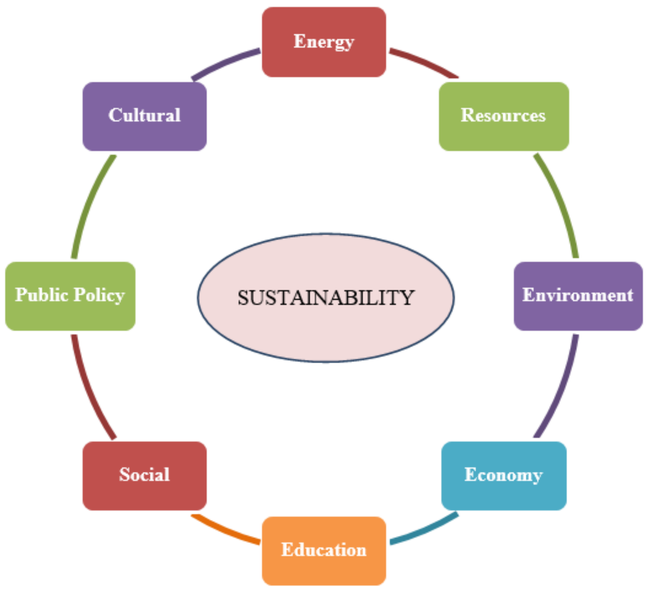

Figure 1. The backbone of sustainable development and the key areas for understanding the concept of sustainable development [18].

Overall, a sound and thorough analysis of every factor and element contributing directly or indirectly to this concept leads to an objective understanding and evaluation of sustainability. Nonetheless, an internationally accepted standard for sustainable assessment is not available. This is largely because models are often blamed for their subjectivity, their sense of sustainability, or their lack of clarity [18].

2.2. Elements of Sustainability

Optimization methods for environmental sustainability—social and economic—are developed separately. [19]. Since, energy can be seen as a key factor in poverty reduction and the improvement of living standards, energy resources and the sustainability dimensions must integrate together. Thus, technical dimension relating to functional and technological advantages is considered by some authors as energy resources sustainability. In this case, the sustainability measures for optimization consist of environmental, social, economic, and energy resources sustainability.

3. Optimization

Optimization is a search process for a specific problem according to special conditions of that problem. Optimization refers to finding a process of optimal values for a given network parameter using all feasible values for the minimization or maximization of network output. The goal of optimization is to discover the best feasible response with the consideration of the problem constraints. The presence of complex scientific and engineering problems leads to using optimization methods to solve the desired problem. Due to time consuming and complexity of exact methods, utilizing intelligent optimization algorithms has crucial importance.

Optimization of many complex scientific problems which require solutions with accurate computations and appropriate time cannot use classical methodologies. In this situation, nature can be considered as a rich source which, like a powerful mechanism, provides principles and concepts in order to design artificial computational methods for solving such complex optimization problems. Heuristic optimization methods are a set of algorithms for optimization problems which search in problem search space to find optimal response randomly, but purposeful and simple [30,31].

After developing a heuristic optimization algorithm, for instance TS, researchers found that some natural phenomena, despite being random, are interestingly moving toward near-optimal states. These optimization algorithms are usually inspired by nature. The metaheuristic optimization algorithms have outsourced approaches from local optimum and are capable of finding optimum solutions in a wide range of optimization problems [32,33]. General algorithms inspired by nature can be divided into four main categories: EAs, SI algorithms, PCMB algorithms, and finally HB algorithms.

The EAs are a subset of evolutionary computations and are categorized in the AI group. The evolutionary algorithms are inspired by the evolutionary and genetic behaviors of creatures. These algorithms consist of GAs [13], DE [34], BBO [35], and ES [36]. Other well-known algorithms of EAs include PBIL [37], GP [38], VCS [39], and NNA [40].

The second group of metaheuristic optimization algorithms are the SI algorithms which are usually inspired by intelligent behaviors of creatures in nature. A majority of algorithms belongs to the SI category, unlike the EAs class that only utilizes genetic laws. They always take full advantages of each solution in the search space to provide better solutions for optimal solving of a given problem [39].

4. Optimization and Sustainable Development

The definition of the concept of sustainable development is a good starting point for this section. Sustainable development is a term that has been widely used and for which many meanings have been suggested in the past three decades. Several papers have recently discussed the meaning of sustainability [41] and sustainable development [42,43] and how it can be operationalized and identified [44].

Even if they are sometimes considered interchangeably, the concept of sustainable development is slightly separate from sustainable. It should be known that the concept of sustainable development includes a reference to development that is not necessary in order to sustain a system.

Sustainability is defined as "capacity for long-term development", while sustainable development is the mechanism through which sustainable development is achieved or considered [45]. "A dynamic process that allows everyone to realize their own potential and improve their quality of life so as to protect and improve the life-support systems of the world at the same time, as a way to achieve sustainable development as a process" [45] recalls the results of the Forum for the Future. A sustainable development can be the only solution to these problems.

Sustainable development is the synthesis of preservation of energy resources, environmental sustainability, economic sustainability, and social sustainability, as illustrated in Figure 2. Clean energy and technologies are a key component of sustainable development for three main purposes.

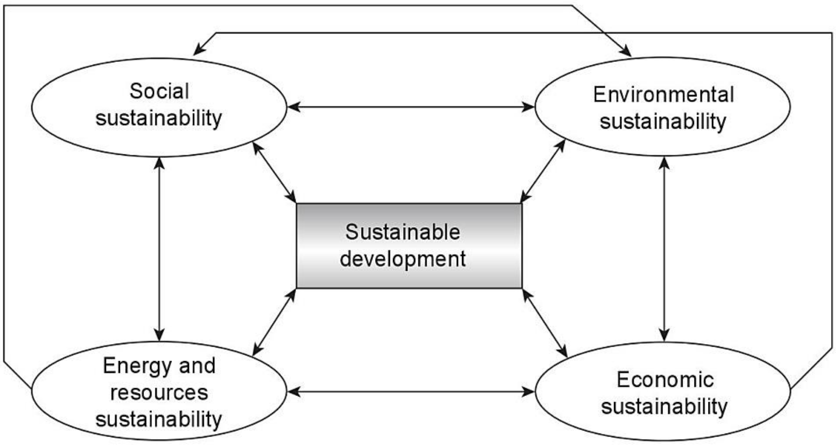

Figure 2. Factors affecting sustainable development interdependence [46].

Firstly, they generally produce less EI than other sources of energy. There are a wide range of green energy options. Secondly, they were not able to be depleted. When used in appropriate applications carefully, green energy resources can provide reliable and sustainable energy almost indefinitely. Thirdly, it promotes decentralization of systems and locally independent solutions, thus increasing the flexibility of the system and offering economic gains to small, fragmented communities. However, the small scale of the equipment also decreases the amount of time required from design to operation to make it more suitable to meet unpredictable production [46].

Indeed, the biggest problem with renewable energy such as wind and solar energies is that they are intermittent. Also, they would require warehouses full of massive batteries, and at this size, a major problem becomes apparent.

However, the life-cycle perspective is of paramount importance when evaluating EI. Moreover, when following this perspective, even in energy systems assimilated as renewable, there is high demand for fossil resources cumulated along the life-cycle stages, even higher than a conventional (fossil) "competitor".

Figure 3 illustrates the major considerations involved in developing green energy technologies including social, EIs, marketing, technological and economic factors. In addition to these considerations, a series of parameters (factors) can be identified which are important for developing green energy policies and strategies. These include information to the general public, environmental education, innovation stimulation, technology promotion, financing, and very important tools and techniques of elaborate evaluations.

For future sustainable energy environments, green energy technologies are expected to play a key role. Energy demand is likely to be the main factor deciding the role of green energy and technologies. Therefore, green electricity from renewable sources, such as hydraulic energy, solar, wind, geothermal energy, wave, biomass, etc., can be produced to address the energy demand. Green energy innovations are largely influenced by strong and influential patterns that are grounded in fundamental human needs. Wastes (e.g., waste-to-energy incineration plants converted into usable forms of energy) and biomass sources are considered to provide renewable energy/green energies.

To achieve a comprehensive sustainable development, using optimization methods and subsequently optimizing the objective functions of the problems in relation to energy resources sustainability, environmental sustainability, economic sustainability, and social sustainability is very essential. Green energy resources, systems, and technologies are the key components of accomplishing sustainable development, in the following optimization methods. They are applied to the sustainable energy and buildings in the literature, and are discussed and analyzed in detail.

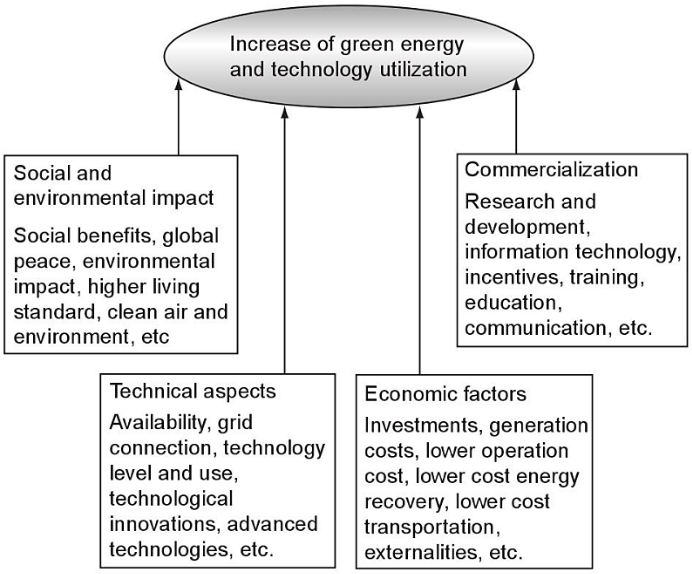

Figure 3. Considerations involved in development of green energy technologies [46].

4.1. Optimization and Sustainable Energy

The main focus of sustainable energy is to move towards electricity production and powering equipment by means other than fossil fuel consumption. Recently, there has been a shift in focus because the quantities of fossil fuel used to produce energy are too big. This means that dependence on fossil fuels was once considered untenable because these resources would be eradicated in the world. Today, however, because of the environmental impact of burning them, that dependency has been considered unsustainable. Now that the issue of global climate change has emerged, it is clear that the burning of fossil fuels is the primary cause for the release of carbon dioxide into the atmosphere. Therefore, because the fossil fuels have many carbon dioxide emissions, finding sustainable alternatives has become an imperative.

As a result, those interested in climate protection advocate sustainable energy as a means for reducing carbon emissions. This will inevitably lead to an increasing reliance on energy sources such as solar, wind, geothermal, hydro-electric, and sometimes nuclear. This focus on renewables is a somewhat narrower version of the concept of sustainable energy.

Another more comprehensive concept is to reduce the energy demand generated by consumer goods production. For example, by increasing the efficiency of energy resource usage, and/or by replacing toxic energy resources with less environmentally friendly energy sources, energy consumption typically decreases environmental effects. Such behavior will promote sustainable development and raise living standards through a cleaner climate. A sustainable supply of sources of energy, to be accomplished through the following, is provided by sustainable development:

- Sustainable energy resources available at a reasonable cost which can be used for all necessary tasks without detrimental societal effects. The generally accepted endpoints are energy resources like fossil fuels (coal, oil, and natural gas), and uranium. Others, such as sunshine, wind, and falls in water are generally regarded as renewable and relatively long-term sustainable [47]. Wastes and biomass fuel are sometimes seen as sustainable energy sources (convertible to useful energies through waste-to-energy incineration and other processes).

- Efficient utilization of energy resources for improving their benefits while preventing their use. That recognizes that all energy resources are to a certain extent limitable, enabling them to contribute to the long-term growth and thus to a more sustainable development. In addition to energy sources which can eventually make cost-performing changes, the need for resources (energetic, material, etc.) will be reduced to create and sustain energy systems and devices and the related environmental impacts will also be reduced. [47].

Figure 4 shows that approximately 1/4 of global final energy consumption in 2017 was made by the residential sector (a total of 8918 Mtoe). Over the last few decades, this share has not changed significantly and it is projected to continue to be similar. The data source given in Figure 4 is the International Energy Agency. It describes the residential sector as the combined pool of all households in the region, also known as the household market [47].

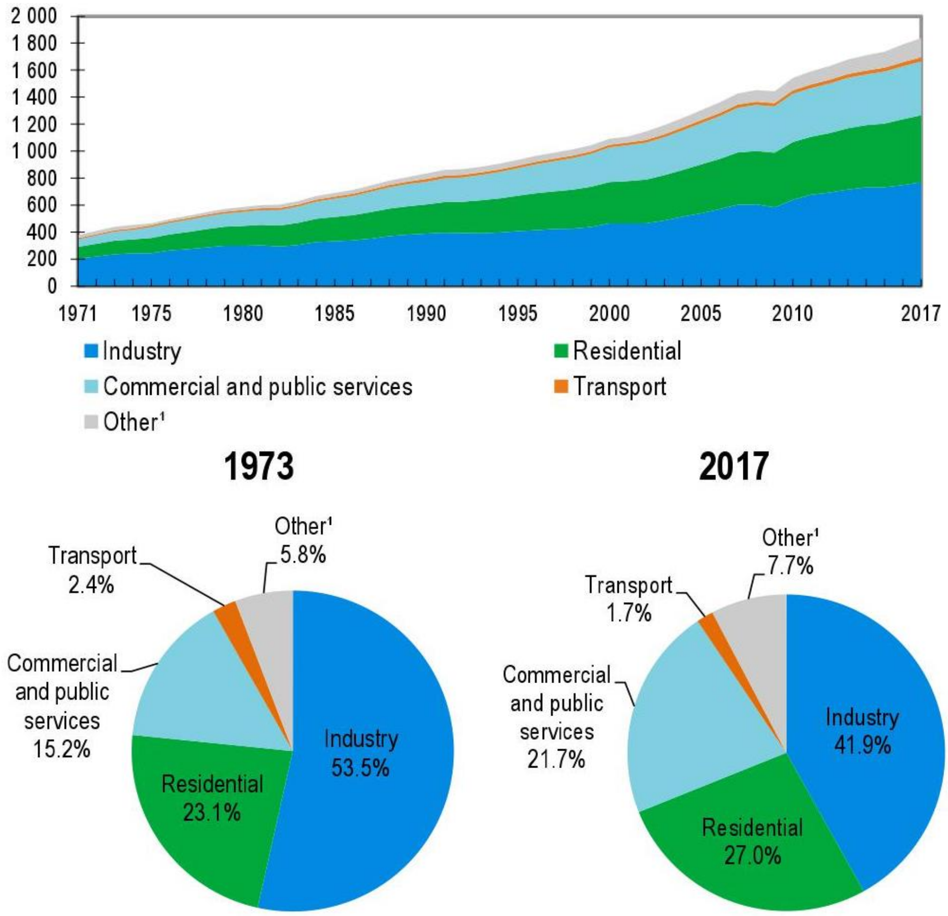

Figure 4. 1973 and 2017 shares of world electricity final consumption (Source: IEA, World Energy Balances, 2019).

In the transportation sector, roughly half the supply of renewable primary energy is used to produce electricity and heat in countries of the OECD. However, the majority of renewables in the residential, commercial, and public services sectors are being consumed globally. This is a result of the extensive use of organic solid fuels in developing countries' residential sectors. The global electricity and heat production are based on 38.6 percent of renewable energy; while 41.7 percent is spent on the residential, commercial, and government sector (see Figure 5).

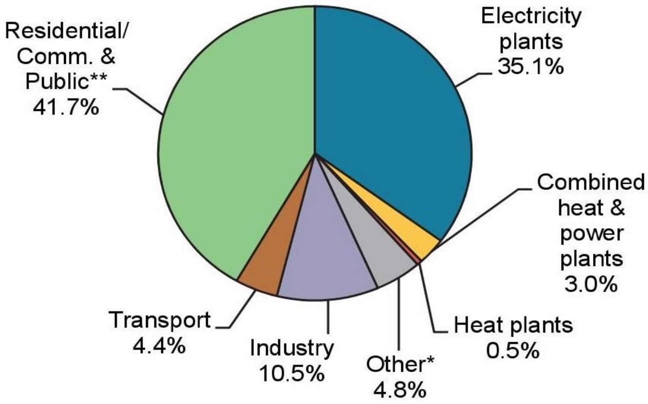

Figure 5. International sectoral renewable energy used in 2017.

In the following, the review was made on recent published papers in this topic. Table 2 shows the reviewed papers in the literature.

Table 2. Main characteristics of some the reviewed papers in the literature.

Ref.	Problem	Optimization Method	Objective Function	Optimization		Year
				Single-objective	Multi-objective	
[48]	Optimal power flow	MJAYA	• Fuel cost • Emission cost • Power loss	×	✓	2019
[49]	Optimization of Renewable Energy Sources in a Microgrid	AFSA	Cost of generation	✓	×	2016
[50]	Optimal integration of renewable energy sources for autonomous tri-generation combined cooling, heating, and power system	PSO	• Total cost	✓	×	2018
[51]	Optimal design of Microgrid's network topology and location of the distributed renewable energy resources	HS	• Cost • Power loss	×	✓	2019
[52]	Sustainable renewable energy planning and wind farming optimization	GAs	• Cost of Energy (LCOE)	✓	×	2018
[53]	Sustainable Indonesian electricity system	Multi-objective optimization model	• Cost of generation • Lowest CO2 emissions	×	✓	2015
[54]	Design of distributed energy supply systems	Mixed-integer linear programming (MILP)	• Investment costs • Total annualized costs	×	✓	2017
[55]	Sustainable energy-generating induction machine	Random restart local search optimization	• Slip • Rotor current • Power factor • Starting toque	×	✓	2019
[56]	Sustainable energy systems	P-graph model	• System cost	✓	×	2017
[57]	Sustainable NOx emission reduction at a coal-fired power station	Online neural network modeling and PSO	• NOx emission rate	✓	×	2019
[58]	Optimal design of HRES	Monte Carlo simulation and (STRONG)	• Power shortage cost • Energy storage cost • Power generation cost • Carbon emission	×	✓	2015
[59]	CHPED	SRPSO	• Generation cost	✓	×	2019

In [48], Jaya's new version called MJAYA was presented with four different targets, reflecting the minimization of fuel cost, emission minimization, transmission power loss reduction, and the improvement of the tension profile, to solve the problem of the OPF. Comparing other reported approaches suggests that the MJAYA algorithm is preferable to other methods. The MJAYA proposal is a population-based optimization algorithm consisting of simple steps only using common control parameters (i.e., maximum number of iteration and population sizes). For further explanation, Figure 6 displays the suggested flowchart for the MJAYA algorithm for OPF resolution.

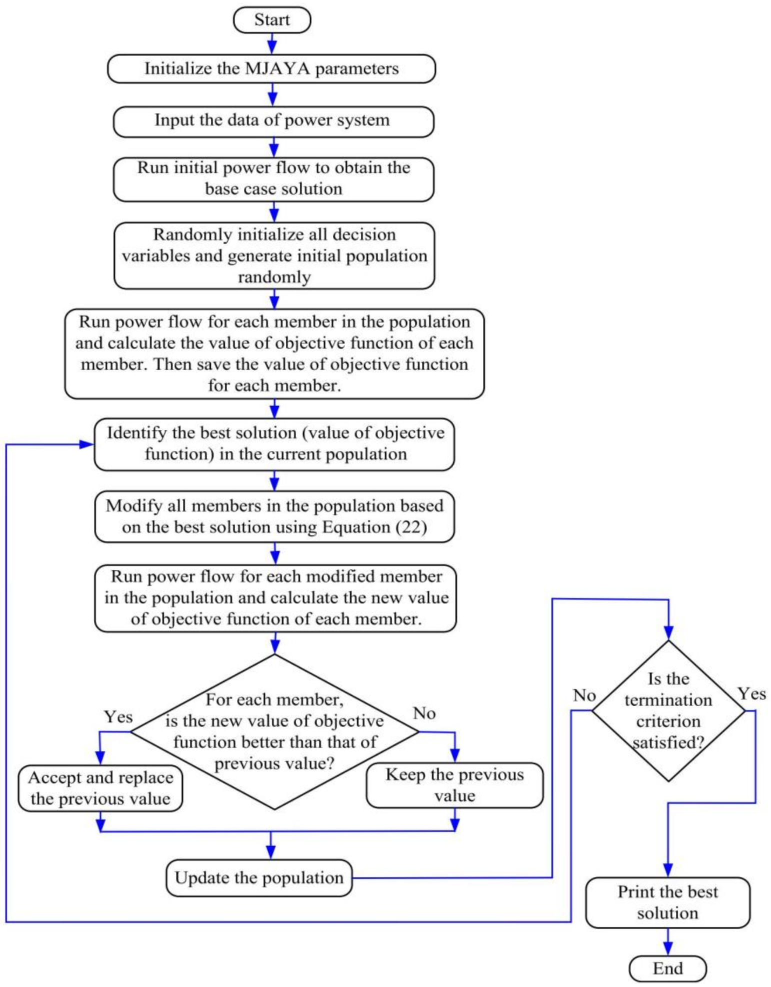

Figure 6. Diagram of MJAYA's proposed solution for the OPF [48].

In [60], a comparison was performed among four optimization algorithms in order to reduce power loss in the power distribution network equipped with renewable energy resources. These algorithms are GSA, BA, ICA and FPA. Placing RDGs such as wind energy and photovoltaic energy can lead to a reduction of power loss in an electrical power network. The suggested heuristic algorithms are used in this research to find the best site and size for RDGs in the distribution network to reduce energy loss. The results of ICA show its efficiency and superiority over the other algorithms that have been suggested.

In [49], an optimization algorithm is used for the optimal energy scheduling problem and the optimization of renewable energy sources in the micro-grid, called the Artificial Fish Swarm Algorithm. The efficiency of the algorithm is checked through a microgrid scenario to schedule generation. The findings are checked by comparison to the established multiplicative reduction algorithm for additive increase.

In [50], a simulation model was developed for optimization of different configuration alternatives of autonomous renewable energy sources and CCHP systems for meeting cooling, heating, and electrical loads, based on the photovoltaic-thermal panel, wind turbine, thermal energy storage, electrical energy storage, absorption chiller, electric chiller, and electric heater. To optimize the process, a newly developed E-PSO algorithm is examined and validated. Figure 7 displays the simulation phase flowchart.

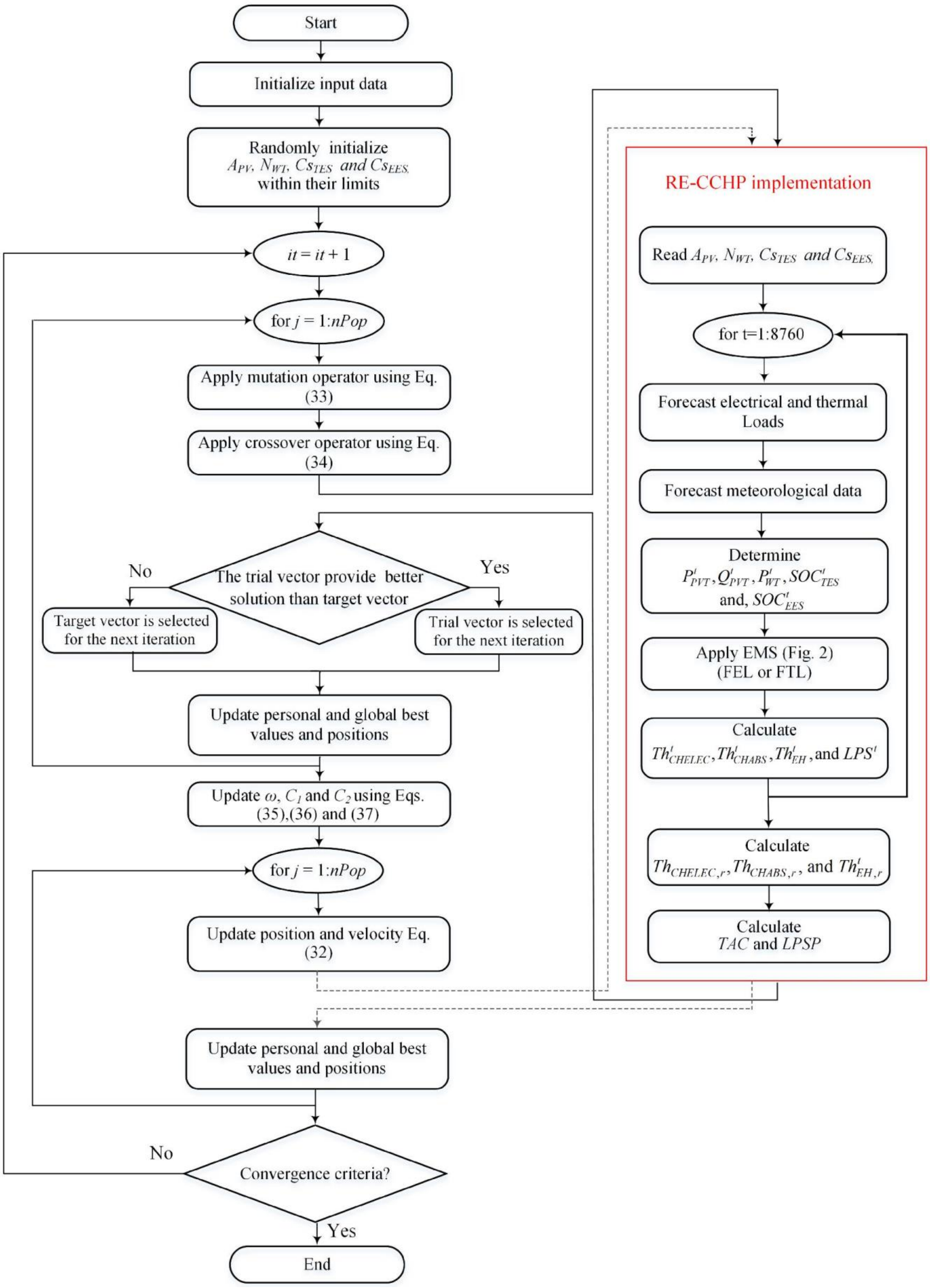

Figure 7. Diagram of the E-PSO algorithm simulation phase [50].

In [51], the combined topology of the network and the optimum placement of distributed renewables in a micro grid were addressed. To solve this problem of mutual optimization, the efficacy of the HS metaheuristic solver inspired by the jazz band music was analyzed. In this paper, two different approaches were considered. The first is a single objective problem formulation in which the classic HS is applied with certain adjustments. The second approach is to take into consideration a multi-target HS algorithm, which will develop a whole family of solutions at Pareto.

In [61], a hybrid ANP-BOCR-TOPSIS evaluation method was suggested to build a comprehensive assessment index system for selecting sustainable energy storage node optimization. At the same time, it was demonstrated that this technique can efficiently resolve such problems and be used in other areas. The system combination is seen in Figure 8.

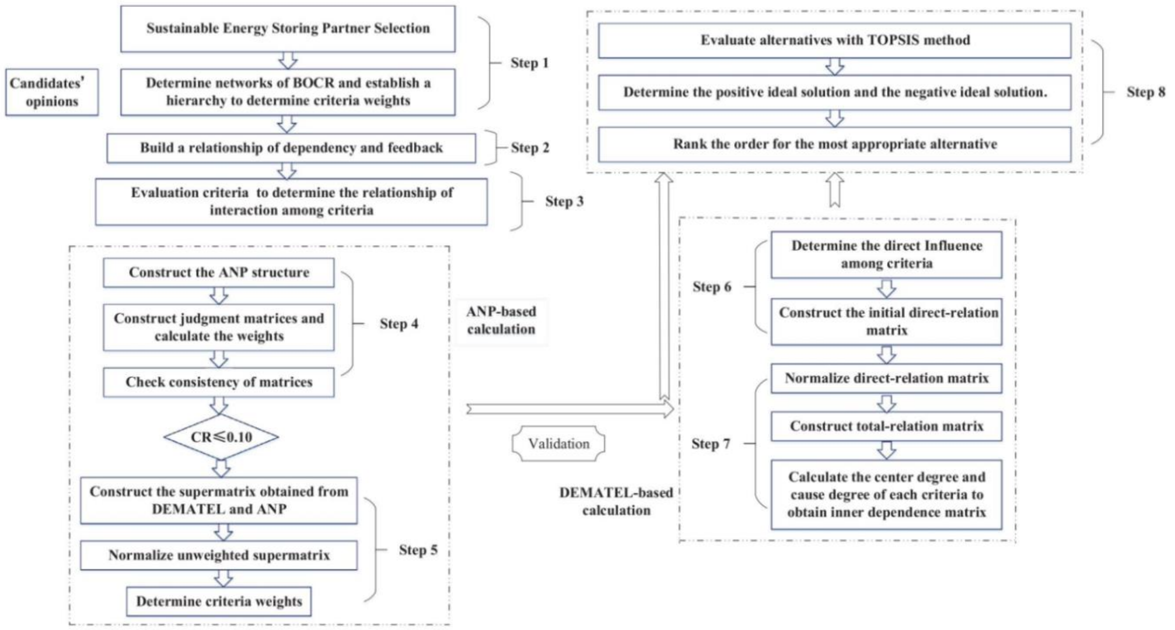

Figure 8. The ANP-BOCR-DEMATEL-TOPSE integrated system framework [61].

In order to determine the weights of all parameters, the approach BOCR was applied and the standards used by ANP were defined. Then the TOPSIS-based approach to classifying alternate firms was suggested. In order to assess the overall accuracy, the DEMATEL method was adopted. Eventually, the findings of ANP-BOCR-TOPSIS, DEMATEL-TOPSIS, and AHP-TOPSIS were related. The findings were also contrasted. The results show that the approach introduced had the potential to evaluate the parameters and was very effective for solving similar problems.

The effects of climate change, driven largely by fossil fuel consumption and unhealthy lifestyle use, promote a strong and far-reaching use of renewable energy sources. Reference [52] suggests the approach of computational GAs to optimize wind farms for the detection of both the sitting of the wind turbines and the levelized cost of energy to guarantee the optimal production of electricity and sustain fragile ecosystems. The model was used to determine suitable locations for the position of wind turbines on a complex field around a flight and evaluated the electricity offset in terms of demand and supply to facilitate localized, more stable energy networks.

Two steps are taken to improve the preparation and development of a wind farm: *a*) Using GAs to determine suitable wind turbine designs provided the circumstances in which winds are viewed, and; (*b*) Economic analyses focused on the expected wind turbine energy generation, calculating marginal costs of increasing energy production in the wind farm region. A flowchart in Figure 9 revealed the optimization pattern.

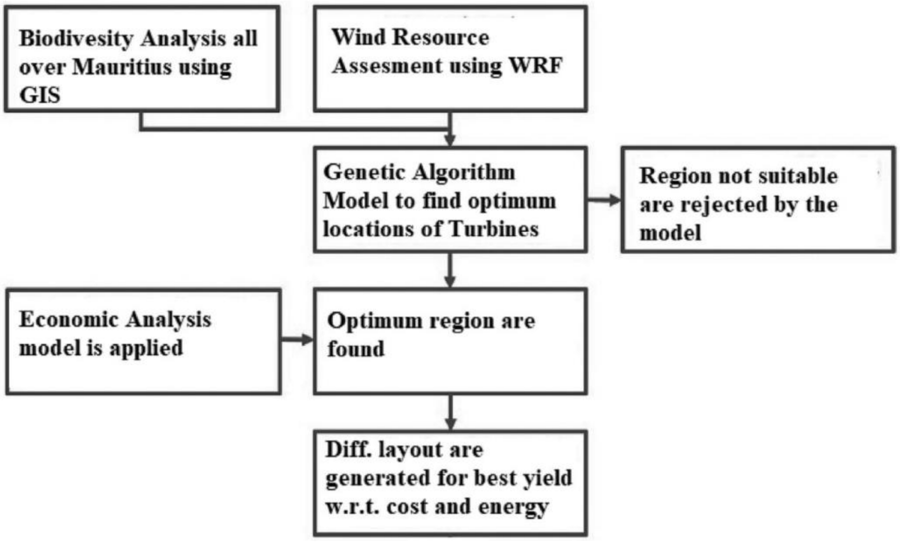

Figure 9. A flow chart that shows the pattern for optimization [52].

The results show the model's reliability and its future applicability to other locations pursuing sustainable energy preparation while at the same time maintaining economic stability and protecting the fragile ecosystems they have inherited.

Reference [62] used two models to analyze the consequences of these objectives, based on a number of mid and long-term scenarios, on the sustainable European energy system as well as the rest of the world. Firstly, the optimal configuration of the European electricity system is accomplished between 2030 and 2050 using the linear programming optimization approach for capability extension and unit contribution. The results for Germany are then used as inputs in the Multi-Regional Input-Output Analysis with the aim of analyzing the environmental and socio-economic effects of the new energy system. The results show this method's capacity for emissions of GHGs, cumulative energy demand and added value, and the creation of jobs.

In [53], a multi-target optimization model for a long-term power generation network in Indonesia was introduced. Between 2011 and 2050, the optimization model is performed. This paper seeks to assess local energy sources' cultural and environmental adequacy. The model includes two competing goal functions to obtain the lowest generation cost and lowest CO_2 emissions while taking technology diffusion into consideration. The results show that all renewable energy should be developed in Indonesia and that imported coal and gas is needed.

Reference [63] provides an overview of sustainable energy system design and development focused on the context for superstructure optimization and the guidelines on LCO. There were a series of research challenges, such as (1) systematic generation of comprehensive super-structures for processes, (2) super structured optimization models that integrate technology-economic assessment and LCO, (3) effective computational algorithms to resolve non-linear optimization issues.

For the design of sustainable energy supply systems, the concept of min-max robust multi-objective optimization was applied in [54]. This article introduces a mixed-integer linear problem formula, incorporating uncertainties in sustainable energy system design. A Pareto front can therefore still be derived. The problem formulation represented transfers the important theoretical concept of min-max robust multipurpose optimization to engineering for the design of energy systems that are sustainable.

A random restart of the local search optimization process for efficient induction production of energy was examined in [55]. Several experiments have recently been designed to improve induction machines operating efficiency with optimization technology. However, current techniques failed to improve the induction machines efficiencies. An HC-LSO technology was designed to resolve this efficiency problem. Figure 10 shows the HC-LSO technique structure diagram.

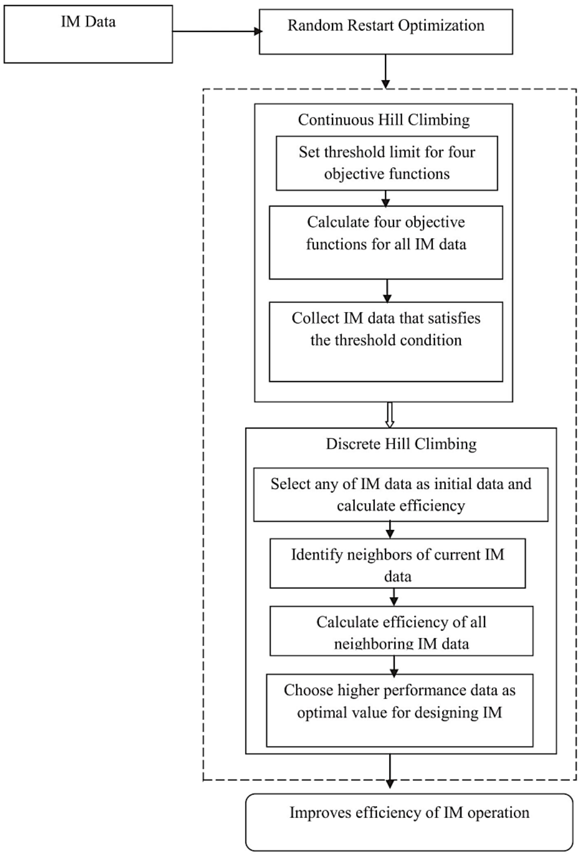

Figure 10. Hill climbing-optimization of HC-LSO (Hill-LSO) system configuration diagram [55].

A P-graph model is developed in [56] to optimize sustainable energy systems over a multi-period period. The model is capable of synthesizing scalable structures that are capable of addressing differences in the supply and demand of raw materials. In addition, the P-graph model is also capable of generating near-optimal solutions that provide information that may be important to decision-makers, such as structural features that are specific to a range of good solutions. The method built in this study is outlined in two case studies.

In [57], using ANNs model and PSO over two years of operation a 490 gross megawatt subcritical tangential coal fired boiler is built and implemented. There is also a hybrid optimization and control strategy using multiple methods of optimization and control, including machine learning [57].

In [64], the recent model of energy planning, energy projection models, and renewable energy integration models were studied and reviewed in numerous ways for minimum cost of energy, minimum CO_2, and sustainable development. Various techniques and tools for modeling are also investigated and discussed.

In [65], a summary of trends in science (1999–2009) was provided regarding the utilization of the optimization methods for design, planning, and control problems related to renewable resources and sustainable energy. A review of more than 200 papers in the fields of renewable energy and computer optimization from leading publications provides interesting conclusions which can be of use for researchers in fields of green energy.

In [66], the power and supply sector developments were reviewed. The role of modeling and optimization as a tool for sustainable energy systems was analyzed as well as the future prospect of optimization modeling. Additionally, in [67], the different methodologies of optimal sizing of renewable hybrids energy systems were reviewed.

In [58], the use of simulation from Monte Carlo and simulation optimization techniques for optimal HRES design in uncertain environments were investigated. The proposed model takes into consideration not only the power generation, allocation, and transportation systems within the HRES framework, but PV equipment, wind and diesel electric power generators, and energy storage systems at each power plant.

In [68], numerous different tools for modeling a renewable energy project were examined for simulation and optimization. The models examined in this document were divided into various project subgroups: 'Multi-scale RE Tools', 'District Level Tools', and 'Regional Level Tools'. Tools for similarities and differences are contrasted among the different categories. Reference [69] provides a timely review of state-of-the-art energy planning for multi-target energy resources.

In addition, Reference [70] presents an exhaustive review of applied optimization algorithms for energy-efficient scheduling based on constraints and objectives related to energy. In this article, many methods including swarm and evolutionary algorithms for solving energy-based problems were discussed and analyzed. Figure 11 identifies swarm and evolutionary algorithms used to solve energy-related scheduling problems.

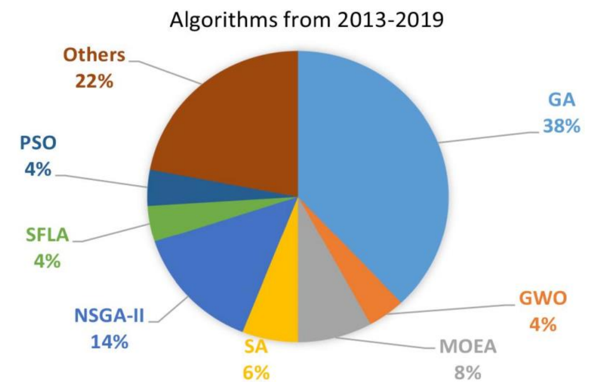

Figure 11. Swarm and evolutionary algorithms for solving energy-related scheduling problems.

Reference [71] also discusses HS algorithm implementations in energy systems. Various improved versions of the HS approach are implemented in the present study, and a comprehensive review in the field of HS implementation for energy system issues is conducted.

The SRPSO algorithm was used in a comparison to solve the problem of CHPED by taking into account fuel costs and power losses, and thereafter to obtain sustainable energy [59]. The SRPSO algorithm is an improved form of PSO.

4.2. Optimization and Sustainable Buildings

Buildings around the world consume a substantial amount of energy, about 1/3 of the total primary energy resources. In those conditions, effective building energy management is critical in achieving a low carbon environment and potentially faster sustainability. The future generation of buildings is increasingly moving through energy-efficient buildings that allow smart building control. Furthermore, the energy source is an important element in building sustainability. Thus, in world sustainable development strategies, the building industry is attracting increased attention. This is due to its energy consumption and emissions of GHGs in the construction sector.

The concepts of sustainable design, which are widely considered in the sustainable assessment frameworks, were formulated by Hill and Bowen [72]. However, there is still no common definition of a sustainable building. While lowering the energy demand of buildings, lower Canada dealt with climate change criteria for sustainable construction in 2007 and stressed the importance of emissions of GHG [73].

In principle, a sustainable building, based on ecological values and resource efficiency, was in theory often seen as a safe building environment [74]. In countering this idea, a highly efficient building is described by improving the situation, design, construction, operation, maintenance, and removal of energy, which has less impact on health and the environment and fewer electricity, water, and materials throughout the lifetime [75].

The U.S. EPA reported that sustainable construction is the realistic practice of building structures by using environmentally responsible technologies, resource efficiencies, and the minimization of their lives from location until deconstruction [76]. Table 3 lists impacts that the EPA states are expected to minimize sustainable buildings (in view of their role, environmental effects are primarily taken into consideration).

Table 3. Environmental resources and impacts reduced by EPA re-adaptation in a sustainable building [77].

Resource Consumption	Environmental Impact	→	Ultimate Effects
• Energy • Water • Materials • Site • Biodiversity	• Waste • Air pollution • Water pollution and storm-water run off • Indoor pollution • Heat islands	→	• Harm to Human Health • Environment Degradation • Loss of Resources

Many studies have been performed regarding low-energy buildings. Figure 12 illustrates the numbers of studies on low energy buildings obtained in the Science Direct database after 2000, by searching for "low," "energy," and "built-up" [78].

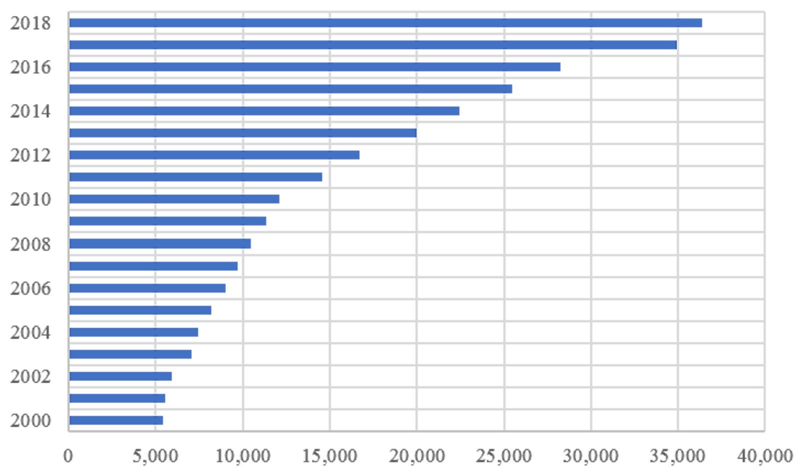

Figure 12. Number of Science Direct studies in the energy-efficient buildings after 2000.

The proposed literature review shows that optimization of BEO is an extremely complex process involving a broad range of potential objective functions and design variables as shown in this Figure 13. The main issues are mentioned. The target functions can include measures of energy, climate, economics, and/or comfort. Building structure, envelope, and energy systems can be related to the design variables.

There are many objective functions and main design variables in literature. In this study, the review was performed on papers concerning sustainable buildings from the energy perspective. Table 4 shows the reviewed papers in the literature.

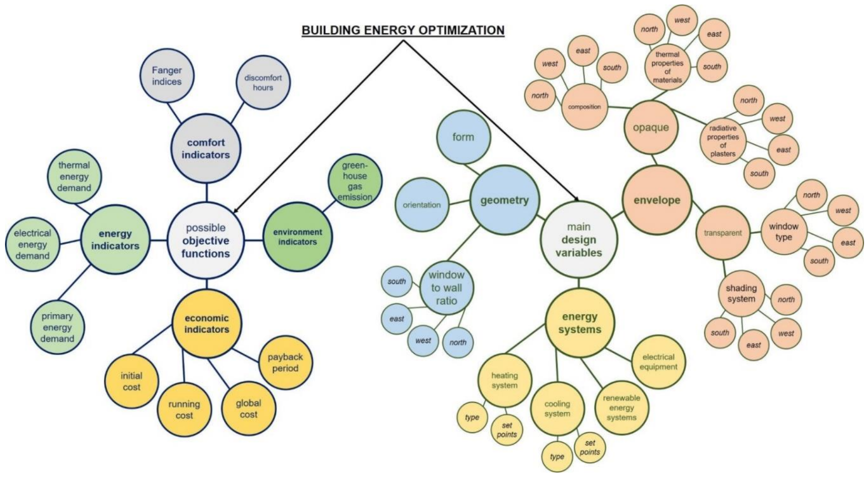

Figure 13. Optimization of Building Energy (BEO) including possible target functions and architecture core variables.

Table 4. Main characteristics of the reviewed papers in the literature.

Ref.	Problem	Optimization Method	Objective Function	Objective Type		Year
				Single	Multi	
[79]	Benchmark of BEO problems	SA, GAs and etc.	the energy consumption	✓	×	2019
[80]	Explore the best plan to maximize energy efficiency in buildings	GAs	Air conditioning and lighting energy consumption	×	✓	2019
[81]	To predict building energy consumption	An enhanced hybrid model based on the ARIMA, SVRs and PSO	energy consumption	✓	×	2019
[82]	Stand-alone and grid-connected zero/low energy buildings and their energy systems	Coordinated optimal design method	• Total cost • the accumulated unmet power • the accumulated unmet cooling load	×	✓	2019
[83]	Building Energy Design	GAs	• annual thermal energy demand • annual electrical energy demand • annual percentage of discomfort hours over occupied hours	×	✓	2019
[84]	Thermal Energy Performance of an Academic Building	GAs	• Temperature profile • Electricity Consumption • Thermal Comfort	×	✓	2019
[85]	Building energy optimization	MACO	Building annual end-use energy	✓	×	2018
[86]	Reduce energy demand for buildings and maximize thermal comfort	• ANN • NSGA-II • Monte Carlo method	• Energy demand • Comfort time	×	✓	2018
[87]	HVAC setpoint scheduling aiming at reducing energy consumption	• ANN • GAs	• Energy demand • Energy cost	×	✓	2018
[88]	The model predictive control based on the historical building data	• Regression tree • Random forest	• Thermal comfort • Energy use	×	✓	2018
[89]	Energy performance improvement of residential buildings	• ANN • NSGA-II • MOPSO • MOGA • MODE	• Energy demand • Lifecycle cost • CO_2 emissions • Thermal comfort	×	✓	2017

Table 4. *Cont.*

Ref.	Problem	Optimization Method	Objective Function	Objective Type		Year
				Single	Multi	
[90]	The optimization of the thermal behavior of building envelope	GAs	• Energy consumption • Net present value • Payback period	×	✓	2017
[91]	Exergy and exergoeconomic optimization as concerns building energy design	NSGA-II & MCDM methods	• Energy and Exergy use • Exergy efficiency • Exergy destruction • Thermal comfort • CO_2 emissions • Financial indicators	×	✓	2017
[92]	Minimizing lifecycle cost and emissions, ensuring, at the same time, higher thermal satisfaction of building occupants	HS	• Lifecycle cost • Lifecycle emissions • Thermal comfort	×	✓	2017
[93]	Increase the energy performance for space heating and domestic hot water production in residential buildings	GAs	• energy consumption • Financial indicators	×	✓	2017
[94]	Building energy retrofit	Multi-objective energy hub optimization	• Lifecycle cost • Lifecycle GHGs emissions	×	✓	2017
[95]	The energy performance of green building envelopes	NSGA-II	• Envelope construction cost • Thermal energy demand • Window opening rate	×	✓	2017
[96]	Optimize the thermal and daylight performance of school buildings	SPEA-2	• Energy demand • Useful daylight illuminance • Summer thermal discomfort	×	✓	2017
[97]	Find resilient cost-optimal retrofit solutions	NSGA-II	• Thermal energy demand • energy consumption • Global cost	×	✓	2016
[98]	The improvement of the global overall energy performance of office buildings	Multi-criterion building envelope optimization	• Energy demand • Visual comfort	×	✓	2016
[99]	The design optimization of a residential building	• GAs • Morris screening method for sensitivity analysis	• Energy demand • Discomfort hours	×	✓	2016
[100]	Building energy behavior simulation-based optimization	NSGA-II	• Cooling energy demand • Lighting energy demand	×	✓	2016
[101]	Sustainable building design	NSGA-II	• Thermal energy demand • Electricity demand • Investment NPV • CO_2 emissions • Comfort level	×	✓	2016
[102]	Finding optimal solutions of envelope design	Mono- and MOPSO	• Hating energy demand • Cooling energy demand • Lighting energy demand	×	✓	2016
[103]	Design of energy systems for buildings	NSGA-II	• Energy use (heating, cooling) • Investment cost	×	✓	2015
[104]	Building energy optimization	• NSGA-II • MILP	• Annual carbon emissions • Annual running costs • Investment cost	×	✓	2015
[105]	During design retrofit, multi-objective optimization	• GAs • ANNs	• Energy demand (heating, cooling) • Retrofit cost • Thermal discomfort hours	×	✓	2014

In [106], for solving near-zero energy-building design problems, multi-objective optimizing algorithms were compared. [107] provides the software to support the selection of energy efficiency measures both for newly constructed buildings and for existing ones. The methodology of optimization is a MINLP problem. This study addressed issues of building optimization, both single and multi-objective. The objective is to generate annual energy consumption.

A new systematic method for tackling this difficult task was introduced in [83]. It is called "Harlequin," and it optimizes building energy efficiency multi-phase and multi-objectivity. Many architecture variables related to building structure, envelope, and energy systems are designed in three steps. Harlequin is a multi-stage and multi-target method for building energy design optimization. This indicates three phases as shown in Figure 14.

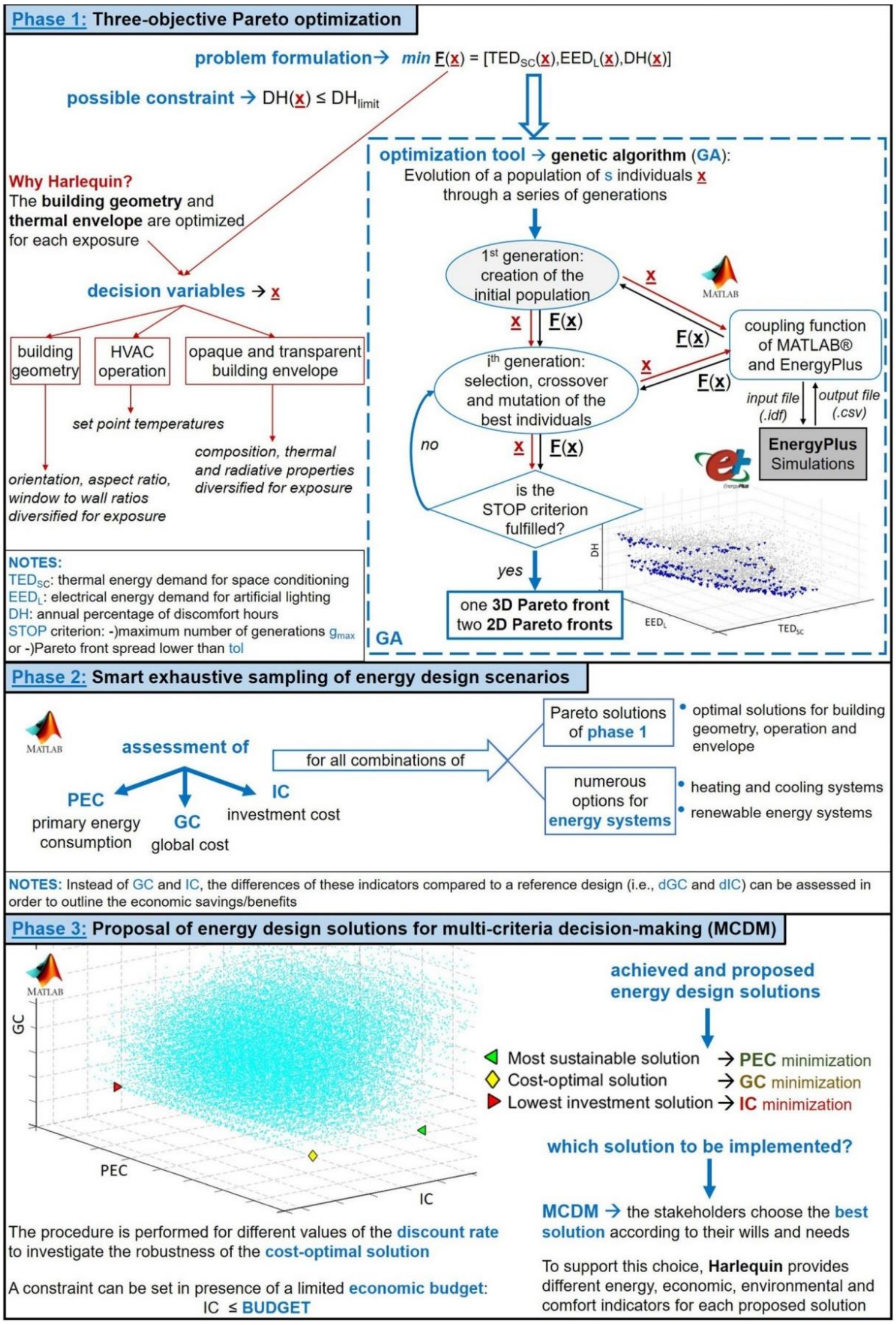

Figure 14. Scheme of the system proposed: Harlequin [83].

In [108], the latest intelligent control systems for energy and comfort control in smart energy buildings were thoroughly and extensively reviewed. [109] represented a simulation model which enables the finding of optimal values for different building parameters and the associated effects which decrease the energy demand or consumption of the building.

In [110], the optimization approaches for sustainable building problems were thoroughly examined. The heuristic algorithms widely used to cover direct searches, evolutionary methods, and other organically influenced algorithms are summarized. These algorithms are included GAs [111], EP [112], GP [113], CMA-ES [114], and DE [115]. The main specifications of 74 articles related to the application of mentioned algorithms to various domains of sustainable building design are present in this study.

In [116], the potential of the prefabricated structures for use in new buildings for sustainability, eco-efficiency, and building optimization was discussed, concentrating on the study of a novel dry–dry beam–column relation with various reliability scenarios and re-use scenarios. Additionally, in [117], optimizing building sustainability assessment was presented using building information modeling. In view of criteria for safer and more sustainable buildings, the BSA processes within a BIM framework must be incorporated and streamlined. In [118], an energy optimization was conducted in the various climatic zones of a residential building. In this analysis, the best energy used in a house due to a heating–cooling system was explored through various options under the national code of uniform R values.

In [119], comprehensive agent-based modeling frameworks and methodologies were developed to optimize sustainable building operation in terms of indoor/outdoor thermal comfort and energy consumption levels.

In [120], an optimization model was designed to optimize the efficiency of existing buildings and to test the performance of a proposed project by using a public building in a case study. Reference [121] presents a model of multinational optimization for retrofit planning of buildings with the objective of maximizing energy savings and economic benefits from the given investment budget.

In [122], in order to find an optimal construction envelope design that minimizes life cycle costs and emissions, the multi-objective optimization model based on harmony search algorithms was developed. The pattern has been used in the south of the United States for a typical single-family home. A number of optimal solutions from Pareto solutions were described to help designers better understand the trade relationship between economic and environmental efficiency.

In [123], optimizing the thermal performance of building envelopes for energy consumption saving was performed in office buildings in China for various climates. In [124], multi-objective optimization and the analysis of parametric of a solar heating system were investigated for different building envelopes. In addition, in [125], multi-objective optimization for energy cost management was represented in semi-public buildings using thermal discomfort information.

In [126], evolutionary many-objective optimizations were proposed for retrofit planning in public buildings where NSGA-III resulted in better diversity and where convergence outperforms the conventional NSGA-II. Additionally, [127] integrated distributed generation technologies on sustainable buildings by using multi-objective dimensional method. In their study, objective functions consist of energy generation, total annual cost, emissions generated, and water consumption of the system.

In [128], energy performance of a building, considering different configurations and types of phase change materials, was evaluated by means of multi-objective optimization in five cities of Iran: Tehran, Tabriz, Bandar Abas, Shiraz, and Yazd—each having distinctive climate. In [129], optimization of the HVAC system energy consumption in a building was performed using ANNs and MOGA. The results show that the proposed algorithm has good quality in finding optimum values.

In [130], the MOGA optimization algorithm based on Pareto optimization was applied to the energy design of the building envelope and to minimize primary energy consumption, energy-related global cost, and discomfort hours. Their proposed method was used with four diverse climatic zones in Italy. In [131], also, the MOGA was employed for cost-optimal and low-carbon design of high-rise reinforced concrete buildings. Furthermore, [132] used the improved MOPSO algorithm for campus energy plant operation based on building heating load scenarios. Operating costs, system efficiency, and thermal comfort are considered as targets of optimization in their study.

4.3. Sustainable Environment

Energy, culture, and living standards are often difficult to describe and are linked in complex ways. Energy choices have influenced cultural and economic development strongly throughout history, as well as living standards. The environmental impact often has an important impact on energy sources and it also impacts society and living standards. The long-term sustainability of the growth of a nation is also impacted by environmental issues.

Due to increased population in the world, living standards, resource use, and industrial activities, the environmental impact of human activities has increased substantially in recent decades. Figure 15 shows the temporal relation between the consumption of energy and the emissions of CO_2, where consumption and emissions have similar patterns, showing a strong relationship [47].

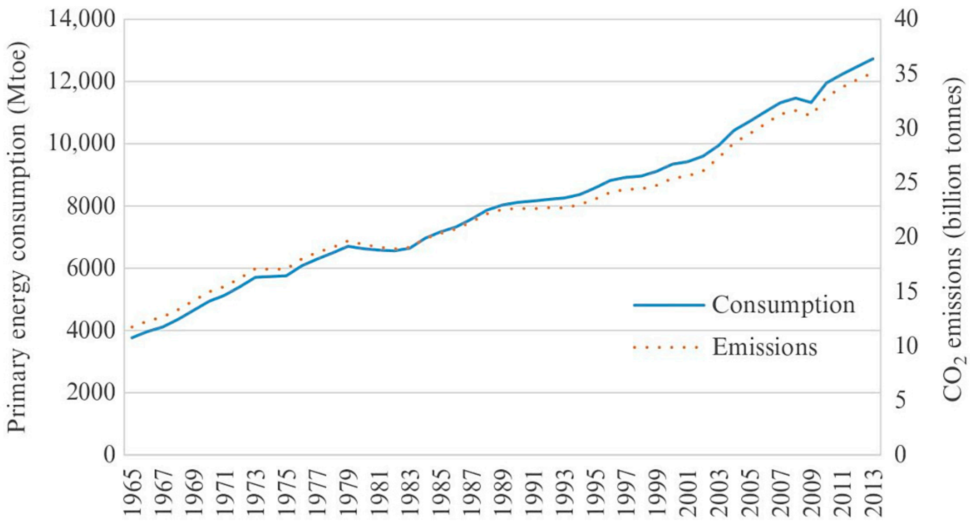

Figure 15. The relation between world consumption of primary energy and CO_2 emissions from 1965 to 2013.

Energy-related environmental concerns range from pollutant and accident emissions to environmental degradation and ecosystems. Table 5 provides descriptions of their sources and environmental and human health impacts for several types of pollutants [47].

Table 5. Chosen contaminants and some of their origins and threats.

Pollutant	Source	Risks
CO	Incomplete combustion of fuels	Urban air pollution
SO_2	Natural processes (e.g., volcanic activity)	Biological and human health threats
	Sulfur-containing fuels, oil refining, electricity generation, pulp and paper industry	Acid precipitation, respiratory problems
NO_x	Combustion of fuels at high temperatures	Respiratory problems, low-level ozone formation, creation of acids
VOCs	Petroleum and solvent vapors	Impede the formation of ozone
Particulates (e.g., fly ash)	Natural and anthropogenic sources	Acid precipitation, toxic effects

In recent years, industry, the government, and the public have increasingly paid attention to environmental issues, especially as those considerations become an integral part of living standards. Environmental issues therefore also affect culture growth. Energy-related environmental problems have impacted local and regional communities, as well as national and global governments in recent decades (such as climate change and ozone depletion). The main environmental concerns related to power consumption are summarized in Table 6.

Table 6. Summary of major environmental concerns related to energy use and their causes and impacts.

Environmental Concern	Causes	Impacts
Global climate change	Greenhouse gases (CO_2, CH_4, CFCs, halons, N_2O) emissions, coal mining, deforestation, general energy-related activities	Earth surface and sea level increase; coastal floods; fertile displacement of the area; lack of freshwater;
Stratospheric ozone depletion	CFCs, halons, N_2O emissions	UV radiation increase (skin cancer, eye damage)
Acid precipitation	SO_2, NO_x, VOC emissions, electricity generation, residential heating, industrial energy use, sour gas treatment, transportation	Acidification of lakes, streams, and ground waters; damage to forests and agricultural crops; deterioration of materials (buildings, metal structures, fabrics)

The following are also additional environmental concerns, many of which have their principal causes and sources listed below [47]:

- Water pollution: Dangerous energy plant and refinery chemicals, mineral acid drainage, geothermal releases of toxic chemicals, and thermal pollution associated with power plant cooling systems releases.
- Maritime pollution: Operations for shipping and accidental oil spills.
- Solid wastes and their disposal: Industries of chemicals, metals, etc.
- Ambient air quality: SO_2, NO_x, CO, VOCs, and particulate matter emissions.
- Hazardous air pollutants: Lead-based fuel additives, emissions from the municipal waste incinerator during oil and gas mining, treatment and combustion, and mercury, chlorinated dioxins, and furans.
- Indoor air quality: CO, CO_2, smoke from stoves and fireplaces, gaseous nitrogen and sulfur oxidizes from furnaces, stray natural gas and oil furnaces, natural gas and soil-burning radon, cigarette smoke and plywood and glues of formaldehyde.
- Land use and siting impact: Refining of fuel, electricity generation, solid waste disposal sites including radioactive waste, hydroelectric reservoirs, mining sites, biomass surface needs, and large-scale renewable energy utilization.
- Radiation and radioactivity: Power (fossil combustion, uranium mining and milling, etc.) processing, decommissioning of nuclear waste, and related substances.
- Major environmental accidents: Fires at refineries, factories, reservoirs and dams, and hydroelectric dam failures causing floods and falls, nuclear accidents, and mining explosions.

There are also optimization approaches for coping with various environmental and ecological problems [133–137].

5. Discussions

The combination of "sustainability and optimization" is one of the most important and well-known challenging combinations in today's world. It has attracted considerable attention and insights, especially in recent years. In this regard, the optimal use of resources related to human needs is considered an excellent sustainable goal: environmental, social, and economic goals.

Energy is a key factor for poverty reduction and the improvement of living standards. Energy resources and the dimensions of sustainability need to be integrated together. Thus, some scholars [46] also find a strategic dimension related to technological advantages known as sustainability of energy resources in addition to the other three dimensions.

In this review study, more than hundred papers on area of the sustainable energy resources and sustainable buildings were reviewed. It is anticipated that green energy technology will play a crucial role in future sustainable energy environments. Energy demand is likely to be the main factor deciding the role of green energy and technologies. Green electricity from renewable sources including hydraulic energy, solar, wind, geothermal energy, wave, and biomass can be produced to address energy demand.

In the domain of the "optimization and sustainable energy", particularly in the field of energy and building, there are several objectives given in Sections 4.1 and 4.2. In addition, several review papers regarding the state-of-the-art in multi-objective distributed energy resources planning was provided in the recent years.

Buildings worldwide consume a large amount of energy, about one-third of total primary energy supplies. Appropriate energy management in construction has abundant significance to a low carbon world and potentially faster sustainable development under these conditions. Since energy is a principal source and element in building sustainability, and in world sustainable development strategies as well, methods to reduce energy consumption and greenhouse gas emissions in the building sector have been investigated by several sources. Optimization of building energies is an extremely complex process since it involves a broad range of objectives and design variables. Evaluating main characteristics of the reviewed papers on this subject show a growing focus on target functions, particularly in the last decade.

Metaheuristics such as swarm intelligence and evolutionary algorithms are effective for solving energy efficiency problem planning, especially for large-scale and multi-objective problems. However, the analysis demonstrates that the GAs, NSGA-II, PSO and their variants are used more frequently than other optimization algorithms. This is due to the large scope of problems in these papers. In high-dimensional problems, global search-based algorithms are more successful than algorithms that utilize local search strategies such as the TS in finding an optimal solution.

The increasing number of articles published in recent years makes the use of energy efficiency resources for sustainable development and sustainability an interesting subject. Modeling, optimization, and simulation methods have been developed and they have opened new horizons for researchers to use these technologies and instruments for energy resources and energy planning and management. Research and development activities in this sector can now take place.

Using published articles, several research trends and their characteristics can be identified according to the contribution of countries or continents. Optimization targets, single-objective and multi-objective optimization, and optimization algorithms can also be identified.

5.1. Distribution of Papers to Different Continents

In Figures 16 and 17, distribution of studied papers are shown with respect to the authors' affiliation to a country or continent. In this regard, Figure 16 indicates distribution of papers based on sustainable energy resources. With respect to the number of research papers, Asia has 54% of publications in the current research regarding the sustainable energy resources. This development mostly takes place in India [50,59,62] and China [53,69] for understandable reasons. Both countries are emerging and must support their growth and development by looking for renewable and sustainable energy sources. Moreover, China and India contribute approximately 29% and 7% of world CO_2 emissions combustion in accordance with the statistics of IEA (CO_2 Emissions from Fuel Combustion, 2019) and are trying to decrease it.

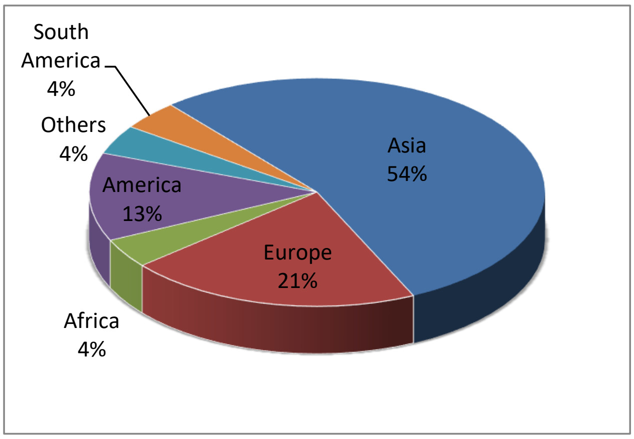

Figure 16. Distribution of papers based on sustainable energy resources to different continents.

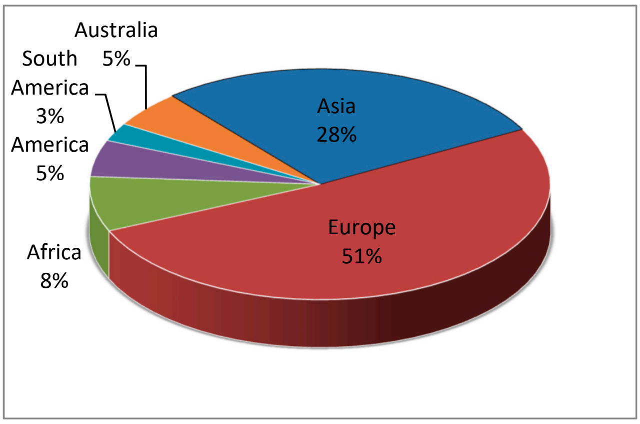

Figure 17. Distribution of papers based on sustainable buildings to different continents.

Figure 17 also depicts distribution of papers based on sustainable buildings in various continents. Due to the number of research papers, Europe has 51% of publications in the current research related to sustainable buildings. A majority of development in the green continent is related to England [81,87,91,107,110] and Italy [83,88,93,97,101]. The presence of advanced building technologies and skills in these countries and the 20% share of buildings in energy consumption as a significant contribution based on the IEA database have led these countries to have the most research and published articles on optimization of sustainable buildings.

5.2. Optimization Objectives

In many articles referenced in this review paper, optimization was performed only to minimize costs. However, due to different economic, social, and other conditions, other goals must also be considered in order to achieve sustainability and sustainable development. In this regard, the study of the reviewed articles shows that in addition to minimizing the energy cost, other energy-related goals have been considered.

In Figure 18, objective functions related to energy are demonstrated, including sustainable energy sources and sustainable buildings. It can be seen from Figure 18 that the share of energy cost is 23%, which is more than other objectives identified in literature. This means that the economic dimension in assessing energy issues remains a top priority. The second, third, and fourth objectives are energy demand with 21%, energy consumption with 17%, and CO_2 emissions with 15%.

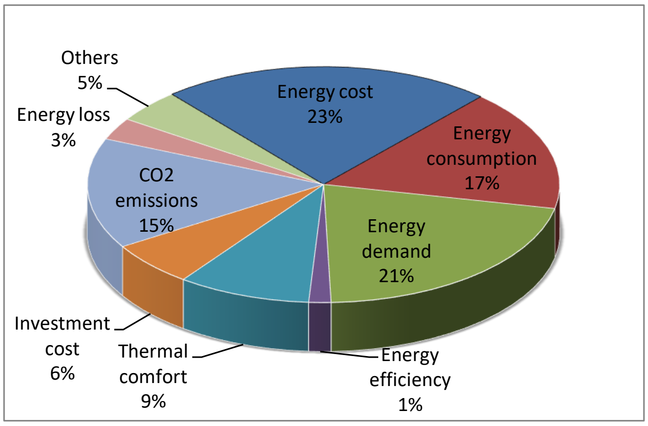

Figure 18. Distribution of objective functions related to energy in reviewed papers.

It appears that optimizing energy consumption and demand in the literature are made in an effort to reduce the pollution caused by energy production. In this regard, many researchers focused on the environmental research related to energy operations, ranging from pollutant emissions and accidents to environmental degradation and ecosystems [89,91]. However, to improve energy efficiency, more and more research needs to be performed on energy-related optimization goals and the relationships between them.

5.3. Single Objective and Multi-Objective Optimization

Many traditional optimization problems related to energy sustainability in the previous years have been solved without considering the actual dimensions, using only single-objective optimization algorithms. Thus, many publications have considered the targets related to sustainable energy and buildings as a single objective. However, over time and especially in the recent years, the complexity of the issues and the need to consider the actual dimensions and elements, as well as the newness of many optimization objectives, have led researchers and the scientific community to use multi-objective optimization algorithms for optimization in order to optimize and solve sustainability problems precisely. Therefore, the number of papers for the multi-objectives related to sustainable energy and buildings from 2014 to 2019 is much larger than those for a single objective in the reviewed papers (see Figure 19). This suggests the comprehensive evaluation of issues to achieve real and practical optimization should be considered in the form of multi-objective optimization.

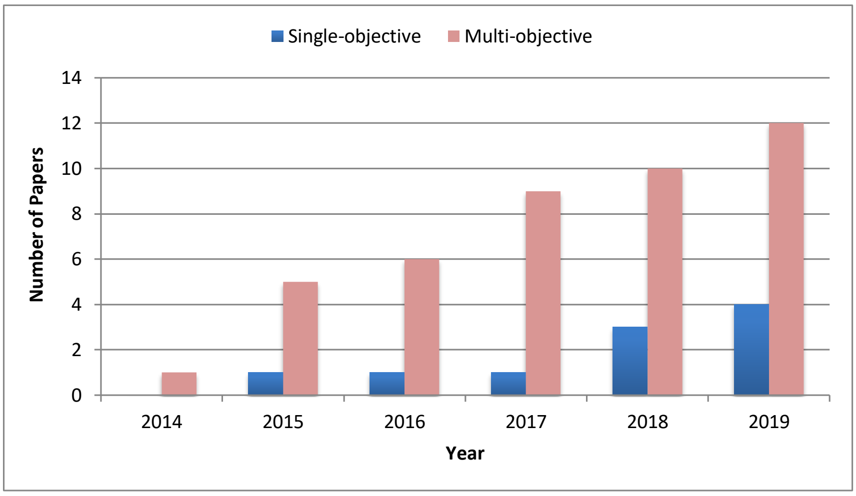

Figure 19. Comparisons of single objective and multi-objective papers by year.

Flexibility of multi-objective optimization rather than single objective optimization for solving optimization problems, despite several conflicting goals, is another advantage of this approach. Therefore, a desire for solving multi-objective problems led researchers to utilize more exact and complicated processes and patterns based on Pareto front strategy for increasing energy efficiency [28,52,58,122].

5.4. Optimization Algorithms

Due to the characteristics and features of problems represented in this review related to sustainable energy resources and sustainable buildings, different and diverse optimization approaches are utilized for solving such problems. Figure 20 displays optimization algorithms used in published articles. In Figure 20, the GAs, NSGA-II, and PSO are the most applicable algorithms for addressing sustainability problems among use optimizers. In this regard, the GAs, NSGA-II, and PSO shares of applied approaches are equal to 25%, 17%, and 11%, respectively. Moreover, the total share of GAs and NSGA-II algorithms is about 42% among all used algorithms. The main reasons of the popularity and efficiency of GAs over other optimizers can be considered as its discrete nature for optimal solving of sustainability problems and being the state-of-the-art algorithm.

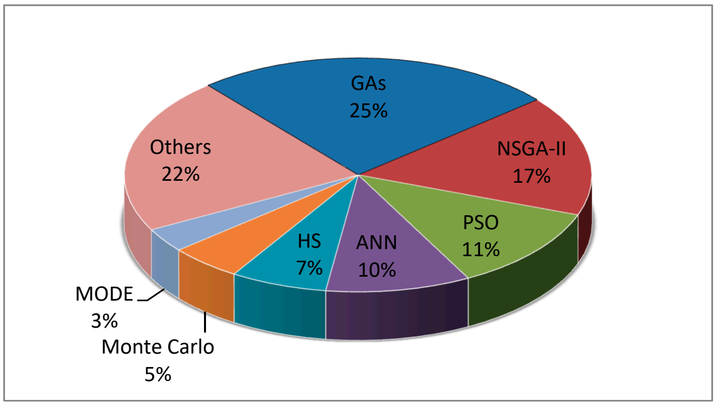

Figure 20. Contribution of optimization algorithms used in the reviewed papers.

6. Conclusions

This review paper focuses on relationships between sustainability and optimization methods. The concept and elements of the sustainability have been represented, and the review of the optimization metaheuristic algorithms used in the recent published articles relating to sustainability and sustainable development has been conducted. While studying and analyzing many and various research articles related to the subject from 2014 to present, effort has been made to construct and create a strong understanding of the topic for readers by discussing and summarizing findings found in recent scientific papers. Since energy and energy resources play an important role in sustainable development, in mostly sustainable energy sources, buildings, and environment, these topics are discussed. The results obtained from studies clearly demonstrate the growth in popularity of optimization for the sustainable development including the energy resources and buildings and of multi-objective optimizations in particular. This is partly due to the importance of using the optimization methods to address problems related to the sustainability. Another explanation for the growing interest in optimization is that activists in this field recognize that such approaches have great potential for sustainable development. Additionally, the results of optimizations indicate that energy consumption, power costs, and CO_2 emissions are significantly reduced by employing optimization approaches. It is noteworthy that the growth and trend of energy efficiency and deployment of green energies are an interesting and challenging topic relating to sustainability. They are receiving more attention in our society. From the different analyses, the following findings can be summarized:

- Asia is more focused on sustainable energy resources due to its huge population compared to other continents, while Europe is more focused on sustainable buildings.
- Tendencies of modeling and using multi-objective optimizers compared with single objective models are currently increasing considering more and real objectives inside the optimization model.
- The GAs and other phenomenon-mimicking algorithms are widely used for optimal solutions for sustainable energy resources and sustainable buildings.

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

Abbreviations

AFSA	Artificial Fish Swarm Algorithm
AHP	Analytic Hierarchy Process
ANN	Artificial Neural Networks
ANP-BOCR-DEMATEL-TOPSE	Analytic Network Process-Benefits Opportunities Costs Risks-Decision-Making Trial and Evaluation Laboratory- Technique for Order of Preference by Similarity to Ideal Solution
ANP-BOCR-TOPSIS	Analytic Network Process-Benefits Opportunities Costs Risks-Technique for Order of Preference by Similarity to Ideal Solution
ARIMA	Autoregressive Integrated Moving Average
BA	Bat Algorithm
BBO	Biogeography-Based Optimization
BEO	Building Energies Optimization
BIM	Building Information Modeling
BSA	Building Sustainability Assessment
CCHP	Combined Cooling, Heating and Power
CHPED	Combined Heat and Energy Efficiency Dispatch
CMA-ES	Covariance Matrix Adaptation Evolutionary Strategy
CO	Carbon monoxide
DE	Differential Evolution
DEMATEL	Decision-Making Trial and Evaluation Laboratory
DER	Distributed Energy Resources
EA	Evolutionary Algorithm
EI	Environmental Impact
EPA	Environmental Protection Agency
E-PSO	Evolutionary Particle Swarm Optimization
ES	Evolution Strategy
FPA	Flower Pollination Algorithm
GAs	Genetic Algorithms
GHGs	Greenhouse Gases
GP	Genetic Programming
GSA	Gravitational Search Algorithm
GSO	Glow-worm Swarm Optimization
HB	Human Based
HC-LSO	Hill Climbing based Local Search Optimization
HRES	Hybrid Renewable Energy System
HS	Harmony Search

HVAC	Heating, Ventilating and Air Conditioning
ICA	Imperialist Competitive Algorithm
IEA	International Energy Agency
LCO	Life Cycle Optimization
MACO	Modified Ant colony optimization
MCDM	Multi Criteria Decision Making
MILP	Mixed-Integer Linear Programming
MINLP	Multi-Objective Nonlinear Mixed-Integer
MJAYA	Modified JAYA
MODE	Multi-Objective Differential Evolution
MOEA	Multi-Objective Evolutionary Algorithm
MOGA	Multi-Objective Genetic Algorithm
MOOP	Multi-Objective Optimization Problem
MOPSO	Mono- and multi-Objective Particle Swarm Optimization
NNA	Neural Network Algorithm
NOx	Nitrogen Oxides
NSGA-II	Non-dominated Sorting Genetic Algorithm II
OECD	Organization for Economic Co-operation and Development
OPF	Optimal Power Flow
PBIL	Population-Based Incremental Learning
PCMB	Physics-Chemistry-Math Based
PSO	Particle Swarm Optimization
PV	Photovoltaic
RDGs	Renewable Distributed Generators
RE	Renewable Energy
SA	Simulated Annealing
SI	Swarm Intelligence
SO2	Sulfur Dioxide
SPEA-2	Strength Pareto Evolutionary Algorithm
SRPSO	Self-Regulating Particle Swarm Optimization
STRONG	Stochastic Trust-Region Response Surface Method
SVRs	Support Vector Regression
TLBO	Teaching-Learning Based Optimization
TS	Tabu Search
TTS	Time-To-Sustainability
VCS	Virus Colony Search
VOCs	Volatile Organic Compounds
WCA	Water Cycle Algorithm

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