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Review

A Comprehensive Review of Sizing and Energy Management Strategies for Optimal Planning of Microgrids with PV and Other Renewable Integration

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Abstract: This article comprehensively reviews strategies for optimal microgrid planning, focusing on integrating renewable energy sources. The study explores heuristic, mathematical, and hybrid methods for microgrid sizing and optimization-based energy management approaches, addressing the need for detailed energy planning and seamless integration between these stages. Key findings emphasize the importance of optimal sizing to minimize costs and reduce carbon dioxide (CO_2) emissions while ensuring system reliability. In a pedagogical manner, this review highlights the integrated methodologies that simultaneously address sizing and energy management and the potential of emerging technologies, such as smart grids and electric vehicles, to enhance energy efficiency and sustainability. This study outlines the importance of accurate load modeling and carefully selecting models for renewable energy sources and energy storage systems, including degradation models, to achieve long-term operational efficiency and sustainability in microgrid design and operation. Future research should focus on developing multi-objective optimization techniques and incorporating cutting-edge technologies for improved microgrid planning and operation.

Keywords: microgrid; renewable energy integration; energy management; optimal sizing; hybrid methodologies; optimization algorithms; sustainability; smart grids

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1. Introduction

Microgrids (MGs) are distributed energy systems that can operate autonomously or be interconnected to the primary power grid, efficiently managing energy generation, storage, and consumption within a defined electrical community [1,2]. These local grids could integrate diverse distributed energy resources (DER), including photovoltaic (PV) systems, wind turbines (WTs), and small hydroelectric power plants. Integrating renewable energy sources is a crucial feature of microgrids, introducing specific challenges due to the intermittency of these sources [3,4]. A microgrid design typically considers minimizing the loss of power supply probability (LPSP) [5]. Furthermore, microgrids could integrate load-shedding schemes, where non-critical loads can be selectively disconnected when the demand exceeds the supply capacity [6,7]. Energy management is crucial in microgrid operation to meet energy demands appropriately. It refers to controlling and optimizing energy generation, storage, and consumption to meet the community's needs. Therefore, detailed and focused energy management, coupled with an adequate energy storage system (ESS), is critical to the successful operation of microgrids, especially in non-interconnected regions where reliability and autonomy are critical. Given the complexity and importance of these systems, it is essential to pay close attention to the design and operation of a microgrid. One of the primary stages in this process is energy planning, which includes selecting energy sources and sizing the sources chosen as a core step [8]. It also involves strategically configuring the microgrid components and balancing energy production and consumption to minimize initial investments, operating costs, maintenance, and replacement costs [9].

Microgrid energy planning has gained considerable attention in the scientific community and among power system stakeholders due to its potential beneficial impacts on efficiency, emissions, and carbon footprint reduction. It is a crucial element in the design of sustainable energy infrastructures [10]. Numerous strategies have been developed for microgrid energy planning, which is helpful but also needs to be clarified, as the variety of methods makes it difficult to determine a suitable method for each situation. The choice of energy planning methodology depends mainly on the design objectives and the specific needs being addressed. Complex methodologies could consider much information to provide exact results for particular cases. For example, Figure 1 presents a breakdown of the data used in [11] for the energy planning of a microgrid, where a detailed scan of a remote rural region was performed. The region was divided into small subareas; each matrix position represented the subarea's latitude and longitude location. The hypermatrix was composed of layers recording the characteristics of each point, such as the location of houses, terrain altitude, solar potential, wind potential, hydraulic potential, and ecologically protected zones. This information matrix was used to develop the energy planning of an isolated microgrid to power the houses enclosed in the study region. This type of study typically generates high-accuracy results. However, they entail a high degree complexity and require a lot of resources to survey the data and reach an optimal solution. The energy planning of a microgrid generally involves these steps: (i) the selection of energy sources, (ii) the sizing of these sources, and (iii) the definition of the energy management strategy. The level of detail in each phase might vary depending on the design objective [12]. Researchers have developed methodologies that combine these steps in different ways, either sequentially, simultaneously, or in a hybrid approach. Figure 2 shows the basic steps of microgrid energy planning and the order in which they could be addressed sequentially or simultaneously.

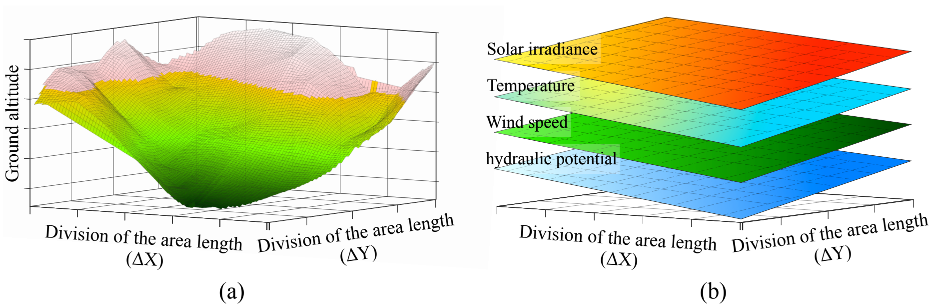

Figure 1. Overview of information processing in [11] for accurate energy planning of an isolated rural microgrid. (**a**) Division of the study region into subareas; (**b**) Layers recording the characteristics of the subareas.

Given the importance of guiding energy planning methodologies, several researchers have conducted reviews in this area. One aspect that has attracted the most attention is the definition of an energy management strategy (EMS), whether at the design or microgrid operation stage. For example, Liu et al. [13] developed a comprehensive review on energy management in microgrids with ESS. This review discusses recent advances in microgrid architecture, energy management models, solution methodologies, and future research directions. The microgrid architecture is classified into alternating current (AC), direct current (DC), hybrid AC/DC, and multi-energy microgrids. Each type is analyzed in terms of efficiency, flexibility, and resilience and their ability to integrate ESS and renewable sources. This research also evaluates different approaches to energy management in microgrids, including mathematical programming, adaptive dynamic programming, and deep reinforcement learning. It covers a wide range of ESS technologies, highlighting their crucial role in the reliable and stable operation of microgrids in grid-connected and islanded modes. It identifies gaps in problem formulation, especially in low carbon and resilience management applications, and suggests the need for more efficient computational solutions considering information security. It also highlights the need for further resilience management and information security research. In the same regard, Abdi [14] conducted a review of surveys of microgrid EMS. This review synthesized previous studies, providing an overview of the advances and challenges in microgrid energy management and examining different structures and schemes, including centralized, decentralized, and distributed approaches. It also reviewed optimization techniques used in energy management, such as mathematical programming, heuristic methods, and machine learning models. It also focused on the challenges of integrating renewable energy, cyber security, and microgrid control strategies. This review guides researchers interested in energy management in microgrids, covering aspects of power flow optimization, reliability assessment, and the application of advanced control techniques.

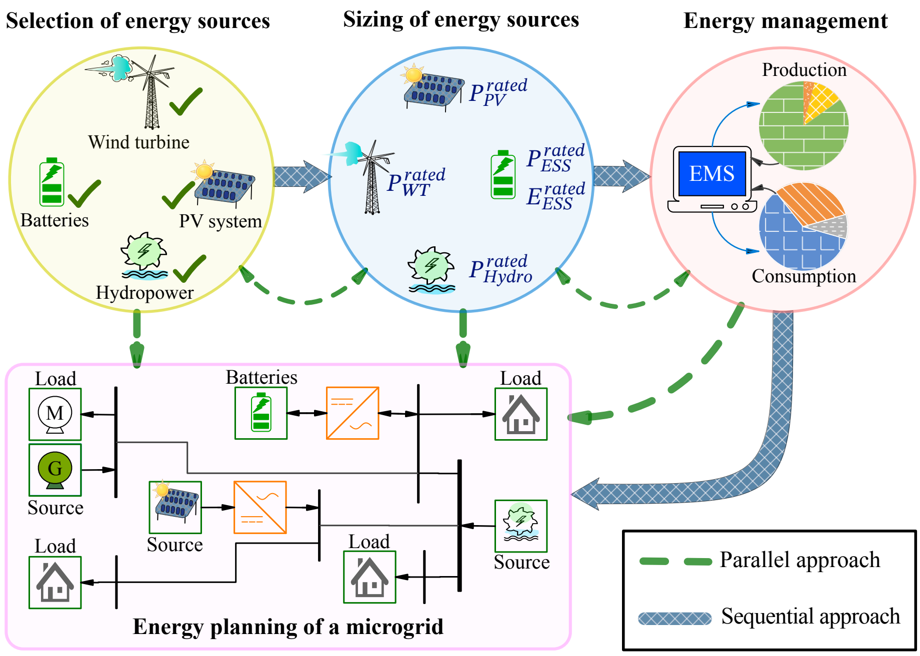

Figure 2. Basic steps in the energy planning of a microgrid.

Meanwhile, Shafiullah et al. [15] focused on analyzing the state-of-the-art of EMS for microgrids. This review covers a comprehensive analysis of EMS, applied optimization methods, and implementation challenges associated with microgrids in grid-connected systems. It discusses management strategies for a microgrid's main components, including charging, generation, and ESS. It reviews optimization approaches, such as classical, meta-heuristic, and artificial intelligence-based methods, to improve the operational efficiency of microgrids and reduce costs. This research also addresses the technical, social, economic, and regulatory challenges facing microgrids, highlighting the need for robust regulatory frameworks and policies that facilitate the effective integration of microgrids and deepen the operational efficiency, integration of renewable sources, and resilience of microgrids in future scenarios. Jirdehi et al. [2] conducted a comprehensive review on the management of microgrid components, network structures, operation modes, ESS, load types, problem modeling, resolution procedures, and other relevant aspects from the perspective of microgrid management. They highlighted the importance of optimized energy management and control methods for microgrid operation, addressing energy balance, cost optimization, and energy loss reduction. The review also analyzed the effect on the operation of generators, ESS, and loads, and addressed structural configurations of microgrids, such as AC, DC, and hybrid networks. It explored advanced mathematical modeling techniques and optimization methods, highlighting their application in managing and controlling microgrids under uncertainty and varying conditions. A particularly interesting aspect of this review is its focus on the statistical comparison of different methods and approaches used in microgrid management. This comparison provides a clear perspective on current developments and trends in the field, allowing researchers to identify critical areas for future research.

Similarly, Ahmad et al. [16] presented a comprehensive review of microgrids' energy management and control strategies. This review analyzed the methodologies and techniques employed for microgrid energy management and control optimization, focusing on recent advances and future challenges. It examined various optimization techniques, from mathematical methods to metaheuristic algorithms, used to maximize operational efficiency and minimize costs in microgrid energy management. It also reviewed real-time control strategies for maintaining system stability, including voltage, frequency, and power control in different microgrid operating scenarios. A distinctive aspect of this review is its focus on the connection between theory and practice. It discusses the influence of IEEE standards 1547 [17], 1547.3 [18], 1547.6 [19], and 2030 [20] on implementing management and control strategies in microgrids. Battula et al. [21] also developed an outstanding review on EMS approaches in microgrids, highlighting classical, heuristic, and intelligent methods to optimize operation and efficiency. They examined energy management methodologies, including classical mathematical programming, metaheuristic algorithms, and artificial intelligence-based techniques. Each approach was discussed in terms of its applicability and effectiveness in different microgrid scenarios. They delved into methods considering multiple objectives such as cost minimization, reliability improvement, and emission reduction, emphasizing the complexity of managing these factors simultaneously. The review also addressed the ancillary infrastructure needed, such as the Internet of Things and smart meters, to effectively implement management strategies in microgrids.

These outstanding reviews from the scientific community have pointed out the importance of energy management in microgrids. This compilation also reveals the importance of deepening the integration of the sizing and energy management stages and the definition of the objective function for microgrid energy planning. These stages could be integrated differently, giving rise to many variations in microgrid planning methodology. Addressing this concern, this paper develops a detailed review of the most relevant sizing and energy management strategies for microgrid energy planning and how these techniques could be integrated to address specific objectives. It is intended to guide readers on the energy planning strategy most appropriate for their needs and goals. The methodology employed for this review follows a structured approach to ensure comprehensive coverage of the literature. The primary focus was on the energy planning of microgrids integrating renewable energy sources (RES). The steps taken in this literature review were as follows: (i) Literature search. A thorough search of research articles was conducted using search terms such as "microgrid energy planning", "renewable integration in microgrids", "microgrid sizing methodologies", and "energy management in microgrids". (ii) Selection criteria. The articles selected for review were chosen based on their relevance to microgrid energy planning, specifically focusing on integrating RES, sizing methodologies, and energy management strategies. Only peer-reviewed articles, high-quality conference papers, and doctoral theses published in the last decade were considered. (iii) Identification of key methodologies. The main microgrid sizing and energy management methodologies were identified and categorized. This involved analyzing the approaches used in various studies and their effectiveness in addressing the challenges associated with microgrid planning. (iv) Comparison of sequential and simultaneous optimization. The review also contrasted methodologies that employ sequential optimization of sizing and energy management with those that utilize simultaneous optimization. This comparison aimed to highlight the advantages and disadvantages of each approach.

This review comprehensively analyzes sizing and energy management strategies tailored to microgrids integrating renewable energy sources. It addresses the gap in the literature by thoroughly comparing sequential and simultaneous optimization techniques, highlighting their effectiveness in balancing energy production, cost minimization, and system sustainability. Additionally, it discusses integrating emerging technologies, such as electric vehicles and smart grids, which present significant potential for enhancing microgrid efficiency. This study emphasizes methodologies and approaches that support decision-making in energy planning and management under varying conditions, including the intermittency of renewable sources and the complexities of non-interconnected regions. Furthermore, it is intended to serve as a pedagogical resource for researchers and practitioners new to microgrid planning, energy management, and sizing. This paper contributes, in a pedagogical manner, to the existing knowledge of microgrid energy planning; its key contributions are as follows:

- Comprehensive review: The paper thoroughly reviews the current methodologies for microgrid energy planning, highlighting the main strategies for both sizing and energy management.
- Methodological comparison: This paper compares sequential and simultaneous optimization approaches, providing insights into their benefits and challenges.
- Integration strategies: This study discusses various integration strategies for renewable energy sources within microgrids, emphasizing the importance of efficient energy management to address the intermittency of renewables.
- Practical guidance: By synthesizing the findings from numerous studies, this paper provides practical advice for researchers and practitioners on selecting the most appropriate energy planning strategy based on specific needs and objectives.

The remainder of this review paper is structured in the following sections: Section 2 remarks on the topology of microgrids, including isolated and interconnected systems, and their operational modes in AC and DC configurations. Section 3 reviews different methodologies for microgrid sizing, including heuristic, mathematical, and hybrid approaches. Section 4 explores various energy management approaches within microgrids, highlighting optimization-based methods and commercial software tools. Section 5 discusses optimization approaches in microgrids' sizing and energy management, and analyses their advantages and challenges. Lastly, Section 6 provides concluding remarks and insights on future work relating to this study.

2. Remarks on the Topology of Microgrid

A microgrid is a local energy system integrating distributed generation, energy storage, and controllable loads within a defined electrical network. Microgrids stand out among low-power generation systems for their ability to operate independently of the primary grid and manage the energy sources that comprise them. Typically, energy management integrates an algorithm to optimize operation [3]. These networks could be classified according to their connection and mode of operation. According to the connection, there are isolated and grid-connected microgrids. Isolated microgrids operate independently of a primary power grid, rendering them suitable for remote areas without access to conventional electrical infrastructure. On the other hand, grid-connected microgrids operate synchronously with a primary power grid, allowing the import and export of energy as needed [12,22]. Microgrids can operate in AC, DC, or a hybrid combination. AC microgrids are the most common due to their compatibility with existing electrical infrastructure and conventional devices. DC microgrids, although less common, are gaining popularity for specific applications. Hybrid configurations combine AC and DC, offering greater flexibility and efficiency by optimizing the operation of different types of loads and generation sources [23]. Microgrids, with their ability to manage generation intermittency, represent a promising solution for integrating RES. Their significant role in improving local energy efficiency offers feasibility for a more sustainable future.

Researchers have suggested categorizations for microgrids given the above scenarios. Figure 3 highlights some commonly used configurations, modes of operation, and applications in this field. The following sections address these classifications. Section 2.1 presents the alternative microgrid operation modes. Section 2.2 provides comments on integrating RES. Then, Section 2.3 focuses on microgrid applications. Finally, Section 2.4 provides a general framework for the cost of microgrids in planning.

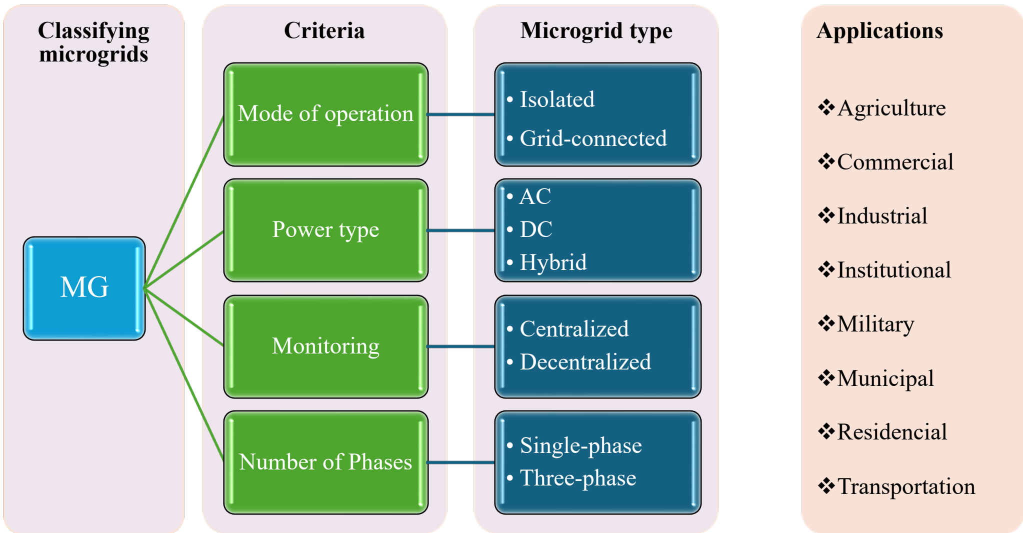

Figure 3. Standard classifications of microgrids in terms of operation.

2.1. Interconnection and Mode of Operation of Microgrids

The topology of a microgrid is essential for determining its efficiency, stability, and ability to integrate with other energy systems. Interconnection and operation mode influence the overall performance of a microgrid. Microgrids can operate in two modes: (i) grid-connected and (ii) isolated. In grid-connected mode, the microgrid is synchronized with the primary electrical grid, allowing bidirectional energy exchange [24,25]. This setup enhances system stability and demand management, as the primary grid can serve as a backup during fluctuations in local generation or demand. However, this mode requires a robust infrastructure and precise coordination to maintain frequency and voltage at the point of common coupling. The microgrid operates independently in isolated mode, crucial in remote areas or during emergencies. This mode presents additional challenges, such as balancing generation and consumption in real time. Integrating ESS, like batteries, is vital to managing the intermittency of renewable sources and ensuring a continuous energy supply [26].

On the other hand, most microgrids operate in AC due to compatibility with traditional electrical systems and the majority of electrical equipment that runs on AC. Once phase and frequency synchronization is maintained, AC microgrids can integrate various generation sources, such as diesel generators, WT, and PV systems [27]. DC microgrids are gaining popularity, especially in applications with critical energy efficiency, such as PV systems and battery storage. DC operation eliminates losses associated with AC-DC conversions, leading to higher energy efficiency. However, integrating with existing grid infrastructure and ensuring system protection pose significant challenges [28]. Hybrid mode combines the advantages of AC and DC systems within a single microgrid. This approach allows greater flexibility in managing diverse generation and storage sources. Hybrid microgrids can leverage the efficiency of DC systems for specific applications, such as electric vehicle charging, while maintaining compatibility with existing AC infrastructure [29]. Table 1 compares microgrids' operation modes and power supply types. It highlights key features, challenges, and typical applications associated with each mode, understanding their advantages and limitations.

Table 1. Operating modes and types of power supply for microgrids.

Feature	Grid-Connected Mode	Isolated Mode	AC Operation	DC Operation	Hybrid Operation (AC/DC)
Connectivity	Connected to the main grid.	Independent.	Compatible with traditional systems.	Efficient for specific systems.	Integration of AC and DC.
Flexibility	High, but depends on the main grid.	Limited by local capacity.	High for integrating diverse sources.	Limited by equipment and applications.	High, allows specific use of AC and DC.
Efficiency	Moderate, depends on grid.	Variable, depends on ESS.	Moderate due to conversion losses.	High, eliminates conversion losses.	High, optimizes based on source.
Challenges	Requires synchronization and stability.	Real-time generation and load management.	Frequency and phase synchronization.	System protection and conversion.	Integration and management of different standards.
Applications	Urban areas, grid support.	Remote areas, critical sites.	Traditional systems, existing infrastructure.	PV systems, batteries, EVs.	Modern infrastructure, mixed installations.

2.2. Integration of Renewable Energy Sources

Given the increasing focus on RES to achieve sustainability goals, their integration into microgrids should be emphasized. Understanding the challenges and benefits of different types of RES provides the basis for design strategies and optimization methods. This section explores the role of RES in microgrid systems, and the following sections discuss their impact on energy management. RES have been increasingly integrated worldwide in recent years due to their outstanding potential to mitigate climate change, improve energy security, promote economic development, create employment, and offer sustainable access to energy, especially in regions with limited access [30]. Leading RES institutions such as the Renewable Energy Policy Network for the 21st Century (REN21) [30], the International Energy Agency (IEA) [31], and the International Renewable Energy Agency (IRENA) [32] agree with the following definition: renewable energies are those obtained from natural sources that are continuously replenished and could be considered inexhaustible in the human time scale. Their environmental impact is considerably reduced compared to traditional fossil fuels. The following are examples of renewable energy which are detailed in the 2024 REN21 report [30]:

- Solar energy comes from solar radiation that can be converted into electricity or heat. It is one of the most abundant and accessible sources of renewable energy.
- Wind energy generated from the wind moves the blades of wind turbines to produce electricity. It is incredibly efficient in regions with strong and constant winds.
- Hydroelectric power harnesses water movement, generally in rivers or dams, to generate electricity. It is one of the most traditional forms of renewable energy.
- Geothermal energy originates from the natural heat of the Earth's interior. It can be used to generate electricity or for direct heating in geothermal areas.
- Biomass from organic materials such as wood, agricultural residues, and organic waste can generate energy through combustion or conversion into biofuels.

RES have been successfully integrated into microgrids for power generation through various approaches. Their integration is crucial in microgrid planning due to the increasing need for sustainability and carbon emission reduction. They offer significant advantages, such as availability and low environmental impact [33]. However, there are several challenges associated with these sources' intermittent and variable nature. Addressing these challenges requires optimizing the size and combination of these resources, balancing generation and demand, minimizing costs, and maximizing efficiency [34]. It could also involving generating the hybridization of AC and DC operation modes, involving several stages of power conversion, and making an indispensable EMS that guarantees the control of energy sources and the supply to the demand. Figure 4 shows an approach to the connection diagram of a microgrid integrating RES and power conversion stages. This diagram shows that microgrids with RES could also include controllable power sources, such as a diesel generator, to help ensure the reliability of the power system. This figure also outlines the AC and DC operation of a microgrid. Each side has a central operating bus. The DC bus interconnects sources and loads of a DC nature, even allowing the connection of an electric vehicle (EV) as a flexible load. The AC side interconnects traditional AC loads and is interconnected with the local AC power network. A bi-directional DC/AC converter interconnects the DC and AC sides. The following section discusses general applications of microgrids.

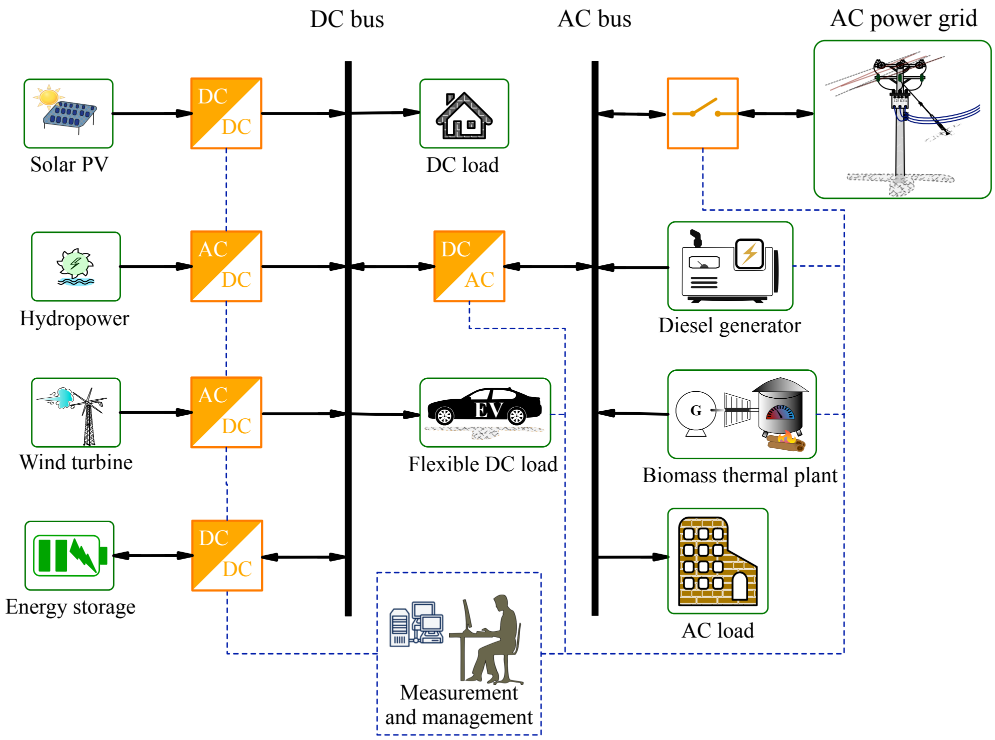

Figure 4. Schematic of a microgrid with renewable energy integration.

2.3. Microgrid Applications

Microgrid applications are diverse, with the most common being rural electrification in remote areas, industrial facilities requiring efficient energy management and resilience, military installations seeking energy independence and security, and urban or commercial environments benefiting from increased energy reliability. They can be implemented in various configurations, isolated from or connected to the main power grid, to address each sector's specific needs and challenges [35]. In rural areas, microgrids provide a viable solution for electrification, reducing dependence on fossil fuels and improving the quality of life. Operating in isolated mode is particularly useful in these areas, where the central grid infrastructure may need to be improved or non-existent [11]. In the industrial sector, microgrids enable more efficient energy management and the integration of DER. By reducing operational costs and enhancing the resilience of the facility's energy system, microgrids contribute significantly to overall efficiency [36]. Microgrids also have applications in the military sector, where energy independence and security are priorities. Operating autonomously and ensuring a continuous energy supply in emergencies is crucial.

The following are outstanding examples of the practical implementation of optimal microgrid planning, which also present challenges inherent to their specific environments. First, the study in [11] describes using an particle swarm optimization (PSO) algorithm for energy planning of an isolated microgrid in Colombia. This system is designed to supply energy to a remote population of seven houses in a region with difficult access and high resource transportation costs. The optimization strategy focused on taking advantage of local natural resources, mainly due to the limited availability of conventional energy sources and logistical difficulties for regular supply. This application illustrates how geographic and access particularities can condition design decisions in microgrid planning, focusing on sustainability and energy autonomy.

On the other hand, the Gorona del Viento project on the island of El Hierro, Spain, implements a hybrid renewable energy system that combines wind energy with pumped hydroelectric storage. This project has enabled the island to operate nearly self-sufficiently, significantly reducing its dependence on traditional diesel generators. The system design takes advantage of the island's topography, using the La Caldera crater as an upper reservoir for water storage, which facilitates the accumulation of energy during periods of high wind production. However, challenges were faced during implementation, mainly due to the limited storage capacity of the reservoir, which resulted in reduced grid stability during periods of low wind speed [37]. This case highlights the importance of adapting system components to the geological and climatic characteristics of the site and how the combination of energy sources and storage strategies can help mitigate the intermittency of renewable sources.

These examples highlight how the selection of optimization strategies and microgrid configuration can vary according to the local context and available resources, impacting both costs and carbon emission reductions. Table 2 provides an overview of microgrid applications across different sectors.

Table 2. Applications of microgrids in some sectors.

Sector	Applications	Benefits
Rural	Electrification of remote areas.	Reduces dependence on fossil fuels, improves quality of life.
Industrial	Efficient energy management, integration of DER.	Reduces operational costs, increases energy efficiency.
Military	Energy independence, security.	Reliable operation in critical situations, risk reduction.

The topology of microgrids is essential for their efficiency, stability, and sustainability, especially when integrating renewable sources. The choice of operation mode and electrical configuration influences a microgrid's flexibility and technical feasibility and adaptation to various applications, from rural areas to industrial and military environments. The following sections discuss sizing methodologies Moreover, exploring energy management strategies that optimize microgrid operation provides a comprehensive analysis of tools in microgrid energy planning. Optimizing the sizing and operation of microgrids in various applications requires considering the characteristics of each environment and sector, along with the relevant indicators for energy source selection. Further analysis of these factors, including optimal resource use, system resilience, and constraints tailored to different operating conditions, refines energy planning. Grid-interconnected microgrids, for example, improve system resilience and flexibility with star, ring, or mesh configurations, enabling power sharing and improving the reliability of critical loads [38,39].

In remote or resource-constrained environments, measures such as "mass per unit load" (MPUL) provide an indicator of efficiency by assessing system mass relative to power demand, making this measure applicable in regions with high transportation and installation costs [40]. Adequate microgrid protection relies on adaptive strategies, such as directional overcurrent relays and coordinated algorithms, to maintain stability amid fluctuating loads and bidirectional power flows [38]. Advanced battery degradation models further aid in selecting durable energy storage options and optimizing system lifetime under harsh conditions [40]. This planning approach, which integrates adaptive architectures, efficient resource use, and robust protection strategies, improves the performance of microgrids in various application scenarios.

2.4. Cost Framework in Microgrid Energy Planning

Defining the cost function is crucial in microgrid energy planning as it guides the objectives influencing the microgrid's sizing and energy management. Researchers commonly employ indicators such as the levelized cost of energy (LCOE) and the levelized carbon emission (LCE), which provide insight into the cost per unit of energy generated and the environmental impact per unit of energy generated. These objectives are typically tailored to each case [41]. From a general perspective, it is often more practical to calculate the annualized cost of a microgrid C_{annual} during the planning phase [11]. This section focuses on that approach, with (1) detailing C_{annual}.

$$C_{annual} = CRF \cdot C_{total} \tag{1}$$

Here, CRF is a capital recovery factor, and C_{total} is the total cost over the project lifetime. CRF is a financial metric used to determine the annual capital cost from the project lifetime cost [42]. CRF and C_{total} are outlined in (2) and (3), respectively.

$$CRF = \frac{d \cdot (1+d)^Q}{(1+d)^Q - 1} \tag{2}$$

$$C_{total} = C_{inv} + C_{O\&M} + C_{rep} + C_{EG} - C_{sv} + C_{special} \tag{3}$$

Here, d is the annual rate of return, and Q is the project's lifetime. C_{inv}, $C_{O\&M}$, C_{rep}, C_{EG}, and C_{sv} are the investment, maintenance, replacement, grid, and salvage value costs, respectively, which are calculated in (3)–(7). $C_{special}$ encompasses special costs such as component degradation, transport in difficult-to-access areas, and other specific factors depending on the case under study.

$$C_{inv} = \sum_{k=1}^{K} C_{inv}^k \cdot N^k + C_{dep} \tag{4}$$

$$C_{O\&M} = \sum_{k=1}^{K} C_{O\&M}^k \cdot N^k \cdot \sum_{q=1}^{Q} \left(\frac{1+\varepsilon}{1+d}\right)^q \tag{5}$$

$$C_{rep} = \sum_{k=1}^{K} C_{rep}^k \cdot N^k \cdot \sum_{r=1}^{NOR} \left(\frac{1+\varepsilon}{1+d}\right)^r \tag{6}$$

$$C_{EG} = \left(C_{sub} - \Delta t \cdot \sum_{t_0}^{t_f} \left(p_{EG}^s(t) \cdot \lambda^s(t) + p_{EG}^{in}(t) \cdot \lambda^{in}\right)\right) \cdot \sum_{q=1}^{Q} \left(\frac{1+\varepsilon}{1+d}\right)^q \tag{7}$$

Here, N^k is the total number of the k-th microgrid component, and k is the index representing the k-th microgrid component. C_{inv}^k and C_{dep} are the k-th component investment and the deployment cost, respectively. The microgrid deployment cost includes installing the microgrid components such as wiring, concrete, steel, wood, and electrical connections, along with labor and indirect costs associated with the microgrid installation. $C_{O\&M}^k$ is the operation and maintenance cos for the k-th component; ε is the escalation rate; and C_{rep}^k is the replacement cost. NOR is the number of r-th component replacements over the project lifetime, and q and r are the year and replacement indices, respectively. λ^s and λ^{in} are the grid tariffs for power supply when buying from the grid and injection selling to the grid, respectively. Finally, C_{sub} represents a fixed subscription cost for the power grid, a fixed annual fee imposed by electrical energy provider companies [42]. The salvage cost C_{sv} is considered a cost in favor of the installed capacity of renewable energy. It is generally determined as a percentage of the acquisition cost [41].

3. Microgrid Sizing Approaches

The sizing of microgrids is a complex optimization problem that is typically addressed through a variety of methodologies, as illustrated in Figure 5. These methodologies include commercial software such as HOMER and DER-CAM, heuristic algorithms such as genetic algorithms (GA), PSO, mathematical programming techniques such as mixed integer linear program (MILP), quadratic programming (QP), and hybrid approaches combining the strengths of different methods such as JAYA and GWO, and Simulated Annealing and Tabu

Search. These methodologies are selected for their efficiency in exploring and exploiting the solution space. They balance the trade-offs between computational time, accuracy, and the challenges of handling the multi-dimensional and multi-objective aspects of microgrid sizing. The selection of a specific approach over others depends on the requirements of the microgrid project, including but not limited to cost minimization, reliability maximization, and environmental impact reduction. The advantages and disadvantages of each approach are presented in Table 3, and the following sections address them in detail.

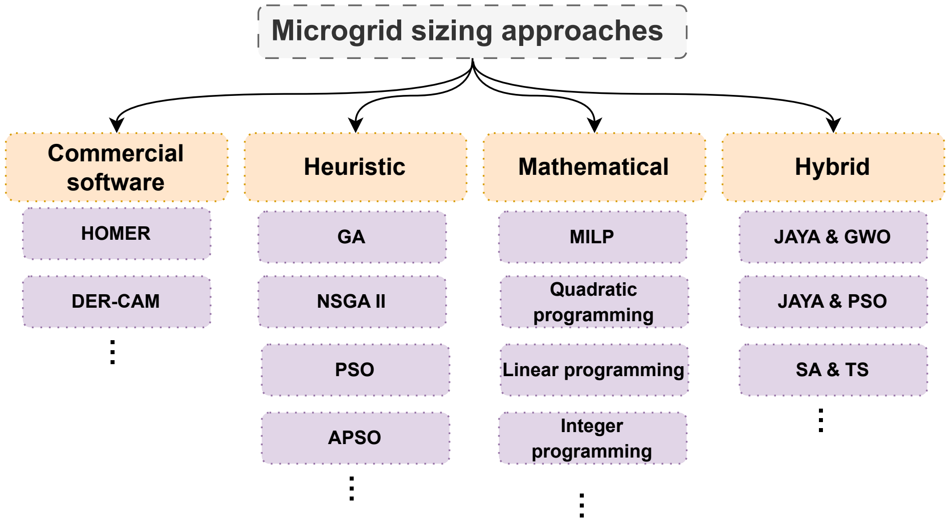

Figure 5. Microgrid sizing approaches.

Table 3. Advantages and disadvantages of each microgrid sizing approach.

Approach	Advantages	Disadvantages
Commercial software (HOMER)	User-friendly graphical interface, updated to the latest technologies and improvements.	Lacks support for multi-objective problems, does not accommodate intra-hour variability. Additionally, it exhibits extended computational times for intricate problem scenarios.
Heuristic	Heuristic algorithms efficiently address complex optimization problems, including sizing problems within a reduced computation time. Moreover, they can handle non-linear equations.	It does not guarantee a global optimum and may get stuck in a local optimum. Additionally, each algorithm has specific parameters that require expert knowledge to be adjusted properly, preventing high computation time and infeasible solutions.
Mathematical	An effective technique to ensure a global optimal solution in the search space.	It cannot solve complex optimization problems due to the substantial computation time, thereby limiting server capabilities. Additionally, it has limitations in handling stochastic environments and is unsuitable for highly complex and non-linear problems.
Hybrid	It converges faster than heuristic methods and takes advantage of each algorithm used. This approach typically addresses multi-dimensional optimization problems	Coordinating the tuning of parameters for each heuristic algorithm poses a challenge. There is also a risk of becoming trapped in a local optimum.

3.1. Commercial Software

Commercial software tools play a crucial role in the optimal sizing of microgrids, with the Optimization Model for Electric Renewables (HOMER) standing out as a particularly prominent example. Developed by the National Renewable Energy Laboratory in the United States, HOMER is distinguished by its comprehensive economic evaluation capabilities. Alongside HOMER, there are several other notable tools, including the Hybrid Power System Simulation Model (HYBRID2) by the Renewable Energy Research Laboratory, the General Algebraic Modeling System (GAMS), and the Optimization of Renewable Intermittent Energies with Hydrogen for Autonomous Electrification (ORIENTE), among others. These tools offer diverse approaches and functionalities for sizing microgrids, highlighting their applicability as rich resources for researchers and practitioners.

HOMER software is essential in designing and economically evaluating microgrids, whether or not they are connected to the power grid. It operates through a three-phase simulation, optimization, and sensitivity analysis process. This process utilizes weather data, demand forecasting, and economic and technical considerations, among other inputs, to help identify the optimal sizes of DER for achieving the minimum overall net present value (NPV). This optimization strategy is crucial for designing and evaluating sustainable and efficient energy systems. A notable application of HOMER is in optimizing PV-fuel cells (FCs) microgrids, as discussed in [43]. The study aimed to enhance system efficiency and sustainability through the optimal integration of DER, FCs, and ESSs. The results demonstrated the potential of the proposed microgrid configuration to reduce reliance on conventional energy sources. This configuration also showcased significant improvements in energy management and a reduction in the overall system cost. Similarly, the study in [5] employed HOMER to optimize a microgrid configuration consisting of PV panels, WT, and battery energy storage system (BESS). The optimization focused on minimizing the microgrid's NPV. The system's reliability was also assessed through a sensitivity analysis on the LPSP for evaluating the impact of variations in the microgrid's size and cost.

Research in [44] explored integrating and optimizing multi-microgrids utilizing HOMER Grid software in Goma, DRC. Considering technical and economic aspects, the objective was to minimize the NPV over a 12.5-year horizon. The study highlighted the feasibility of a system configuration without PV, which achieved nearly the same NPV with a significantly lower initial capital cost, albeit with higher operational and maintenance expenses affecting the levelized cost of energy (LCOE). Furthermore, the study in [45] utilized HOMER to determine the optimal configurations for PV/Diesel/Pump-hydro and PV/Diesel/BESS systems. This study emphasized calculating payback periods while identifying cost-effective solutions for energy systems. The study in [46] developed a techno-economic methodology for the development of a standalone, renewable energy-based electric vehicle charging station (EVCS) in Qatar by employing HOMER for optimization. The aim was to minimize installation and lifetime operating costs among all technically feasible configurations that met the daily EVCS demand. The optimal configuration's NPV was found to range between $2.53 M to $2.92 M, with electricity costs varying from $0.285 to $0.329 per kWh. In Vietnam, the optimization of EVCS in major cities was the focus of [47], using HOMER Grid for analysis. The study aimed to reduce NPV and enhance efficiency by considering local solar conditions and economic factors. It proposed optimal system configurations for Hanoi, Da Nang, and Ho Chi Minh City, highlighting the impact of solar irradiation on investment and operational performance.

Additionally, the study in [48] optimized an isolated microgrid for rural electrification in India using GA and HOMER. The study aimed to minimize the NPV and the LCOE by comparing various hybrid configurations. The GA optimization yielded an optimal solution with the lowest LCOE at $0.163 per kWh. The potential of DER in off-grid microgrid optimization was explored in [49] using MILP and HOMER. The study aimed to minimize the NPV while highlighting significant cost savings and efficiency improvements from implementing DER. Lastly, HOMER Pro, an advanced version of HOMER [50], was used in [51] for optimizing hybrid microgrids for green hydrogen production in Fiji. The study focused on achieving the most cost-effective configuration for hydrogen production, critical for powering fuel cell buses, aiming to minimize the NPV. The economic viability of microgrids across various geographic locations and with different DER combinations has been assessed using HOMER software. Notably, analyses have been conducted on a PV-WT-hydro-biodiesel hybrid system in India [52], a PV-WT-diesel system in Sri Lanka [53], and a WT-biogas hybrid system in Canada [54].

These studies highlight the adaptability and effectiveness of HOMER in optimizing microgrid configurations to improve sustainability, cost-efficiency, and energy reliability. The advantages of HOMER software include:

- User-friendly interface;
- Comprehensive financial analysis capabilities, including cash flow analysis and payback period calculations;
- Integration capability with Geographic Information Systems for enhanced project planning and site selection;
- Advanced sensitivity analysis to evaluate the impact of variable parameters on project outcomes;
- The ability to process hourly data for detailed and accurate modeling of energy systems.

However, HOMER also has certain limitations:

- Utilizes a "black box" approach to its code, which can limit transparency and customizability;
- Lacks the functionality to formulate multi-objective optimization problems, which limits its applicability in scenarios requiring the balancing of multiple goals;
- Does not account for intra-hour variability, which could affect the accuracy of simulations for systems sensitive to short-term fluctuations;
- It omits the consideration of the DoD BESS, potentially overlooking an important factor in the lifespan and efficiency of ESS, suggesting a need for a more customized and detailed battery degradation model.

3.2. Heuristic Approaches

In the domain of heuristic optimization for microgrid configurations, several studies have employed a variety of algorithms to optimize their design and operational efficiencies. For instance, the work in [41] demonstrated the use of GA to size both grid-connected and isolated microgrids, aiming to optimize the LCOE with configurations including PV panels and BESS. In a similar study presented in [55], GA was applied to optimize a microgrid comprising PV, WT, BESS, and loads. The primary objectives of this optimization were to minimize greenhouse gas emissions, reduce the life cycle cost (LCC), and decrease non-renewable energy consumption. Further research [56] explored multiple microgrid configurations to find a balance between factors such as greenhouse gas emissions versus global cost and microgrid autonomy versus global cost. The study in [57] targeted the sizing of an autonomous AC microgrid to minimize energy and installation costs while enhancing reliability by reducing the LPSP. In addition, ref. [58] aimed at reducing energy and installation costs and maximizing reliability through GA for determining the capacity of BESS, PV, and other components. Lastly, the research presented in [59] discussed integrating life cycle analysis into the hybrid microgrid design process to optimize design and minimize environmental impact while ensuring technical and economic feasibility. The study in [39] critically evaluated a range of metaheuristic algorithms for reducing the NPV of a microgrid system that incorporates residential, commercial, and EV loads, in addition to PV panels, WTs, and BESS. Among these algorithms, the Moth-Flame optimization algorithm stood out for its superior performance, while the Equilibrium optimizer was noted for its relatively lower efficiency. Another study [60] applied the Multi-Objective PSO technique to size the microgrid to minimize the dependency on non-renewable energy imports and the system's annualized cost. The outcomes were illustrated via a Pareto front by highlighting the trade-offs between the two objectives. Furthermore, in [61], a two-step methodology was employed for the optimization and analysis of a standalone hybrid system consisting of PV, WT, BESS, and a diesel generator, which was specifically designed to fulfill the electricity demands of a remote village, Fanisau, in northern Nigeria. This approach, executed in the MATLAB (Version 9.3) environment using a GA solver, aimed to efficiently and economically cater to the unique energy needs of the region. The optimized hybrid renewable energy system proposed for Fanisau included 273 PV modules, 148 batteries, and a 100.31-W diesel generator, capable of producing 200,792 kWh annually at a total annualized cost of $43,807 USD with a cost of energy $0.25 USD/kWh. In [62], the study applies the Non-Dominated Sorting GA II (NSGA-II) for microgrid sizing, aiming to minimize annualized costs, emissions, and energy imports from the electrical grid. The study elucidates optimal configurations via the Pareto front and employs the Topsis method for decision analysis. The study in [63] outlines the development of a hybrid renewable energy system optimization using the PSO algorithm-based Monte Carlo simulation to minimize total annual costs, accounting for resource and load uncertainties. It focuses on microgrid components such as WT, PV panels, and BESS. The findings demonstrate the algorithm's efficiency in enhancing system reliability and cost-effectiveness for off-grid energy solutions. In [64], the grasshopper optimization algorithm (GOA) is used to optimize an autonomous microgrid comprising PV panels, WT, BESS, and a diesel generator. The objective function minimizes the LPSP and the LCOE. The main numerical results demonstrate the GOA efficiency over PSO and Cuckoo Search algorithms. GOA achieves a reduction in system capital cost by 14% and 19.3%, respectively. The optimal configuration includes 26 PV panels, 4 WTs, and a 40 kW BESS. In [65], the article explores microgrid optimization using the fuzzified Grey Wolf optimizer (GWO) to minimize costs and maximize renewable energy use. It covers PV, WT, BESS, and generators, achieving notable cost reductions and efficiency gains, demonstrating significant advancements in sustainable energy management through the application of heuristic algorithms. In the domain of microgrid optimization through metaheuristic techniques, the review paper [66] revealed that approximately 25% of the research in this field employs the PSO method. Additionally, GA and GWO are used by nearly 10% and 5% of the studies analyzed in the paper to enhance the performance of microgrids, respectively.

3.3. Mathematical Approaches

Within the realm of mathematical approaches, MILP has a significant role [67]. This technique is selected for its capacity to secure a globally optimal solution to the optimization problem. In [68], a convex optimization approach was used to determine an island microgrid's optimal sizing and energy management while considering the battery degradation. In [69], the study focuses on a battery's optimal sizing, placement, and daily charge/discharge scheduling within the distribution network. In [70], the paper focuses on utilizing a two-stage stochastic programming. The model addresses uncertainties in DER power and load demand by ensuring a reliable PV power supply for essential services. In [71], an investigation is conducted on a microgrid system in an island territory, which incorporated multiple technologies such as PV, WT, biomass, and geothermal sources, among others, with the objective function of minimizing the overall costs of the system. The authors in [72] conducted a temporal decomposition using Benders' algorithm to determine the optimal sizing and operation of a hybrid railway power substation annually. In [73], the study explores multi-year economic energy planning optimization in microgrids using a MILP method. The authors in [74] utilized linear programming to minimize costs or emissions. They explored the effects of policy on generation investment choices.

As the literature shows, non-linear approaches significantly optimize microgrid systems, where various complex problem formulations are addressed using advanced mathematical models. A mixed integer non-linear program (MINLP) is notably applied to tackle multi-objective optimization problems, such as the one from [75], which focuses on minimizing the system cost related to equipment sizing and emissions. This application highlights the capability of MINLP to simultaneously address multiple aspects of microgrid optimization. It provides solutions that balance economic and environmental concerns. A single objective function is presented in [76] to minimize the system's costs through a non-linear problem formulation. This study extends the application of non-linear optimization to managing multiple microgrids by incorporating probabilistic modeling of energy resources and load demand. Doing so accounts for the inherent uncertainties in energy production and consumption. This approach enhances the decision-making process for microgrid operation and planning. These non-linear approaches underline the complexity and multi-dimensional nature of optimizing microgrid systems. They reflect the ongoing advancements in mathematical modeling techniques to achieve more sustainable and cost-effective energy solutions.

3.4. Hybrid Approaches

Hybrid approaches, which involve the integration of multiple algorithms, are increasingly utilized to improve various aspects of microgrid efficiency. The research presented in [67] employs a synergistic application of the JAYA and GWO algorithms to simultaneously minimize annualized cost and carbon emissions and improve the microgrid's reliability. This approach is recognized for its swift convergence and high accuracy. Conversely, in [77], the authors explore a hybrid model that merges Simulated Annealing and Tabu Search techniques to achieve optimal sizing for autonomous systems, thereby streamlining computational efficiency. Another significant contribution is reported in [78], where a combination of JAYA, PSO, and Harmony Search algorithms is used in designing hybrid DER. This configuration, comprising PV systems, biomass, WT, and ESS, is tailored to meet consumer demand in an efficient, cost-effective, and reliable manner. Additionally, in [79], a hybrid strategy combining NSGA-II and multi-objective PSO is implemented to simultaneously reduce carbon dioxide emissions and the total cost of an isolated microgrid configuration. Furthermore, ref. [80] shows the application of ant colony optimization (ACO) with continuous domain integer programming (CDIP), achieving remarkable accuracy and rapid convergence.

4. Microgrid Energy Management Approaches

The integration of DER into microgrids is beneficial for sustainability, but brings challenges related to reliability and stability because of the unpredictable nature of renewable energy. To mitigate these drawbacks in microgrids, implementing an efficient EMS is essential [81]. Numerous studies have explored energy management within microgrids by employing diverse methodologies. Some of these studies have utilized a rule-based approach, which relies on predefined rules for managing RES and ESS. On the other hand, various studies have adopted optimization-based methods, which seek to find the most efficient solution by optimizing specific objectives, such as minimizing costs or maximizing energy efficiency. The diversity and application of these optimization-based methods within microgrid energy management are illustrated in Figure 6, and the following sections address these in depth.

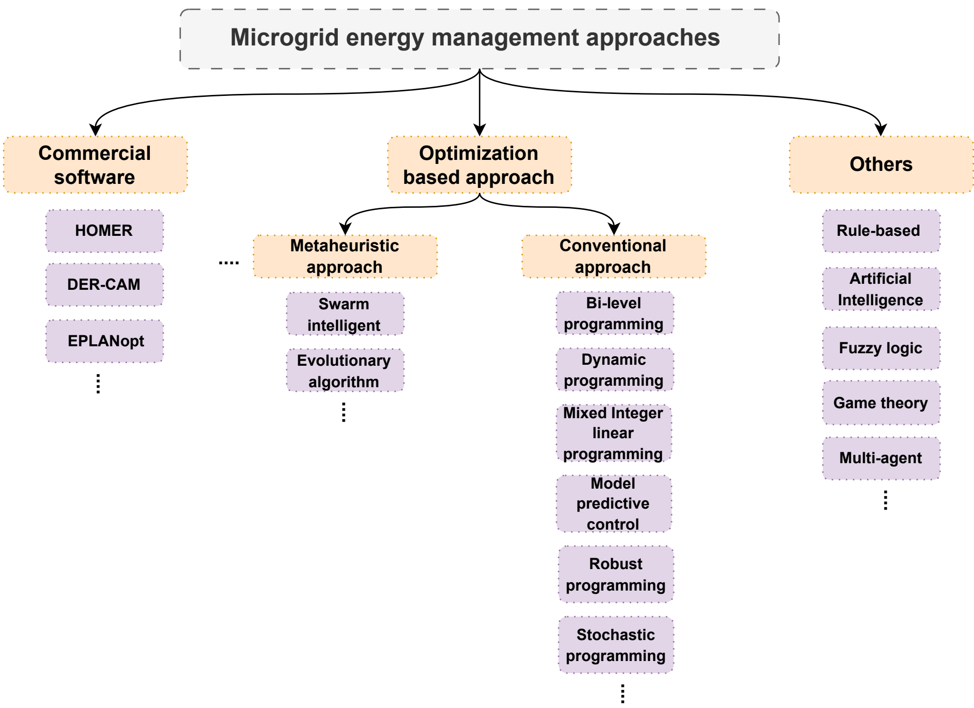

Figure 6. Microgrid energy management approaches.

4.1. Commercial Software

As with microgrid sizing, commercial software such as HOMER, DER-CAM, and EPLANopt are also used to plan energy management within the microgrid. In [82], the EPLANopt software is utilized alongside a multi-objective evolutionary algorithm to optimize the energy system of Favignana Island for sustainability by the year 2050. EPLANopt models and simulates various energy system configurations, incorporating data such as energy demand and renewable energy potential. The evolutionary algorithm analyzes these configurations, evolving a set of solutions through processes like mutation and selection. While EPLANopt provides detailed simulations, the evolutionary algorithm identifies the most efficient and sustainable solutions by balancing objectives such as cost, emissions, and renewable energy usage. In [83], the RETScreen Expert software is used to examine a grid-connected microgrid wind farm in Ghana, evaluating its technical, financial, and environmental benefits. It investigates the NPV, the internal rate of return, the cost of electricity production, and the emission savings to gauge the project's feasibility and its role in sustainable energy progress. RETScreen Expert software is also used in [84–87]. In [88], a comprehensive study is presented on integrating DER into healthcare systems, focusing on a hospital case study in Azad Jammu and Kashmir. The study uses HOMER Pro and RETScreen Expert software to analyze a proposed hybrid renewable energy system against the current energy setup. The result indicates that HOMER Pro and RETScreen Expert predict the increased energy output with the proposed system, though RETScreen Expert tends to give more optimistic projections. The study highlights the efficiency and sustainability of integrating renewable energy into healthcare while demonstrating significant potential for enhancing infrastructure resilience and reducing costs. HOMER is the most used software in the literature for energy management. In [89], the research details an optimal microgrid design for Basco Island in the Philippines using HOMER software. It integrates PVs, WTs, diesel generators, and BESSs to boost power reliability and sustainability. The study identifies the most efficient and cost-effective system setup by evaluating technical and economic factors. HOMER's simulations, optimizations, and sensitivity analyses are crucial for balancing energy demand, resource availability, and operational cost reduction. In [90], the article explores the best configuration for a hybrid microgrid at a desalination facility in Sfax, Tunisia, by employing HOMER software for simulations and FAHP-PROMETHEE for evaluating multiple criteria. The result shows a dramatic 50.2% cut in energy cost for producing desalinated water, which illustrates hybrid microgrids' significant role in making desalination processes more sustainable and economically viable, especially in areas with inconsistent conventional energy supplies.

4.2. Optimization Based Approach

Figure 6 illustrates the optimization-based strategy for energy management in microgrids. Two categories, metaheuristic and conventional approaches, are defined and analyzed in detail.

4.2.1. Metaheurstic Approaches

Metaheuristic method-based energy management used in microgrid systems is mainly categorized into three major groups: evolutionary algorithms and other metaheuristic algorithms, such as GA and simulated annealing. Evolutionary algorithms, inspired by biological evolution processes such as mutation, recombination, selection, and reproduction, have found extensive applications in computational research. The study in [91] introduces an innovative approach, which proposed a Niching Evolutionary algorithm to optimize the allocation of RES and ESS within isolated microgrids. The research presented in [92] proposed an enhanced memetic algorithm for microgrid demand-side management in microgrids. Another noteworthy contribution is detailed in [93], where the water cycle algorithm is applied to the energy management of microgrids. This approach minimizes operational costs and emissions by efficiently coordinating distributed generation units alongside ESS. Lastly, the study in [94] explores using a GA, the most commonly encountered evolutionary algorithm in the literature, for optimizing day-ahead demand scheduling under uncertainty. This research highlights the algorithm's robustness in dealing with the stochastic nature of microgrid energy management, further underlining the critical role of evolutionary algorithms in advancing smart city initiatives.

Swarm intelligence draws inspiration from the natural world's social living creatures, which exhibit coordinated behaviors in groups without central control. These phenomena, observable in entities such as ant colonies engaging in foraging, birds moving in unison, animals grouping for migration, hawks coordinating in pursuit of prey, and fish swimming in schools, serve as the foundation for algorithms designed to tackle intricate challenges through collective effort. Among these, the PSO algorithm stands out for its widespread application. This algorithm mimics the social behavior of birds and fish to navigate toward optimal solutions in a multidimensional space, which effectively addresses various computational and optimization problems. The study in [95] presents a probabilistic approach methodology for the enhancement of energy management in microgrids equipped with DER and ESS. The study introduces a self-adaptive modified q-PSO algorithm optimizing the energy management process by adapting to changes dynamically. Thus, it ensures efficient and reliable microgrid operations under diverse conditions. In [96], the study introduces an innovative approach for the energy management of isolated microgrids using a multi-layer ant colony optimization algorithm. This algorithm is designed to minimize electricity production costs by optimizing both day-ahead and real-time scheduling. In [97], the adaptive modified firefly algorithm is introduced for a scenario-based stochastic optimization framework for a microgrid including WT, PV, micro-turbines, FC, and ESS. Beyond swarm optimization and evolutionary algorithm-based metaheuristic techniques, several other metaheuristic algorithms have been employed to enhance the energy management of the microgrid. The study in [98] examines a microgrid in Oshawa, Ontario, Canada, by employing variable load models, which utilize the interior search algorithm to optimize hour-by-hour scheduling for day-ahead power scheduling issues. The two-stage scenario-based optimization approach is used for forecasting within a coordinated scheduling model, as detailed in [99].

4.2.2. Conventional Approaches

Conventional approaches have six categories, as illustrated in Figure 6. In [100], a bi-level optimization model is employed where the Karush–Kuhn–Tucker approach for problem reformulation into a single-level optimization is used with a combination of binary PSO and QP. In [101], a dynamic programming solution was implemented to address a convex optimization problem to reduce the microgrid's total operation cost. An energy cost optimization using MILP is introduced in [102]. In the context of model predictive control, a receding horizon control-based model for the optimal scheduling of batteries was introduced in [103]. The study in [104] presents a robust counterpart formulation designed to manage peak demand and smooth out load variations amid energy generation and demand uncertainties within a microgrid using a robust programming strategy. In [105], a stochastic energy scheduling system for a microgrid with DER was assessed, including a case study on a modified IEEE-37 bus test feeder setup. Findings from this research underscored the efficiency and precision of the proposed stochastic programming-based algorithm for microgrid energy scheduling.

4.2.3. Other Optimization Based Approaches

In addition to metaheuristic, conventional, and artificial intelligence (AI) approaches, other methods are also discussed in the literature. Some of these alternative approaches are cited here. In [106], the deployment of an EMS within a standalone microgrid is explored. Utilizing a probabilistic framework grounded in Bayesian networks coupled with Monte Carlo simulations, the study effectively captures the unpredictable aspects of electricity demand, which enhances system profitability. The simulation was conducted for a year, finding that the EMS contributes to a reduction in energy expenses by 11.3% while elevating the utilization of solar energy to 54%. In [107], the study focuses on enhancing the operation and design of microgrids that incorporate DER using a holistic strategy to minimize energy costs and emissions through the commitment and dispatch of distributed devices. The uncertainties associated with PV generation are captured through a Markovian process, while a branch-and-cut method is applied to address the optimization challenges. In [108], the study presents a methodology employing Hong's Two-Point Estimate method for day-ahead scheduling, considering the uncertainties in load consumption and WT generation. The primary goal is to reduce operational costs while maintaining system reliability.

4.3. Other Energy Management Approaches

Rule-based, artificial intelligence, fuzzy logic, game theory, and multi-agent approaches are also utilized for energy management of microgrids. Rule-based approaches, characterized by predefined "if-else" strategies, are extensively explored in the literature for energy management within microgrids. These methodologies often involve establishing a hierarchy among energy sources and storage systems based on user preference or availability. Representative rule-based decision-making in microgrid energy management is presented in Figure 7, widely used in the literature. If the solar and wind output are sufficient, the power is distributed to the load, and any excess power is stored in the BESS. If the renewable energy output is insufficient, power is drawn from the BESS if the battery level is adequate. If the BESS level is low, load shedding is implemented, or power is purchased from the electrical grid. Optionally, the battery discharge can be prioritized to ensure critical loads are powered during nighttime or periods without RES generation. In [56], a priority sequence is determined, allowing PV systems, BESS, or biomass to be selected as the primary energy source contingent upon the user's selection. Similarly, ref. [41] details a rule-based method wherein surplus energy from PV panels is initially stored in the BESS before being dispatched to the electrical grid. They illustrate how rule-based strategies can be adapted to manage diverse configurations of microgrid components, including PV-WT-BESS, PV-Hydrogen, PV-Pumped Hydroelectric, WT-BESS, and PV-BESS systems. Another exemplary implementation of rule-based management strategies is showcased in [109], which proposes a model for an isolated microgrid integrating PV, WT, a diesel generator, and the power grid.

The study in [110] introduces a multi-objective EMS tailored for microgrids, focusing on minimizing overall operational expenses and carbon emissions. This system enhances the BESS management process by utilizing a fuzzy logic approach to manage uncertainties in microgrid operations. It determines the optimal timing and rate for charging or discharging the BESS, considering variables such as RES power production, demand load, and electricity costs. The method employs input membership functions to steer the inference engine in assessing the rules. Furthermore, the study in [111] presents an EMS that utilizes a fuzzy logic controller, which is developed and monitored using LabVIEW, for the regulation of a DC microgrid. This EMS employs fuzzy logic to manage the state of charge (SOC) of lithium-ion batteries, thereby enhancing their life cycle. The study in [112] introduces a strategy for a real-time decentralized demand-side management system in a grid-connected microgrid. Every client linked to the microgrid predicts their daily load demand within this system. Utilizing these predictions, the EMS partakes in a mixed-strategy non-cooperative game, proceeding until a Nash equilibrium is achieved. At this equilibrium, consumption forecasts are modified to aim for the lowest possible electricity cost. In [113], the study proposes a hierarchical control strategy for an isolated microgrid based on a multi-agent system, which focuses on maintaining stable voltage levels while optimizing the economic and environmental aspects of the system. In [114], an EMS model is presented for an isolated hybrid microgrid. The model utilizes PSO in combination with artificial neural networks to enhance energy management strategies. In [115], the authors introduce an EMS powered by recurrent neural networks and complement it with a multi-agent-based weather forecasting method. In [116], a reinforcement learning algorithm was applied to enhance the coordination among various ESS in a microgrid.

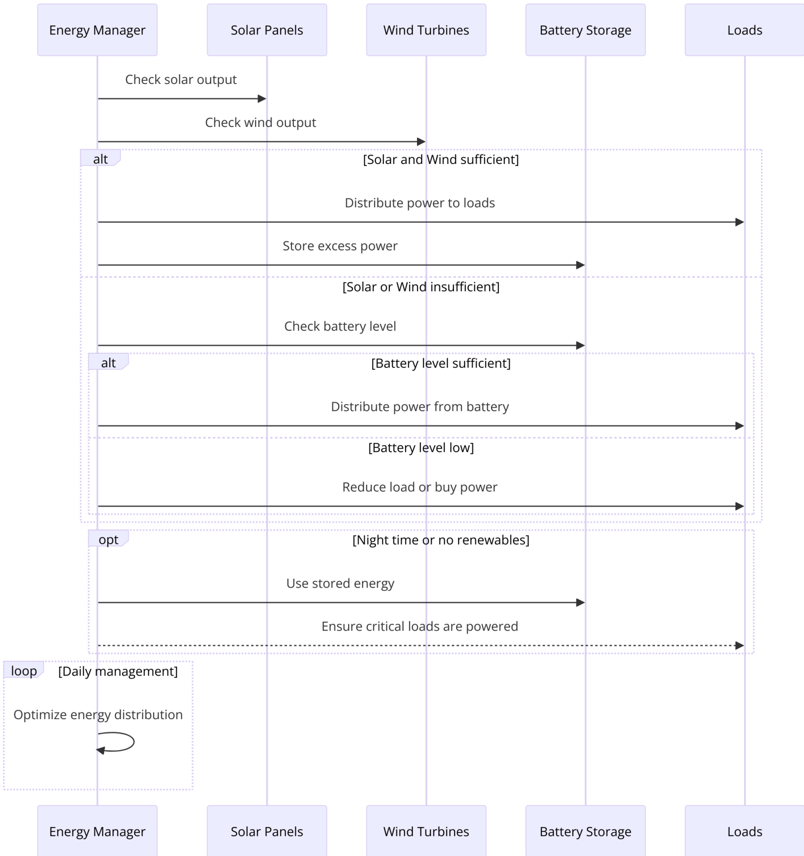

Figure 7. Rule-based decision making in microgrid energy management (alt: alternative, opt: optional).

5. Discussion

Optimal microgrid sizing and system energy management can be optimized using a single-stage or a multi-stage methodology. A single-stage optimization approach poses a considerable challenge in promising a globally optimal solution. The wide range of constraints and decision variables that optimization solvers must navigate and the long-term optimization horizon, which could span the project's lifetime, make this approach complex beyond the computational capabilities of conventional computer systems. On the other hand, a multi-stage approach addresses the component sizing dilemma, followed by resolving the energy management challenge in a subsequent phase. This paper discusses single-stage and multi-stage approaches and a multi-objective functions approach in the following sections.

5.1. Single-Stage Co-Optimization of Microgrid Sizing and Energy Management

Figure 8 illustrates the general framework of the single-stage optimization problem. This approach has few references in the literature due to the computational challenges. Within this approach, MILP is one of the most widely used utilities for solving single-stage optimization problems by meeting microgrids' sizing and energy management. In [71], a MILP framework integrates sizing and energy management into one optimization problem by analyzing scenarios for Reunion Island's transition to renewable energy by 2030 and 2050. Another example can be found in [117], where the optimization problem addresses the optimal sizing and energy dispatch of a residential microgrid incorporating PV, a WT, and the power grid connection. In [118], the authors demonstrate a cost optimization approach incorporating hourly dispatch and load demand within an isolated microgrid. In [119], cost minimization is performed through MILP, complemented by an additional sensitivity analysis conducted over the LPSP. Similarly, in [120], a multi-objective function is formulated using MILP and a trade-off constraint approach, aiming to minimize costs and emissions simultaneously. Concentrating on minimizing the LCOE, the research presented in [121] also formulates the optimization problem using MILP. The results highlight that a microgrid composed of WT, PV, diesel, and BESS exhibits the lowest LCOE compared to alternative combinations. In [122], MILP is similarly employed; the authors explore scenarios wherein a PV-FC-BESS system fulfills residential energy requirements within a grid-connected microgrid environment. The study in [123] introduces a multi-objective optimization approach for the planning and operation of grid-connected microgrids, incorporating DER. It focuses on achieving economic efficiency and enhancing customer satisfaction by implementing demand-side management and employing a fuzzy logic-based method to maximize satisfaction. In [124–126], sizing and energy management are addressed through a single-stage optimization problem using a MILP approach to fully meet the load requirements in grid-connected microgrids and isolated operation modes. The objective function in [124] aims to minimize the cost and emissions over the project lifetime, whereas the objective function in [125,126] focuses solely on cost minimization.

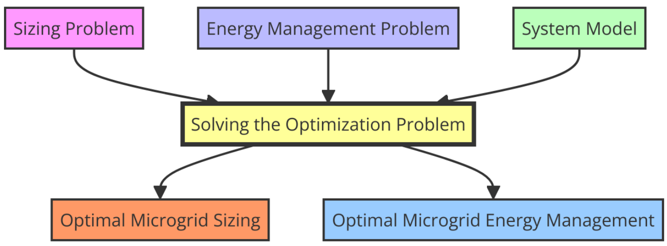

Figure 8. General framework of the single stage problem.

5.2. Multi-Stage Co-Optimization of Microgrid Sizing and Energy Management

In the multi-stage approach, two methodologies are predominantly discussed in the literature. The first methodology begins by addressing the component sizing dilemma, followed by resolving the energy management challenge in a subsequent phase. This sequential methodology leverages optimization-based methods, commercial software solutions, or rule-based strategies for problem formulation. Figure 9 illustrates the outline of this methodology. This methodology has been widely used by researchers. For example, the study [127] contrasts hydrogen and BESS in PV systems by employing a GA for optimal sizing and a rule-based strategy. It focuses on self-sufficiency, NPV, and the impact on the power grid. In [109], the multi-stage methodology is also applied. The stochastic fractal search (SFS) and the symbiotic organisms search (SOS) algorithms are used for sizing, while the energy management uses a rule-based strategy.

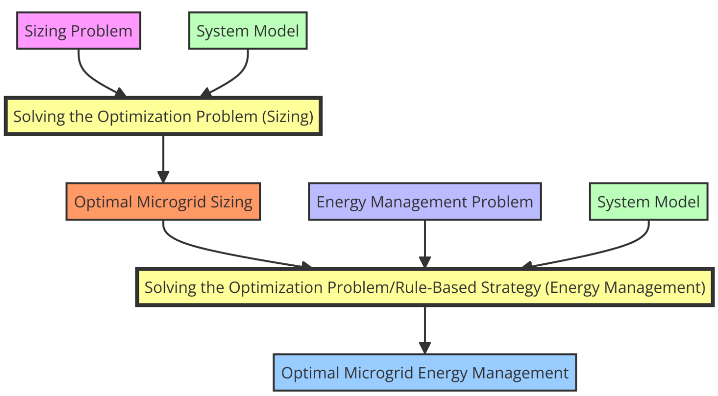

Figure 9. General framework of the multi-stage optimization problem.

Another example can be found in [41,55], where GA is used for sizing and a rule-based approach is used for energy management. The NSGA-II with several rule-based options is presented in [56]. The same approach is presented in [60], with the PSO algorithm used for sizing of the grid-connected microgrid. Shifting from heuristic approaches for sizing and rules-based approaches for energy management, some studies have implemented optimization algorithms for both stages. In [100], the model uses the Karush—Kuhn—Tucker approach to simplify the bi-level problem into a single-level one. A mix of binary PSO and QP finds the optimal BESS size and operation schedule to enhance microgrid design and reliability. In [128], the methodology applies the two-stage method, where the first stage focuses on determining the size of the microgrid. In contrast, the second stage addresses the daily energy management considerations. This study implements MILP optimization techniques in both stages. In [129], the first stage employs an evolutionary algorithm to handle the sizing task, exploring a vast solution space to identify viable configurations. In the second stage, MILP fine-tunes these configurations by meticulously scheduling microgrid assets to balance demand fulfillment with the dual objectives of cost minimization and reliability maximization. A similar approach is found in [130], where the study uses a GA to identify optimal sizing solutions that concurrently lower the lifecycle CO_2 emissions and total costs of the microgrid. Moreover, an EMS is developed, employing a MILP algorithm to efficiently distribute power flow while also reducing CO_2 emissions. In [131], a stochastic two-stage model is presented for optimizing microgrid design by addressing the uncertainties in DER. The initial stage focuses on setting capacities for PV, WT, diesel generation, and ESS. In contrast, the second stage targets operational decisions, such as diesel and ESS usage. The study in [132] introduces a method for optimizing microgrid components in "El Espino" community. It uses linear programming (LP), firstly to minimize costs while meeting energy needs, and secondly to incorporate operational and reliability constraints. In [133], the paper applies a two-stage stochastic optimization approach to minimize both capital and operational costs considering uncertainties in demand.

The second form of multi-stage optimization utilizes decomposition algorithms, notably the Dantzig–Wolfe decomposition [134]. This method entails an iterative process that includes several subproblems and a master problem. Each iteration introduces a new variable to the master problem, facilitating a gradual convergence towards the solution. Another key decomposition algorithm is the alternating direction method of multipliers [135], which segments the optimization challenge into multiple sub-problems without incorporating a master problem. Here, each subproblem iteratively shares its solution with the others, aiding in convergence to a global solution. Prominently, Benders' decomposition [136], proposed by Benders [137], is designed to solve mixed-variable optimization problems, with Geoffrion later extending the approach to address non-linear convex problems [138]. Benders' decomposition effectively bifurcates the target problem into two simpler components: the master problem and one or more sub-problems [139]. The master problem, a simplified model, includes a subset of the original variables and constraints, representing a relaxed version of the problem [140]. Conversely, the sub-problems mirror the original problem's complexity, conditioned on the premise that the variables derived from the master problem are fixed.

Figure 10 provides an overview of Benders' decomposition framework. In an optimization problem concerning energy management and component sizing, the master problem involves energy management within the microgrid. At the same time, the sub-problem addresses the sizing of the components. The capacity of each microgrid component is adjusted according to the energy management constraints imposed by the optimization algorithm.

Benders' decomposition algorithm has been used extensively in research. For instance, the study in [141] showcases a multi-stage optimization process for microgrid sizing and energy management using the iterative Benders' decomposition algorithm. In [142], the optimization is decomposed into two principal components: investment decision-making as a master problem and energy management as a sub-problem. By distinguishing between design decision variables and energy management variables, this strategy enhances the efficiency of solving the planning problem. It iteratively addresses these interconnected components, optimizing microgrid management's investment and operational phases. The study in [143] outlines a two-stage stochastic MILP model for optimizing investments in renewable energy within DER. Its goal is to lower costs associated with investments in PV and WT, as well as operational and total substation expenses, which include energy purchases and losses. This study's innovative aspect is using Benders' decomposition, which simplifies the complex problem by separating investment from operational decisions. In [144], the study presents a parallel multi-period optimal scheduling algorithm for microgrids incorporating ESS and addressing the challenges of DER integration. It optimizes microgrid operations by decomposing inter-temporal constraints and utilizing generalized Benders' and optimality condition decomposition. Based on the optimization models analyzed, the following section delves into the objectives that could be targeted in microgrids' sizing and energy management framework. These objectives cover cost minimization, improved system autonomy, and reduced environmental impact.

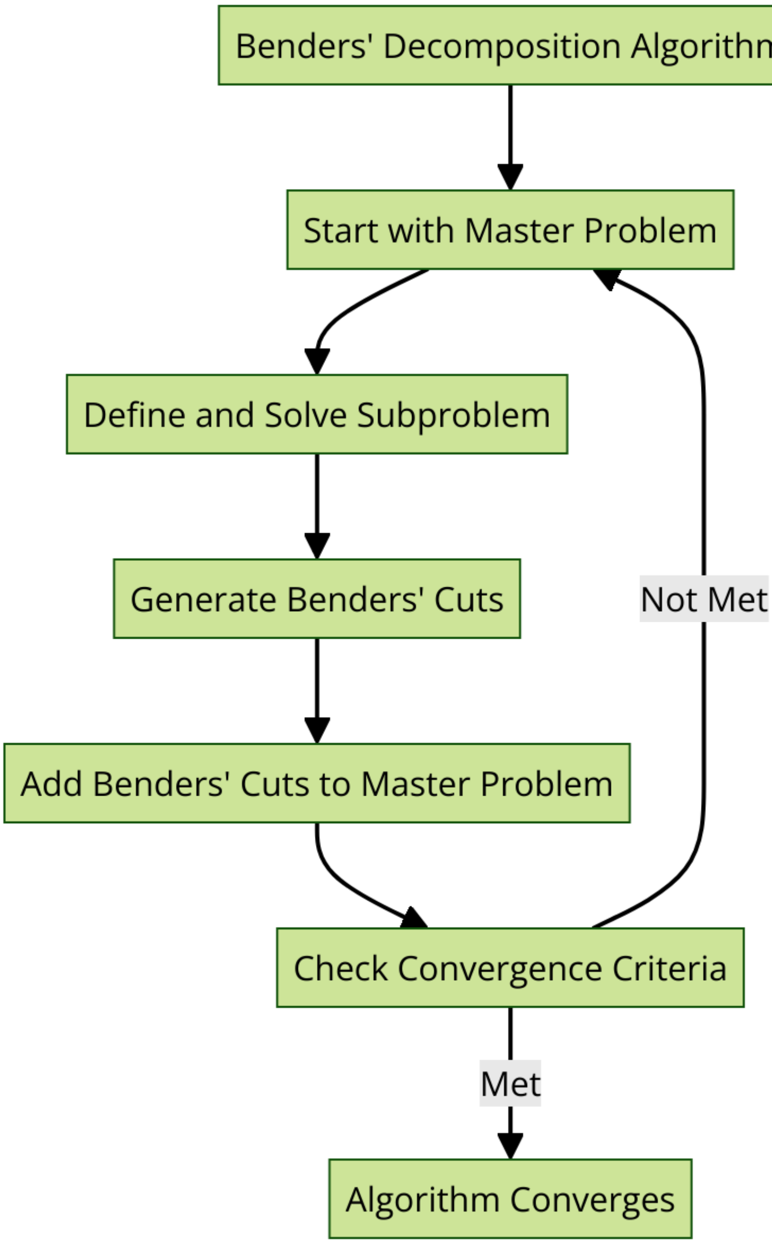

Figure 10. General framework of Benders' decomposition algorithm.

5.3. Objective Function

Optimization objectives in energy sizing and management have been addressed in several ways. Some studies focus on minimizing annual costs and cost per kilowatt-hour produced LCOE [145] or NPC [39]. Others aim to improve the autonomy of the microgrid [60] or reduce emissions of CO_2 [59]. Case-specific research considers a single objective. However, some studies address multiple objectives simultaneously. Several approaches can be employed to address these complexities, such as the weighted sum approach, the hierarchical optimization method, the trade-off method, the global criterion method, and the goal programming method. Some approaches for dealing with multi-objective problems simultaneously are described below.

5.3.1. Weighted Sum

- Advantages: The weighted sum approach is appreciated for its simplicity due to its straightforward implementation and understanding. It allows the adjustment of weights according to the significance of each objective, providing a clear way to prioritize among different goals. It simplifies optimization by transforming multiple objectives into a single composite objective using weights. This consolidation renders the multi-objective problem compatible with traditional optimization techniques and tools, which makes the solution process manageable.
- Disadvantages: The effectiveness of the weighted sum approach significantly relies on the selection of weights for each objective. Different sets of weights lead to vastly different solutions; thus, identifying the optimal weights to balance the importance of each objective is critical and challenging. Moreover, when objectives are on substantially different scales, assigning weights that accurately reflect each objective's relative importance becomes complicated. It often necessitates the normalization of objectives to a standard scale, which introduces additional complexity to the optimization process.

5.3.2. Hierarchical Optimization Method

- Advantages: This method's prioritization strategy guarantees that the most critical objectives are addressed first, which is paramount in scenarios where failing to meet primary objectives could negate the relevance of secondary objectives. In environments where some objectives cannot be compromised, such as safety-critical systems, environmental conservation, or healthcare, prioritizing these ensures alignment with the scenario's overarching goals and ethical considerations. This approach ensures that the optimization process respects the most critical requirements.
- Disadvantages: There is a substantial risk that lower-priority objectives might not be considered sufficiently if high-priority objectives significantly consume resources. It could yield solutions that, albeit satisfying primary goals, are sub-optimal in the context of the broader problem. The potential depletion of resources on high-priority objectives might marginalize secondary goals, undermining the comprehensive quality of the solution. Furthermore, optimizing objectives sequentially by importance can introduce challenges when objectives are highly interdependent. Enhancing one objective might impair another. This approach complicates pursuing a balanced and globally optimal solution.

5.3.3. Trade-Off Method

- Advantages: Trade-off analysis aids in identifying Pareto optimal solutions, where improving any objective would lead to the detriment of at least one other objective. It is crucial to ensure that chosen solutions are efficient from a multi-objective standpoint.
- Disadvantages: Analyzing trade-offs can become increasingly complex as the number of objectives grows. This complexity necessitates the use of advanced tools and expertise.

5.3.4. Global Criterion Method

- Advantages: Targets the identification of a solution that optimizes all objectives concurrently, potentially yielding more balanced and universally acceptable outcomes. Moreover, concentrating on a singular, global criterion enhances efficiency in discovering a solution that moderately satisfies all objectives, diminishing the necessity for iterative or repeated optimization processes.
- Disadvantages: Developing a global criterion that accurately encapsulates the significance of all objectives poses a challenge, particularly in scenarios where the objectives significantly conflict or are difficult to quantify. Furthermore, a singular focus on a global criterion may result in missing some Pareto optimal solutions, especially those poorly represented by the selected global criterion.

5.3.5. Goal Programming Method

- Advantages: Goal programming enables concurrently considering various goals, possibly assigning different priorities. This adaptability proves advantageous in intricate decision-making contexts, where navigating trade-offs among conflicting objectives is essential.
- Disadvantages: This approach depends significantly on the decision-maker's capacity to establish and rank goals precisely. Such reliance can inject subjectivity into the process, potentially skewing the results.

A fundamental multi-objective optimization concept is the Pareto front, which represents the trade-offs between conflicting objectives. It draws attention to dominated and non-dominated solutions, demonstrating the trade-offs necessary to achieve optimal results. Each approach to optimizing objectives presents specific advantages and challenges, from the weighted sum to trade-off analysis. The choice of methodology depends on project priorities, so balancing multiple criteria is essential to designing efficient and sustainable microgrids. In addressing uncertainties in renewable generation and demand, advanced optimization techniques such as chance-constrained programming (CCP) have shown potential for real-time adaptation in complex energy systems. Research [146] demonstrates that a CCP-based strategy balances user comfort and system economy in a multi-agent energy system by adjusting confidence levels to manage renewable generation and external temperature uncertainties. This approach could be explored further in microgrid optimization, especially for enhancing cost, reliability, and sustainability trade-offs under uncertainty. The following section presents the key conclusions drawn from this review, highlighting the main contributions and potential avenues for future research.

6. Conclusions

This paper comprehensively reviews the optimal sizing and energy management approaches for energy planning of microgrids. It highlights the importance of detailed energy planning and integrating the sizing and energy management stages to ensure efficient and sustainable operation. The review covers energy planning approaches incorporating renewable energy sources such as PV systems, WTs, and small hydropower plants, and discusses sizing approaches, including heuristic, mathematical, and hybrid methods. Additionally, it emphasizes energy management strategies based on optimization and commercial software. By thoroughly comparing these approaches, this paper underscores the significance of proper sizing in minimizing initial, operational, and maintenance costs, which ensures reliable and stable operation. Hybrid methodologies show high efficiency in solving complex sizing problems and finding optimal solutions. EMS based on algorithms such as genetic algorithms and mathematical programming demonstrate superior efficiency in addressing the power intermittency of renewable sources and enhancing the stability of the energy supply. Commercial software such as HOMER and DER-CAM facilitates energy planning by providing economic evaluation and sensitivity analysis. Furthermore, this review acknowledges the challenges posed by the intermittent power production of renewable sources, which can lead to instability. However, efficient ESS and EMS mitigate these issues and improve supply reliability.

Two paradigms are identified when looking at multi-stage and single-stage sizing and energy management optimization approaches. The multi-stage approach offers the advantage of modularity and simplification, where component sizing is addressed first, followed by energy management in the second stage. It allows the application of algorithms such as the Dantzig–Wolfe decomposition, which segments the problem into subproblems and facilitates iterative convergence. On the other hand, in the single-stage approach, simultaneous integration of sizing and energy management decisions can lead to optimal solutions, but high computational demands limit the process. This methodology directly addresses the simultaneity of decisions, resulting in a more efficient but computationally expensive overall optimization. In addition, decomposition algorithms, such as Benders', allow complex problems to be broken down into more manageable parts, facilitating the solution of nonlinear and mixed problems. The advantage of this methodology is that it allows for handling uncertainties in renewable energy production and provides a robust approach to energy planning.

This paper contributes to microgrid energy planning and management. First, it provides a comparative analysis of heuristic, mathematical, and hybrid sizing methodologies, underscoring their applicability in different operational contexts. Second, it introduces a detailed discussion of energy management strategies based on optimization techniques, offering practical insights for addressing the challenges associated with integrating renewable energy sources. By combining sizing and energy management stages, this work presents a framework for optimizing cost and performance in microgrid systems. Furthermore, it highlights the potential of multi-objective optimization techniques, which are essential for improving system autonomy, reducing carbon emissions, and ensuring the reliability of microgrids in diverse environments. One of the existing challenges identified in this review is the difficulty of implementing real-time control strategies that effectively leverage optimization results while managing uncertainties. The dynamic nature of microgrid operation, combined with the variability of RES, introduces substantial complexity into real-time decision-making processes. In addition, uncertainties, such as those related to fluctuating energy demand, unpredictable weather conditions, and degradation of the ESS, pose a considerable obstacle to the practical application of optimization techniques. These uncertainties could lead to suboptimal decisions if not adequately considered in the microgrid's planning and operational phases.

This review highlighted the advantage of developing methodologies that integrate the sizing and energy management stages and address them simultaneously, which could provide more accurate solutions. Effective integration of the sizing and energy management stages, with the use of advanced methodologies and emerging technologies, will significantly improve the efficiency and reliability of microgrids. Integrating technologies such as electric vehicles and smart grids into the planning and operation of microgrids is a promising avenue for energy efficiency and sustainability. Future research could focus on improving the robustness of optimization algorithms to handle uncertainties better, ensuring that real-time control systems can respond dynamically to changing conditions without compromising the stability or efficiency of the microgrid. Research in this area could provide opportunities for microgrid planning and energy management optimization. Also, upcoming works could address multi-objective optimization, including cost minimization, CO_2 emission reduction, and autonomy. Advanced multi-objective energy management techniques could significantly improve energy planning.

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