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Review

A Review of Methodologies for Managing Energy Flexibility Resources in Buildings

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Abstract: The integration of renewable energy and flexible energy sources in buildings brings numerous benefits. However, the integration of new technologies has increased the complexity and despite the progress of optimization algorithms and technologies, new research challenges emerge. With the increasing availability of data and advanced modeling tools, stakeholders in the building sector are actively seeking a more comprehensive understanding of the implementation and potential benefits of energy optimization and an extensive up-to-date survey of optimization in the context of buildings and communities is missing in the literature. This study comprehensively reviews over 180 relevant publications on the management and optimization of energy flexibility resources in buildings. The primary objective was to examine and analyze prior research, with emphasis on the used methods, objectives, and scope. The method of content analysis was used to ensure a thorough examination of the existing literature on the subject. It was concluded that multi-objective optimization is crucial to enhance the utilization of flexible resources within individual buildings and communities. Moreover, the study successfully pinpointed key challenges and opportunities for future research, such as the need for accurate data, the complexity of the optimization process, and the potential trade-offs between different objectives.

Keywords: energy optimization; buildings; energy communities; building energy management systems; intelligent energy optimization

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1. Introduction

It is expected that the building sector will contribute to 30% of global CO_2 emissions and consume 40% of the total energy by 2030 [1], leading to a significant global impact. The "Clean Energy for All Europeans" package [2] sets energy policies for 2030, with buildings playing a crucial role in Europe's transition to clean energy. Cutting energy demand and boosting efficiency in buildings [3] and industries [4] through energy-saving programs is an effective way to mitigate the impact of fossil-based resources. The "energy efficiency first" principle [5] calls for taking the utmost account of cost-efficient energy efficiency measures in shaping energy policy and making relevant investment decisions. The Renewable Energy Directive [6] and Energy Performance of Buildings Directive (EPBD) [7] promote, among other aspects, on-site renewable energy generation and self-consumption in EU countries.

The motivation behind the advancement of green technologies is the desire to diminish the environmental consequences and alleviate the increasing costs associated with electricity. In this context, photovoltaic (PV) systems are the most popular solutions among the most favored technologies due to their ability to generate small-scale electricity and easy integration into buildings [8]. End-users equipped with PV systems connected to the grid can generate electricity for self-consumption and sell the generation surplus to other buildings or the grid [9]. Energy distribution losses are reduced by generating electricity at the point of use [10] and the advances in technology have decreased the cost of PV panels, making them more attractive for building use [11]. However, integrating solar energy into buildings is challenging due to its variability [12]. Solar energy is only available during the daytime and is affected by climate, location, season, and time [13]. Therefore, the increasing integration of variable and intermittent renewables can cause a mismatch between supply and demand, disrupting power system stability, efficiency, quality, and reliability [14–16].

1.1. The Evolution of Energy in Buildings

To better understand the efforts to reduce energy consumption in buildings, a brief overview of the evolution of energy in buildings is presented in Figure 1. The building sector has undergone a significant transformation, starting with a passive approach to reducing energy consumption using passive solutions [17]. Then, nearly zero-energy buildings (nZEBs) were developed to balance energy demand and renewable generation through on-site RES production [18]. Later, the concept of energy-flexible buildings was introduced by the IEA EBC Annex 67 [19], enabling buildings to manage energy generation and demand based on factors such as weather conditions, user needs, and grid requirements. The latest phase of this evolution is smart buildings, which participate in the energy infrastructure, acting as both energy sellers and buyers [20].

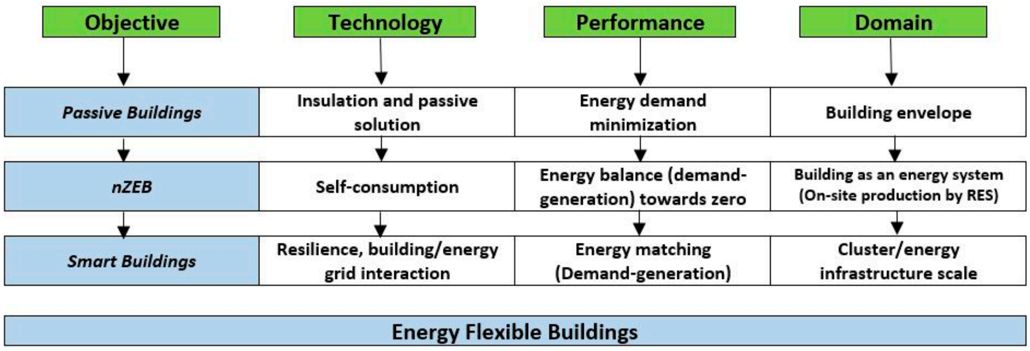

Figure 1. The evolution of buildings over time.

Integrating buildings into communities through the exchange of renewable generation surplus is a suitable solution to tackle the technical and economic challenges of energy management. The concept of a renewable energy community is defined in both the "Directive on the Promotion of the Use of Energy from Renewable Sources" [6] and the "Directive on Common Rules for the Internal Electricity Market" [21]. It must be emphasized that a building's energy demand is variable, and the worst case is when several customers' peak consumption occurs simultaneously, especially if this occurs during a period of low renewable energy generation availability. This issue is a serious challenge to the balance of renewable supply and demand. Energy systems require flexibility to align with the varying energy demand over time, a necessity particularly emphasized in electric energy systems, where demand and supply must be matched at every moment [22]. Therefore, energy storage systems (ESS) and demand response (DR) play crucial roles in providing the needed flexibility to ensure the matching between renewable generation and demand [23,24]. The integration of PV and ESS systems into a community of buildings helps to ensure that end-users can use energy locally produced according to their needs while minimizing the negative impacts on the reliability of the grid [25]. The cost of static batteries has been high in the past decades, which is one of the reasons for batteries not being already widely used in the building sector. Fortunately, the cost of batteries has been decreasing due to technological advancements and is expected to trend downwards [26].

Moreover, electric vehicles (EVs) complement static batteries with their flexibility. With vehicle-to-building (V2B) systems, EV batteries' excess capacity can supply energy to buildings [27]. EV batteries traditionally charge off-peak, or when energy is being produced locally, and provide energy during peak periods or later in the day when no local generation is available [28–30]. As relevant demand-side consumers, building communities can apply DR to optimize local generation integration and utilize energy storage systems [31]. In this context, shiftable loads also play a critical role in DR programs by allowing them to reduce peak demand [32]. Shiftable loads refer to electrical devices or appliances that can be scheduled to operate during periods of lower energy demand or when energy is more abundant and less expensive. Several loads in buildings are flexible, and their usage periods or cycles can be changed without affecting the comfort required by the occupants [33]. DR can be implemented via time-based and incentive-based programs [34].

In addition, building energy management systems (BEMS) play a critical role concerning energy management in the building sector and can be used to monitor and control energy demand [35]. Advanced energy management technologies, like BEMS, improve reliability and lower energy costs in buildings. BEMS can be used to optimize the matching between local energy generation and consumption and to reduce costs without sacrificing residents' comfort in smart buildings [36,37]. In a literature review, Shareef et al. [38] analyzed the use of artificial intelligence (AI)-based controllers, such as artificial neural networks (ANN), fuzzy logic control, and adaptive neural fuzzy inference systems, in home energy management systems (HEMS) based on DR and intelligent controllers, discussing the strengths and weaknesses of each. Addressing the complexity of data is a common challenge for BEMS to ensure effective functionality. However, using the Internet of Energy (IoE) for the transfer of energy data at the required time and place, with applications in electricity distribution, network monitoring, communication, and ESS, can significantly reduce these issues [39,40].

Additionally, the Internet of Things (IoT), which connects new sensing and communication technologies to anything from anywhere at any time, is widely used in intelligent buildings [41–43] and can have a significant impact on reducing energy consumption when adequately integrated into BEMS systems [44]. In addition, the smart readiness indicator (SRI), proposed to rate buildings based on their ability to adapt operations to residents' requirements, optimize energy efficiency, ensure overall performance, and respond appropriately to grid signals [45] plays a vital role in this context [46,47]. According to the Energy Performance of Buildings Directive (EPBD), buildings with a high SRI actively contribute to an intelligent energy system [48].

1.2. Energy Optimization in Buildings

Energy optimization plays a critical role in the building sector, being the main goal to minimize the energy consumption and energy costs of buildings while still providing comfort for the occupants [49]. Nowadays, energy optimization can have complex objectives, and the use of decision-making models and tools plays a crucial role. Operational research (OR) models and methods, such as multicriteria analysis (MCA), used to analyze possible alternatives and preferences and evaluate them under different criteria, and multi-objective optimization (MOO), which deals with optimizing solutions that satisfy multiple objectives, are effective in the energy sector for decision-making [50,51]. A system that considers technical, environmental, and economic factors is necessary for energy management, and the decisions should encompass sometimes conflicting objectives [52,53]. The importance of considering energy management is highlighted by A. Kumar et al. [54], and decision-making is critical when decisions have to be made based on several contradictory indicators [55].

In such a context, MCA involves evaluating multiple objectives and criteria to determine preferences among options in decision-making [56]. Despite MCA's strengths in structuring and framing complex issues, it has some weaknesses in achieving optimal decisions and solutions [57]. For instance, in numerous applications of MCA, the selection of objectives and criteria often neglects proper consideration of the geographical and temporal aspects of the analysis [58]. Furthermore, MCA-based methods do not provide the designer with information on how sensitive each criterion is to changes in the other criteria. The literature shows a gap between theory and practice in MCA's application [57]. MOO is important because it can model real-world problems with multiple conflicting objectives [59,60]. To address the various challenges in the building energy sector, energy optimization applying MOO is essential to meet users' needs while also reducing technical issues and energy usage in the building energy sector.

Currently, there is a lack of extensive and up-to-date survey investigation regarding MOO in the context of buildings and communities. This gap in extensive and up-to-date survey investigation can imply some points. First, it suggests that there might not be enough information available to fully understand the potential of MOO in optimizing communities of buildings. Without comprehensive surveys, it becomes difficult to identify the current state of implementation, challenges faced, and potential benefits of applying MOO in communities of buildings. Secondly, the lack of up-to-date investigations could indicate that advancements in technology, computational methods, or sustainability practices might not have been adequately incorporated into the studies. This hinders the development of innovative approaches and hampers progress in optimizing building communities. This study aims to partially fill this gap by conducting a more comprehensive review of MOO issues and their analysis within the building sector. The primary focus of this research is to examine the diverse objectives and constraints associated with optimization and explore the utilization of various methods and techniques employed in buildings. The ultimate objective is to present a broader understanding of the current state of MOO in the building sector and provide valuable insights that can guide future research endeavors.

The remainder of this paper is structured as follows. Section 2 provides an overview of the methodology used in the literature review. The methodology section outlines the specific keywords of the literature review, the databases used to gather information and the limitations that were encountered during the process. Section 3 presents a comprehensive examination of MOO problem analysis in the building sector. The section provides a review of MOO studies in the building sector since 2011, with a specific emphasis on the use of flexible energy sources and different optimization approaches, especially in the context of communities of buildings. Section 4 discusses the outcomes of the present work providing an overview and analysis of the key findings and insights on this topic. Moreover, the actual limitations of the literature are discussed, and a framework to guide forthcoming investigations is suggested. Finally, the conclusions of this study are presented in Section 5.

2. Materials and Methods

The method of content analysis [61] was employed in conducting this literature review. In this case, the method was used to examine a set of existing related articles and studies which are published in databases, such as Google Scholar, Scopus, and Mendeley. The search used keywords such as "multi-objective optimization", "energy optimization in buildings", "energy optimization in a community of buildings", "energy optimization in building societies", "building energy management systems", and "intelligent energy optimization methods in buildings". The article titles, abstracts, and contents were then skimmed to find the relevant articles. The selected articles were analyzed to find research gaps, solutions, and suggestions to address the mentioned gaps.

2.1. Research Objectives

To the best of our knowledge, a comprehensive review of recent research on optimization for buildings and communities, with a focus on MOO, is lacking. This study aims to partially fulfill this gap by providing a more in-depth review of MOO problems and their analysis in the building sector. This paper is focused on examining various objectives and constraints involved in MOO and exploring the application of several methods and techniques used in the energy optimization of the building(s). The main goal is to present a broader perspective on the state of the art of MOO in the building sector and provide insights to guide potential future research.

2.2. Limitations of Literature Review

To maintain a focus on more recent studies, the selection of articles for this study was limited to those published between 2011 and June 2023. This time frame was chosen because it represents the most recent works in the field and allows for an up-to-date and comprehensive review of the current state of the arts and best practices. The used keywords are another limitation, and in the future other keywords associated with new topics can be added. This article presents a narrative review of relevant articles, which means that a systematic perspective was not adopted. Moreover, the authors focused on exploring articles concerning multi-objective optimization and paid limited attention to single-objective optimization studies. Lastly, studies about another methodology in operations research, namely MCA, were excluded from consideration.

3. Results

Nowadays, it is essential to prioritize actions aimed at reducing energy costs and consumption, increasing efficiency, promoting sustainability, and preserving the environment. As a result, effective management and optimization of the energy sector play a crucial role in society. With the advancement of technology in the energy sector, the optimization scale has become more extensive and even more complex. In MOO, the need to satisfy multiple goals, sometimes conflicting, makes these problems more challenging to solve.

As previously mentioned, buildings are big energy consumers and one of the main reasons for greenhouse gas (GHG) emissions. For years, efforts have been made to reduce energy consumption in buildings to minimize the impacts of excessive energy consumption on the environment. In addition, energy cost reduction in buildings is an important issue that must be addressed. Therefore, various stakeholders, including researchers, policymakers, and industry professionals, are trying to reduce energy consumption by modeling, controlling, managing, and optimizing energy for non-RES and RES in buildings without compromising the comfort perceived by the users. In general, the articles in the field of energy optimization can be divided according to the method used, objectives, and/or scope (Figure 2).

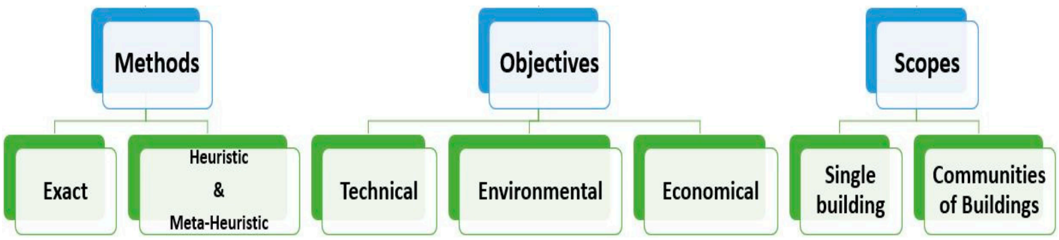

Figure 2. A brief overview of articles in the field of optimization.

3.1. Method-Based Analysis

Optimization involves finding solutions for problems where the goal is to minimize or/and maximize one or more objectives [62]. The problem must be defined and modeled with mathematical logic and expressions, then solved using the appropriate technique to obtain the optimal solution(s) [63,64]. However, finding the optimal solution may not be easily possible in some cases, requiring a high computational time which might not be acceptable in some contexts [65]. Approximate methods like ANN and heuristics can be employed in these situations, instead of using conventional methods, chosen according to the characteristics of the problems, such as linear programming (LP), Lagrangian relaxation, Nelder–Mead simplex, quadratic programming (QP), and gradient-based methods, among others [65].

Concerning MOO, the Pareto method generates dominated and non-dominated solutions via a continually updated algorithm, resulting in a compromise solution shown on a Pareto optimality chart [66]. The Pareto frontier represents a set of optimal points that can be used as solutions [67]. As all points are valid, the optimal solution is chosen based on the decision-maker's preferences [68]. Energy consumption optimization through the Pareto front was discussed in [69–71]. Another approach to deal with multiple and sometimes conflicting objectives is the scalarization method, which aggregates the multiple objectives into a single function using equal weights, rank order centroid weights, or rank sum weights being the solution of a scalar function [72]. In [73] a multi-objective mixed-binary linear programming is presented to minimize the electricity consumption cost, the electricity consumption from the power grid, and the peak load, considering the scheduling of the charging/discharging process for electric vehicles and battery energy storage system. As a result, the peak load and the total consumption cost of the residential building were reduced by 45.52% and 35.56%, respectively.

3.1.1. Exact Optimization

Exact algorithms can provide the best solution (or group of solutions) for optimization problems [74]. They can prove that the identified solution is the absolute best if the problem size is finite. These algorithms can provide a solution within a finite amount of time that may vary depending on the specific problem and can also show if there is no feasible solution for the given optimization problem [74].

Georgiou et al. [75] presented a review of convex optimization (CO) methods in real time to reduce the energy demand in buildings. LP, mixed-integer linear optimization or programming (MILP), QP, non-linear optimization or programming (NLP), and mixed-integer non-linear optimization or programming (MINLP) are the most popular CO methods to solve real-time energy management obstacles [75]. Concerning MINLP and MILP, one of the main differences is the use of nonlinear functions and constraints. Also, the processing time in the MINLP method is higher than MILP, and more processing power is required. A QP optimization technique is suitable for specific applications where quadratic functions are used. Among the mentioned techniques, MILP is the most popular because of its simplicity, convexity, and ability to control different variables (electrical appliances, ventilation and air conditioning (HVAC), thermal energy, and RES with ESS). It should be noted that in most cases, the accuracy of convex methods is higher than other optimization methods.

Georgiou et al. [76] aimed to minimize the power flow between one building and the grid using LP optimization, considering the use of a PV system and ESS along with a weighted sum approach. The results showed that the import and export of energy and the stored energy could be adjusted. Using the same optimization method and considering the PV system and ESS in a building, the optimal use of the produced PV energy was the objective [77]. In addition, maximizing the benefit by maximizing the self-consumption of generation, and using the energy stored in the ESS to feed the rest of the demand were important results of the study.

Applying MILP, Henggeler et al. [78] developed an automated energy decision model for buildings by considering the operation of shiftable, thermostatic, and interruptible loads under dynamic tariffs. The results show that consumers achieved high savings on energy costs. Similarly, Wang et al. [79] introduced an MILP for optimizing the dispatch of the ESS. The stochastic MILP model reduced the operational cost but needed more computational time compared to a deterministic DSM.

Using QP, Ref. [80] intended to optimally manage the microgrid's (MG) energy, which was equipped with ESSs, while ensuring the power reserve rate, peak power shaving, and improving optimization speed. Based on a similar method, a model was developed to minimize the operational costs of a system with PV and ESS and the impact of the voltage increment due to high PV exports on the distributed network, being applied in residential buildings [81]. The most important outcome was operational savings for most customers based on incentives for electricity generation and the minimization of the peak demand.

A collaborative DR approach for nZEB that utilizes NLP and building clustering was introduced [82]. The approach considers renewable energy generation, energy demand,

and energy storage and aims to improve dynamic pricing. The developed method was compared with a game-theory-based non-collaborative DR control. The results illustrated that electricity bills and peak energy exchanges were reduced by 45.2% and 18%, respectively, with remarkable computational demand reduction.

Based on MINLP, an optimized battery dispatch (charged only from the grid) was presented to manage the energy demand of several heat pump water heaters, considering local PV in a hotel [83], increasing the matching between local generation and demand. Similarly, MINLP, under several operating scenarios with real data, was used to develop a HEMS for improving the energy efficiency of conventional smart MG [84]. In addition to reducing costs, the model ensured the required comfort levels.

3.1.2. Heuristic and Meta-Heuristic Methods

Heuristic methods do not necessarily provide optimal solutions but can quickly provide satisfactory solutions to complex problems. Generalized heuristic algorithms are called meta-heuristics, employed for a wide range of problems, and require few rectifications to be adjusted to a particular case [85]. In general, some widely used meta-heuristic algorithms are Scatter Search [86], Genetic Algorithm (GA) [87], Evolutionary Algorithms (EA) [88], Memetic Algorithms [89,90], Path Relinking [91], Differential Evolution (DE) [92], Particle Swarm Optimization (PSO) [93], Ant Colony Optimization [94,95], Artificial Bee Colony Optimization [96] and Estimation of Distribution Algorithm.

GA is one of the most well-known used algorithms for optimization in the building sector. GA, proposed by Holland in 1992 [97], is classified in the meta-heuristic algorithms class based on the biological evolution process of the Darwinian theory [98]. Among the various building optimization methods, GA accounts for approximately 35% of the mentioned approaches [99]. In a comparative study, the MILP model and GA were compared to be embedded in a HEMS, considering dynamic tariffs to minimize the electricity cost [100]. Based on the obtained results, GA had a better performance for implementation in HEMS.

The thermodynamic behavior in buildings was also optimized by applying GA [101]. This optimization aimed at controlling the heating/cooling systems operation to minimize costs, considering renewable resources and hourly costs in the small MG. In another study, an algorithm was developed to maximize energy self-sufficiency [102]. Furthermore, the immediate environment factors, energy generation, and demand were predicted based on weather information and consumers' behaviors measured daily.

An integrated GA approach was presented in [103] to optimize all energy sources using real-time data and based on the optimization of three objectives (the consumption of external energy resources, the environmental impact, and the costs). Jean-Luc et al. [104] proposed a method based on GA to manage the interaction between local renewable energy production, power grid, and local ESS by considering users' habits and weather forecast data. The objective function includes costs, energy independence, and environmental criteria, simultaneously.

In [105], a building was optimized with Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to detect optimal solutions to renewable energy integration based on PV and battery storage. The overall goal was the minimization of life cycle costs (LCC) and carbon emissions by using MOO. Lu et al. developed a model [106] to optimally design renewable energy systems in buildings by integrating simplified air conditioning models to reduce GHG emissions, total costs, and the impact on the grid. In addition, a single-objective optimization approach based on GA and a MOO method based on NSGA-II was developed. The results show that the performance of the model has been evaluated as acceptable in order to reduce all three mentioned objectives.

Izadi et al. [107], investigated a hybrid renewable energy system (HRES) for zero-energy buildings (ZEB), in four different regions by applying neural network GA optimization, achieving a higher share of RES when combining renewable resources with hydrogen storage. Huang et al. [108] developed a model to analyze the effects of demand flexibility on solar-based distributed energy systems by applying NSGA-II to optimize the capacities of the mentioned energy system. Reducing annual costs was the achievement of research.

By considering life-cycle environmental effects, a multi-objective model was introduced to optimize HRES on a small scale [109], to reduce the environmental impact and minimize the costs. X. Wu et al. [110] developed a grid-connected integrated energy system by considering solar energy, geothermal energy, and heat storage. The MOO problem was applied for the coupling mode of heat energy, cold energy, and electric energy. The accomplishment of the research was the reduction of operational costs. Sala et al. [111] presented a multi-variable and multi-objective energy optimization model by considering the effects of local conditions based on EnergyPlus and NSGA-II. The objectives were the reduction of annual energy demand, the minimization of annual energy operating costs, and GHG emissions.

Applying Taguchi's method and GA, a model was proposed to optimize thermal and electrical efficiencies in a PV thermal water-based collector (PVT) [112,113]. In another study, a model was introduced to optimize the energy demand of buildings by employing GA and EnergyPlus to assess energy consumption, while using an ANN with a multi-layer perceptron model [114].

In addition to the optimization methods already mentioned, researchers have also been interested in exploring other algorithms and methods. Some of these will be discussed below.

Based on a multi-objective DE optimization methodology, electrical energy management was introduced in a residential building to implement an appliance scheduling routine to decrease electrical energy costs [115]. Applying a similar algorithm, a single-objective optimization aimed at keeping a net zero balance of energy for one year in a grid-connected PV system in a Net-ZEB was presented in [116].

Fayaz et al. [117], proposed a method aimed at supplying electricity to the home, based on PV generation and the priority of the loads, and ensuring the comfort level of the residents. The energy consumption was minimized, and the customers' welfare was managed based on a bat algorithm (an exploratory algorithm operated by simulation of a bat's echolocation behavior to optimize problems) and fuzzy logic in residential buildings. Similarly, using fuzzy logic [118], an energy management technique was presented to supply a home equipped with a PV system and connected to the grid. Applying the evolutionary neural fuzzy approach [119], an intelligent energy management system was also developed based on a hybrid soft-computing-based frame to minimize the energy demand.

Moreover, a real-time dynamic model was presented to integrate RES and an ESS to supply the electrical and thermal energy needed for the building [120]. The model predictive control (MPC) was used in a green building to satisfy environmental and economic objectives. MPC updated the system state and predicted the demand variations and power flows considering the impact of renewable sources. MPC was also used by [121] to reduce the consumption of cooling and heating loads in a building. A cost function was needed to set the benchmark output near the goal. With two various weight sets, the MPC efficiency was analyzed by tuning the controller and changing the cost function, achieving a 2% energy bill reduction.

Alzahrani et al. [122] formulated an online energy management system within the Lyapunov optimization technique (LOT) framework using convex optimization. The model possesses the advantages of both non-mandatory a priori knowledge of system inputs and low computational complexity. The developed model reduces energy costs and thermal discomfort. In [123], a hybrid algorithm based on Multi-Objective Particle Swarm Optimization (MOPSO) and NSGA-II to satisfy MOO was developed. Moreover, the technique for order preference by similarity to an ideal solution (TOPSIS) was utilized to identify a solution that strikes a balance between conflicting objectives in the optimization problem. Applying Harmony Search (HS) optimization, Ref. [124] focused on optimally designing standalone PVBES and PV/BES/diesel generator systems. The objective of it was twofold: to minimize the total annual cost while simultaneously maximizing the reliability of the system. As well, Khan et al. [125] also proposed a solution to the scheduling problem in a smart building using a hybrid algorithm called Bacterial Foraging Ant Colony Optimization (HB-ACO) which incorporated two pricing schemes, namely time of use and critical peak pricing. It is worth mentioning that HB-ACO combines the properties of both the Ant Colony Optimization (ACO) algorithm and the bacterial foraging optimization (BFO) algorithm.

3.2. Objective-Based Analysis

In recent years, the building sector has shown increasing interest in MOO due to its ability to help in the decision-making processes compared with approaches that achieve a single solution, while still offering the flexibility to select from a set of solutions [126]. In this sub-section, the studies carried out focusing on technical, environmental, and economic goals are reviewed.

3.2.1. Technical Objectives

Achieving technical objectives is a crucial MOO goal in the building sector. Due to the proven benefits of renewable energy, its use in buildings has recently received much more attention. Given that the generation of RES is affected by weather conditions, there can be an imbalance between renewable generation and demand. Therefore, the full integration of renewables into the system brings technical challenges [127]. One of the most crucial technical objectives is to maximize the balance between renewable energy generation and energy demand in buildings.

Applying static batteries and EVs improves balance and increases flexibility [128]. Therefore, optimal battery charging and discharging plans should be determined according to the conditions, which could be a technical aspect leading to electricity cost optimization. In addition, demand-side management (DSM) is another crucial technical aspect that has the potential to drive optimization [129]. In this case, the optimization includes rescheduling and reducing some of the loads to achieve the desired objective. In addition, energy use [130] and increasing residents' comfort, such as thermal comfort [131,132], are technical potential objectives.

Due to the importance of maximizing the balance between renewable energy production and demand, researchers have paid particular attention to this issue. Luthander et al. [133] reviewed articles about improving PV self-consumption focused on ES and DSM. Figure 3 illustrates the solar energy self-generation and load consumption in the building, which shows the high potential of ES, DSM, and cooperation in a community of buildings. If the generation is higher than the demand in the building, the surplus could be sold to the grid or in a community of buildings. Additionally, with the use of ES and DSM, adequate management strategies can be defined so that self-consumption is increased.

Vieira et al. [134] aimed to increase the matching between electrical generation and consumption profiles and reduce bill costs by using lithium-ion batteries in residential buildings with PV systems. It was found that, in most households, PV electricity generation during sunnier months can exceed household consumption, and there is a low matching between the peak demand and PV production.

Additionally, several studies, such as [135,136] examined various approaches to optimize energy management in buildings through PV systems, building energy storage systems (BESS), vehicle-to-home (V2H) cooperation, and load matching algorithms. In [135], stochastic programming optimized the cooperation between V2H and renewables aiming at minimizing costs through optimal regulation of all resources and an optimized EV charging–discharging pattern. Based on MILP and CPLEX solvers, the problem of matching local load with on-site PV generation, using a storage system and DR solutions to maximize PV utilization, was solved [136].

Kikusato et al. [137] presented a line drop compensator (LDC) method for managing EV charging and discharging based on a simulation model of the Japanese distribution system, intending to maximize the use of energy produced by the PV system. An EV charge–discharge management framework was introduced, to effectively utilize PV output by coordinating information exchange between the home energy management system (HEMS) and grid energy management system (GEMS). Finally, various energy-saving methods that use home-distributed photovoltaics (HDPV) and/or vehicle-to-grid (V2G) were studied in smart homes [138]. The study considered atmospheric conditions and the distance traveled by EVs, along with PV sub-systems. By utilizing corresponding power dispatching algorithms and cost–benefit models, the results demonstrated that transferring PV and valley electricity through V2H enhances the utilization rate of both valley electricity and PV, leading to significant economic advantages. Figure 4 shows a schematic representation of HDPV-V2H.

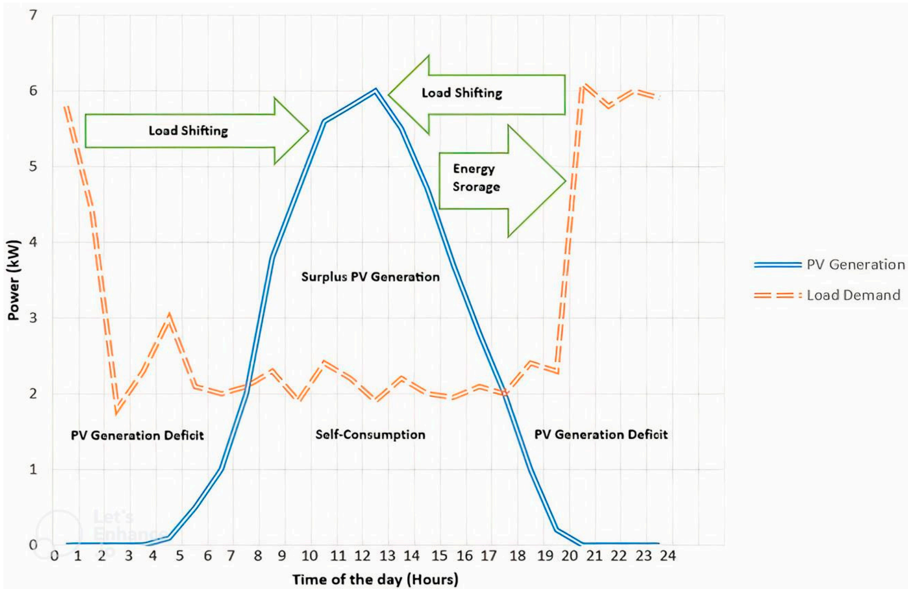

Figure 3. On-site PV generation and power consumption.

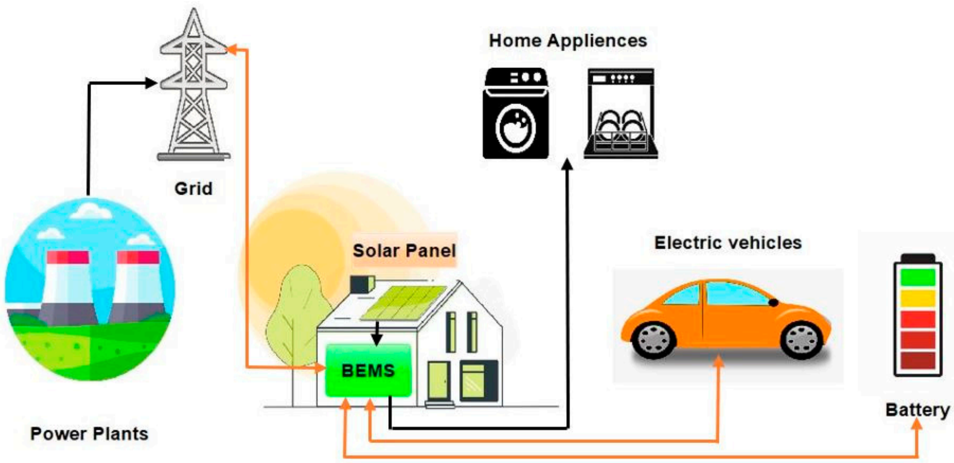

Figure 4. A schematic of HDPV-V2H.

Table 1 showcases various methods for matching renewable generation and demand in buildings, along with the results obtained from simulation studies, and future works proposed by the authors. It presents a comprehensive overview of diverse approaches employed for effectively matching renewable generation with the demand in buildings as one of the most important technical objectives to ensure optimal utilization and efficient utilization of available energy sources. These methodologies were evaluated through rigorous simulation studies, enabling the authors to gain valuable insights into their respective outcomes. The authors also provide future research directions and extensions to enhance the current methods.

Table 1. Renewable generation and demand matching in buildings at a glance.

Method(s)	Aim	Results	Ref.
• Dynamic models of the real systems • Maximum power point tracking (MPPT) models	• Matching between consumption and demand increase • Reduction of costs	• The energy injected and consumed from the grid is reduced by 76% and 78%, respectively • Energy bill reduction of 87.2%	[134]
Stochastic programming	• Daily operational cost minimization	• Significant cost reduction when operating all capacity resources • Cost increment when, wind energy, diesel generator, DR program, and V2H are not employed by 900%, 322%, 230%, and 84%	[135]
MILP	• Maximizing self-consumption	• Performance improvement • The load-matching index (LMI) improvements for the spring and summer were 18.05 and 33.51% by using storage • The LMI improvements for the spring and summer were 34 and 38.58% by using DR • The LMI improvements for the spring and summer were 46.05% and 53.7% by using storage and DR	[136]
LDC method	• Minimizing operation cost	• Operating cost reduction • PV restrictions reduction • The minimum utilized state of charge (SoC) range is 50.4% • The maximum utilized SoC range is 62.5%	[137]
• HDPV • V2H model • Cost–benefit	• Minimizing the net electricity costs	• Improvement of self-consumption with and without V2H on sunny, cloudy, and rainy days are 38%, 59%, and 53% • Reduction of net electricity cost only with V2H on short, mid and long-distance journeys by 29.8%, 26.3%, and 22.9%	[138]

3.2.2. Environmental Objectives

This section presents an evaluation of the importance of environmental concerns by analyzing various studies that employ different methods and algorithms. The analysis includes a review of several articles that have been published in recent years, mainly focused on the topics of life cycle assessment (LCA) and green building rating systems (GBRS).

As previously mentioned, due to the energy consumption in buildings worldwide, environmental objectives in the building sector hold critical significance [139]. Thus, improving energy efficiency in buildings is essential to achieve climate objectives [140]. A combination of various solutions might be utilized to meet environmental objectives, including efficient solutions for windows, insulation thickness, material types, thermal insulation, and RES [141,142]. The LCA method is a crucial tool for evaluating the potential environmental effect in the building sector [143]. LCA is a methodology to estimate and assess the environmental impacts related to a product's life cycle [144], which includes construction, operation and maintenance, and demolition, as reported by the International Organization for Standardization [145].

Considering weighted scalarization approaches to combine LCA and life-cycle environmental impact, a GA model was applied to optimize life-cycle environmental impacts [146]. Results demonstrated that GA has a good performance in locating the optimal region in the building. The drawback of weighted sum techniques is that only one solution is found from an optimization (for each weight set).

Based on EA and risk analysis, a MOO was developed to optimize a combined cooling, heating, and power system for full-load operation in urban areas [147]. The goal was transformed into a cost function to evaluate the environmental objective.

Due to climate change and environmental concerns, the building and construction sector's significance in addressing these issues has led to the emergence of the concept of net zero carbon building (NZCB), which intends to achieve zero emissions within the building sector [148]. Another systematic review gathered related research to assess how LCA is included at different phases of the building design and what improvements are essential to achieve NZCB [149]. Feng et al. [150] a review of the Whole Building Life Cycle Assessment, exploring its uncertainties and potential solutions. Additionally, the study proposed a conceptual framework outlining its typology, catering to LCA practitioners.

GBRS is another approach generally applied to analyze environmental impact assessment tools in the building sector. Generally, GBRS is based on a list of numerous quality standards. LCA has been incorporated as part of the evaluation system into some GBRS [151].

3.2.3. Economic Objectives

Satisfying economic objectives is another significant MOO goal in the building sector. From the end-users' perspective, the most crucial target is cost minimization, which considers investment and operating costs. In such a context, the life cycle cost (LCC) includes all the costs and revenues during the life of the buildings [152]. Hasan et al. [153] introduced a model to minimize LCC in a detached house, applying integrated optimization and simulation. Based on NSGA-II, an approach was implemented to optimize LCC and life cycle carbon footprint in a single building [154]. In another study, by applying a multi-objective GA, a model was introduced to optimize the costs and energy performance levels during the life cycle [155].

Furthermore, by considering net present value, studies [156,157] developed models for the LCC analysis. These papers presented MOO models for LCC analysis based on DE and NSGA-II, respectively. In addition, based on using NSGA-II and the mixture of grey correlation multi-level comprehensive evaluation, an optimization method was developed in which one of the most important objectives is the economic impacts [158].

Table 2 summarizes the analysis performed in this section based on LCC considerations, which includes details regarding the regions examined, the software employed for analysis purposes, and the specific algorithms utilized during the study. This approach ensures a well-informed assessment of the subject matter, fostering scientific rigor and enhancing the reliability of the results. The role of the regions in LCC is significant because it takes into consideration cost variations, regulations and standards, maintenance and repair factors, energy costs, and market demand in different regions.

Table 2. Life cycle cost analysis.

Region	Software/Algorithm	Results	Ref.
Finland	• IDA ICE 3.0 • GPSPSOCCHJ algorithm	A considerable reduction in the optimized house heating energy (23–49%)	[153]
	• Excel-based model • IDA ICE • MOBO • NSGA-II	The share of ECF is 28% of the life cycle carbon footprint, in the optimal cost	[154]
	• MATLAB • GA	• High exploration speed • The economic and environmental objectives do not necessarily contradict	[155]
South Africa	DE	The effectiveness of cost and energy efficiency in the developed the MOO model	[156]
Canada	• jEPlus + EA • NSGA-II	A remarkable amount of energy savings (33% annually).	[157]
China	• eQuest • NSGA-II	Achieving economic issues	[158]

3.3. Scope-Based Analysis

Studies on the building sector can focus on a single building or a community of buildings. Most studies have traditionally examined individual buildings neglecting the cooperation between buildings. The cooperation between buildings can enhance the performance at the community level by allowing a controller to share renewable generation surpluses and manage the combined use of flexibility resources. The International Energy Agency (IEA) launched the Energy in Buildings and Communities Program (EBC), Annex 67 [19], to explore "Energy Flexible Buildings", which refers to residential and non-residential buildings and clusters that can manage demand and self-generation based on weather, user needs, and grid provisions.

Most studies conducted for communities demonstrate the potential for enhancing diverse forms of flexibility to ensure multiple optimization objectives and their transformative impact on society. A community of renewable generation buildings can be managed based on the predicted demand [159]. Bucking et al. [159] introduced a method to optimize energy-saving trade-offs among buildings and regional energy systems to schedule energy. Heine et al. [160] analyzed the potential of cool thermal ES in a single building and a community of buildings. Applying MILP optimization, it was found that the total annual cooling energy costs can be reduced by 17.8%, after accounting for the cost of storage. Further, by applying GA, a hierarchical model for distributed static batteries in shared solar power building communities was developed [161], which can reduce the capacity of batteries and minimize energy losses in the sharing process. In the developed method, surplus generation and storage can be shared in the community of buildings.

Sun et al. [162] evaluated the performance of a Net-ZEB community utilizing conventional control strategies focusing on costs, grid interaction, and the matching between renewable generation and demand. Lopes, et al. [163] evaluated load-matching improvement using GA in a community of Net-ZEBs. The evaluation considered the mismatch between building generation and demand. In addition, multiple controllable energy-consuming devices, and higher generation of on-site renewables for enhanced load matching at the community level were considered. The findings indicated that Net-ZEBs can enhance the coverage of electrical demand through on-site electricity generation by up to 21% over a year. Additionally, the on-site generation utilized by the building can be increased by up to 15%.

Gao and Sun [164] suggested the utilization of a demand response control based on GA to reduce the peak demand of a group of buildings while ensuring energy management. The outcomes revealed that the proposed control had a better performance in limiting the peak demand of building groups and reducing additional energy consumption. Based on the elitist GA-based algorithm [165], an approach for managing EV charging with on-site PV generation was proposed. This approach involves a real-time, transactive energy system for managing EV charging that was integrated into the BEMS. The proposed model enables the BEMS to effectively schedule the exchange of electricity with the external grid, even in the case of uncertainty surrounding EV parking and PV generation. Figure 5 shows an overview of the interconnection of a Net-ZEBs community with the grid.

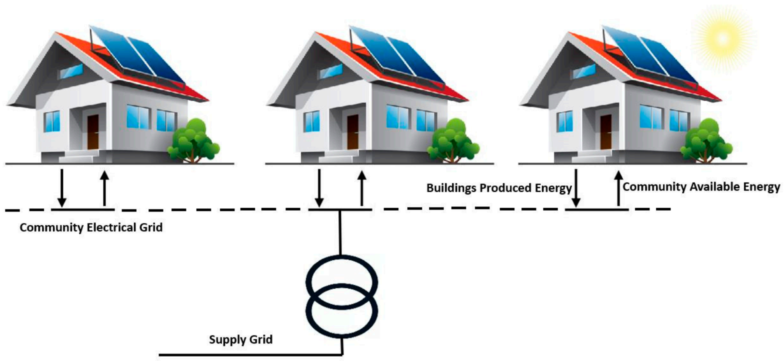

Figure 5. Overview of a Net-ZEBs community cooperation.

Additionally, an intelligent renewable generation and demand management system in a networked environment was developed [166], applying NSGA-II optimization and fuzzy controllers based on five objectives which were minimizing total power consumption cost, total power consumption expenses, micro smart grid loss of power supply probability, maximizing the amount of RES utilization, and end-users' welfare. By applying the integration of hydrogen storage, heat storage, and battery storage, Fan et al. [167] introduced a near-zero energy community energy system. An energy management approach was then developed using fuzzy logic to optimize the allocation of electricity between the hydrogen and battery storage systems, without neglecting the health status of each of the components.

Using the Gurobi optimizer, Soares et al. [168] developed a framework for energy storage optimization in a transactive energy community, located on a university campus. The proposed methodology aimed at minimizing the total costs from the community perspective by coordinating dedicated storage systems with renewable generation systems. According to the results, the community-level management of the energy systems provided greater technical and economic advantages. Similarly, on a university campus, Moura et al. [169] developed a model to address energy sharing in community microgrids by utilizing static batteries and EVs through a transactive energy market. The findings indicated that the proposed approach resulted in a rise in renewable self-consumption levels for both individual buildings and the community, along with a reduction in the overall electricity costs.

Likewise, a transactive control method for DR in commercial building heating, ventilation, and HVAC was proposed [170]. Results showed that this approach was extremely effective in reducing peak energy demand, and load shifting in commercial buildings. Moreover, Moura et al. [171] presented a method for effectively managing the sharing of renewable generation surplus among buildings, utilizing EVs as a flexible resource. The results of simulations demonstrate that the approach can lead to increased self-consumption of renewable energy both at the individual building and community levels while reducing the overall electricity costs.

Ouammi [172] focused on optimal management in a smart network of residential buildings using bidirectional communication and MPC (model predictive control) technique with a master controller to coordinate, manage and distribute power in the community. MPC schedules the building community's charging and discharging modes of static batteries, EV charging modes, power exchange, etc. In another study, an LCMA (Lyapunov-based cost minimization algorithm) was developed for the coordinated and decentralized optimization of flexible energy resources and intelligent appliances in smart buildings [173]. The algorithm's performance was improved by increasing battery capacity and if energy loads are mostly elastic.

Garcia et al. [174] used a simulation based on 3-year monitored historical PV data and a random demand model (based on Markov chains probability theory and Monte Carlo techniques) to predict the PV production and ES capacity at the community level, in order to maximize the matching between generation and demand. Wu et al. [175] tackled the obstacles of scheduling energy in office buildings with PV and workplace EV charging. Stochastic programming was employed to handle the uncertainties that come with EV charging demand.

Moreover, PV generation and electricity demand were analyzed for households and a community of buildings on a 15-min basis, compared to a single home using a data-based approach [176]. Further, Gupta et al. [177] looked at the energy flexibility and resilience gained from PV systems and batteries in a community of buildings. By aggregating PV and storage at a community level, the utilization of batteries resulted in an 8% reduction in peak grid electricity demand. Fachrizal et al. [178] developed intelligent charging schemes to minimize residential building load profile variability and specify optimal EV charging schedules through self-consumption enhancement and peak shaving.

As an essential result, it can be mentioned that in a community of buildings, centralizing charging is more efficient, and in [179] the overall energy costs were minimized by incorporating EVs (V2B and V2G), flexible loads, batteries, clean energy sources, bi-directional power flow, and an hourly pricing scheme based on MILP method. Henggeler et al. [180] introduced a modular set of MILP models to facilitate their integration into HEMS. These models enabled the integrated optimization of all energy resources, including exchanges with the grid, EVs, static batteries, load management, and local microgeneration. Similarly, a MILP optimization model was developed to evaluate multi-energy systems in a building's energy community, while taking into account the difference between investors and users [181]. In addition, using hourly consumption data for appliances, heating, and EVs, the optimal configuration and dispatch of the energy system can be determined. Similarly in [182], a collaborative decision model was proposed to optimize the flow of electricity between commercial buildings, EV charging stations, and the power grid, applying MILP and a two-stage stochastic programming model.

Additionally, customer satisfaction was maximized by planning energy consumption across households and appliances while protecting user data through a PL-Generalized Benders Algorithm (PL-GBA), which satisfies the property (P) and is L-dual adequate [183,184]. Based on game theory, demand-side loads were managed through a grid-connected MG method and community energy storage (CES)/PV systems [185]. The result was a Pareto-efficient Nash balance solution that allows residents to optimize energy trading. Using PV and ESSs in a community of buildings the objectives were the reduction of the consumption from the electrical grid and the increase in self-consumption [186]. The results showed that employing shared storage instead of individual storage increased the self-consumption ratio.

J. Sardi et al. [187] developed an integrated CES unit model for a building community with PV. They use three approaches to improve network performance: (1) determining the CES location to minimize energy loss, (2) identifying the right CES capacity to increase system load factor, and (3) flattening the daily load profile to improve the voltage profile using the center of gravity (COG) theory, load-following control, and a method to estimate optimal CES operational characteristics. The proposed framework considered both the probability of PV generation and load variations. The PV generation model uses a beta probability distribution function, and the model results are compared with exhaustive load flow results.

Ebrahimi and Abedini [188] conducted a study that involved various shiftable loads in the smart grid, such as residential, industrial, and commercial microgrids. The load shift technique was then formulated as a MOO problem to manage the consumption of shiftable loads in the smart grid. Simulations were performed using two methods, namely simplex and Improved Grey Wolf Optimization (IGWO), and the effects of implementation were compared. The CPLEX solver generally yielded better results than the IGWO in several cases. In [189], a zero-energy community was established through the effective utilization of hybrid renewable energy systems. To achieve flexibility and economic efficiency, a time-of-use grid penalty cost model was developed which evaluated both grid import and export during on-peak and off-peak periods. In another study, a sharing economic model was used to share both storage capacity and solar generation in a residential energy community [190]. Based on the results, substantial cost savings can be attained when compared to using these assets individually.

Table 3 provides a summary of various optimization techniques applied to an individual or a community of buildings, the applied flexibility resources, and results obtained from simulation studies.

Table 3. Multi-objective optimization in a building/a community of buildings at a glance.

Main Method	Other Methods	Scope	Aim	Ref.
GA	-	Single	• Minimizing costs • Minimizing net electricity consumption	[101]
			• Real-time energy generation and consumption optimization • Real-time storage optimization	[102]
			• Reduction of the environmental impact	[103]
			• External energy consumption optimization • Cost optimization • Ecological impact optimization	[104]
	NSGA-II		• Minimizing GHG emissions • Minimizing LCC	[105]
			• Minimization of total costs • Minimization of CO_2 emissions • Grid interaction	[106]
	ANN		• Reduction of dependency on the grid power • Reliability of the renewable system	[107]
	NSGA-II		• Economic performance • Technical performance • Environmental performance	[108]
	-		• Reduction of environmental impacts • Cost minimization	[109]
	NSGA-II		• Operation cost • Energic efficiency • Pollution gas emission penalty cost	[110]
			• Reduction of annual specific energy demand • Reduction of construction installation costs • Reduction of annual energy operating costs • Reduction of GHG emissions	[111]
	Taguchi's method		• Improvement of electrical efficiencies in PVT • Improvement of thermal efficiencies in PVT	[113]
	ANN	Community	• Energy consumption reduction • Energy cost reduction	[114]
	-		• Reducing the battery capacity • Reducing energy loss in the sharing process	[161]
			• Evaluate the performance of a group of Net-ZEBs • Economic cost reduction • Load matching	[162]
			• Load matching improvement in Net-ZEBs	[163]
			• Minimize the peak demand with energy efficiency	[164]
	Stochastic		• Developing real-time EV charging management	[165]
	NSGA-II		• Maximum user comfort • Maximum amount of renewable energy employment • Minimize total power consumption cost • Minimize total energy consumption at peak time • Minimize MSG loss of power supply probability	[166]

Table 3. *Cont.*

Main Method	Other Methods	Scope	Aim	Ref.
DE	-	Single	• Electrical energy cost saving • Minimum electrical energy discomfort • Minimization of carbon footprints	[115]
			• Achieve a net zero balance energy • Cost savings • Carbon footprint reduction	[116]
Fuzzy logic	Bat Algorithm		• Energy consumption reduction • Increase user comfort	[117]
	-		• Energy demand satisfaction by PV generation • User's comfort	[118]
			• Optimization of energy resources • Energy consumption reconciliation	[119]
	NSGA-II	Community	• Community energy system that combines electricity, hydrogen, and heat storage • Energy management of the stored energy	[167]
MPC	-	Single	• Dynamic optimization model	[120]
			• Consumption reduction • Cost reduction	[121]
		Community	• Controlling an interconnected network of smart residential buildings. • Scheduling and management of energy exchanges at the grid level	[172]
Transactive mechanisms	Gurobi		• Developing a framework for the optimization of energy storage	[168]
	-		• Addressing energy sharing through a transactive energy market	[169]
			• Developing a transactive control model to engage several HVAC subsystems • Developing a double-auction market structure and mechanism to coordinate them for DR	[170]
			• Developing a model to aggregate and manage the sharing of generation surplus	[171]
Stochastic Programming	LCMA		• Minimization of the total energy cost in a household •Minimization of the total energy cost in a neighborhood	[173]
	• Markov chains • Monte Carlo		• Evaluating the PV power • Evaluating storage capacity	[174]
CPLEX	• Stochastic Programming • ANN		• Reducing total costs	[175]
	IGWO		• Reducing the cost of customer bills • Reducing the peak load • Reducing losses • Improving network voltage	[188]
MILP	-		• Total energy procurement cost minimization	[179]
			• The integrated optimization of all energy resources	[180]
			• Developing a fundamental techno-economic model of optimal energy system configurations	[181]
	Stochastic programming		• Design an efficient collaborative scheme between the charging stations and commercial buildings	[182]
Other methods and algorithms	Convex in LOT framework	Single	• Total cost reduction • Thermal discomfort reduction • Batteries and EV charging/discharging optimization	[122]
	• MOPSO • NSGA-II • TOPSIS		• DSM to optimize the operation of appliances • Electricity bill minimization • User dissatisfaction minimization	[123]
	HS		• Development of an EMS for smart building electrification in remote areas • Minimizing the total annual cost • Maximizing the reliability of the system	[124]
	HB-ACO		• Shifting demand from on-peak to off-peak hours	[125]

Table 3. *Cont.*

Main Method	Other Methods	Scope	Aim	Ref.
	Clustering	Community	• Investigation of battery storage role in individual household and community level	[176]
	• Empirical • Socio-technical		• Evaluation of energy resilience achieved through the deployment of several solar PV systems and batteries	[177]
	• Distributed charging • Centralized charging • Quadratic programming		• Minimize the net load variability • Flatten the net load profile	[178]
	Generalized Benders		• Multi-residential electricity load scheduling • Maximize satisfaction levels of residences	[184]
	Game theory		• Energy trading management	[185]
	Shared grid connection		• Self-consumption • Integration of battery • Peak shaving	[186]
	• COG • Load following		• Minimizing energy loss, annually • Flattening the daily demand profile • Improving the voltage profile	[187]
	• TRNSYS • jEplus + EA		• Improving self-consumption • Improving load coverage • Grid penalty cost reductions	[189]
	Economy model		• Sharing solar generation and storage capacity by an economy model	[190]

Upon analyzing Table 3, it was concluded that 45.28% of the studies are focused on MOO within a single building, while 54.72% present MOO for communities of buildings. Upon analysis of the studies conducted in a single building, it was determined that GA was utilized as the primary method in 54.18% of the studies. Additionally, DE, MPC, and fuzzy logic accounted for 8.33%, 8.33%, and 12.5%, respectively. The remaining 16.66% of studies employed various other methods and algorithms, as presented in Figure 6.

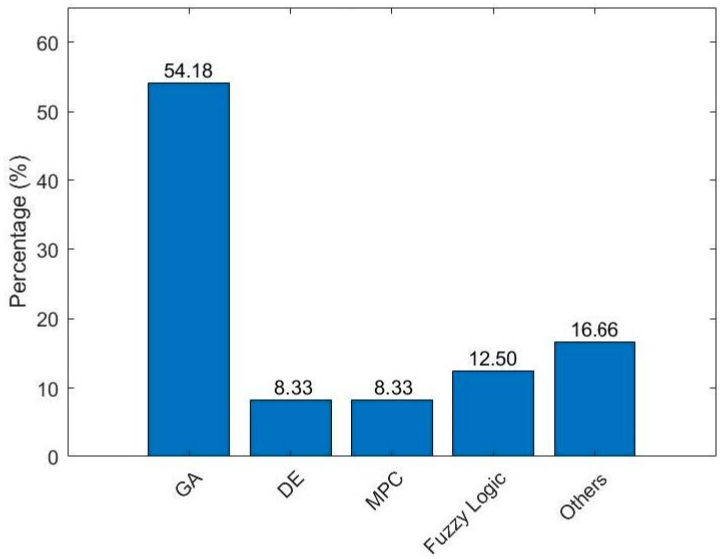

Figure 6. Algorithms and methods applied for MOO in single buildings.

An analysis was also conducted on the statistical data about the research conducted on building communities. In this case, the majority of the studies (20.69%) were also focused on GA. Meanwhile, MILP, transactive mechanisms, CPLEX, stochastic programming, MPC, and fuzzy logic accounted for 13.8%, 13.8%, 6.9%, 6.9%, 3.45%, and 3.45% of the studies, respectively. The remaining 31% of studies utilized other methods and algorithms, as presented in Figure 7.

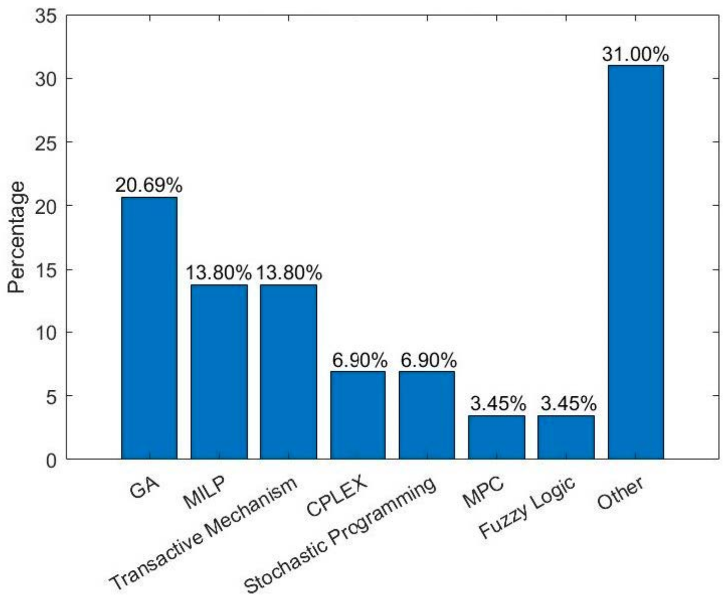

Figure 7. Algorithms and methods applied for MOO in a community of buildings.

Within the last decade, the world has faced a significant increase in the amount of available distributed energy resources [191]. In addition, a more decentralized and open energy market can be achieved because of the proliferation of prosumers [191]. Thus, the peer-to-peer (P2P) energy trading paradigm emerges, allowing consumers and prosumers to exchange energy without the need for a broker [191]. In addition, P2P energy trading seems essential for increasing system adaptability for the shift to low-carbon energy. As P2P energy trading is still a relatively new field, more research is needed to implement the real-world approach successfully [191].

In the building sector, P2P energy trading enables buildings to sell renewable generation surplus, such as PV, to other buildings within the same community. Energy producers and consumers can benefit from P2P by reducing losses and costs. Articles [192–196] are examples of research that has been conducted in this field.

In Table 4, various mechanisms of P2P energy trading, along with the challenges and results gained from the simulations, are illustrated. An effort was undertaken to explore the potential of communities of buildings that can efficiently share renewable energy surplus and energy resources. The table highlights the resources considered in the optimization process, which can include on-site renewable energy generation, integrated energy management systems, and energy storage technologies. The used techniques to provide flexibility are focused on the use of demand response and energy storage systems. Furthermore, the table outlines the results achieved from the simulation studies conducted for each optimization approach. These results demonstrate the improvements achieved in terms of energy consumption reduction, peak demand management, carbon footprint mitigation, cost savings, and overall building performance enhancement.

Table 4. P2P mechanism at a glance.

Method(s)	Limitations	Opportunities	Ref.
Two-stage stochastic programming	• The local market in the smart grid environments the proposed local market was only compatible with the smart grid. • Assuming full information exchange between all technological devices.	• P2P trade reduces bills by 20–30% • Battery storage reduces bills by 20–30% • P2P trade and battery reduce bills by 60%	[192]
Iterative double auction mechanism	• Does not consider other applicable business models.	• Balancing electricity supply and demand • Data security • Social well-being increment	[193]

Table 4. *Cont.*

Method(s)	Limitations	Opportunities	Ref.
Mixed methods approach	• Failure to evaluate the generalizability of the findings in larger experiments and different socio-economic contexts.	• Load-shifting • Self-consumption increase • DREs development	[194]
Canonical coalition game	• User participation in P2P trading under grid limitations such as voltage constraints. • The proposed coalition stability is affected by multiple P2P energy trading platform providers in the network that offer different pricing schemes.	• Cost saving to each prosumer • Consumer-centric property	[195]
Quadratic programming	• How the first optimization procedures are affected if some P2P market price information is available in advance. • Failure to take into consideration, other applicable business models.	• Reduction of EV charging effects on the power grid during peak hours. • Reduction of energy expenses up to 71%, daily	[196]

4. Discussion

The discussion section aims to provide the key findings on this topic. Based on the tables presented in the previous section(s), the outcome of this literature review on optimization in the building sector concerning flexible resources is expected to provide insights into state-of-the-art research in this field. By summarizing and analyzing the existing literature, researchers could identify the most effective methods and strategies for optimizing flexible resources in buildings and building communities and highlight key challenges and opportunities for future research. Hence, the outcomes of the study and research gaps in the literature are analyzed, aiming to pave the way for future research.

4.1. Outcomes

The reviewed studies demonstrate the significant potential for MOO in the building sector to reduce energy consumption, costs, and environmental impacts, in a context with PV generation, flexibility resources, and communities of buildings. Several potential outcomes include:

- Assessment of potential benefits of MOO in the building sector: There is a potential for MOO to improve the utilization of flexible resources in both single buildings and building communities, with a range of sources of flexibility identified as key areas for optimization. It is important to assess the potential benefits of these optimization strategies in terms of reducing energy costs, minimizing environmental impacts, and increasing the efficiency and resilience of energy systems in buildings.
- Identification of key challenges and opportunities for future research: This review also identifies the key challenges and uncertainties associated with MOO in the building sector, such as the need for accurate data, the complexity of the optimization process, and the potential trade-offs between different objectives. It is important to explore these challenges and suggest potential avenues for future research, such as exploring emerging technologies and market models, developing new optimization algorithms and methods, and integrating uncertainty and risk into the optimization process.

Overall, the paper reviews the potential of MOO in the building sector, considering PV generation, flexibility resources, and communities of buildings, highlighting the benefits of MOO, including reduced energy consumption, costs, and environmental impacts.

4.2. Gaps and Future Work

It was possible to identify challenges and opportunities for future research, including accurate data collection, optimization complexities, and integrating uncertainty, namely:

- Data availability: To conduct effective MOO, it is important to have access to accurate and comprehensive data on energy demand, PV generation, and other key factors. However, data availability can be a significant challenge in some communities, particularly in older buildings that may not have advanced monitoring, control, and data logger systems in place. More research is needed to explore how to effectively collect, analyze data, and fill in missing data in these contexts.

- Accurate forecasting: To implement the control of flexible resources, accurate forecasting of renewable energy generation and demand is crucial. The impact of weather conditions on renewable generation and of weather conditions and human behavior on energy demand is significant, and these factors are characterized by a high degree of uncertainty. Therefore, there is a clear need for further research to enhance prediction accuracy in these domains.
- Interoperability: As building communities become more complex, it will be important to ensure that different systems and technologies can work together effectively. This requires a focus on interoperability, or the ability of different systems to communicate and exchange information seamlessly. More research is needed to explore how to design and implement interoperable systems in these contexts.
- Scaling and replicability: While the implementation of communities of buildings has demonstrated potential in various contexts, scaling and replicating such initiatives in different communities can be challenging. Factors such as funding, regulatory frameworks, and community engagement can all impact the ability to successfully implement these approaches in new contexts. More research is needed to explore how to effectively scale and replicate successful energy communities with MOO.
- Long-term performance: While many building communities have shown promising results in the short term, it is important to understand how these systems will perform over the long term. Factors such as maintenance, system degradation, and changes in occupancy patterns can all impact the long-term performance of these systems. More research is needed to explore how to design and implement communities that are durable and sustainable over time.
- Health and well-being: It will also be important to understand how the implemented control options impact the health and well-being of residents within a community. MOO is a process of balancing multiple objectives, and as a result, the optimal solution cannot fully satisfy all goals. Therefore, it is crucial to give particular consideration to the well-being of occupants, including their visual and thermal comfort, as well as indoor air quality. Therefore, the well-being of occupants can be included as one of the objectives.
- Social and behavioral factors: While most of the research on the building sector with MOO has focused on technical aspects, most MOO studies typically overlook the influence of behaviors related to consuming energy and do not address the effectiveness of implementing initiatives. Future research could investigate how different communication strategies might be used to encourage residents to adopt the intended behaviors.
- Other aspects: Due to the relatively recent topic of the P2P mechanism and its high potential in the energy sector, sufficient studies have not been carried out in this field. Moreover, MOO in buildings has mostly been completed using GA and less attention has been paid to other algorithms and methods [99]. Therefore, future research can be more focused on the optimization of energy considering the potential of the community, paying more attention to the P2P mechanism, applying different and less used meta-heuristic optimization algorithms and methods, such as Teaching Learning Based Optimization Algorithm, Ant Colony Optimization, and Simulated Annealing, and comparing the results with those from GA. The importance of comparing the results with those from GA lies in their importance for validating the effectiveness and performance of the alternative optimization algorithms and methods being proposed. By comparing the outcomes obtained from different optimization techniques, researchers can gain insights into the strengths and weaknesses of each method. Comparisons help in assessing which algorithm performs better in specific scenarios, and how they fare concerning efficiency and accuracy. It allows researchers to understand whether the new approaches offer improvements over GA or if they need further refinement.

5. Conclusions

The building sector is known to be a significant contributor to energy consumption and GHG emissions, making it a crucial area for implementing measures to reduce its environmental impact. To address this problem, building communities can offer significant value in the transformation of the energy sector by enabling the deployment of distributed generation and embracing sustainable energy practices. In addition, the MOO approach can help to address the challenges faced by the building sector while meeting the needs of both the residents and the utilities.

To provide insights for future research, a study was conducted to comprehensively review the current state of MOO in the building sector. The primary focus of the study was to review the available works on building communities in the energy sector. By integrating building communities, consumers can pursue both their individual and collective economic, environmental, and technical goals while also contributing to the decarbonization of the energy sector. The reviewed articles were categorized based on their methods, objectives, and scopes using a content analysis approach.

The findings of the study indicate that MOO can provide a comprehensive framework for addressing energy flexibility, and environmental sustainability issues in the building sector. In addition, studies have been conducted on optimization methods like exact and meta-heuristic methods in individual buildings and building communities, considering renewable energy and flexible sources. The article reviews both the advantages and areas for future improvement and explores various technical objectives, such as balancing renewable generation and demand, environmental objectives, including LCA, as well as economic objectives, such as LCC.

Despite limited research in the community of buildings sector, there is great potential to maximize self-consumption, reduce costs, and decrease GHG emissions. Building communities can serve as a comprehensive framework for conducting multi-dimensional trade-off analyses of the mentioned benefits. Therefore, this article can provide valuable insights for community members, policymakers, utilities, and investors in making informed decisions regarding energy community development. The energy community concept presents a significant opportunity for energy researchers to delve deeper. Given the recent emergence of the P2P mechanism and its vast potential, there remains a dearth of research on the subject. Moreover, the application of GA in MOO for buildings has received greater attention. Future studies should thus concentrate on optimizing energy consumption while harnessing the potential of the community, with particular emphasis on exploring the P2P mechanism. In addition, utilizing a variety of lesser-known meta-heuristic optimization algorithms and methods, and comparing their results with those obtained using GA will also be insightful to comprehend the capabilities of various algorithms in particular scenarios. Furthermore, this comprehensive analysis also sheds light on the primary obstacles and uncertainties related to MOO within the building sector. These challenges encompass the indispensable requirement for precise data, intricacy in the optimization procedure, and the possibility of compromising conflicting objectives. Delving into these challenges is crucial to propose potential prospects for forthcoming research.

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