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Review

Exploring Evolution and Trends: A Bibliometric Analysis and Scientific Mapping of Multiobjective Optimization Applied to Hybrid Microgrid Systems

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Abstract: Hybrid energy systems (HESs) integrate renewable sources, storage, and optionally conventional energies, offering a sustainable alternative to fossil fuels. Microgrids (MGs) bolster this integration, enhancing energy management, resilience, and reliability across different levels. This study, emphasizing the need for refined optimization methods, investigates three themes: renewable energy, microgrid, and multiobjective optimization (MOO), through a bibliometric analysis of 470 Scopus documents from 2010 to 2023, analyzed using SciMAT v1.1.04 software. It segments the research into two periods, 2010–2019 and 2020–2023, revealing a surge in MOO focus, particularly in the latter period, with a 35% increase in MOO-related research. This indicates a shift toward comprehensive energy ecosystem management that balances environmental, technical, and economic elements. The initial focus on MOO, genetic algorithms, and energy management systems has expanded to include smart grids and electric power systems, with MOO remaining a primary theme in the second period. The increased application of artificial intelligence (AI) in optimizing HMGS within the MOO framework signals a move toward more sustainable, intelligent energy solutions. Despite progress, challenges remain, including high battery costs, the need for reliable MOO data, the intermittency of renewable energy sources, and HMGS network scalability issues, highlighting directions for future research.

Keywords: renewable energy sources; hybrid energy system; microgrid; multiobjective optimization; bibliometric analysis; SciMAT

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1. Introduction

The global energy transition, aimed at achieving significant reductions in carbon emissions across both the energy industry and end-use sectors, necessitates the adoption of renewable energy sources (RESs) such as low-cost solar photovoltaic (SPV), onshore, and offshore wind. To meet the targets set by the International Renewable Energy Agency (IRENA) in the 1.5 °C scenario, a substantial increase in global renewable energy (RE) capacity is essential. This includes expanding the installed renewable electricity generation capacity to more than 11,000 GW [1]. Notably, this transition occurs amidst fluctuations in the energy market, as electricity prices have exhibited heightened volatility, especially during the 2020–2021 pandemic period, compared to preceding years [2]. This highlights the challenges and complexities of achieving renewable energy targets in a volatile energy price environment. According to the International Energy Agency (IEA), renewables are expected to account for 80% of new power capacity additions worldwide by 2030, with SPV alone contributing more than half of this increase. This substantial growth in RE capacity highlights viable strategies for addressing the global climate crisis as well as the fuel crisis in 2022 [3], as depicted in Figure 1.

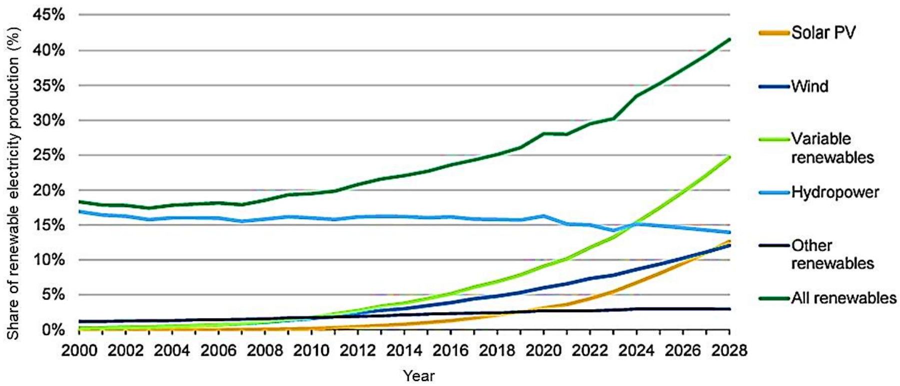

Figure 1. Share of renewable electricity production by source from 2000 to 2028 [3].

RESs play a crucial role as environmentally friendly alternatives but face significant challenges, notably the variability in energy production influenced by factors like solar intensity and wind availability. This issue can be addressed by integrating batteries with RESs to create hybrid renewable energy systems (HRESs) [4]. For enhanced reliability, particularly in off-grid installations or when connected to an unreliable grid where consistent power is critical, these systems may incorporate conventional energy sources such as diesel generators (DGs). This integration broadens their functionality, forming what is known as hybrid energy systems (HESs). Such adaptation allows the systems to maintain power supply continuity and stability, even under variable environmental conditions or grid inconsistencies [5,6]. To shed more light on these two systems, Table 1 provides a comparison between HESs and RESs from different aspects.

Table 1. Comparative analysis of RESs vs. HESs across multiple aspects.

Aspect	Renewable Energy Systems (RESs)	Hybrid Energy Systems (HESs)
Reliability	Weather-dependent, it can be less reliable.	More consistent power supplies reduce reliance on a single source.
Economic	Higher initial cost, lower long-term operational costs.	More cost-effective long-term due to optimized resource use.
Security	Reduces reliance on imported fuels but is sensitive to environmental changes.	Enhanced security through diversified energy sources.
Environment	Minimal emissions, low environmental impact.	Potentially lower impact through optimized energy mix.
Maintenance Requirements	Regular maintenance needed, varies by technology.	Potentially more complex maintenance due to multiple systems, but can be optimized for efficiency.
Stability	Can be unstable due to reliance on a single energy source.	Generally more stable due to diversified energy sources.
Technological Advancement	Dependent on specific technology advancements.	Benefits from advancements in multiple technologies.
Geographical Suitability	Depends on local resource availability.	Better adaptability to various geographical conditions.
Energy Storage and Distribution	Storage solutions are required for inconsistent supply.	More efficient storage and distribution with steady supply.

Economically and technically, HESs provide an optimal solution by ensuring energy supply stability when RESs alone are limited by environmental variability. By integrating multiple energy sources, HESs maintain consistent energy availability [7–9]. However, it is essential to acknowledge that HESs are not without limitations. Several challenges must be addressed for their successful implementation and widespread adoption. The following are some of these limitations.

1. Technical Challenges: HESs face complexities integrating multiple energy sources, ensuring grid stability, and maintaining a consistent energy supply amidst environmental variability [10]. These systems require sophisticated control mechanisms and robust infrastructure to manage diverse energy inputs and outputs effectively.
2. Economic Feasibility: High initial investment costs, ongoing operation and maintenance expenses, and funding challenges can pose barriers to the widespread adoption of HESs. A thorough economic analysis is essential for long-term sustainability [11]. This includes assessing the cost–benefit ratio, potential savings over time, and securing adequate funding for implementation.
3. Environmental Impacts: Assessing the environmental footprint of HESs and implementing strategies for mitigation are critical steps toward ensuring their positive impact on the environment [12]. This includes considering the lifecycle emissions, potential land use impacts, and ways to minimize negative environmental effects through innovative design and operation strategies.
4. Research Scope: The scope of research on HESs may be limited, potentially overlooking crucial factors like regional variations, scalability issues, and emerging trends.
5. Social and Policy Implications: Societal acceptance, public awareness, community engagement, and supportive policies are essential for the successful adoption of HESs. Understanding and addressing these social and policy factors is crucial for the transition to and operation of HESs. Supportive regulatory frameworks, incentives, and educational initiatives can significantly influence the adoption and effectiveness of these systems.

The integration of hybrid systems into the grid necessitates management to maintain operations independently from the main grid as required. This requirement has paved the way for the utilization of microgrids (MGs), which can operate in two modes: connected to the main grid or in an islanded (independent) mode, ensuring coordinated and controlled energy distribution. A microgrid (MG) is a self-sufficient system composed of interconnected loads and distributed energy resources within clearly defined electrical boundaries, acting as a single controllable entity with respect to the grid [13,14]. This integration, referred to as hybrid microgrid systems (HMGSs), not only reduces costs and grid dependence but also lessens environmental impact [15]. The effective use of HMGSs relies heavily on appropriate sizing, simulation, and optimization software tools, which are crucial for avoiding exorbitant installation costs and ensuring the reliability of the power supply. These tools are instrumental in studying, evaluating, and optimizing resource use, playing a critical role in addressing these challenges. Their application enhances system efficiency and contributes to a more balanced and sustainable energy sector.

The optimization of HMGSs has garnered significant attention, as evidenced by a bibliometric study spanning from 2005 to 2021. This study tracked over 2300 scientific papers, revealing a notable increase in publications on this topic. Various artificial intelligence (AI) techniques, tools, and software have been utilized to address challenges associated with HMGS implementation. These approaches have assessed HMGSs from multiple perspectives, including technical, economic, environmental, control, operation, and sizing aspects. Notably, the study identified the adoption of multi-objective optimization (MOO) as the most significant advancement in the field over the last five years [16]. This emphasizes the pivotal role of MOO in enhancing decision-making processes for HMGS development and implementation, underscoring its necessity for detailed analysis. To comprehensively understand the application of MOO to HMGSs, this study is structured into three phases. The first phase focuses on reviewing mathematical models for prevalent HMGS configurations, laying the theoretical groundwork. The subsequent phase delves into critical economic and reliability metrics to evaluate HMGSs. The study culminates in the third phase, which conducts a bibliometric analysis and comparative case studies to identify research trends and gaps, as illustrated in Figure 2.

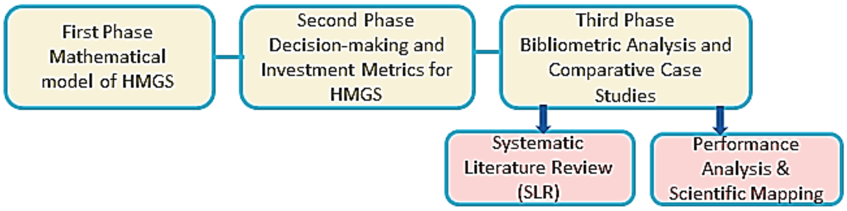

Figure 2. The methodological framework of the research on HMGS optimization.

2. Methodological Framework

As outlined in Figure 2, the study begins with the first phase, which concentrates on the mathematical modeling of HMGSs. This phase is crucial for establishing a solid theoretical foundation, providing the necessary groundwork for subsequent analysis.

2.1. First Phase: Mathematical Model of HMGSs

As mentioned earlier, HMGSs are financially beneficial for both current and future electricity supply needs. The most common form of these systems typically integrates SPV, wind, batteries, and DGs [17,18]. MGs, with their ability to operate both autonomously and in conjunction with the main grid, increase resilience and offer flexibility in power distribution [19]. Figure 3 categorizes MG setups by function, demand, and capacity [20], highlighting the range and scalability of MG configurations.

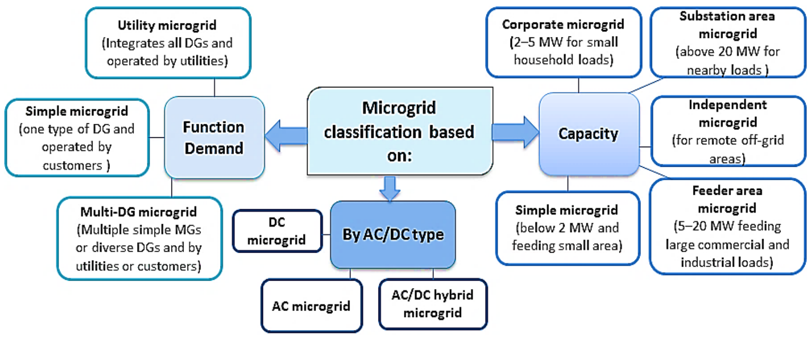

Figure 3. Categorization of MGs by demand, type, and capacity.

The subsequent subsections will detail the mathematical models of each component, offering a detailed understanding of their functions within HMGSs.

2.1.1. SPV System

The SPV system within HMGSs includes the following key elements: SPV panels, an inverter, a charge controller, and a battery storage unit. Detailed discussions of each component will follow.

- SPV: A solar cell, or photovoltaic (PV) cell, is a device that transforms light into electricity through the photovoltaic effect. The behavior of both an ideal SPV cell and a practical SPV device are typically represented in diagrams, such as those depicted in Figure 4.

The current–voltage relationship of an ideal solar cell is described by a fundamental equation from semiconductor theory, shown as Equation (1):

$$I = I_{SPV,cell} - I_{O,cell}[\exp\left(\frac{qV}{\alpha kT}\right) - 1]. \quad (1)$$

Here, $I_{SPV,cell}$ is the SPV current generated by the cell due to incident light, $I_{O,cell}$ is the reverse saturation current of the diode, q is the charge of an electron ($1.60217646 \times 10^{-19}$ Coulomb), K is the Boltzmann constant ($1.38064852 \times 10^{-23}$ Joules/Kelvin), T is the absolute temperature (in Kelvin) of the diode junction, and α is the diode ideality factor.

Since a practical SPV array has series resistance R_s and parallel resistance R_p, Equation (1) does not describe its I–V characteristic. Practical arrays consist of many interconnected SPV cells; this requires the addition of new parameters to the basic equation for accurate monitoring of characteristics in SPV array stations, as demonstrated in Equation (2).

$$I = I_{SPV} - I_O\left[\exp\left(\frac{V + R_s I}{V_t \alpha}\right) - 1\right] - \left(\frac{V + R_s I}{R_p}\right). \quad (2)$$

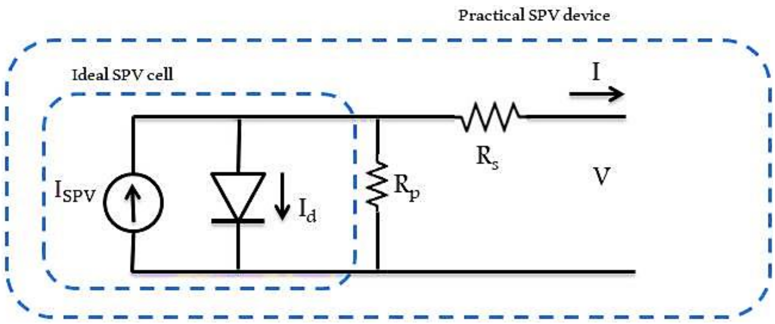

Figure 4. Equivalent circuits of an ideal SPV cell and practical SPV device.

SPV array datasheets typically provide essential information, including the nominal open-circuit voltage ($V_{oc,n}$), the nominal short-circuit current ($I_{sc,n}$), the voltage at the maximum power point (MPP) (V_{mp}), the current at the MPP (I_{mp}), the open-circuit voltage/temperature coefficient (K_V), the short circuit current/temperature coefficient (K_I), and the maximum experimental peak output power ($P_{max,e}$). It is commonly assumed in SPV device modeling that the short-circuit current ($I_{sc,n}$) is approximately equal to the photovoltaic current (I_{SPV}). This assumption holds because, in practical devices, the series resistance is typically low, and the parallel resistance is high, affecting the overall performance. The diode saturation current (I_O) is described by Equation (3).

$$I_O = \frac{I_{sc,n} + K_I \Delta_T}{\exp\left(\frac{V_{oc,n} + K_V \Delta_T}{\alpha V_t}\right) - 1}. \quad (3)$$

The maximum output power $P_{max,m}$ is calculated to the maximum experimental power $P_{max,e}$ when $P_{max,m} = P_{max,e}$ solving the resulting equation for R_s, as detailed in Equation (4).

$$P_{max,m} = V_{mp}\left\{I_{spv} - I_o[\exp\left(\frac{q}{kT}\frac{V_{mp} + R_s I_{mp}}{\alpha N_s}\right) - 1] - \frac{V_{mp} + R_s I_{mp}}{R_p}\right\}. \quad (4)$$

SPV systems are classified into various configurations based on the application's requirements and the coupling of various power sources. Figure 5 depicts various SPV system configurations [21].

- Charge controller: A charge controller, also known as a charge regulator or battery regulator, moderates the flow of electric current to and from the batteries. This control prevents excessive charging and voltage spikes, which can damage the battery, reduce its efficiency, or pose safety concerns. In SPV systems, solar charge controllers adjust the power or DC voltage coming from the solar panels before it is directed to the batteries.
- Inverter: Various inverter models exist, each tailored to the specific requirements of the load. The selection depends on the load's waveform needs and the inverter's efficiency. The choice is also influenced by whether the inverter is standalone or grid-connected. Inverter failure is a leading cause of malfunctions in SPV systems, presenting opportunities for engineers to improve inverter designs. The efficiency of

an inverter (η_{inv}) is typically represented by the ratio of the output power (P_{out}) to the input power (P_{in}), mathematically expressed as:

$$\eta_{inv} = \frac{P_{out}}{P_{in}} < 1, \quad (5)$$

indicating that the output power P_{out} is always less that P_{in} due to inherent system losses. These losses can originate from various sources, such as component resistance, inefficiencies during semiconductor switching, and other imperfections.

- Battery: A battery bank within HMGSs serves dual purposes: as a power source and for energy storage, balancing power needs over time. Surplus energy from RESs is stored in the batteries, which then provide energy during low RES output due to adverse weather. Battery size, determined by the autonomy days (N) and the difference between load demand (E_L) and power from RESs (E_G), is calculated using:

$$C_B = N \cdot \frac{(E_L - E_G)}{\eta_B \times \eta_{inv} \times DOD}. \quad (6)$$

where η_B denotes the battery's efficiency and η_{inv} signifies the efficiency of the inverter, with DOD referring to the depth of discharge [22].

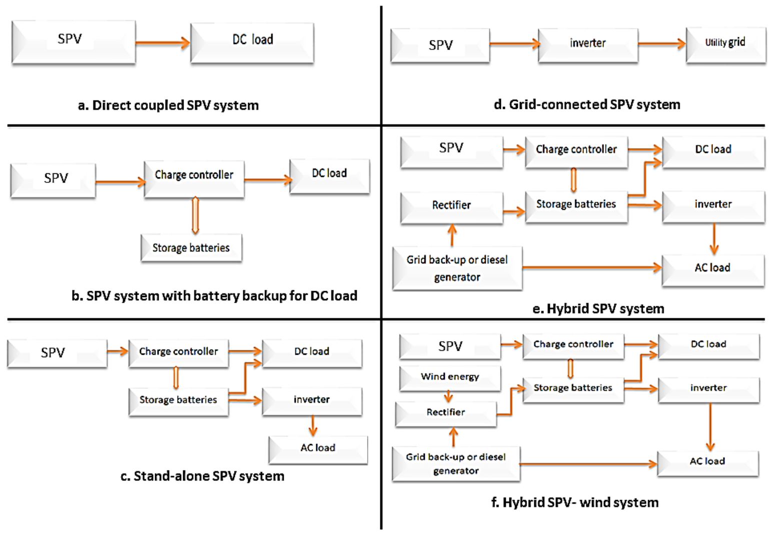

Figure 5. Types of SPV Systems.

2.1.2. Wind Energy

It is crucial to recognize that the power output from a wind turbine (p) varies continuously due to changes in wind speed (V) and differing operational scenarios. To accurately calculate the average power output over a specific period, it is necessary to account for these fluctuations by integrating the power equation over that duration. Additionally, a wind turbine's power generation is capped by its rated power P_r, which is the maximum power it can generate under optimal wind conditions. The power output from a wind turbine, taking into account the rated wind speed (V_r), the cut-in speed (V_{cut-in}), and the cut-out speed ($V_{cut-out}$), is determined using the following equation:

$$P(V) = \begin{cases} 0, & \text{if } V < V_{cut-in},\ V > V_{cut-out}, \\ Pr * \left(\frac{V^3 - V_{cut-in}^3}{V_r^3 - V_{cut-in}^3}\right), & \text{if } V_{cut-in} \le V \le V_r, \\ P_r, & \text{if } V_r \le V \le V_{cut-out}. \end{cases} \quad (7)$$

This formula becomes particularly relevant in calculating the power generation potential under varying wind speeds, from the point where the turbine starts operating (V_{cut-in})

to the speed beyond which it must stop to avoid damage ($V_{cut-out}$), including its optimal performance at the rated speed (V_r) [23].

2.1.3. Diesel Generator (DG)

To accommodate power supply variability from RESs, systems operating off standalone setups or connected to unreliable grids often incorporate batteries to store surplus energy generated during peak times, which is then available for use during low production periods. However, due to limitations such as battery capacity and discharge rates, DGs offer an alternative or supplementary solution to ensure a consistent power supply. The hourly fuel consumption of a DG (G_t) is calculated using the following formula:

$$G_t = \gamma \cdot P_{max} + \beta \cdot E_t, \tag{8}$$

where G_t represents hourly fuel consumption, $\gamma(0.24)$ and $\beta(0.084)$ are coefficients for converting fuel to electrical energy, P_{max} is the generator's rated power, and E_t denotes the electrical energy produced during the hour. This equation helps in optimizing fuel usage in response to fluctuating RES outputs, enhancing the system's efficiency [22,24].

2.2. Second Phase: Decision-Making Tools and Investment Metrics for HMGSs

This section outlines the essential metrics for evaluating the economic viability, reliability, sustainability, and investment return of HMGSs. These metrics are pivotal for stakeholders to make informed decisions regarding the implementation and operation of HMGSs.

2.2.1. Decision-Making Tools (LCOE, LCC, NPC, LPSP, RF)

This section focuses on key decision-making tools that offer stakeholders a comprehensive understanding of the cost, reliability, and sustainability of HMGSs.

1. Levelized Cost of Energy (LCOE): This represents the average cost per unit of energy produced by a system throughout its lifecycle, incorporating all lifecycle costs. It is calculated as follows [25]:

$$\mathrm{LCOE} = \frac{\sum_{t=0}^{n} \frac{C_t}{(1+r)^t}}{\sum_{t=0}^{n} \frac{E_t}{(1+r)^t}}. \tag{9}$$

   where C_t is the total costs (capital, operating, maintenance) in year t, E_t is the electricity generated in year t, r is the discount rate, and n is the system's lifetime in years.
2. Life Cycle Cost (LCC): Encompasses the total cost of ownership of the HMGS during its lifespan, including installation, operation, maintenance, and decommissioning costs but excluding system depreciation [26]. The LCC is calculated using the equation:

$$\mathrm{LCC} = C_{CCA} + \sum_{t=1}^{T} \frac{C_{OM,t} + C_{rep,t} - S_t}{(1+I)^t}. \tag{10}$$

   where C_{CCA} is the initial cost, $C_{OM,t}$ the annual operation and maintenance costs, $C_{rep,t}$ are the replacement costs, S_t salvage values, T the system's lifetime, and I the interest rate per annum.
3. Net Present Cost (NPC): Calculates the present value of all costs and profits associated with the HMGS, offering a net-cost perspective over the system's lifecycle [27].

$$\mathrm{NPC} = C_{CCA} + \sum_{t=1}^{T} \frac{C_{OM,t} + C_{rep,t} - R_t}{(1+R)^t} \tag{11}$$

   where R_t represents annual revenues or savings from operation, distinct from the salvage value S_t.
4. Loss of Power Supply Probability (LPSP): Defined as the ratio of the total time the system cannot meet the demanded load to the total observation period (often a

year), indicates the likelihood of power outages. It may be computed using the generic formula:

$$\mathrm{LPSP} = \frac{\sum \text{Unmeet Load Periods}}{\text{Total Observation Period}}. \tag{12}$$

5. Renewable Fraction (RF): Quantifies the fraction of total energy provided by RESs in the HMGS, a key metric for assessing system sustainability [28].

$$\mathrm{RF} = \frac{\text{Total Renewable Energy Generated}}{\text{Total Energy Generated}} \tag{13}$$

Here, the Total Energy Generated represents the overall energy production of the HMGS, including both renewable and non-renewable sources.

2.2.2. Investment Metrics (NPV, EPBT, PBP, ROI)

Understanding the financial and environmental impacts is crucial for HMGS and RE system projects.

1. Net present value (NPV): Calculates the profitability of a project by discounting future cash flows to the present.

$$\mathrm{NPV} = \sum_{t=1}^{n} \frac{\mathrm{Rt}}{(1+i)^{t}} \tag{14}$$

where Rt is net cash inflow–outflows during a single period t, i is discount rate or the cost of capital, t is time in years, and n is total number of periods.

2. Energy Payback Time (EPBT): Determines how long a RE system takes to generate energy equal to its energy input over its lifespan. The EPBT formula is as follows:

$$\mathrm{EPBT} = \frac{\text{Total Energy Investment}}{\text{Annual Energy Production}}, \tag{15}$$

Total Energy Investment refers to the overall quantity of energy used in the system's development, installation, and operation, while Annual Energy Production is the amount of energy generated annually.

3. Payback Period (PBP): Assesses the time it takes for an investment to recoup its value through savings.

$$\mathrm{PBP} = \frac{\text{Cost of Investment}}{\text{Annual Revenue Flow of Savings}} \tag{16}$$

4. Return on Investment (ROI): Measures profitability from an investor's perspective.

$$\mathrm{ROI} = \frac{\text{Net Profit}}{\text{Cost of Investment}} \times 100 \tag{17}$$

Here, Net Profit is the overall financial benefit from the HMGS after subtracting the initial and operational costs, while Cost of Investment encompasses the total initial cost of setting up the HMGS [29–31]. This comprehensive exploration provides insights into both the environmental and financial viability of HMGSs. The complexity of designing HMGSs necessitates the use of MOO to balance cost, reliability, and sustainability effectively. The subsequent section will explore MOO approaches in HMGSs through a bibliometric analysis, shedding light on key trends and influential research in this multidisciplinary area.

2.3. Third Phase: Bibliometric Analysis and Comparative Case Studies

This phase begins by delineating MOO from single-objective optimization (SOO). After establishing this fundamental knowledge, the research further explores the intricacies of bibliometric analysis.

Optimization Overview: Optimization tasks can be broadly classified into two categories: those with a single objective and those with multiple objectives. Let us delve into these concepts.

SOO: In basic terms, SOO focuses on optimizing one specific function. Formally, the objective is to either minimize or maximize $f(x)$, subject to constraints $g_i(x) \leq 0$ for $i = 1, \ldots, m$ and $h_j(x) = 0$ for $i = 1, \ldots, p$, where x is an $n-$dimensional vector, $x = (x_1, \ldots, x_n)$, and belongs to the domain Ω.

MOO: Addresses problems involving multiple objectives, often leading to scenarios where improving one objective adversely affects another, creating a complex balance of trade-offs. Unlike SOO, where the optimal solution is clearly defined, MOO requires a relative definition of 'optimal'. A common method in MOO is to seek Pareto optimal solutions, where any improvement in one objective results in a deterioration of another. This makes MOO a challenge, as it is mathematically represented by multiple objectives that cannot all be maximized or minimized simultaneously due to inherent inter-objective constraints. The general form of MOO is to 'optimize' $f_1(x)$, $f_2(x), \ldots, f_n(x)$, subject to $g_i(x) \leq 0$ for $i = 1, \ldots, m$ and $h_j(x) = 0$ for $i = 1, \ldots, p$, where x is an element of Ω.

Here, the term 'optimize' is as previously defined; each function $f_n(x)$ represents a unique objective function, where 'n' denotes the total number of objectives, and Ω signifies the feasible region or solution space, as noted in [32]. Figure 6 illustrates the differences between SOO and MOO processes, with a particular emphasis on the selection of a Pareto optimum solution.

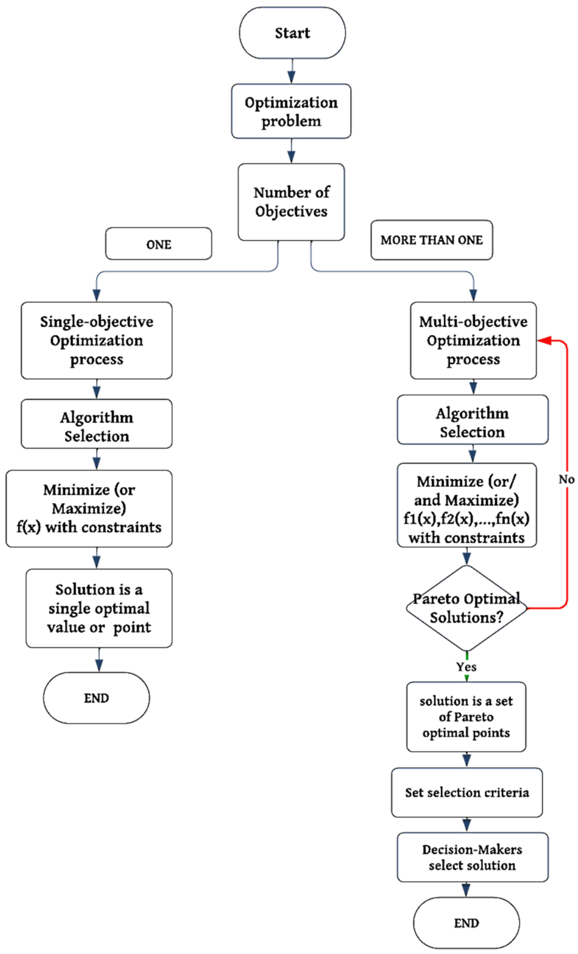

Figure 6. Decision flowchart for SOO vs. MOO processes.

The goal of MOO is to optimize solutions across multiple, sometimes conflicting, criteria simultaneously. This approach introduces the concept of Pareto optimality, where a solution is considered Pareto optimum if any further improvement in one objective would necessarily worsen at least one other objective [33]. The collection of all such Pareto optimum solutions forms the Pareto front, also known as the Pareto border. Often, no single solution satisfies all objectives optimally, leading decision-makers to rely on this set of Pareto optimum solutions to make choices based on their preferences or other considerations [34]. MOO is particularly crucial in HMGSs, balancing complex and varied objectives such as cost, efficiency, and environmental impact [35–37]. As such, MOO strategies are instrumental in navigating the trade-offs inherent in decision-making processes, enabling the integration of cost-effectiveness with sustainability.

Bibliometric Analysis

Bibliometric analysis is a popular and effective method for examining large volumes of scientific data. It facilitates the exploration of the evolutionary dynamics of a specific topic and highlights emerging areas [38]. Figure 7 illustrates the steps of the bibliometric analysis used in this study, employing a dual analysis approach to achieve its objectives.

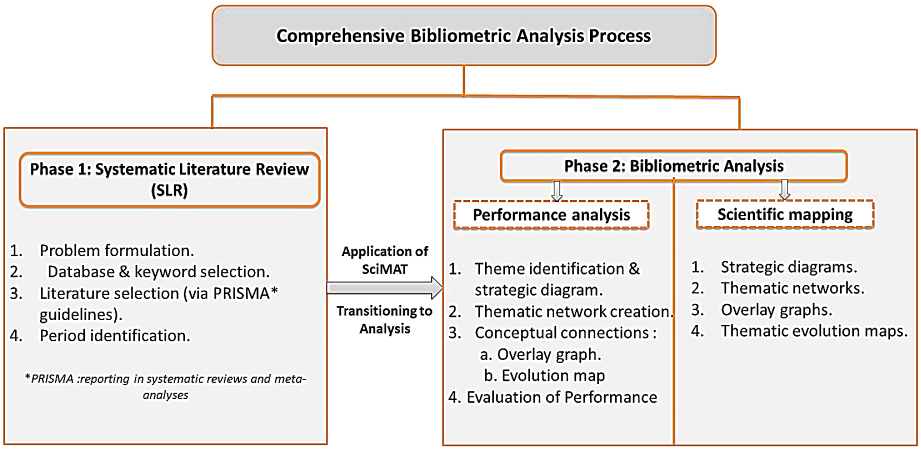

Figure 7. Workflow of bibliometric analysis process.

This analysis comprised the following steps: (i) a systematic literature review (SLR) on MOO as applied to MGs integrated with RESs and (ii) a bibliometric analysis focusing on performance analysis and scientific mapping. The subsequent sections briefly describe each of these phases.

First phase: Systematic literature review (SLR):

The literature review structure follows best practices detailed in [38] (see Figure 7) and was conducted through the following steps:

1. Problem planning and formulation: This initial step establishes the foundation for the study, involving the framing of research questions, deciding on relevant literature criteria, methods for filtering unrelated findings, and outlining possible conclusions.
2. Database(s), keywords, and search string determination: A range of databases was chosen, and a set of important terms was identified for searching. Selecting appropriate terms is crucial to encompass varied research while remaining focused on relevant articles.
3. Literature selection: At this stage, adherence to the PRISMA guidelines, which pertain to systematic reviews and meta-analyses, ensures that the selected articles align with the study's direction [39]. Insights from these articles were systematically extracted.
4. Period identification: This step involves considering elements like the topic's depth, existing literature, and its evolution over time.

Second phase: Bibliometric analysis:

Following the SLR, a bibliometric analysis is conducted in the second phase. This combines scientific mapping, describing the conceptual structure and development of the research, with a performance analysis that assesses the impact of citations. The goal is to demonstrate the relationships among authors, documents, and disciplines. The analysis was performed using SciMAT v1.1.04, an open-source tool that involves the following:

1. Theme identification and strategic diagram: Initially, the software sets up the equivalency index. It then employs a specific methodology to identify the most relevant topics. Subsequently, using the concepts of centrality and density, it strategizes for every theme, illustrating how the core research and related subjects are interconnected. Centrality refers to the degree of influence a theme has over others in the network. Themes with high centrality are vital and positioned on the right side of the diagram. Density analyzes the relationships between terms within a theme to determine its development level. Themes with high density are considered well-developed and placed toward the top of the diagram [40–42]. The diagrams, divided into four sections, as shown in Figure 8, illustrate the various research topic categories.
    - Driving themes: Important and well-understood subjects in the top right, essential for research growth.
    - Highly developed and isolated themes: Topics that stand alone and are well-understood, found in the top left, specialized but separate from the main research.
    - Evolving or receding themes: Topics in the bottom left that are not fully developed or currently significant. Their importance may increase or decrease in the future.
    - Cross-cutting basic themes: Fundamental subjects important to the research but not yet fully developed, occupying the lower right section of the quadrant.
2. Thematic Network Creation: This explores relationships between keywords and subjects to refine strategic diagrams. Each network depicted in Figure 8 is named after its principal keyword. The size of the circles indicates the number of associated papers, while the thickness of the links is determined by the equivalence index.
3. Conceptual Connections: The inclusion index [43] illustrates how themes are interconnected over time:
    - Overlay Graph: Shows prevalent terms alongside keywords that have been added or removed over time.
    - Thematic Evolution Map: Dotted lines represent sub-elements, and solid lines indicate connections to the primary theme. The size of circles and the thickness of lines signify the number of documents and the inclusion index, respectively.
4. Evaluation of Performance: Evaluates research contributions using various metrics. It identifies leading subfields based on indicators such as the number of articles, citation counts, and variations in the h-index.

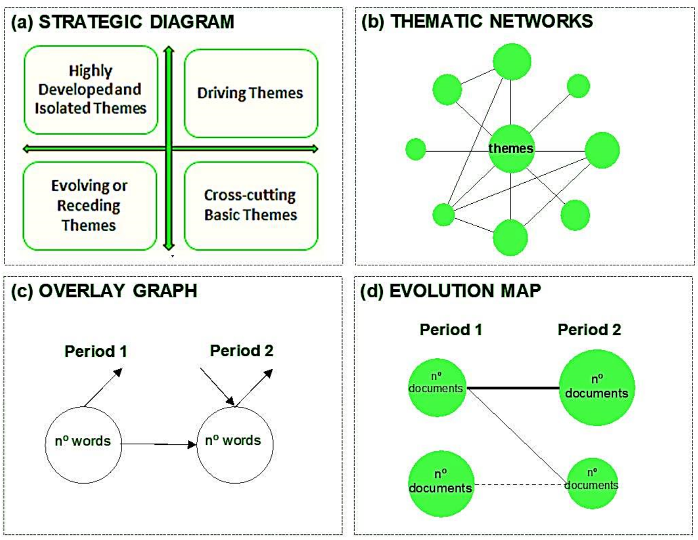

Figure 8. Visual representation of research theme analysis and evolution.

3. Findings and Analysis

The results from the prior sections are detailed and can be viewed in Figures 7–13 as well as Tables 2–5.

3.1. SLR on the Application of MOO for HMGSs

This study aims to explore the current landscape of knowledge concerning the MOO of MGs integrated with RESs, herein referred to as HMGSs. To guide this exploration, the investigation was formulated around the following research questions (RQs):

RQ1: How is current research evolving in the selected field?
RQ2: Which core ideas shape this area of study?
RQ3: Which challenges currently persist in this research domain?
RQ4: What are the pivotal moments or crucial issues related to the topic?
RQ5: What topics attract significant focus and discussion?
RQ6: What gaps or shortcomings can be identified in current studies?
RQ7: Which publications or studies are considered seminal in this field?
RQ8: Who are the leading contributors or prolific writers in this sector of research?

This study utilized the SCOPUS database, which houses numerous significant global scientific publications across various fields. The review focused on microgrids, renewable energy systems, and multi-objective optimization. Keywords relevant to these topics were applied in an advanced SCOPUS search as follows: TITLE-ABS-KEY ("microgrid" OR "micro grid" OR "micro-grid" OR "microgrids") AND ("renewable energy" OR "renewable energy sources" OR "renewable energy systems" OR "hybrid energy" OR "distributed energy resources" OR "hybrid energy systems" OR "hybrid energy sources" OR "hybrid renewable energy system" OR "hybrid power system") AND ("multiobjective optimization" OR "multiobjective optimisation" OR "multi objective optimization" OR "multi objective optimisation" OR "multi-objective optimization" OR "multi-objective optimisation" OR "multi-objective programming" OR "multiobjective programming" OR "vector optimization" OR "multicriteria optimization" OR "multiattribute optimization" OR "Pareto optimization"). A SLR was conducted following the PRISMA flowchart guidelines depicted in Figure 9.

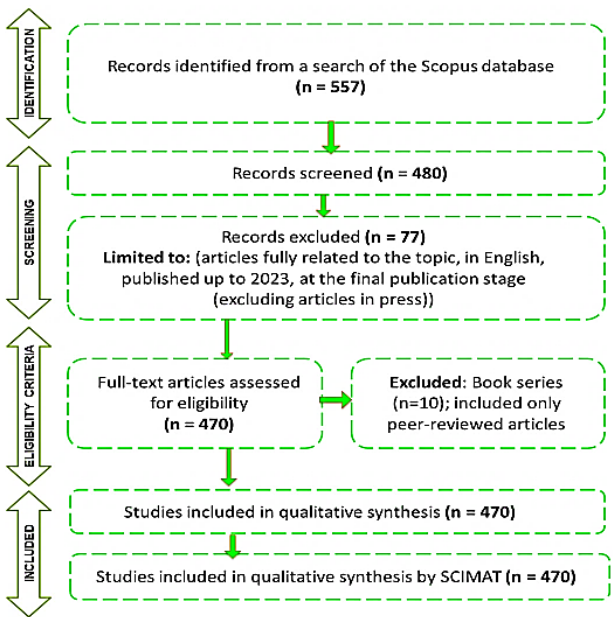

Figure 9. PRISMA flow diagram of article selection from the Scopus database.

Initially, 557 bibliographic records were retrieved from the Scopus database. The selection was refined by applying specific exclusion criteria, leading to the removal of

77 records. These criteria included relevance to the research topic, language (with a focus on articles in English), publication date (considering articles published up until 2023), and publication status (excluding articles in press). In the subsequent eligibility phase, book series were excluded due to their format, resulting in the elimination of an additional 10 sources. This refinement process ensured that the final selection comprised articles directly relevant to the research topic. After the final round of eliminations, 470 pertinent papers remained for analysis.

To study publication trends from 2010 to 2023, the timeframe was divided into two periods based on the number of selected papers and relevant milestones.

First period (2010–2019): 200 articles were recorded. During this period, the US Department of Energy (DOE) held its first workshop on microgrid research areas. SPV module prices saw a significant drop, falling below USD 1 per watt in 2011. The year 2015 was pivotal for RESs, marked by the approval of the United Nations Development Goals (SDGs), specifically target 7.2 of goal 7, and the Paris Climate Conference [44]. The main objective of the Paris Conference was to limit global temperature rises to below 2 °C this century, with RE playing a key role.

Second period (2020–2023): 270 articles were recorded. During this period, research surged, driven by the urgency to address climate change and reduce reliance on fossil fuels. A notable outcome from the DOE Smart Grid R&D Program workshop was the creation of an MG-focused MOO framework using quantitative metrics and dynamic programming, along with the development of specific design tools and a solutions library by 2020 [13]. Figure 10 shows the distribution over time of 470 publications, revealing consistent growth in this field.

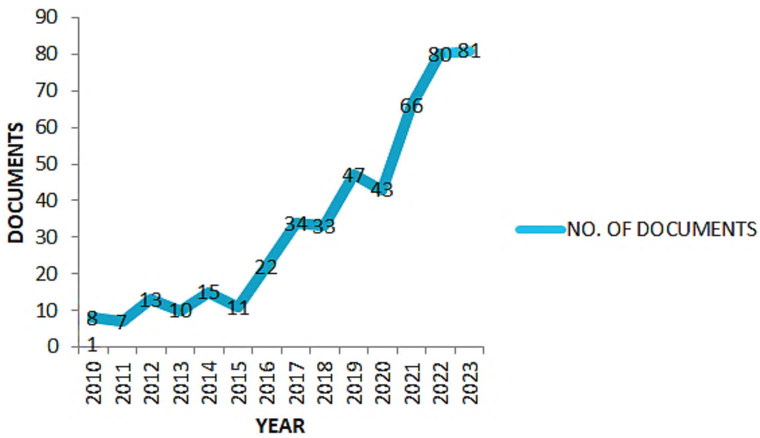

Figure 10. Yearly distribution of documents.

3.2. Bibliometric Analysis: Insights from Science Mapping and Performance Metrics

This section examines various graphical analyses, including strategic diagrams for each period, critical thematic networks, an overlay graph, and a thematic evolution map. Additionally, it assesses the timeline progression of documents, citation counts, top-cited authors, and the overall quality and quantity of the publications.

3.2.1. Strategic Diagrams

Figure 11 depicts strategic diagrams for the periods 2010–2019 and 2020–2023, respectively, illustrating the popularity of research subjects based on publication volume.

The size of each circle in the diagram indicates the relative volume of publications for each research theme. Table 2 summarizes the performance metrics for each theme and period, including the number of documents, h-index, centrality, density, and publication count, providing a quantitative overview of the impact and relevance of each theme within the specified periods.

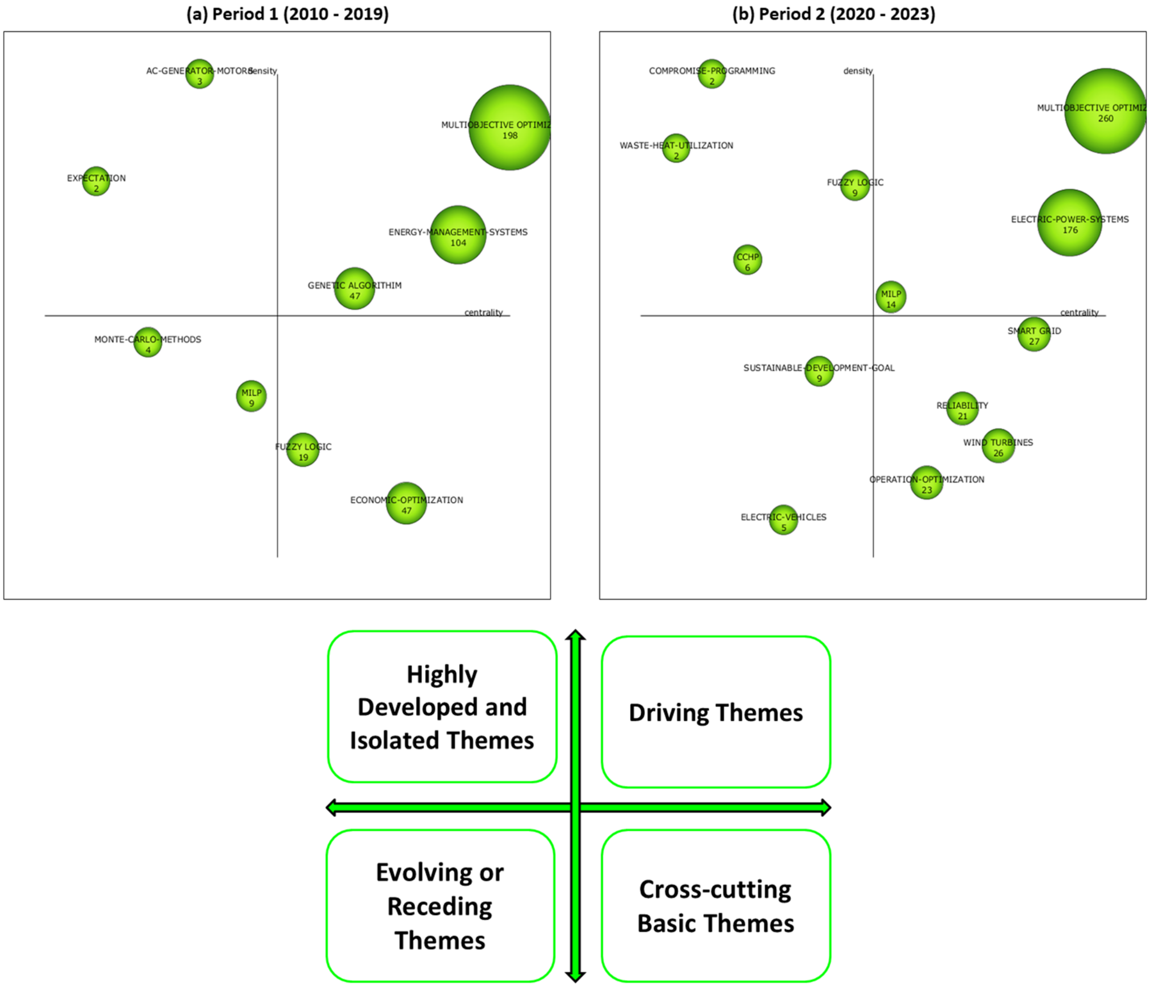

Figure 11. Strategic diagrams for ((**a**) period 1; (**b**) period 2).

Following is a brief overview of the results for each time period.

First period (2010–2019): The analysis of 200 selected articles identified 10 research topics, as shown in Figure 11a's strategic diagram. Three themes—multi-objective optimization, energy management systems, and genetic algorithms—were identified as driving themes, indicating their significance in shaping the field's direction. AC generator motors and expectancy emerged as well-developed yet isolated themes, highlighting areas of focused but separate research. Monte Carlo techniques and MILP were classified as evolving or receding themes, suggesting areas of diminishing focus or emerging interest, while fuzzy logic and economic optimization were identified as foundational yet underdeveloped areas. A comprehensive performance study, as summarized in Table 2, alongside the strategic diagram's insights, revealed that MOO and energy management systems exhibited superior performance metrics, notably achieving the highest h-index values with over 16,000 citations.

Second period (2020–2023): Analyzing 270 papers from this more recent period yielded 13 research themes, as depicted in Figure 11b's strategic diagram. This period saw three driving themes—multi-objective optimization, electric power systems, and MILP—indicating continued or emerging importance. Four themes—fuzzy logic, compromise programming, waste heat utilization, and CCHP—were recognized as developed but isolated, reflecting specialized areas of research with limited cross-theme integration. Sustainable development goals and electric vehicles emerged as evolving or receding themes, pointing to shifting research priorities, while wind turbines, reliability, operation optimization, and smart grids were identified as basic yet foundational themes. Notably, MOO and electric power systems stood out in performance measurements, exhibiting superior h-index and citation impact, as detailed in Table 2.

Table 2. Theme-specific performance metrics.

Period 1 (2010–2019)					
Name of clusters	Documents count	h-index	Citations count	Centrality	Density
Multiobjective optimization	198	51	9630	373.74	131.48
Ac generator motors	3	3	16	59.44	242.5
Energy-management systems	104	43	7351	226.49	24.94
Genetic algorithm	47	19	2956	126.1	19.49
Economic optimization	47	20	2630	134.23	8.16
Fuzzy logic	19	11	1839	89.02	9.76
MILP	9	7	472	70.22	10.63
Expectation	2	1	13	6.49	44.44
Monte Carlo methods	4	4	177	8.82	16.67
Period 2 (2020–2023)					
Name of Clusters	Documents count	h- index	Citations count	Centrality	Density
Multiobjective optimization	260	30	3347	363.59	135.68
Electric-power systems	176	29	2795	245.16	25.61
MILP	14	9	436	46.55	9.67
Smart grid	27	14	686	65.42	8.09
Fuzzy logic	9	5	193	39.26	47.41
Operation optimization	23	9	324	48.7	4.23
Wind turbines	26	9	381	61.39	4.34
Reliability	21	12	365	54.4	4.84
Sustainable-development goal	9	5	116	24.09	6.92
CCHP	6	4	101	16.65	19.67
Compromise programming	2	1	6	5.73	150
Waste-heat utilization	2	1	5	2.81	77.78
Electric vehicles	5	3	121	17.9	3.45

It is worth noting that, over the examined periods, the mixed integer linear programming (MILP) theme shifted from 'evolving or receding' to a 'driving' theme, suggesting an increase in its significance and centrality. Concurrently, fuzzy logic progressed from a 'basic' to a 'developed but isolated' theme, indicating its specialized growth despite limited connection with broader research themes. These transitions illustrate the dynamic nature of research landscapes, emphasizing the importance of tracking topic evolutions to guide future studies. In the context of evolving research approaches, studies such as [45] have MILP to optimize energy management and sizing in HMGS, resulting in significant cost savings and improved resource allocation efficiency. Reference [46] applied MILP to simplify the complexity of energy system scenario analysis, thereby enhancing the manageability and strategic planning of MGs. Reference [47] describes an energy management system for MGs that leverages fuzzy logic for efficient energy dispatch and forecasting. This system adapts to variations in RESs and incorporates expert rules, thereby improving reliability and economic returns.

During the first period, MOO and genetic algorithms were prominent; ref. [48] showed a multi-objective genetic algorithm (MOGA) optimizing system design for size, cost, and availability using high-resolution insolation data, demonstrating a complete techno-economic analysis. Energy management systems were central in the first period, indicating an increasing emphasis on energy efficiency, with ref. [49] developing an optimal management approach for smart-grid sustainability, cost reduction, and carbon emission minimization while incorporating uncertainties and dynamic conditions over a 24-h cycle. Economic optimization appeared as a basic theme; ref. [50] identifies optimal HMGS capacities for reduced costs and environmental impact, alongside a strategy cutting diesel use by 12%, emphasizing the economic aspect. MILP and fuzzy logic emerged as emerging themes, signaling the start of their path to becoming important methodological tools. Furthermore, the use of Monte Carlo techniques, as noted in [51], indicated the use of probabilistic approaches in system analysis and design, which is critical for dealing with uncertainties in [52].

Moving into the second period, there was a notable shift. MOO remained a significant topic, whereas MILP gained prominence and relevance, becoming a key theme in the research environment. The expanding relevance of electric power systems and smart grids, as shown by an emphasis on renewable-rich HMGSs [53], demonstrates the trend toward integrating intelligent technologies for optimal energy distribution while balancing cost, availability, and area limits. Emerging areas like Sustainable Development Goals, electric vehicles, and wind turbines gained focus, signaling a shift toward sustainable and renewable energy solutions. Since 2022, the movement toward clean energy has increased, as seen by a 55% rise in electric vehicle sales, which have surpassed 10 million [54]. Notably, this includes considering the total cost of ownership for electrifying heavy-duty trucks, a critical aspect of the transportation sector's low-carbon transition [55]. Meanwhile, topics like combined cooling heating and power (CCHP) and waste-heat utilization exhibited a continuous yet concentrated focus on specific energy optimization and recovery techniques, demonstrating a sophisticated approach to RE integration, as evidenced in research sources [56,57]. This illustrates a substantial push toward different sources of clean energy, where heat pumps have registered an 11% rise in sales, reaching the 15% growth rate required to fully align with the Net Zero Scenario [58].

Finally, the movement in research subjects from basic methodology to advanced technological applications reflects the field's growing emphasis on sustainability and intelligent energy solutions. The study underscores the significance of flexibility and innovation in solving complex optimization problems, paving the way for future research to enhance the efficiency and resilience of energy systems. This synthesis not only illustrates the field's dynamic nature but also highlights the importance of MOO collaboration in advancing the energy transition.

3.2.2. Thematic Networks

To investigate the thematic networks, a key topic was chosen for each period to examine its relationships with other subjects, revealing the underlying themes associated with the main theme. Consequently, 'MOO' (see Figure 12a) and 'Electric Power Systems' (see Figure 12b) were selected as the driving themes from the first and second periods, respectively.

The analysis in Figure 12a underscores the pivotal role of MOO within MGs, emphasizing its strong connections to 'Microgrid', 'Renewable Energy Resources', and 'Electric Load'. This highlights how MOO is crucial for balancing objectives such as aligning energy supply with demand, integrating RE smoothly into the grid, and enhancing the efficiency and effectiveness of MG operations. In contrast, Figure 12b focuses on the 'Electric Power Systems' theme, detailing its complex interactions with key MOO algorithms like 'Genetic Algorithm' and 'Multi-Objective Particle Swarm Optimization'. This underscores the vital role these advanced algorithms play in enhancing the efficiency of electric power systems, particularly in terms of renewable energy integration and demand management. It delves into 'control systems', 'energy management systems', and 'demand response programs', underscoring the importance of these areas in the broader context of electric power systems optimization. The pronounced use of meta-heuristic methods, especially genetic algorithms, showcases their capability to tackle complex challenges in the energy sector [59].

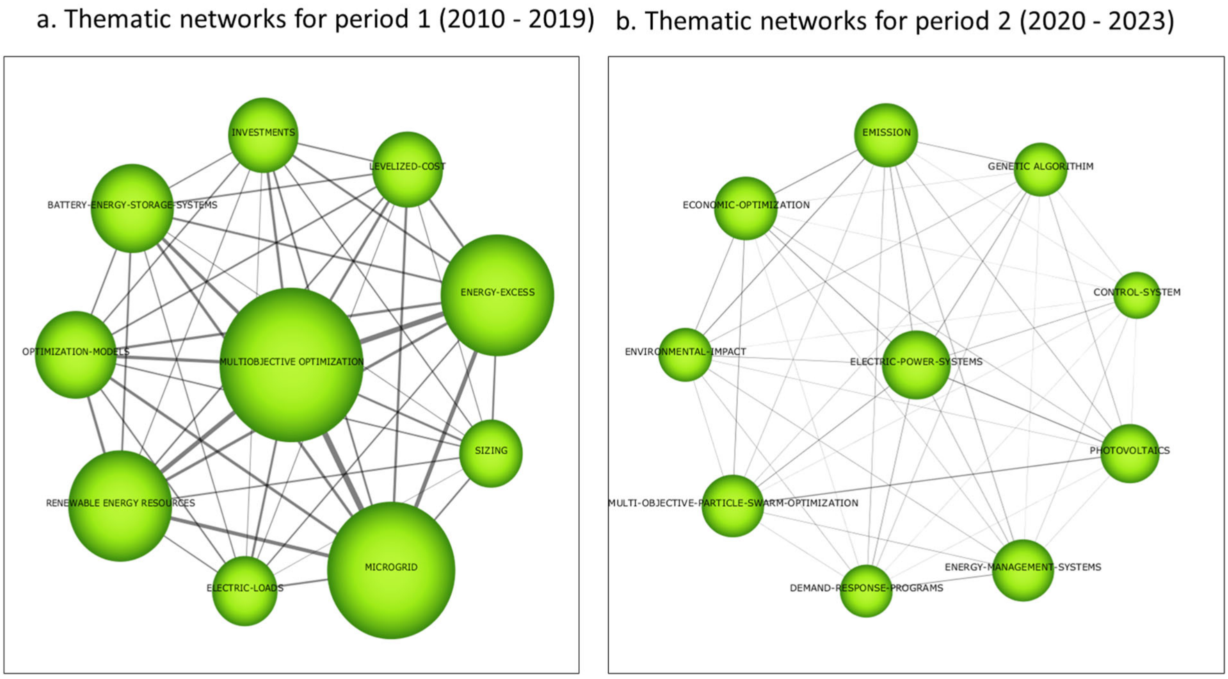

Figure 12. Thematic networks for ((**a**) period 1; (**b**) period 2).

This dual analysis allows us to compare the evolving focus from MOO's application within MGs to the broader challenges of integrating advanced algorithms for optimizing electric power systems. The visualizations also underscore key operational, financial, and efficiency concerns in both periods, from 'Levelized Cost' and 'Sizing' to 'Emission' and 'Environmental Impact', reflecting the sector's shift towards not only technical and operational efficiency but also environmental and economic sustainability.

3.2.3. Graphical Overlay and the Evolution of Theme Mapping

Figure 13 displays two critical aspects of the analysis: Figure 13a presents an overlay graph depicting the evolution of keywords over the study periods, while Figure 13b illustrates a thematic evolution map that outlines the shifts and relationships within the research themes.

Figure 13a illustrates the changing quantity and content of keywords over the years. The number of keywords increased from 726 to 890 from the first to the second period, demonstrating growth rate. Of 726 keywords found in the first period, 27% (196 keywords) were retained in the second period. Additionally, 694 new keywords were added, bringing the total to 890 keywords during the later period. This indicates a significant introduction of new and transitional keywords, as well as overall growth in keyword count over time, suggesting that the field is becoming more thematically diverse. The recurrence of certain phrases in subsequent periods indicates that this emerging subject is increasingly being normalized.

The thematic evolution map (Figure 13b) emphasizes the evolving nature of the research landscape. The MOO node's prominent placement and size reflect a large concentration of investigations and an extensive range of publications in this field, highlighting its ongoing significance and progress within the HMGS domain. Thematic shifts from 'Energy Management Systems', 'Genetic Algorithm', and 'Economic Optimization' in the first period to 'Electric Power Systems' in the second period indicate a move toward integrating these fundamental concepts into a larger framework of power systems. This demonstrates a growing area in which theoretical models are increasingly being applied to real-world energy systems. The map also shows 'Economic Optimization' branching into themes like 'MILP', 'Operation Optimization', and 'Reliability' in the second period, showing the sector's emphasis on operational efficiency, advanced modeling, and reliability of systems. 'MILP' additionally evolves to 'CCHP', 'Wind Turbine', and 'Smart Grid', indicating its analytical importance in optimizing complex energy systems and incorporating renewable technology.

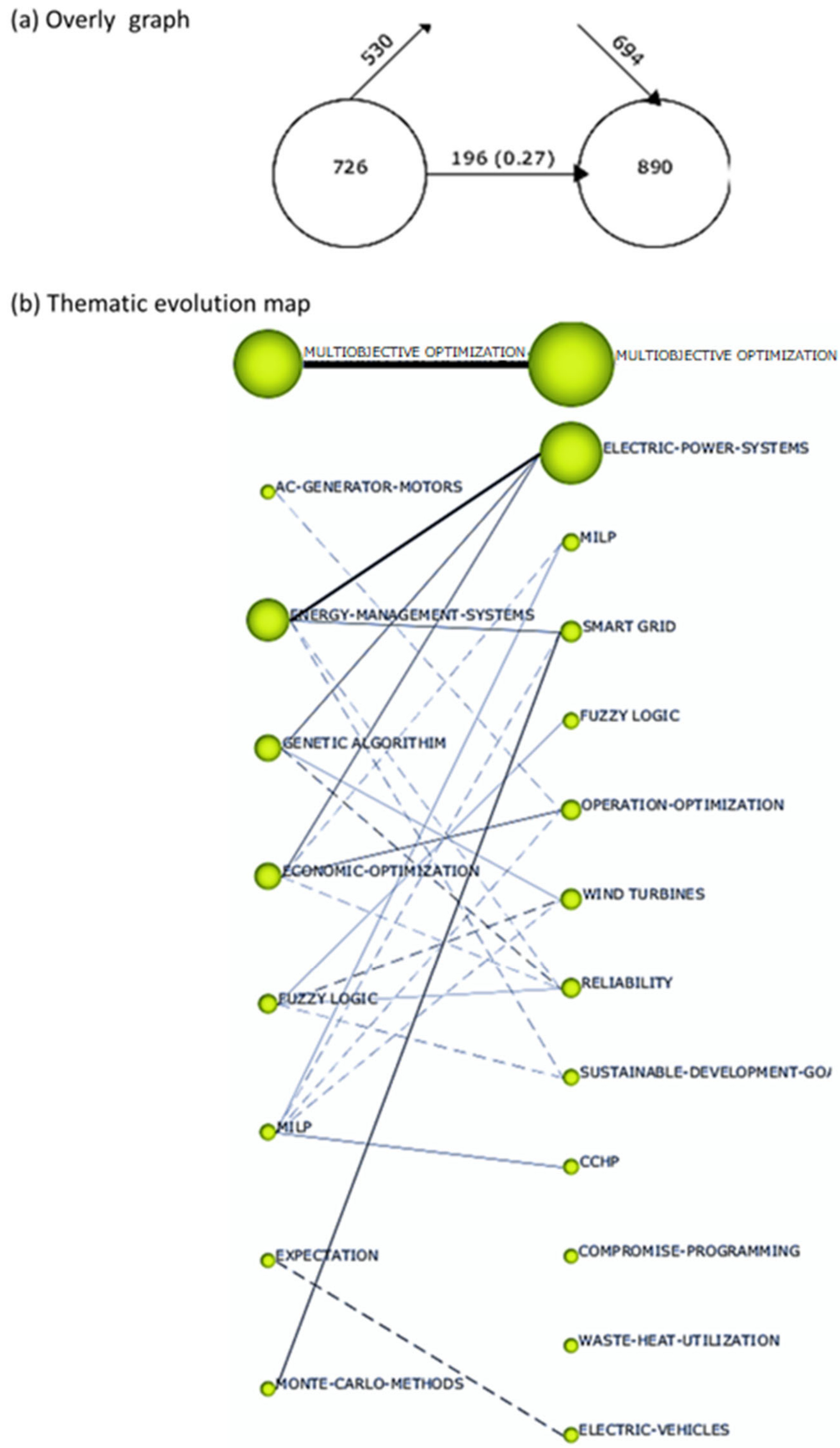

Figure 13. (**a**) Overly graph, (**b**) Thematic evolution map.

Notably, in the first period, 'Fuzzy Logic' connects with itself and progresses to 'Wind Turbine', 'Reliability', and 'Sustainable Development Goals' in the second period, demonstrating its use in mitigating uncertainty in RESs [60], enhancing system dependability, and contributing to sustainability goals. This relevance extends to addressing the complexity of power system outages through innovative strategies like the N-K events scale reduction technique and fuzzy zero-violation clustering for optimizing directional overcurrent relays (DOCRs) [61]. It is worth noting that four topics from the first period migrated to 'Reliability' and three others to 'Electric Power Systems' in the second phase. This trend reflects a research environment in which power system dependability is becoming more important, driven by the integration of varied energy sources and the need for strong power system infrastructures [62].

Overall, the map depicts a field undergoing significant transformation, with MOO and other modeling techniques being employed to tackle novel challenges in power systems. The clearly strong thematic connections and the increasing focus of research underscore a sector on the cusp of innovation. This sector is increasingly driven by concerns for sustainability and economic efficiency, spurred by the need to integrate a variety of RESs into reliable and efficient power systems.

3.2.4. Evaluation of Performance

This study analyzed 245 journals. Table 3 displays the top 10 journals, which contributed 151 papers, accounting for 32.13% of the total documents evaluated.

Table 3. Key journals contributing to the study area.

Name of the Journal	Documents Count	Total Citations	Most Cited Document	Citations Count
Energy	26	2391	[63]	490
Energies	24	264	[64]	29
IEEE Access	22	265	[65]	41
Applied Energy	17	1449	[36]	357
International Journal Of Electrical Power And Energy Systems	15	443	[66]	121
Renewable Energy	10	905	[35]	360
Sustainable Cities And Society	10	386	[67]	121
Energy Conversion And Management	10	609	[68]	200
Journal of cleaner production	9	338	[69]	164
IET Renewable Power Generation	8	271	[70]	96

Note: Citation and document counts are accurate as of 18 January 2024.

Additionally, the table displays the most cited document from each journal. These top-cited publications predominantly discuss the development of MGs optimization and management methods, with a focus on the proper integration of RESs. Key concerns highlighted include increasing energy efficiency, ensuring reliability amidst uncertainties (such as fluctuations in wind and SPV), and balancing environmental and economic objectives within MG operations.

The SLR conducted for this investigation identified 1369 authors who have contributed to the examined topic, as shown in Table 4.

The above table lists authors who have published more than five articles, along with their total number of citations and h-index, an indicator assessing an author's influence and quality based on the frequency with which their research is cited. The articles primarily discuss energy storage management, control techniques, and the optimization of MG operations under uncertainty, with an emphasis on MOO approaches that balance technical, economic, and environmental considerations.

Table 4. Key authors in the research area.

Authors' Names	Documents Count	Total Citations	H-Index	Most Cited Document	Citations Count
Yue Wang	8	186	12	[71]	128
Hongdong Wang	8	130	12	[72]	102
Josep M. Guerrero	8	131	130	[65]	41
Tomnobu Senjyu	6	57	9	[73]	33
Meenakshi De	6	57	5	[74]	20
Yuanzheng Li	6	25	31	[75]	12
Yongjun Zhang	6	71	30	[76]	34
Ziqiang Wang	6	101	14	[77]	52
Maria Luisa Di Silvestre	6	445	22	[78]	147
Hesen Liu	6	53	9	[79]	27

Note: Citation and document counts are accurate as of 18 January 2024.

The SLR concluded by finding the most-cited papers within the area of the review. Out of the 470 documents analyzed, a total of 12,989 citations were recorded. The top ten most-cited papers, which are detailed in Table 5 and account for 3384 citations, or 26% of the total citations observed, largely address the optimization and efficient energy management of MGs employing MOO methods, with an emphasis on the integration of RESs and HESs. Critical topics explored include optimal size, economic dispatch, and the creation of powerful algorithms for boosting the sustainability and reliability of MG operations.

Table 5. Top-cited documents in the study.

Authors' Names	Year	Citation Counts	Most-Cited Document
Chaouachi, A., Kamel, R.M., Andoulsi, R, Nagasaka, K.	2013	545	[37]
Niknam, T., Moghaddam, A.A., Seifi, A., Alizadeh Pahlavani, M.R.	2011	490	[63]
Ramli, M.A.M., Bouchekara, H.R.E.H., Alghamdi, A.S.	2018	360	[35]
Niknam, T., Azizipanah Abarghooee, R, Narimani, M.R.	2012	357	[36]
Aghajani, G., Ghadimi, N.	2018	347	[80]
Borhanazad, H., Gounder Ganapathy, V., Mekhilef, S., Mirtaheri, A., Modiri-Delshad, M.	2014	342	[81]
Eriksson, E.L.V., Gray, E.	2017	264	[62]
Basu, A.K., Bhattacharya, A., Chowdhury, S., Chowdhury, S.P.	2012	250	[82]
Balog, R.S., Shadmand, M.B.	2014	217	[48]
Abapour, S., Mohammadi-Ivatloo, B., Nazari-Heris, M.	2017	212	[83]

Note: Citation counts are accurate as of 18 January 2024.

4. Comparative Analysis of MOO in HMGs: Evaluating Techniques and Algorithms for Enhanced Performance and Sustainability

Table 6 presents a comprehensive review of the evolution in MOO techniques applied to HMGSs from 2010 to 2023, showcasing how these methodologies have addressed changing technological challenges and advancements. The table is organized into two distinct periods, highlighting specific challenges and developments in each era. Studies were meticulously selected for their relevance to the key challenges in HMGS design, their contributions to advancing MOO methodologies, and their impact within the field, as evidenced by their citation metrics.

Table 6. Comparative analysis of HMGS optimization techniques.

First Period (2010–2019)						
Ref.	**Key System Components**	**Primary Objective of Optimization**	**Optimization Technique Used**	**Key Findings**	**Algorithm Performance Comments**	**Publication Year**
[35]	SPV, WT, DG, BT	Optimization of component sizing for economic efficiency and system reliability in HMGS	MOSaDE	The study utilizes the MOSaDE algorithm to optimize the sizing of components in an HMGS in Yanbu, Saudi Arabia, focusing on cost-effectiveness and reliability. 'Sizing' in this context involves determining the optimal capacity and configuration to achieve economic efficiency while maintaining system performance. The analysis demonstrates the algorithm's effectiveness in adapting to varied operational scenarios and its impact on reducing the cost of energy (COE). It confirms the practicality and adaptability of the optimization approach, emphasizing its real-world applicability across different settings.	The MOSaDE algorithm has proven highly effective in optimizing HMGS in this study, adeptly handling multiple objectives such as cost, reliability, and integration of renewable energy sources (RESs). Its ability to generate a Pareto front of solutions enhances the versatility of design options, offering a spectrum of optimal solutions tailored to varying priorities. Additionally, the algorithm's flexibility is underscored by its successful application across different system components, demonstrating its adaptability in real-world settings.	2018
[84]	SPV, CCHP, GSHP, BT	Minimizing LCOE, reducing CO_2 emissions, and alleviating disturbances from uncertainties	MOCE	The integrated scheduling approach for MGs addresses uncertainties caused by intermittent RESs and random loads. Load shifting is introduced as an effective demand response program for industrial customers. The MOCE algorithm minimizes costs and emissions under worst-case scenarios of uncertainties, with robust sets and budgets of uncertainty capturing these effectively. The strong duality-based model transformation method addresses coupling and nonlinearity in the system's formulation. Comparative experiments confirm the approach's superior performance in attenuating disturbances and achieving optimal economic and environmental benefits, outperforming traditional single-objective robust optimization and deterministic MOO approaches.	The MOCE algorithm is selected for its high accuracy and straightforward approach to addressing the proposed formulation. It conceptualizes the optimization problem as an estimation issue, utilizing importance sampling techniques to accurately estimate parameters of probability density functions. Proven highly effective in MOO, this method not only meets all optimization objectives but also delivers a robust solution to the MG scheduling problem under uncertain conditions. This study particularly highlights the algorithm's capability to efficiently handle complex scenarios, making it a reliable choice for real-world applications.	2017
[85]	SPV, WT, BT, DG	Minimizing LCOE, reducing CO_2 emissions, and lowering the LPSP	GA	The author utilizes Pareto front solutions to address a MOO problem, focusing on three critical dimensions: investment costs, emission pollution, and power loss. The optimization process employs a GA, adeptly managing both technical and economic constraints. This method is effective in both grid-connected and standalone HMGS operation modes. The study is particularly noted for its ability to balance the intricate interplay of cost, environmental, and efficiency objectives, presenting a comprehensive and balanced approach to MG planning and resource optimization.	The GA is valued for its effectiveness in solving complex optimization problems. It is particularly suitable for tasks such as DER planning, where both technical and economic constraints are involved. The GA excels in finding optimal solutions within multi-dimensional objective spaces, as demonstrated in this study by its application to the MG across various operational modes.	2016
[60]	WT, SPV, BT, MT, FC	Minimize cost and emissions, with and without responsive loads	MOPSO, Fuzzy-based mechanism, Non-linear sorting system	The study utilized MOPSO, complemented by a fuzzy-based mechanism and a non-linear sorting system, to optimize operations, aiming to reduce operating costs and emissions. Including responsive loads notably decreased power generation by WT and SPV during peak hours. Additionally, the implementation of DR programs led to a 24% reduction in operating costs and a 16% decrease in emissions.	In this study, MOPSO proved highly effective in achieving the dual objectives of cost reduction and emission control, demonstrating significant enhancements in both operational efficiency and environmental impact.	2015

Table 6. *Cont.*

First Period (2010–2019)						
Ref.	**Key System Components**	**Primary Objective of Optimization**	**Optimization Technique Used**	**Key Findings**	**Algorithm Performance Comments**	**Publication Year**
[81]	WT, SPV, BT, DG	Minimizing LCOE, reducing LPSP, and ensuring a system primarily based on RESs	MOPSO	The study demonstrated that MOPSO effectively optimized the system configuration and component sizing, focusing on reducing LCOE and LPSP. Results highlighted the effective use of wind and solar energy in various regional contexts, showing notable enhancements in energy reliability and cost efficiency. The sensitivity analysis validated the optimization outcomes, suggesting that the implementation of hybrid systems can significantly improve access to reliable and sustainable energy in remote areas.	MOPSO was successful in optimizing the system for cost-effectiveness and reliability, demonstrating its utility in managing complex energy systems with a focus on renewable resources.	2014
[86]	WT, SPV, MT, FC, CHP, electrical and thermal storage	Minimizing total operational costs and net emissions in a CHP-based MG	MBFO, Interactive Fuzzy Satisfying Method	The study introduced an integrated energy management system (IEMS) for a CHP-based MG, employing MBFO and an interactive fuzzy satisfying method to minimize operational costs and emissions. This system efficiently managed total electrical and thermal load demands, effectively balancing economic and environmental criteria.	According to the study results, MBFO, enhanced by the interactive fuzzy satisfying method, successfully balanced the trade-offs between cost and emissions, thereby enhancing the MG's performance efficiency.	2013
[82]	MT, DG, DERs	Optimizing economic scheduling of DERs in a CHP-based MG, focusing on balancing fuel costs and emissions	PSO, DE	The study focused on economically deploying DERs in a CHP-based MG, utilizing PSO for optimal sizing and DE for balancing fuel costs and emissions. It assessed various DER combinations, including MTs and DGs, to efficiently distribute electrical and thermal loads. The findings confirmed the effectiveness of these DER mixes in meeting diverse energy demands while maintaining a cost-effective and environmentally friendly balance.	The findings indicated that the integration of PSO and DE was effective for MOO, successfully balancing fuel costs and emissions while promoting economic and efficient MG operations.	2012
[63]	SPV, WT, BT, FC, MT	Minimizing total operating costs and net emissions in a renewable MG	AMPSO, CLS, FSA	This study introduced the AMPSO algorithm to optimize the operations of an MG equipped with RESs and a backup system consisting of MT, FC, and BT. The primary goal was to minimize both operating costs and emissions. SPV and WT were included as part of various distributed generation sources. Enhanced with CLS and FSA, the AMPSO was employed to manage the nonlinear MOO challenge, focusing on balancing power mismatches and optimizing energy storage requirements.	Based on the results, integrating AMPSO with CLS and FSA provided an effective solution for MOO, balancing economic and environmental objectives in MG operations based on RES. AMPSO is adaptable and optimizes quickly but can converge prematurely and requires high computational resources. CLS improves solution diversity and cooperation but is complex to coordinate and scale. FSA effectively explores the solution space and avoids local optima but may be slow to converge and is computationally demanding [87–89].	2011
[90]	GT, SPV	Minimizing emissions (CO_2, CO, NOx) from GTs and reducing fuel consumption in an MG	MATLAB function 'fgoalattain' for MOO	The study focused on optimizing an MG that includes GTs and an SPV-based active generator. MOO was implemented to minimize emissions from the GTs and to maximize the use of the non-polluting SPV-based active generator. This optimization led to a 9.17% reduction in equivalent CO_2 emissions, with the active generator contributing 11% of the total energy to the system.	In this study, the MOO, using the MATLAB function 'fgoalattain', effectively balanced environmental goals with energy management, demonstrating efficiency in reducing emissions and fuel consumption while specifically utilizing SPV systems.	2010

Table 6. *Cont.*

First Period (2010–2019)						
Ref.	**Key System Components**	**Primary Objective of Optimization**	**Optimization Technique Used**	**Key Findings**	**Algorithm Performance Comments**	**Publication Year**
Second Period (2020–2023)						
[91]	SPV, WT, Hydroelectric, Biomass	Minimizing total annualized cost of electricity supply and reducing energy imports from the grid	MOPSO	The article introduces a novel optimization technique for MG production in a Spanish town with inconsistent grid connections. Employing the MOPSO technique, the primary aim is to minimize costs and reduce dependence on the grid. The methodology achieves a practical and feasible solution, demonstrating a 20-year internal rate of return of 8.33%. This is accomplished through a combination of SPV, WT, hydropower, biomass, and turbine-based power production. This approach not only enhances the capacity to meet local energy needs independently but also serves as a model for potentially disconnecting from Spain's national power network.	In this study, the MOPSO algorithm was used to effectively minimize the objective function, achieving a balance between cost and energy imported from the network. The results indicated that higher installed power capacity resulted in reduced energy imports from the network.	2023
[92]	SPV, WT, DG, BT	LCOE, LPSP, RF	MOSSA	This study proposes an optimization design for a stand-alone MG in Djelfa, Algeria, aimed at serving a remote off-grid community. The system, powered by hybrid sources (SPV, WT, BT, DG), utilizes MOSSA to optimize COE and LPSP. The results demonstrate MOSSA's superiority over algorithms like MODA, MOGA, and MOALO, achieving better RF, COE, and LPSP. The study highlights the use of RESs and suggests future enhancements with diverse renewable sources and advanced AI algorithms.	The application of MOSSA in optimizing a stand-alone MG underscores its effectiveness in managing complex energy systems. By focusing on RE integration and cost-efficient operations, it showcases the potential of advanced algorithms to enhance future MG designs, seamlessly blending sustainability with practicality.	2022
[93]	MGT, WT, SPV, Bromide Refrigerator, AC, FC, HESS	Minimizing power generation and environmental treatment costs	(BAS-ABC) Improved ABC	This study introduces an economically optimized MOO model for a CCHP MG, utilizing an enhanced ABC algorithm with the Beetle Antennae Search Algorithm (BAS-ABC). The model strives to minimize both daily power generation dispatching costs and environmental pollutant treatment costs. An analysis of a grid-connected CCHP MG in Shanghai during summer shows that BAS-ABC achieves faster convergence and lower minimum costs compared to traditional ABC. Additionally, it reveals the inherent conflict between minimizing power generation costs and environmental costs, emphasizing the need for a balanced approach to economic efficiency and environmental sustainability.	The integration of the BAS-ABC algorithm into the CCHP MG model marks an advancement over traditional ABC, particularly in terms of convergence speed and cost-efficiency. However, the study also highlights the inherent trade-offs between economic and environmental objectives, emphasizing their importance for sustainable energy management.	2021
[94]	WT, P2G, SOFC/GT, H2 Storage, Electrolyzer	Minimizing system cost and wind curtailment rate	MOGA	This research integrates a micro-energy system (MES) with wind power, P2G, H2 storage, and a SOFC/GT hybrid. Using a MOO approach with a GA, it focuses on minimizing system costs and wind curtailment rate while managing wind power and load variability. The results demonstrate a low wind curtailment rate of 0.63%, high RE penetration at 90.1%, and an optimized life cycle cost of GBP 2,468,093. The SOFC/GT system operates at maximum electrical efficiency of 67.1%, adhering to safety constraints, and a power management strategy is developed to ensure efficient operation amidst fluctuating demands.	This study demonstrates how MOGA can effectively balance competing goals such as cost-efficiency and RE integration, ensuring an optimized and sustainable MG operation.	2020

Table 6. *Cont.*

First Period (2010–2019)						
Ref.	**Key System Components**	**Primary Objective of Optimization**	**Optimization Technique Used**	**Key Findings**	**Algorithm Performance Comments**	**Publication Year**
[95]	SPV, WT, BT	Minimizing annual comprehensive cost and grid dependency	MOCS, TOPSIS	This study establishes a MOO function for a grid-connected MG, focusing on minimizing the annual comprehensive cost and grid dependency. It utilizes the k-medoids method to handle uncertainties of RESs and load demand. The MOCS algorithm is employed to solve the model, and the TOPSIS method is used to identify the optimal compromise solution.	The combination of the MOCS algorithm and the TOPSIS method in this study presents a robust approach to MG configuration under uncertain conditions. It underscores the importance of addressing multiple objectives and managing uncertainties in RESs to achieve both economic and grid reliability goals.	2020

Abbreviation: ABC: Artificial Bee Colony, AC: Air Conditioner, AMPSO: Adaptive Modified Particle Swarm Optimization, BAS: Beetle Antennae Search Algorithm, BT: Battery, CCHP: Combined Cooling Heating and Power, CHP: Combined Heat and Power, CLS: Chaotic Local Search, CO_2: Carbon Dioxide, COE: Cost of Energy, DE: Differential Evolution, DERs: Distributed Energy Resources, DG: Diesel Generator, DR: Demand Response, FC: Fuel Cell, FSA: Fuzzy Self Adaptive, GA: Genetic Algorithm, GSHP: Ground Heat Source Pump, GT: Gas Turbine, HESS: Hybrid Energy Storage System, HMGS: Hybrid Microgrid System, IEMS: Intelligent Energy Management System, LCOE: Levelized Cost of Energy, LPSP: Loss of Power Supply Probability, MBFO: Modified Bacterial Foraging Optimization, MGs: Microgrids, MOALO: Multiobjective Ant Lion Optimizer, MOCE: Multiobjective Cross Entropy, MOCS: Multi-Objective Cuckoo Search, MODA: Multiobjective Dragonfly Algorithm, MOGA: Multiobjective Genetic Algorithm, MOO: Multi-objective Optimization, MOPSO: Multi-objective Particle Swarm Optimization, MOSaDE: Multi-objective Self-Adaptive Differential Evolution, MOSSA: Multi-objective Salp Swarm Algorithm, MGT: Micro Gas Turbine, MT: Micro Turbine, P2G: Power-to-Gas, PSO: Particle Swarm Optimization, RE: Renewable Energy, RESs: Renewable Energy Systems, RF: Renewable Factor, SDG: Sustainable Development Goal, SOFC/GT: Solid Oxide Fuel Cell/Gas Turbine, SPV: Solar Photovoltaic, TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution, WT: Wind Turbine.

A list of all abbreviations used is provided at the end of the table for easy reference.

The research in MG and HMGS optimization significantly evolved from 2010 to 2023. During the earlier period (2010–2019), the focus predominantly centered on managing uncertainties inherent in RESs and load demands, employing algorithms like MOCE, which proved effective in MOO problems. This period utilized a variety of optimization techniques, including GA, MOPSO, MBFO, PSO, and DE, each aimed at balancing economic and environmental objectives, with a common theme of integrating RESs like SPV and WT to minimize operational costs and emissions. The initial adoption of advanced computational algorithms marked an early stage of complexity in MG optimization.

Contrastingly, from 2020 to 2023, more sophisticated computational techniques such as MOPSO, TOPSIS, MOSSA, and BAS-ABC were introduced for comprehensive analyses that encompass economic, environmental, and sustainability aspects. There was a notable shift toward sustainability, aligning with the Sustainable Development Goals (SDGs), with studies like ref. [95] employing TOPSIS alongside SDGs goals for a 100% renewable configuration. This period also expanded MG applications to various geographical regions and included novel technologies like power-to-gas (P2G), solid oxide fuel cell/gas Turbine (SOFC/GT) hybrids, and hydrogen storage, continuing to balance economic efficiency with environmental friendliness through algorithms like MOGA and MOCS. The progression from 2010 to 2023 in HMGS optimization research reflects a significant transition from foundational methods to embracing complexity, sustainability, and broader scopes, mirroring the global trend toward sustainable and efficient energy solutions.

5. Conclusions

Diversifying energy sources has become essential in addressing global challenges, making the integration of renewable energy into hybrid microgrids (HMGSs) a crucial and efficient alternative. This study reviews the economic and reliability metrics of HMGSs and further investigates developments in microgrids (MGs), renewable energy (RE), and their multi-objective optimization (MOO). Utilizing SciMAT bibliometric analysis of literature from 2010 to 2023, sourced from Scopus, the study identifies trends through an overview and a detailed analysis of two distinct periods: 2010–2019 and 2020–2023.

From 2010 to 2019, 200 research articles were published, which increased by 35% to 270 papers between 2020 and 2023. This surge in publication output underscores the critical role of initiatives like the Department of Energy's Microgrid Initiative in steering research toward the development of more sophisticated and efficient MG technologies that align with global renewable energy and climate change mitigation goals. Strategic diagrams were employed to assess the evolution of this research topic, indicating a significant shift from the first period's focus on MOO and energy management systems toward a rising emphasis on advanced, eco-friendly, and intelligent energy management solutions. The second stage highlighted MOO's strategic importance in balancing competing objectives such as cost, efficiency, and environmental impact, with predominant themes being MOO and electric power systems. This shift mirrors the global movement towards sustainable and efficient energy solutions and broader efforts to integrate renewable energy sources and combat climate change. Analysis of keyword overlap and thematic evolution maps by period demonstrated remarkable progress in developing new and transitional keywords, showcasing the continual evolution of research in this field. Thematic networks and strategic diagrams revealed a marked increase in research activity, particularly in employing artificial intelligence (AI) for optimization, with methods like genetic algorithms, particle swarm optimization, and fuzzy logic gaining prominence. The study also underscored significant challenges addressed by researchers, such as economic sizing, environmental concerns, energy management systems, and investment issues, indicating a shift toward more complex, sustainable, and intelligent energy management systems.

Despite recent progress, challenges such as high battery storage costs, data reliability requirements, and managing the intermittency of renewable sources persist. Future research should focus on scalable HMGS designs, cost-effective storage solutions, and improved data analytics for MOO. Leveraging AI to optimize HMGSs will be paramount in addressing energy management challenges. Building on this study's findings, researchers are encouraged to foster adaptation, collaboration, and innovation, which will significantly contribute to the development of robust, resilient, and sustainable energy systems.

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