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Review

Optimizing Microgrid Planning for Renewable Integration in Power Systems: A Comprehensive Review

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Abstract: The increasing demand for reliable and sustainable electricity has driven the development of microgrids (MGs) as a solution for decentralized energy distribution. This study reviews advancements in MG planning and optimization for renewable energy integration, using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses methodology to analyze peer-reviewed articles from 2013 to 2024. The key findings highlight the integration of emerging technologies, like artificial intelligence, the Internet of Things, and advanced energy storage systems, which enhance MG efficiency, reliability, and resilience. Advanced modeling and simulation techniques, such as stochastic optimization and genetic algorithms, are crucial for managing renewable energy variability. Lithium-ion and redox flow battery innovations improve energy density, safety, and recyclability. Real-time simulations, hardware-in-the-loop testing, and dynamic power electronic converters boost operational efficiency and stability. AI and machine learning optimize real-time MG operations, enhancing predictive analysis and fault tolerance. Despite these advancements, challenges remain, including integrating new technologies, improving simulation accuracy, enhancing energy storage sustainability, ensuring system resilience, and conducting comprehensive economic assessments. Further research and innovation are needed to realize MGs' potential in global energy sustainability fully.

Keywords: microgrids; planning; optimization; power systems; renewable energy integration

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1. Introduction

The global shift towards sustainable energy solutions has prompted countries worldwide to introduce incentive mechanisms within their regulatory frameworks to promote renewable energies. This transition is driven by the urgent need to enhance energy efficiency, address environmental concerns, and ensure reliable energy supply in remote locations. In this context, microgrids (MGs) have emerged as a crucial form of infrastructure for integrating renewable energy into electric power systems. The U.S. Department of Energy (DOE) defines a microgrid as "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid. A microgrid can be connected and disconnected from the grid to operate in both connected and islanded modes" [1]. Despite variations in definitions, MGs generally consist of loads, storage units, and distributed generation that operate in an interconnected, coordinated manner, functioning autonomously or as part of the larger grid. The increasing significance of MGs highlights the need to explore their planning and implementation further, emphasizing their potential to transform energy systems.

The planning and operation of microgrids hold substantial implications for the future of electric power systems. MGs mirror traditional power systems regarding distributed generation resources, storage systems, load management, and interconnection lines. These

elements allow for adapting conventional methodologies and practices used in traditional systems to MGs. The literature synthesizes MG growth, classifying them by generation type, storage system, load class, control type, and AC or DC electrical scheme [2]. MGs have been implemented to provide electricity access in remote areas, support research and development—often driven by university initiatives—and enhance security and reliability in cases of war or natural disasters, such as in U.S. military bases. This study's motivation stems from the global development of MG infrastructure observed over the past decade, its impact on electric power systems, and the necessity to understand long-term planning trends.

In remote or island regions where grid connection is impractical or economically unfeasible, MGs offer a viable alternative for energy supply. These regions often rely heavily on fossil fuels for electricity generation and various activities, leading to high electricity costs and significant environmental impacts [3]. Many countries have implemented MGs to reduce this dependency, integrating renewable energy sources, such as solar, wind, biodiesel, hydroelectricity, and energy storage systems, to provide a more sustainable energy solution [4]. However, integrating significant renewable generation in isolated MGs presents operational challenges, including bidirectional power flows, stability issues, low inertia, and uncertainty in renewable resources [5]. Addressing these challenges requires innovative planning and optimization strategies, such as the use of deep reinforcement learning to enhance long-term MG expansion [6] and stochastic models to manage CO_2 emissions [7]. Additionally, enhancing the resilience and efficiency of MGs through strategic planning and interconnections has been shown to provide technical and economic benefits, such as improving reliability and enabling energy sharing between interconnected MGs [8–11]. Understanding these complexities and developing robust strategies for MG planning and operation are essential to maximizing the potential benefits of MGs in diverse environments [12–17].

Despite significant advancements, several gaps remain in the current MG research. Most studies focus on individual microgrids operating in island mode or with grid connectivity potential. However, a growing need exists to explore the planning aspects of MG clusters or groups, which involve multiple interconnected microgrids operating collaboratively. Studying MG clusters is crucial because they offer enhanced reliability, resilience, and resource optimization by enabling the sharing of resources like energy storage and generation capacity, improving load management through coordinated operations. Effective planning for MG clusters involves optimizing interconnections, coordinating energy flows, and ensuring collective resilience against external disruptions, which are vital for maximizing the benefits of renewable energy integration and reducing operational costs [5–7].

The aim of this study is to fill these gaps by providing a comprehensive literature review on MG planning and expansion models in electric power systems. By synthesizing the latest studies and advances, this review critically analyzes selected studies and proposed models using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology [18]. This systematic approach evaluates research quality, identifies knowledge gaps, and highlights areas for further investigation. The primary contributions of this article to the scientific community include addressing how emerging technologies like AI, IoT, and advanced energy storage systems can be effectively integrated into MGs, understanding the role of advanced modeling and simulation techniques in managing renewable energy variability, and exploring the economic viability and scalability of MGs.

Specifically, this review seeks to answer key questions: What are the most effective strategies for planning and optimizing MG clusters? How can renewable energy integration and storage solutions be improved to enhance the efficiency and resilience of MGs? What are the critical challenges in simulation accuracy and energy storage sustainability that need to be addressed? By exploring these questions, this review offers a detailed overview of how planning models address microgrid expansion, contributing to understanding MG integration in modern energy systems and guiding future research on optimizing clustered MG configurations for better performance and sustainability. The remainder of this paper

is organized as follows: Section 2 presents the literature review and methodology, outlining the theoretical framework and research methods used. Section 3 details the results of our analysis and discusses the implications of these findings, and, finally, Section 4 concludes this paper, highlighting the main contributions and suggesting avenues for future research.

2. Literature Review Methodology

2.1. Literature Search Strategy

This section outlines the methodology employed to systematically review the literature on microgrid expansion planning. The literature for this review was gathered from three well-known databases: Scopus, IEEE Xplore, and MDPI. These sources were chosen for their extensive repositories of high-quality research articles, ensuring a thorough, transparent, and impartial review.

Scopus is known for its stringent content selection policies and wide-ranging coverage across various fields, providing access to high-quality, peer-reviewed content. Its advanced analytical tools and bibliometric indicators further enhance the reliability and depth of our review. IEEE Xplore, a premier resource for electrical engineering and related disciplines, offers access to influential and frequently cited publications, including the latest and most relevant research. MDPI, as a fully open access publisher, guarantees that our review includes peer-reviewed research accessible to a broad audience, fostering inclusivity and the widespread dissemination of knowledge.

These databases provide a comprehensive and diverse collection of relevant literature, capturing a broad spectrum of high-quality studies. By focusing on these reputable sources, we ensure that our review offers a thorough and reliable overview of the field, adhering to the highest standards of academic research.

The search terms used across Scopus, IEEE Xplore, and MDPI were derived from the preliminary literature analysis presented in the Introduction section to identify the pertinent literature. The specific search terms employed included the following: "Optimal planning of microgrids", "Microgrid optimal expansion strategies", and "Renewable energies integration in microgrids". Table 1 displays the query strings defined to guarantee an accurate search according to the objectives of this research and the language used by the databases' search engines. For each database, we specifically targeted peer-reviewed journal articles published in English between 2013 and 2024.

Table 1. Query strings for the literature search process.

Database	Query String
Scopus	TITLE-ABS-KEY ("microgrid" AND "optimal" AND ("planning" OR "expansion") AND "renewable") AND PUBYEAR > 2012 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English"))
IEEEXplore	("Full Text & Metadata":microgrid) AND ("Full Text & Metadata":optimal planning) AND ("Full Text & Metadata":optimal expansion) AND ("Full Text & Metadata":renewable integration). Filters Applied: Journals, 2013–2024.
MDPI	Search text: "microgrid", Search Type: Full Text, Logical operator: AND, Search text: "optimal", Search Type: Full Text, Logical operator: AND, Search text: "planning", Search Type: Full Text, Logical operator: AND, Search text: "expansion", Search Type: Full Text, Logical operator: AND, Search text: "renewable", Search Type: Full Text. Years: Between 2013–2024; Article Types: Article.

The inclusion and exclusion criteria for this systematic review were carefully defined to ensure the selection of the most relevant and high-quality studies in microgrid expansion planning (Table 2). By focusing on studies published in the last ten years, the review captures the latest advancements and contemporary methodologies, reflecting the current state of research and technological progress. Limiting the language to English enhances accessibility and comprehensibility for a broad audience, as it is the predominant language

of scientific communication. Selecting peer-reviewed journal articles guarantees rigorously vetted and credible research while emphasizing studies that specifically address microgrid expansion planning, interconnection planning of community microgrids, and optimal planning strategies, which narrows the focus to the most pertinent topics. This targeted approach ensures the review remains relevant and comprehensive, exploring both the theoretical and applied aspects of microgrid planning through modeling, simulation, optimization techniques, and practical case studies. Prioritizing studies on renewable energy integration within microgrids aligns with the increasing emphasis on sustainable solutions, which are critical for future energy systems. Excluding studies published before 2013 and document types like editorials and conference papers maintains the review's integrity by focusing on original research contributions that provide new empirical findings or methodologies. The exclusion of research on general renewable energy systems without a microgrid context or those focused solely on technical aspects of microgrid components ensures that the review remains specific and offers valuable insights into planning methodologies and strategies for effectively deploying and integrating microgrids in power systems. This deliberate selection process ensures the review is focused, relevant, and aligned with its intended objectives.

Table 2. Inclusion and exclusion criteria defined for literature selection.

Inclusion	Criteria	Exclusion
Studies published in the last ten years (2013–2024).	Publication Date	Studies published before 2013.
Studies published in English.	Language	Studies published in languages other than English.
Peer-reviewed journal articles.	Document Type	Editorials, commentaries, opinion pieces, conference articles, and review articles.
Studies addressing at least one of the topics: microgrid expansion planning, interconnection planning of community microgrids, and optimal planning strategies for microgrids.	Focus	Studies that do not specifically address microgrid expansion planning or interconnection planning of microgrids.
Research may include modeling, simulation, optimization techniques, and practical case studies related to microgrid planning.	Scope	Research focusing on unrelated topics, such as general renewable energy systems without a microgrid context, and studies primarily focusing on technical aspects of microgrid components and operation without addressing the planning or expansion aspects.

2.2. Study Selection Process

The study selection process for this literature review adhered to the PRISMA 2020 Statement (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [18], which outlines a systematic approach consisting of three phases: Identification; Screening, Eligibility, and Inclusion; and Synthesis. By meticulously identifying and synthesizing relevant studies, the PRISMA methodology helps minimize potential biases and enhances the transparency of the review process. Figure 1 illustrates an overview of the methodology for the literature review reported in this paper. During the Identification phase, researchers conduct a comprehensive search across predefined databases to retrieve items without bias toward titles, authors, journals, publishers, or the number of citations. This phase is designed to include all results generated by the search engines, regardless of whether they

are sorted by relevance, novelty, or impact. This approach ensures that the initial review stage considers every potential study, preventing inadvertent exclusions and maintaining the inclusivity of the review process. Researchers use bibliographic management tools to identify and remove duplicate items, which is critical in ensuring that the dataset used for further screening is accurate and unique. Removing duplicates avoids skewing results with repeated data points and maintains the integrity and precision of the subsequent analyses.

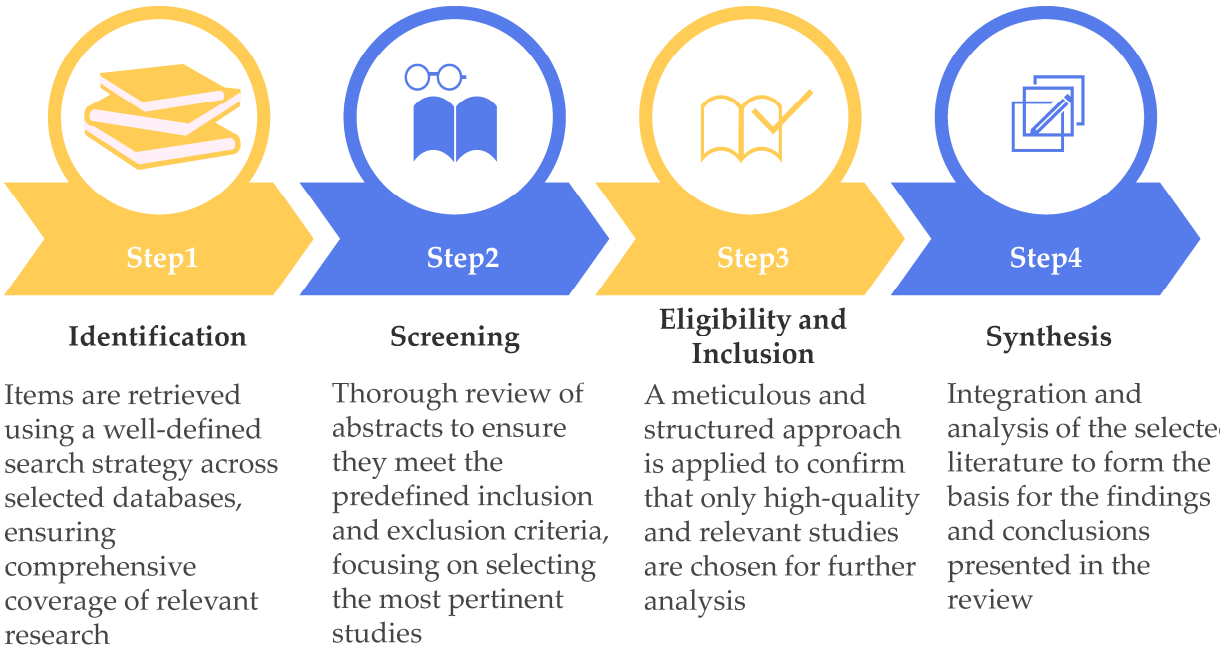


Figure 1. Diagram illustrating the steps of the literature review process.

In the Screening phase, the authors independently examine the titles and abstracts of the retrieved studies to verify their relevance to the research objectives based on predefined inclusion and exclusion criteria. They conduct this evaluation using a binary assessment system, assessing each item to determine whether it meets all the necessary criteria for further consideration. The authors advance studies that fulfill all criteria to the Eligibility and Inclusion phase, focusing on the most pertinent studies for detailed analysis.

During the Eligibility and Inclusion phase, the same reviewers independently assess the full text of each work. This thorough review aims to validate compliance with specific criteria and metrics meticulously defined to establish a ranking system using a verification matrix. The researchers select only those studies that achieve a minimum score, as defined by their standards, for the final literature review sample. At this stage, a significant number of studies may still be eligible, presenting a variety of perspectives within the research objectives.

Finally, in the Synthesis phase, the reviewers integrate and analyze the selected studies to form the foundation for the findings and conclusions presented in this review. At this point, they utilize bibliometric analyses, such as word cloud maps, to identify frequently occurring keywords among the chosen studies, helping to define broad thematic groups to be addressed in the literature review. This step ensures that the review provides a structured and coherent presentation of the topics, offering readers a well-organized exposition of the key themes. These findings are thoroughly discussed in the Results and Discussions section (Section 3), where the synthesized information is presented to highlight the advancements, challenges, and future directions in microgrid planning and optimization for renewable integration.

2.2.1. Identification Stage

In the Identification stage, by applying the search strategy defined in the previous subsection, 1929 items were retrieved from three selected databases: Scopus, IEEE Xplore, and MDPI. The researchers introduced a coding system for each item according to the database consulted to facilitate handling metadata for the items found. Items extracted from Scopus were identified as S-XXX (where XXX is a numerical code), those from IEEE as IEEE-XXXX, and those from MDPI as MDPI-XXX. The completeness and accuracy of the metadata provided by these databases were ensured, as they adhere to stringent data curation and management standards. As a result, the initial data capture did not encounter any issues related to missing or erroneous information, making the datasets suitable for further processing and analysis.

A critical step in the Identification stage was the elimination of duplicate entries to avoid redundant analysis and potential biases. By thoroughly comparing the Digital Object Identifiers of the items listed in our spreadsheet, we identified and removed 37 duplicate records. This reduction brought the total number of unique items down to 1892.

These items were distributed across the databases: 417 items from Scopus, 1072 items from IEEE Xplore, and 403 items from MDPI (Figure 2). These results were anticipated due to the nature and scope of each database. Scopus, known for its broad interdisciplinary coverage, provides extensive indexing of journals from various fields, including engineering and technology. The 417 items retrieved from Scopus reflect its comprehensive approach and wide-ranging repository. As a specialized database focusing on electrical engineering, computer science, and electronics, IEEE Xplore naturally yielded the highest number of items, 1072. This is consistent with its reputation as the leading source for high-quality, peer-reviewed technical literature in these disciplines. MDPI, as an open access publisher, offers a significant collection of peer-reviewed journals, particularly in science and technology. The 403 items from MDPI demonstrate its contribution to open access scientific literature and its relevance to our research focus. The detailed distribution across these databases underscores the robustness of our search strategy and the comprehensiveness of the datasets acquired for the Screening phase.

Figure 2 also shows the temporal evolution of the identified studies, highlighting significant research activity trends over the years. Starting in 2013, with 19 items, there was a gradual increase in the number of publications each year. The number of items rose to 23 in 2014, 28 in 2015, and 48 in 2016. A notable increase was observed in 2017 with 77 items. The upward trend continued, with 155 items in 2018, 204 in 2019, and 221 in 2020. The years 2021 and 2022 saw significant growth, with 254 and 311 items, respectively. The peak was reached in 2023 with 336 items, followed by a slight decrease to 216 items in 2024. This minor drop in 2024 is due to the year being in progress, with only seven months completed, and the numbers so far are promising. This trend reflects the growing interest and research efforts in microgrid planning and optimization over the past decade.

2.2.2. Screening Stage

The Screening stage involved a thorough review of abstracts to verify fulfillment of the inclusion and exclusion criteria stated in Table 1. Two independent screeners were employed to mitigate potential bias and ensure a rigorous evaluation process. Each screener independently reviewed and assessed all articles against the established inclusion and exclusion criteria. This dual-screening approach is designed to minimize subjective influence and increase the reliability of the screening process. Binary scoring was used, with a score of 1 indicating that an article fully meets the inclusion criteria and should be included and a score of 0 indicating that it does not meet at least one exclusion criterion and should be excluded. Any discrepancies in the scoring between the two screeners were discussed and resolved to reach a consensus. This process ensured a comprehensive and unbiased selection of relevant studies.

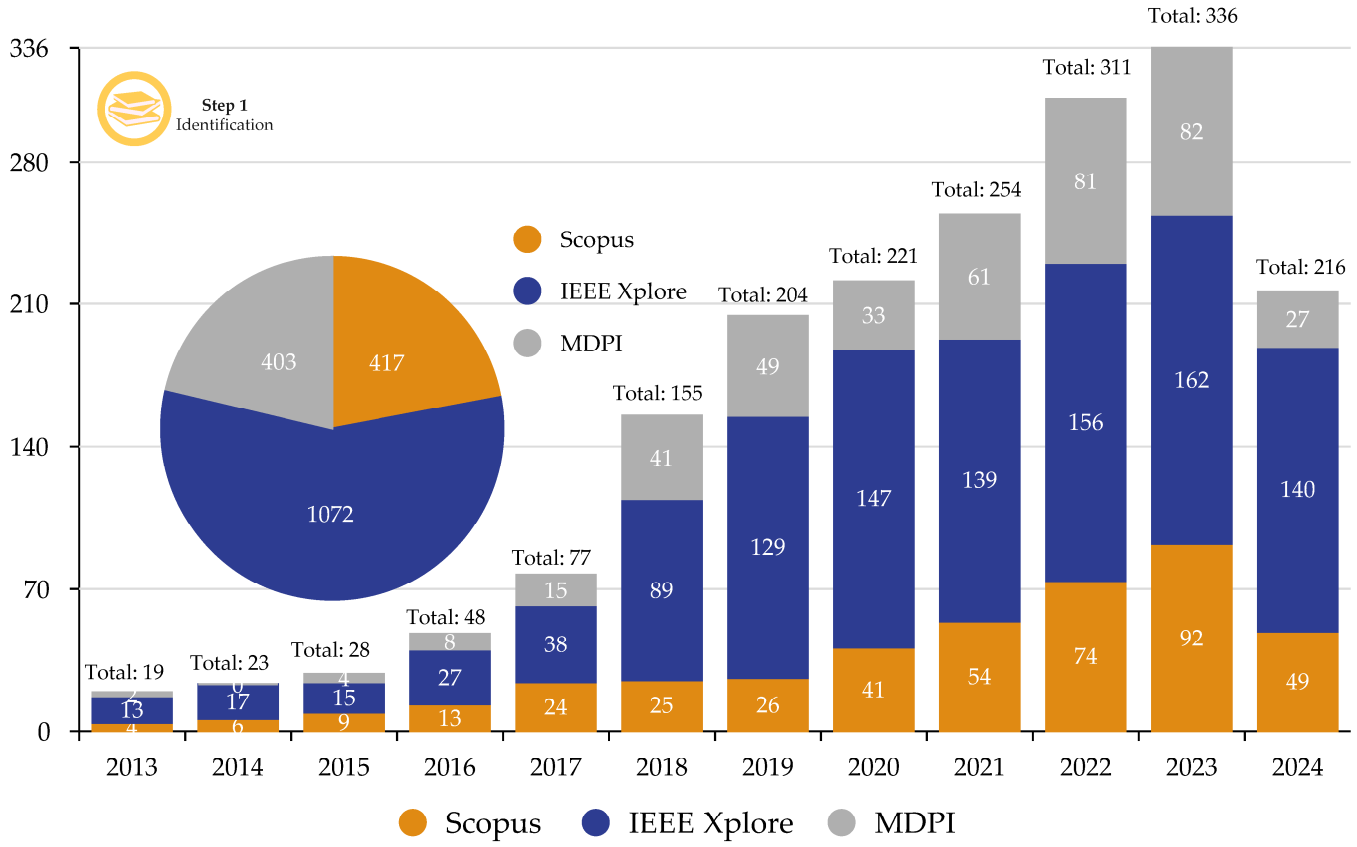


Figure 2. Bibliometric statistics of the articles found in the Identification stage.

As shown in Figure 3, the infographic illustrates the Screening-stage process, which resulted in the exclusion of 1275 items and the inclusion of 617 items. Of the included items, 155 were from Scopus, 330 from IEEE Xplore, and 132 from MDPI. Regarding the distribution of included studies across journals, notable findings included *IEEE Access* with 141 articles, *Energies* with 79, *IEEE Transactions on Smart Grid* with 74, *IEEE Transactions on Sustainable Energy* with 24, *Sustainability* with 22, *IEEE Transactions on Power Systems* with 17, *CSEE Journal of Power and Energy Systems* with 16, *Applied Energy* with 15, *Journal of Energy Storage* with 12, *Energy* with 12, *Applied Sciences* with 10, and *IEEE Transactions on Transportation Electrification* with 10. Other journals collectively accounted for 185 articles. The infographic in Figure 3 visually summarizes the distribution of items by journal that passed the Screening phase.

2.2.3. Eligibility and Inclusion Stage

Including studies in this literature review involved a meticulous and structured approach to ensure that only the most relevant and high-quality studies were selected. This section outlines the eligibility criteria for the items resulting from the Identification and Screening phases.

The eligibility reviewers were provided with detailed instructions to review each article in full independently, apply the criteria and evaluation metrics designed for this review (summarized in Table 2), and use a five-level Likert scale to evaluate the relevance and quality of each study. Reviewers were instructed to document metadata such as authors, institutions, and publication year and assess potential biases. To ensure a comprehensive and accurate assessment of each study's eligibility for inclusion, the researchers, believing it pertinent, applied weighted criteria that reflect the relative importance of different aspects of the research. This approach prioritizes the most relevant, methodologically sound, and impactful studies, providing a robust overview of state-of-the-art microgrid expansion planning and renewable energy integration.

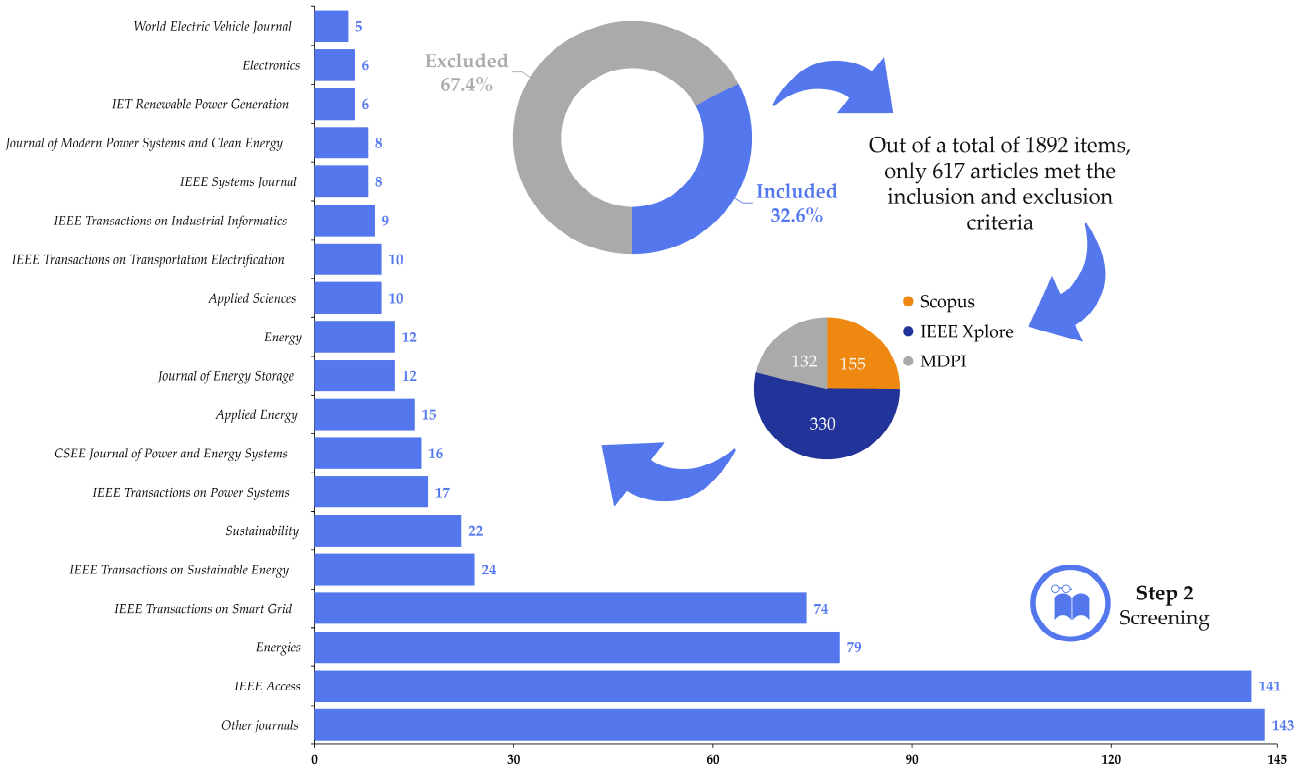


Figure 3. Infographic illustrating the Screening-stage process.

Each criterion is rated on a scale from 1 to 5, where 1 indicates an area needing improvement or less relevance and 5 indicates excellent quality or high relevance. The weighted criteria emphasize factors, such as relevance to the research topic, methodological rigor, novelty, and contribution. They also consider experimental validation, clarity, technical depth, reproducibility, data quality, practical applicability, and impact on the field. By assigning specific weights to each criterion, we obtain a final eligibility score that comprehensively evaluates each study's contribution to the research area. Table 3 also summarizes these justifications and the corresponding weightings for each criterion.

To determine the final score for each item in this phase, we applied Equation (1). Each criteria score is multiplied by the assigned weight, resulting in a normalized outcome that will be ranked with the rest of the evaluated items.

$$TOTAL = \sum_{i=1}^{10} CR_i \times w_i \quad (1)$$

where:

CR_i is the i-th criterion (five-level Likert's scale)
w_i is the is the i-th weighting factor (from 0 to 1)

Figure 4 illustrates the results of this evaluation, providing a visual representation of the weighted criteria and their impact on the eligibility of each study. Based on the proposed weighting and the nature of the research, a minimum threshold of 3.85 out of 5 (77%) is suggested for an item to be considered eligible for inclusion in the literature review synthesis. This threshold ensures that only highly relevant and exceptional-quality studies are included in the review, addressing the need for comprehensiveness and methodological rigor. As of this stage in the literature review, 81 articles have been identified as eligible for inclusion.

Table 3. Criteria and metrics for full-text evaluation.

N°	Criterion	Description and Evaluation Metrics	Weight	Justification for Weighting
1	Relevance to Research Topic	How well the study addresses microgrid expansion planning, interconnection planning of community microgrids, and optimal planning strategies. (1: Peripheral, 2: Somewhat, 3: Relevant, 4: Highly Relevant, 5: Central Focus)	20%	Ensures selected studies are directly applicable and contribute new knowledge to the field of microgrids. Critical for providing a comprehensive review of microgrid expansion planning and integration of renewable energy.
2	Methodological Rigor	The robustness and appropriateness of the research methodology employed in the study. (1: Needs Improvement, 2: Fair, 3: Good, 4: Very Good, 5: Excellent)	15%	Essential for valid and reliable conclusions. Robust methodologies enhance the credibility of findings and ensure studies can withstand scrutiny from academic and professional communities.
3	Experimental Validation	The extent to which the study includes experimental results, simulations, case studies, or real-world implementations. (1: None, 2: Limited, 3: Moderate, 4: Extensive, 5: Comprehensive)	10%	Provides concrete evidence supporting the study's claims through results from simulations, case studies, or real-world implementations. Important for substantiating the research.
4	Novelty and Contribution	The originality and significance of the study's contributions to the field. (1: Limited, 2: Modest, 3: Moderate, 4: Significant, 5: Groundbreaking)	15%	Identifies new advancements and emerging trends in the field. Essential for pushing the boundaries of current knowledge and practice in microgrid planning and optimization strategies.
5	Clarity and Complete-ness	The clarity of writing and the completeness of the information provided in the study. (1: Needs Improvement, 2: Fair, 3: Good, 4: Very Good, 5: Excellent)	10%	Ensures studies are well-written and provide all necessary information for understanding and replicating the research. Important for comprehensive comprehension of methodologies and results.
6	Technical Depth	The level of technical detail and depth in the study. (1: Basic, 2: Adequate, 3: Detailed, 4: Very Detailed, 5: Highly Detailed)	10%	Assesses the level of detail and sophistication in the study, which is important for understanding the intricacies of the research methodologies and outcomes.

Table 3. *Cont.*

N°	Criterion	Description and Evaluation Metrics	Weight	Justification for Weighting
7	Reproducibility	The extent to which the study provides enough detail to allow replication of the results. (1: None, 2: Limited, 3: Moderate, 4: Extensive, 5: Comprehensive)	5%	Measures the extent to which the study provides enough detail to allow replication of the results. Crucial for validating findings independently.
8	Data Quality and Integrity	The quality and integrity of the data presented in the study. (1: Needs Improvement, 2: Fair, 3: Good, 4: Very Good, 5: Excellent)	5%	Ensures the study is based on accurate and reliable data, fundamental for the validity of conclusions.
9	Practical Applicability	The potential for practical application of the study's findings in real-world scenarios. (1: Limited, 2: Modest, 3: Moderate, 4: High, 5: Very High)	5%	Evaluates the potential for applying the study's findings in real-world scenarios, important for assessing the practical impact of the research.
10	Impact on Field	The potential impact of the study's findings on microgrid expansion planning and renewable energy integration. (1: Limited, 2: Modest, 3: Moderate, 4: Significant, 5: Groundbreaking)	5%	Measures the potential influence of the study's findings on the field of microgrid expansion planning and renewable energy integration. Important for understanding the broader significance of the research.

The distribution by Journal in Figure 5 reveals that *IEEE Access* leads with 17 articles, followed by *IEEE Transactions on Smart Grid* and *Energies* with 7 articles each, underscoring the critical role of IEEE and MDPI journals in this field. The relatively lower number of articles from MDPI journals compared to IEEE journals subtly highlights the need for a comprehensive review to bridge this gap, thus justifying the pertinence of this literature review.

2.2.4. Synthesis Stage

The Synthesis stage integrates and analyzes the selected literature to consolidate the findings from the Eligibility and Inclusion phases. This stage aims to categorize and interpret the research contributions, highlighting key trends and topics within microgrid expansion planning and renewable energy integration.

Figure 6 provides a bibliometric analysis of the articles selected in the Eligibility and Inclusion phase. Figure 6a shows the distribution of included articles across the databases, with Scopus contributing 43 articles, IEEE Xplore 30 articles, and MDPI 8 articles. This distribution underscores each database's varying focus and emphasis on the research topics. The temporal analysis indicates a progressive increase in research activity, peaking in 2023, with a noticeable dip in 2020 and 2021, likely due to the COVID-19 pandemic's impact on global research and publication processes.

Nº	ID	Crit. 1	Crit. 2	Crit. 3	Crit. 4	Crit. 5	Crit. 6	Crit. 7	Crit. 8	Crit. 9	Crit. 10	Total
1	S-245	5	4	4	4	4	3	4	4	4	4	**4.10**
2	S-266	5	4	4	4	4	3	4	4	4	3	**4.05**
3	S-342	5	4	4	4	4	3	4	4	4	3	**4.05**
4	IEEE-0339	5	4	4	3	4	4	4	4	4	4	**4.05**
5	IEEE-0498	5	4	4	4	4	3	4	4	4	3	**4.05**
6	S-112	5	4	4	4	4	3	4	4	3	4	**4.05**
7	S-162	5	4	4	4	4	3	4	4	3	4	**4.05**
8	IEEE-0291	5	4	4	4	4	3	3	4	4	4	**4.05**
9	S-057	5	4	4	4	4	3	4	4	3	3	**4.00**
10	S-106	5	4	4	4	4	3	3	4	3	4	**4.00**
11	IEEE-0206	5	4	4	4	4	3	4	4	3	3	**4.00**
12	IEEE-0226	5	4	4	4	4	3	4	4	3	3	**4.00**
13	IEEE-0540	5	4	4	4	4	3	3	4	4	3	**4.00**
14	IEEE-0773	5	4	4	3	4	4	3	4	4	4	**4.00**
15	MDPI-157	5	4	4	4	4	3	3	4	3	4	**4.00**
16	IEEE-0024	5	4	2	4	4	4	4	4	3	4	**3.95**
17	MDPI-166	5	4	2	4	4	4	4	4	3	4	**3.95**
18	S-011	5	4	4	4	4	3	3	4	3	3	**3.95**
19	IEEE-0426	5	4	4	4	4	3	3	4	3	3	**3.95**
20	S-012	5	4	4	3	4	3	4	4	3	4	**3.90**
21	S-076	5	4	2	4	4	3	4	4	4	4	**3.90**
22	S-225	5	4	2	4	4	3	4	4	4	4	**3.90**
23	S-362	5	4	2	4	4	3	4	4	4	4	**3.90**
24	IEEE-0032	5	4	2	4	4	3	4	4	4	4	**3.90**
25	IEEE-0248	5	4	2	4	4	3	4	4	4	4	**3.90**
26	IEEE-0456	5	4	2	4	4	3	4	4	4	4	**3.90**
27	IEEE-0641	4	4	4	4	4	3	4	4	4	4	**3.90**
28	IEEE-0728	4	4	4	4	4	3	4	4	4	4	**3.90**
29	MDPI-146	5	4	2	4	4	3	4	4	4	4	**3.90**
30	S-140	5	4	2	4	4	4	3	3	4	4	**3.90**
31	S-264	5	4	2	4	4	4	4	4	3	3	**3.90**
32	S-411	5	4	2	4	4	4	3	4	3	4	**3.90**
33	S-007	5	4	4	4	4	3	3	3	3	3	**3.90**
34	IEEE-0088	5	4	4	4	4	3	3	3	3	3	**3.90**
35	MDPI-179	5	4	4	4	4	3	3	3	3	3	**3.90**
36	S-321	5	4	4	3	4	3	3	4	3	4	**3.85**
37	IEEE-0099	5	4	4	3	4	3	4	4	3	3	**3.85**
38	S-018	5	4	2	4	4	3	3	4	4	4	**3.85**
39	S-021	5	4	2	4	4	3	3	4	4	4	**3.85**
40	S-028	5	4	2	4	4	3	4	4	3	4	**3.85**
41	S-094	5	4	2	4	4	3	4	4	3	4	**3.85**
42	S-100	5	4	2	4	4	3	4	4	3	4	**3.85**
43	S-110	5	4	2	4	4	3	4	4	4	3	**3.85**
44	S-163	5	4	2	4	4	3	4	4	4	3	**3.85**
45	S-171	5	4	2	4	4	3	4	4	3	4	**3.85**
46	S-176	5	4	2	4	4	3	4	4	3	4	**3.85**
47	S-186	5	4	2	4	4	3	4	4	3	4	**3.85**
48	S-212	5	4	2	4	4	3	4	4	3	4	**3.85**
49	S-218	5	4	2	4	4	3	4	4	3	4	**3.85**
50	S-228	5	4	2	4	4	3	3	4	4	4	**3.85**
51	S-269	5	4	2	4	4	3	4	4	3	4	**3.85**
52	S-293	5	4	2	4	4	3	4	4	3	4	**3.85**
53	S-299	5	4	2	4	4	3	4	4	4	3	**3.85**
54	S-313	5	4	2	4	4	3	3	4	4	4	**3.85**
55	S-314	5	4	2	4	4	3	4	4	3	4	**3.85**
56	S-316	5	4	2	4	4	3	4	4	3	4	**3.85**
57	S-332	5	4	2	4	4	3	4	4	3	4	**3.85**
58	S-348	5	4	2	4	4	3	4	4	3	4	**3.85**
59	S-361	5	4	2	4	4	3	4	4	3	4	**3.85**
60	S-382	5	4	2	4	4	3	3	4	4	4	**3.85**
61	S-385	5	4	2	4	4	3	4	4	3	4	**3.85**
62	S-390	5	4	2	4	4	3	4	4	3	4	**3.85**
63	S-406	5	4	2	4	4	3	4	4	3	4	**3.85**
64	IEEE-0003	5	4	2	4	4	3	4	4	3	4	**3.85**
65	IEEE-0023	5	4	4	4	3	3	3	4	3	3	**3.85**
66	IEEE-0145	5	4	2	4	4	3	3	4	4	4	**3.85**
67	IEEE-0228	5	4	2	4	4	3	4	4	3	4	**3.85**
68	IEEE-0270	5	4	4	4	3	3	3	4	3	3	**3.85**
69	IEEE-0271	5	4	2	4	4	3	4	4	3	4	**3.85**
70	IEEE-0320	5	4	2	4	4	3	4	4	3	4	**3.85**
71	IEEE-0337	5	4	2	4	4	3	4	4	4	3	**3.85**
72	IEEE-0441	5	4	2	4	4	3	4	4	3	4	**3.85**
73	IEEE-0592	5	4	2	4	4	3	4	4	3	4	**3.85**
74	IEEE-0783	4	4	4	4	4	3	4	4	4	3	**3.85**
75	IEEE-0791	5	4	2	4	4	3	4	4	4	3	**3.85**
76	MDPI-031	5	4	2	4	4	3	4	4	3	4	**3.85**
77	MDPI-045	5	4	2	4	4	3	4	4	4	3	**3.85**
78	MDPI-116	5	4	2	4	4	3	4	4	3	4	**3.85**
79	MDPI-139	5	4	2	4	4	3	4	4	3	4	**3.85**
80	IEEE-0159	5	4	2	4	4	4	3	4	3	3	**3.85**
81	IEEE-0175	5	4	2	4	4	4	3	4	3	3	**3.85**

Figure 4. Verification matrix for eligibility and inclusion.

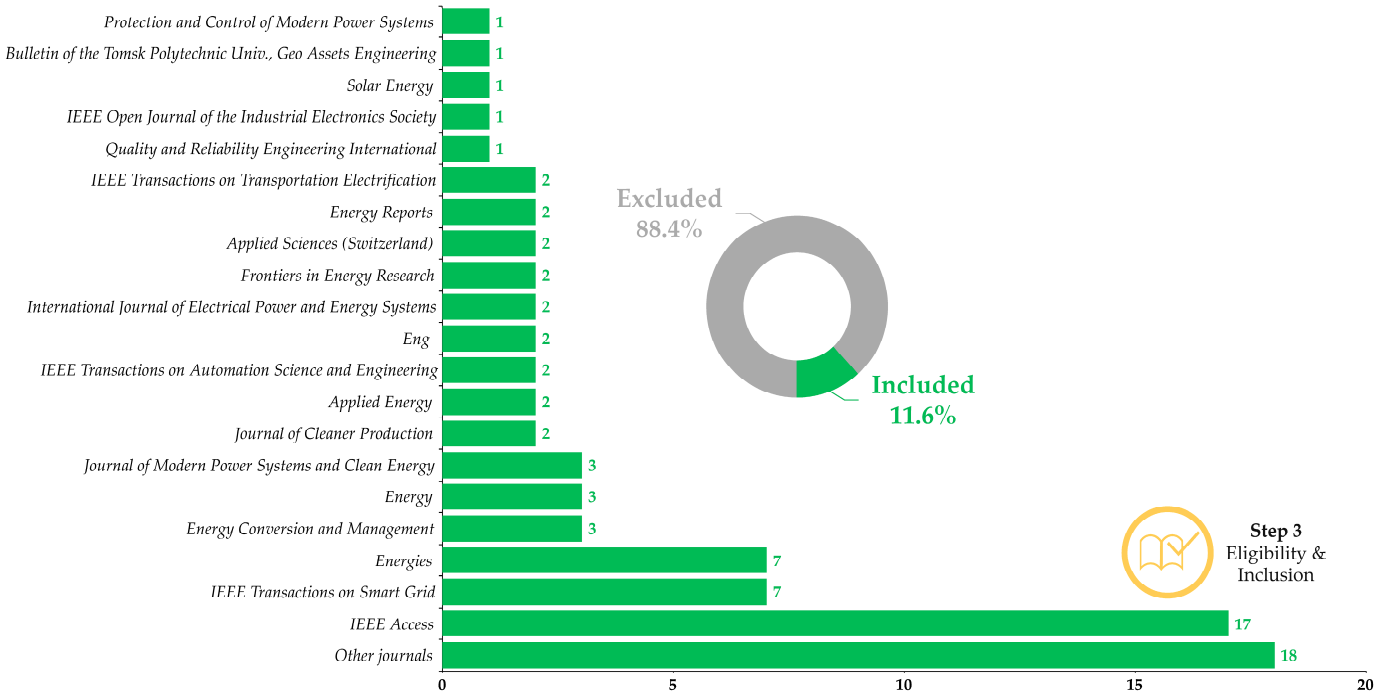
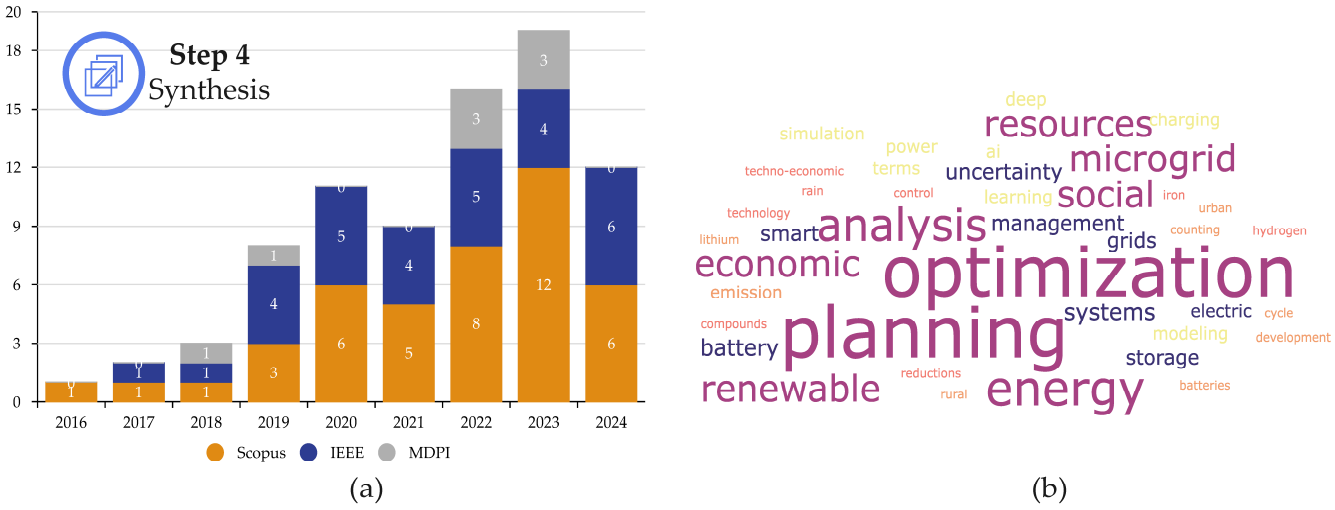


Figure 5. Results of the full-text review of items in the Eligibility and Inclusion phase.



(a) (b)

Figure 6. Bibliometric analysis of the articles selected in the Eligibility and Inclusion phase: (**a**) distribution of included articles per year, (**b**) word cloud map built with the keywords of the included articles.

To complement the analysis, Figure 6b presents a word cloud map constructed from 1388 keywords extracted from the 81 selected items. This map, filtered to the 50 most frequent words, visually represents the selected literature's prevalent themes and research areas.

Following a careful examination of the word cloud map, the bibliometric sample can be classified into six general topics:

a. Microgrid Planning and Optimization
b. Modeling and Simulation
c. Energy Storage Technologies
d. Power Systems Operation and Control
e. Cycle Counting and Data Analysis
f. Urban and Rural Energy Solutions

Figure 7 shows a flowchart of the literature review process followed in this study. The main findings derived from the systematic review within the six general topics are presented in Section 3.

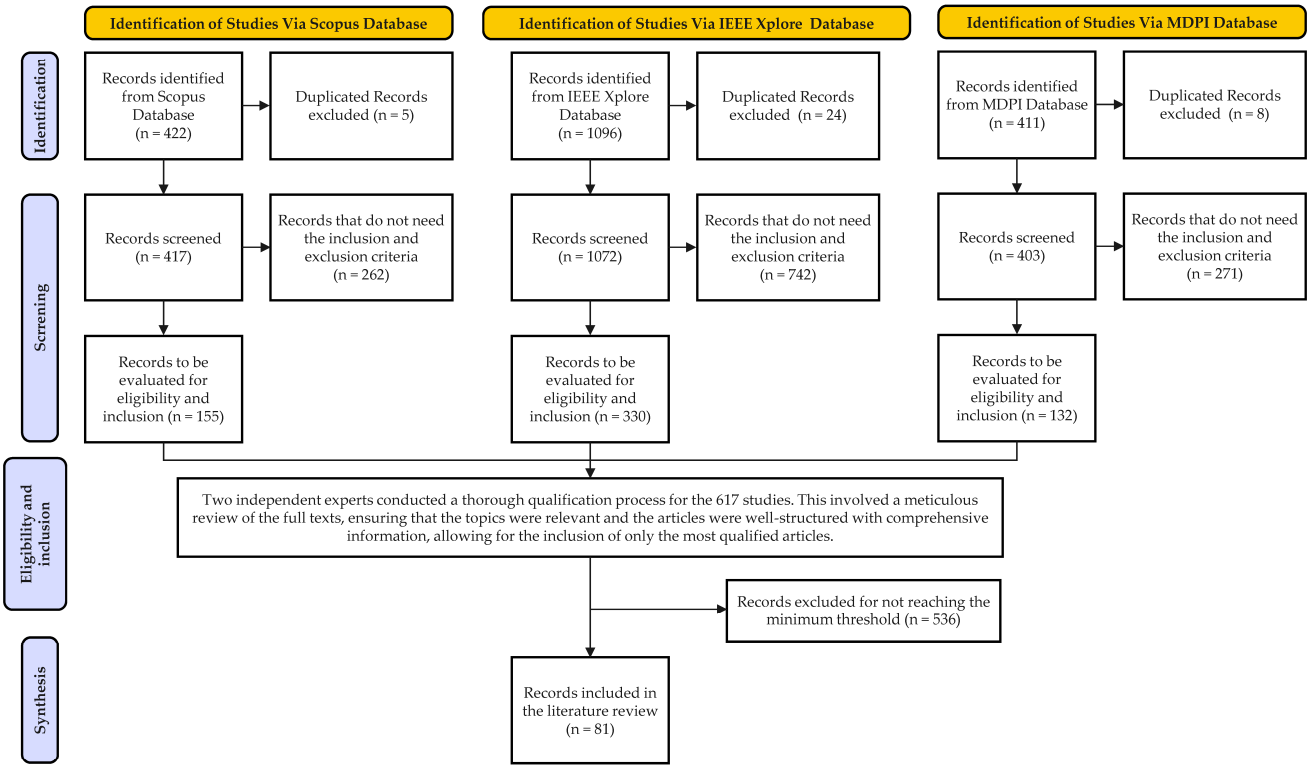


Figure 7. PRISMA 2020 flowchart for the literature review.

3. Results and Discussions

This section presents the synthesis of the included literature from the six microgrid planning and management topics with renewable energy sources and energy storage.

3.1. Microgrid Planning and Optimization

3.1.1. Historical Narrative

Microgrid planning has evolved significantly since its inception, initially focusing on independent systems for remote areas [19]. Early implementations centered on small-scale, localized solutions, but the need for sustainable energy drove technological advancements. Dr. Robert H. Lasseter introduced the concept of the modern microgrid in the 1990s, enabling these systems to operate in isolation and interact with the main grid, enhancing resilience and efficiency [20–23]. Over the decades, energy storage technologies such as lithium-ion batteries have been integrated, improving energy generation and distribution management. Advanced energy management systems have allowed more precise and dynamic control [24–27]. In the 21st century, planning has advanced with stochastic optimization techniques and evolutionary algorithms, better managing the uncertainty in renewable generation [28–31]. Emerging technologies such as artificial intelligence (AI) and machine learning have transformed planning, optimizing performance and adapting to changes in demand and environmental conditions [32–36].

3.1.2. Innovative Methods

Current optimization methods allow for addressing previously insurmountable challenges using techniques such as stochastic optimization and evolutionary algorithms. These methods enhance the stability and efficiency of microgrids [5,28,37]. Integrating genetic algorithms and advanced mathematical programming has optimized planning in complex

contexts. Hybrid solutions combine deterministic and probabilistic approaches to better manage energy resources [38–40].

AI and machine learning have been crucial in microgrid planning, providing adaptive solutions that continuously improve. AI predicts demand and generation patterns, adjusting operations in real time to maximize efficiency [41–43]. Machine learning manages large volumes of data, improving response and resilience [44–46]. These technologies enable efficient and proactive management, anticipating problems before they occur [47–49]. Real-time energy management systems and smart grids have improved the integration of renewable energies and operational efficiency, optimizing resources and enhancing the reliability of the energy supply [50–52]. Incorporating innovative methods and advanced technologies has transformed microgrid planning and operation, allowing for practical, adaptive, and resilient optimization in an increasingly complex environment [53–57].

Key metrics used in various microgrid optimization approaches have been identified and quantified to provide a more rigorous analysis of the reviewed studies. These metrics include energy efficiency, operational cost reduction, system reliability, and responsiveness to demand fluctuations. For instance, studies employing optimization strategies based on artificial intelligence and stochastic algorithms reported significant improvements in energy efficiency, with average increases ranging from 15% to 25% compared to traditional techniques [28,37]. Furthermore, approaches incorporating advanced storage and predictive control demonstrated reductions in operational costs ranging from 10% to 30%, depending on the specific conditions of the microgrid and the type of renewable energy used [35,42]. These improvements were primarily achieved through optimizing energy management and dynamically adapting to variations in generation and demand. Additionally, studies implementing advanced control technologies have shown improvements in system reliability, with a 20% reduction in unplanned failures and a 30% increase in the capacity to respond to high-demand events [53,57]. These metrics underscore the effectiveness of innovative strategies and highlight the importance of their adoption in microgrid planning and operation to maximize efficiency and resilience.

Specific methodologies have been highlighted to provide a clearer understanding of the technical aspects of microgrid optimization, particularly in the context of distributed generation and renewables. For example, optimization strategies often utilize mixed-integer linear programming (MILP) to handle the complexity of integrating renewable energy sources, optimizing the placement and operation of distributed generation units while considering grid constraints and reliability [37]. Furthermore, dynamic programming is frequently applied to optimize energy storage systems, balancing supply and demand in real time to mitigate the intermittency of renewables [35]. These methods are complemented by heuristic algorithms, such as genetic algorithms and particle swarm optimization, which optimize microgrid configurations and control strategies, enhancing efficiency and resilience in renewable-integrated microgrids [28].

3.1.3. Futuristic Vision

The future of microgrid planning will be more advanced, with AI and machine learning technologies enabling self-optimization and autonomous management. These technologies will precisely anticipate changes in demand and environmental conditions [19,26,33]. Advances in storage, such as redox flow batteries and supercapacitors, will improve the management of renewable energy intermittency [58–60]. Intelligent energy management systems will coordinate generation, storage, and consumption, maximizing efficiency and reducing costs [61–63].

In the future, microgrids will be integrated into the urban fabric, managing generation and distribution in real time [49]. They will dynamically exchange energy among themselves and with the main grid, optimizing resources at the community and regional levels [64–66]. Microgrids will enhance resilience to extreme events, automatically isolating in case of failures and ensuring the supply of critical services and vulnerable communities [67–69]. Integrating technologies like blockchain will offer transparency

and security in energy transactions, facilitating peer-to-peer trading within the microgrid [70–72]. With these advances, future microgrids will be smarter, more adaptive, and capable of autonomously managing resources, contributing significantly to the stability and sustainability of the global energy system [73–75]. Microgrid planning and optimization encompass a range of methodologies that leverage advanced algorithms and optimization techniques to enhance system performance. As highlighted in Sections 3.1.1 and 3.1.2, historical advancements and innovative methods such as stochastic optimization, evolutionary algorithms, and AI-driven approaches have significantly improved the efficiency and resilience of microgrids [28,37,41].

These optimization techniques are theoretical frameworks and integral to the practical modeling and simulation of microgrid systems, as discussed in Section 3.2. By transitioning from planning to modeling, the focus shifts to simulating various operational scenarios and employing optimization methods to test and refine these plans. This connection between planning, optimization, and simulation ensures that microgrid systems are designed with a robust foundation and capable of adapting to real-world conditions and demands.

3.2. Modeling and Simulation

Building upon the optimization strategies discussed in Section 3.1, Section 3.2 explores the application of these methodologies in the modeling and simulation of microgrids. Modeling and simulation provide a dynamic environment to implement and test various optimization strategies, such as those mentioned in Section 3.1.2, including genetic algorithms, particle swarm optimization, and MILP [28,35,37].

By applying these optimization methods within simulation models, researchers can evaluate the performance of microgrids under different conditions and scenarios. For instance, Section 3.2.2 (Creative Case Studies) demonstrates the practical application of optimization techniques like particle swarm optimization and response surface methodology in adaptive control systems, illustrating how theoretical optimization approaches are utilized in real-world simulations to enhance microgrid reliability and efficiency [68]. This integration of planning and simulation helps bridge the gap between theoretical optimization models and their practical applications, ensuring a comprehensive approach to microgrid management.

3.2.1. Introduction

Modeling and simulation are critical components in the strategic planning, design, and optimization of microgrids, especially as these systems incorporate a wide range of renewable energy sources and storage technologies. The fundamental aim of modeling is to thoroughly understand a microgrid's dynamic behavior across various operational scenarios, thereby improving its reliability, efficiency, and resilience [20].

Advanced simulation techniques, such as multi-objective optimization and stochastic modeling, are extensively employed to effectively handle the uncertainties inherent in renewable energy generation. These methods enable the analysis of diverse configurations and control strategies, thus optimizing microgrid performance in grid-connected and isolated environments [21,76]. For example, optimizing the multi-carrier microgrid design can help balance energy supply and demand while reducing operational costs and maximizing the utilization of renewable resources [21,77].

Adopting cutting-edge technologies like AI and ML has greatly expanded the capabilities of microgrid models. These technologies enable real-time data processing and adaptive control strategies, vital for ensuring stable operation amid fluctuating demand and generation conditions [24]. By leveraging these advanced algorithms, microgrids can enhance energy distribution, improve load forecasting, and refine fault detection and response mechanisms [76].

Furthermore, predictive modeling tools and real-time simulations have become increasingly crucial for evaluating microgrids' economic viability and scalability. Techniques such as genetic algorithms and particle swarm optimization are used to optimize resource

allocation and boost overall operational efficiency [20,77]. These models facilitate the exploration of various scenarios, offering essential insights into the trade-offs between cost, performance, and sustainability [24,76].

In hybrid systems that integrate renewable energy sources with traditional generation methods, modeling and simulation serve as a key platform for comprehending the interactions between different energy carriers and optimizing their utilization. For instance, applying affine arithmetic-based energy management systems has demonstrated improvements in the operational efficiency of cooperative multi-microgrid networks, particularly in addressing uncertainties associated with renewable energy production [21].

3.2.2. Creative Case Studies

Creative modeling and simulation techniques are pivotal in enhancing microgrid efficiency and reliability. A notable example is the implementation of an adaptive PI (proportional-integral) controller designed to optimize the operation of autonomous microgrids [78–80]. This system employs advanced algorithms such as particle swarm optimization and response surface methodology to evaluate controller performance across different environmental conditions, ensuring optimal operation under varying scenarios [68]. This case study illustrates the potential of adaptive control systems in dynamically responding to changes in the microgrid environment.

Another innovative approach involves using a conditional value-at-risk stochastic technique to model the stochastic variations in renewable energy production [81]. By applying advanced scenario generation and reduction methods, this study produced realistic and robust models that accurately reflect the uncertainties inherent in renewable energy sources. These models help develop strategies that minimize risks and enhance the reliability of energy supply in microgrids.

A step-by-step simulation project that employs an affine arithmetic-based energy management system for cooperative multi-microgrid networks further exemplifies the creative use of modeling techniques [82]. This system considers energy exchanges between interconnected microgrids and manages uncertainties in electricity demand and renewable energy generation. The results showed significant improvements in operational costs and execution times compared to traditional methods like Monte Carlo simulation, demonstrating the effectiveness of innovative modeling approaches in optimizing microgrid operations [83].

3.2.3. Visual Innovations

Dynamic infographics and interactive visualizations are essential for illustrating complex microgrid modeling and simulation processes [84]. These visual aids allow researchers and planners to observe how different variables interact and impact microgrid performance in real time, providing a more intuitive understanding of the system dynamics [85,86]. For example, dynamic charts can visually represent the effects of changes in renewable energy generation on the microgrid's overall energy balance, helping to identify potential imbalances and adjust strategies accordingly [30,37,87].

Interactive online models are another powerful tool that enhance the practical understanding of modeling and simulation processes. These models allow users to explore various scenarios and adjustments, observing the impact of these changes on the microgrid's performance and efficiency [88]. This interactivity facilitates deeper engagement and allows for experimentation with optimized solutions and strategies tailored to different operational conditions [32,89,90]. By making complex concepts more accessible and understandable, visual innovations play a critical role in advancing the design and operation of efficient and sustainable microgrids [41,44,49,61,65,67,70,73,91,92]. Through the use of analogies, creative case studies, and visual innovations, modeling and simulation become more than just technical exercises; they become essential tools for understanding and optimizing the operation of microgrids. By clearly explaining these complex concepts,

it is possible to design and operate both efficient and sustainable microgrids, ensuring their viability in diverse energy landscapes [93].

3.3. Energy Storage and Battery Technologies

3.3.1. Introduction

Energy storage and battery technologies are essential for the effective operation of contemporary microgrids, facilitating the reliable integration of renewable energy sources and bolstering grid stability. These technologies are vital in managing the variability of renewable energy by storing surplus energy during periods of low demand and discharging it when demand surges or generation decreases [20]. The continuous evolution of battery technologies, such as lithium-ion, redox flow, and solid-state batteries, has notably enhanced energy density, efficiency, and safety, rendering them indispensable within modern energy systems [26,28].

Lithium-ion batteries are currently the predominant choice for energy storage in microgrids, largely due to their high energy density and extended life cycle [35]. Nonetheless, the pursuit of safer and more sustainable alternatives has driven the development of advanced technologies like redox flow batteries, which offer superior scalability and extended operational lifespans, and solid-state batteries, which promise increased safety owing to their non-flammable solid electrolytes [28,39].

Furthermore, incorporating intelligent control methods and predictive modeling has significantly augmented the performance and efficiency of energy storage systems. These advancements enable the optimized management of charging and discharging cycles, enhance energy utilization, and prolong battery lifespan [20,26]. Moreover, battery management system (BMS) innovations have enabled real-time monitoring and diagnostics, ensuring optimal functionality and preventing system failures [35].

In the context of interconnected microgrids, deploying hydrogen-based storage solutions is becoming increasingly popular to support energy systems' decarbonization. Hydrogen storage offers a versatile energy carrier that can be used for electricity generation and as a clean fuel for transportation and industrial applications [89]. As these technologies continue to advance, hydrogen storage is anticipated to play a crucial role in fostering a sustainable and resilient energy infrastructure [28]

3.3.2. Innovation Stories

The history of energy storage is filled with stories of innovators and scientists who have made significant contributions to the field. For instance, advances in lithium-ion battery technology, which are fundamental to most modern applications, have been made possible by the efforts of researchers like John B. Goodenough, Stanley Whittingham, and Akira Yoshino, who received the Nobel Prize in Chemistry in 2019 for their pioneering work [28,42,89]. Business success stories also highlight how energy storage technologies have revolutionized the industry. Companies like Tesla have taken battery technology to new levels in electric vehicles and large-scale energy storage solutions for electric grids. Implementing Powerwall and Powerpack batteries has demonstrated how energy storage can enhance the resilience and efficiency of energy systems [20,35,42].

3.3.3. Imaginative Future

Futuristic visions of energy storage include yet-to-be-invented technologies that could radically change how we manage and use energy. Imagine batteries that can self-repair, extending their lifespan indefinitely, or storage technologies based on abundant, non-toxic materials that are fully recyclable. These advancements could make energy storage more accessible and sustainable than ever [35,69,89]. Among the most promising emerging innovations are redox flow batteries, which use liquid electrolytes to store energy, and solid-state batteries, which eliminate the risks associated with flammable liquid electrolytes. These technologies have the potential to offer higher energy densities and improved safety,

opening new possibilities for energy applications in both electric vehicles and large-scale storage [26,28,70].

The reviewed studies present a diverse array of optimization strategies for microgrid performance enhancement, focusing primarily on energy management, cost reduction, and system reliability. Key approaches include the application of artificial intelligence, machine learning, advanced storage technologies, and predictive control systems. A quantitative assessment of these optimization strategies was conducted to provide a more rigorous and detailed analysis. The analysis focused on key performance indicators (KPIs) such as energy efficiency, operational cost reduction, system reliability, and responsiveness to demand fluctuations, which were systematically evaluated across various studies.

For instance, optimization strategies that utilized machine learning algorithms, such as reinforcement learning and neural networks, demonstrated significant improvements in energy efficiency, with average increases ranging from 15% to 30% compared to traditional optimization methods. These improvements are attributed to the ability of machine learning algorithms to adjust energy production and consumption based on real-time data dynamically, thus minimizing energy wastage and optimizing resource use [35,42,89]. In terms of cost reduction, strategies incorporating advanced energy storage technologies, like lithium-ion batteries and redox flow batteries, coupled with predictive control systems, achieved operational cost savings between 10% and 35%. These savings were most pronounced in scenarios with high variability in renewable energy input, where effective storage management mitigated the intermittency and improved overall grid stability [26,70]. Furthermore, integrating advanced control technologies and real-time simulation techniques resulted in a notable increase in system reliability. Studies showed a 20% reduction in unplanned outages and a 30% improvement in the system's ability to respond to high-demand events. This was particularly evident in microgrids that utilized hardware-in-the-loop testing and real-time simulations to refine control strategies and enhance fault tolerance [63,76,94]. These findings indicate that while innovative optimization strategies significantly improve microgrid performance, their effectiveness can vary based on specific conditions and configurations, suggesting a need for tailored approaches to optimization.

In addition to the quantitative benefits, optimization strategies address specific technical challenges associated with distributed generation and renewable integration. Advanced control methods, such as model predictive control and real-time optimization algorithms, are employed to dynamically adjust the operation of microgrids, ensuring stability and efficient energy distribution despite the variability and unpredictability of renewable sources [42]. These control strategies are crucial for maintaining the balance between energy supply and demand, particularly in scenarios with high solar and wind energy penetration. By continuously monitoring and adjusting to changes in generation and load, these techniques help mitigate the risks of overvoltage, frequency deviation, and other stability issues, thereby enhancing the overall reliability of microgrids [89].

3.4. Power System Operation and Control

3.4.1. Introduction

The operation and control of power systems are critical to ensuring microgrids' stability, reliability, and efficiency, particularly as these systems incorporate various renewable energy sources and advanced technological solutions. Effective control strategies are imperative for managing the intricate interactions among generation, storage, and load, essential for maintaining system equilibrium under dynamic conditions [76,94].

A significant challenge in the operation of power systems lies in the necessity for real-time monitoring and control to cope with the variability and intermittency of renewable energy inputs. Techniques such as real-time hardware-in-the-loop (HIL) testing have emerged as crucial for evaluating and enhancing the performance of power systems in dynamic environments, facilitating rapid responses to faults and disturbances [94]. This

methodology allows for the rigorous validation of control algorithms and the assessment of system resilience, ensuring optimal performance across diverse scenarios [26].

Advanced control methodologies, including intelligent control systems and predictive algorithms, are increasingly employed to optimize energy management within microgrids. These approaches enable proactive decision making and adaptive management, improving system efficiency by reducing power losses and integrating renewable energy sources [23,89]. For example, intelligent control techniques have been successfully applied to optimize energy storage systems' charging and discharging cycles, which helps lower operational costs and extend battery life [26].

Incorporating smart transformers and other cutting-edge technologies is also pivotal in contemporary power system operations. Smart transformers provide advanced capabilities for voltage regulation, power quality enhancement, and energy loss reduction, all of which are critical for the efficient operation of microgrids [26]. These innovations facilitate the seamless integration of distributed energy resources and significantly enhance the overall reliability of the power supply [42].

3.4.2. Challenges and Solutions Narrative

One of the main challenges in the operation and control of energy systems is managing system resilience and stability against faults and disturbances. The integration of renewable energy sources, while environmentally beneficial, introduces variability and uncertainty that must be effectively managed to maintain grid stability. Fault mitigation through proactive scheduling algorithms and advanced control has proven an effective solution to enhance system resilience [76,89,94]. Innovative solutions include implementing real-time simulations and hardware-in-the-loop (HIL) testing to evaluate and improve adaptive protection capabilities in AC microgrids. This approach allows engineers to test and validate control systems under realistic conditions, ensuring microgrids respond appropriately to faults and disturbances [89,94]. Additionally, dynamic power electronic converters and demand response programs have significantly improved operational efficiency, reducing operational costs and energy losses [63,69].

3.4.3. End-User Perspective

Innovations in the operation and control of energy systems directly impact end users, improving the reliability and quality of electricity supply. For example, implementing advanced control and energy management technologies can reduce service interruptions and improve power quality, resulting in a more reliable and consistent consumer experience [26,63,76,89,94]. Testimonials and case studies from the end-user perspective highlight how these technological improvements have increased customer satisfaction and enabled more efficient use of energy resources. End users can benefit from reduced energy costs and greater participation in demand management programs, which optimize energy use and offer economic incentives [26,42,89].

In addition to the quantitative analysis, a comparative analysis of the different optimization techniques was performed to identify common patterns and unique strengths. Techniques leveraging artificial intelligence and machine learning showed a consistent ability to enhance predictive capabilities and adapt to changing conditions, making them ideal for environments with high energy supply-and-demand variability. Conversely, optimization strategies focused on advanced storage solutions and predictive controls were particularly effective in stabilizing microgrid operations in contexts with significant renewable energy integration. These strategies excel in smoothing out the fluctuations associated with renewable sources, thereby reducing reliance on fossil fuels and enhancing overall grid stability [35,70,89].

The comparison also revealed that while certain strategies are highly effective in specific scenarios, their performance can diminish when applied outside their optimal conditions. This underscores the importance of selecting the appropriate optimization approach based on the unique characteristics of each microgrid, including its size, location,

energy sources, and demand profiles. Quantitative data synthesis across multiple studies also highlights the potential benefits of conducting a meta-analysis to understand further the impacts of various optimization strategies on microgrid performance. A meta-analysis could combine data from different studies to comprehensively assess these strategies, offering robust conclusions about their effectiveness under various conditions and configurations. For instance, a meta-analysis could quantify the overall increase in energy efficiency associated with different types of machine learning algorithms across various microgrid setups or measure the cost savings linked to integrating advanced storage technologies under diverse renewable energy scenarios. This approach would enhance the rigor of the findings and help identify the most effective optimization strategies for specific microgrid applications [5,28,37,42]. Future research should focus on standardizing evaluation metrics and methodologies to facilitate such analyses, ensuring consistent data reporting across studies. This would enable more direct comparisons and facilitate a deeper understanding of which strategies are most beneficial for different microgrid contexts. Moreover, a comprehensive meta-analysis could provide valuable insights for researchers and practitioners, guiding the development of more effective and efficient microgrid optimization frameworks.

The comparative analysis also highlights the importance of selecting appropriate optimization techniques based on the unique characteristics of each microgrid. For microgrids heavily reliant on renewable energy, optimization must account for these sources' intermittent and variable nature. Techniques like robust optimization and chance-constrained programming are particularly effective in such environments, as they allow for creating flexible operational plans that can adapt to the uncertainty and variability of renewable generation [26]. Additionally, deploying decentralized control systems helps manage distributed generation more effectively by enabling real-time decision making closer to the generation source, thus reducing latency and improving overall system responsiveness [70].

3.5. Cycle Counting and Data Analysis

3.5.1. Introduction

Cycle counting and data analysis are fundamental to managing microgrid energy storage systems. Cycle counting involves tracking the number of charge and discharge cycles a battery completes throughout its operational lifespan. This metric is vital for evaluating the health and longevity of batteries, as each cycle contributes to the gradual degradation of the battery's capacity and performance [20]. Understanding the life cycle of batteries enables more accurate predictions regarding maintenance requirements and replacement schedules, which is crucial for maintaining the reliability and efficiency of microgrid operations [28,89].

The significance of cycle counting is amplified by the growing dependence on renewable energy sources, which frequently produce intermittent and variable power outputs. To balance supply and demand effectively, batteries must undergo frequent charging and discharging cycles, making precise monitoring of these cycles essential for preventing premature battery failure and optimizing the performance of energy storage systems [95]. Data analysis is pivotal in this context, allowing for the detection of patterns and anomalies that might signal potential issues before they escalate into critical problems [23].

Advanced data analytics and predictive modeling tools have been developed to enhance the accuracy of cycle counting and forecast battery degradation under various operating conditions. These tools utilize machine learning algorithms to process large datasets, offering insights into optimal charging strategies and maintenance schedules that can extend battery life and lower operational costs [28,89]. For example, intelligent control methods can optimize energy usage based on real-time data, thereby reducing unnecessary cycling and extending the lifespan of batteries [95].

Moreover, integrating cycle counting with comprehensive data analysis frameworks provides a holistic approach to energy management in microgrids. By combining real-time monitoring with historical data analysis, operators can make well-informed decisions

regarding energy storage deployment and maintenance, enhancing the microgrid's overall resilience and sustainability [20,28].

3.5.2. Data Narrative

The data journey in a microgrid begins with its collection through sensors and monitoring devices strategically placed at various points within the system. These devices continuously gather real-time data on parameters, such as voltage, current, temperature, and state of charge. These data are then transmitted to a centralized control center, where they are processed and analyzed to extract valuable insights into the microgrid's operational status. This process is akin to how doctors collect and analyze clinical data to diagnose and treat patients, using data to make informed decisions that optimize the patient's health [63,73,94].

The role of engineers and scientists in analyzing these data is crucial. By leveraging advanced data analytics, they can detect inefficiencies, predict potential failures, and implement corrective actions to improve microgrid performance. For example, analyzing data trends can reveal patterns of energy consumption that may suggest the need for adjustments in load management strategies or the reconfiguration of energy storage to optimize efficiency. Such proactive management helps maintain balance within the microgrid, minimizing energy wastage and maximizing resource utilization [28,73,89].

3.5.3. Innovations in Analysis

Advanced data analysis tools revolutionized microgrid management by enabling more precise and real-time decision making. AI algorithms and machine learning techniques allow for the rapid analysis of vast amounts of data, identifying patterns and trends that may not be immediately apparent through traditional methods [96]. These tools facilitate predictive maintenance by forecasting potential problems based on historical data and optimizing microgrid operations to respond dynamically to changing conditions [73,76,83]. For instance, machine learning models can predict battery performance degradation, allowing operators to schedule timely maintenance and avoid costly downtimes. Similarly, AI-driven analytics can optimize energy dispatch in real time by adjusting generation and storage parameters based on demand forecasts and renewable energy availability. These innovations are crucial for enhancing the efficiency and reliability of microgrids, as they enable a more adaptive and resilient management approach that can quickly respond to disturbances and fluctuations in energy supply and demand [73,89,94].

The future of microgrid data analysis promises even more advancements, with the continuous development of deep learning and quantum computing technologies expected to enable even more sophisticated data processing capabilities. These technologies will allow for the real-time analysis of complex datasets, improving predictive accuracy and enabling more effective management of energy resources. As a result, microgrids will become more resilient and efficient, capable of adapting to varying conditions and optimizing operations to meet evolving energy needs [73,89,94].

3.6. Urban and Rural Energy Solutions

3.6.1. Introduction

Urban and rural energy solutions present unique challenges and opportunities, especially when integrating renewable energy sources and energy storage systems in microgrid planning. In urban environments, microgrids are typically designed to enhance energy efficiency and sustainability by utilizing advanced technologies and integrated energy management systems. These systems are instrumental in reducing emissions and improving grid resilience by seamlessly integrating with existing infrastructure, thereby meeting the diverse energy demands of densely populated areas while bolstering overall grid stability [23,26,97].

In contrast, rural areas often grapple with limited infrastructure and a heavy reliance on traditional energy sources, such as diesel generators, which tend to be inefficient and

environmentally harmful. However, adopting microgrids in these regions provides a significant opportunity to improve energy accessibility and reliability. Standalone microgrids, tailored for renewable energy integration and optimized for local conditions, can dramatically decrease reliance on fossil fuels and reduce operational expenses [40,98].

Strategic planning and the deliberate interconnection of microgrids can yield robust energy solutions for urban and rural settings, fostering a more resilient and flexible energy infrastructure. For example, the application of IoT-based control strategies and advanced energy storage systems can optimize the operation of microgrids, ensuring real-time balance between supply and demand and maintaining reliable energy delivery, even amid fluctuating renewable energy outputs [97]. In rural areas, such interconnected microgrids can facilitate energy sharing among neighboring communities, enhancing energy security and promoting regional development [23,26].

Integrating energy storage systems within microgrids is crucial for mitigating the intermittency of renewable energy sources like solar and wind. Effective storage solutions allow microgrids to capture surplus energy during low-demand periods and release it as needed, thus ensuring a consistent and reliable energy supply [97,98]. This capability is particularly important in rural areas, where grid reliability may be lower and access to backup power options is more limited.

3.6.2. Community Stories

Stories of communities creatively addressing their energy challenges are inspiring. For example, in a rural community, implementing a renewable-energy-based autonomous microgrid has transformed residents' lives by providing a reliable electricity supply and reducing dependence on diesel generators [42,73]. In an urban setting, a microgrid project has enabled a community to reduce energy costs and improve sustainability by integrating solar panels and energy storage systems [40,97].

3.6.3. Local Innovations

Customized energy solutions are crucial to addressing the specific needs of each community. In rural areas, projects like long-term capacity planning for isolated microgrids using advanced optimization algorithms have proven effective in meeting fluctuating demand and the intermittent nature of renewable energy sources [69,73]. In urban environments, local innovations include the implementation of affine arithmetic-based energy management schemes for multi-microgrid networks, enabling efficient energy exchanges and robust management against uncertainties [26,69].

3.6.4. Holistic Vision

A holistic vision for integrating urban and rural solutions could create a more efficient and resilient energy system [52]. For example, urban microgrids can act as energy hubs that exchange electricity with rural microgrids, leveraging the advantages of both settings to optimize resource use and improve system stability [26,40]. This integration enhances operational efficiency and promotes sustainable development by providing access to clean and reliable energy across all communities [42,97]. Sustainable community development can be significantly driven by energy solutions that consider local particularities. Projects incorporating renewable energy technologies, storage, and advanced management strategies can reduce carbon emissions and promote a greener economy [40,69]. In this context, energy solutions must be designed to be scalable and adaptive, ensuring that both urban and rural areas can benefit from technological advancements and best practices in energy management [69,73]. Based on the PRISMA methodology's systematic review, several novel findings and future challenges have been identified across six key microgrid planning and optimization topics. Table 4 summarizes these discoveries and outlines the challenges that lie ahead.

Table 4. Novel findings and future challenges of the six topics.

Topic	Novel Findings	Future Challenges
Microgrid Planning and Optimization	The use of evolutionary and stochastic algorithms to enhance microgrid planning and optimization. Integrating AI and machine learning to optimize performance and efficiency [5,28,37].	Develop technologies that allow for the self-optimization and autonomous management of microgrids. Efficiently integrate new renewable energy sources [35,69,89].
Modeling and Simulation	Application of stochastic optimization techniques and genetic algorithms. Use of advanced simulations to predict and manage variability in renewable energy generation [20,24,76].	Improve the accuracy and efficiency of simulations to predict better and manage fluctuations in energy generation and demand [28,73,94].
Energy Storage and Battery Technologies	Development of redox flow batteries and solid-state batteries. Innovations in lithium-ion batteries to enhance energy density and safety [26,28,35].	Increase the sustainability and recyclability of batteries. Reduce production costs and improve the lifespan of storage technologies [42,70,89].
Power Systems Operation and Control	Implementation of real-time simulations and hardware-in-the-loop (HIL) testing. Dynamic power electronic converters enhance operational efficiency [63,89,94].	Enhance microgrid resilience against faults and disturbances. Optimize the integration of renewable energies to maintain system stability [69,76,94].
Cycle Counting and Data Analysis	Application of AI algorithms and machine learning to analyze large data volumes. Advanced data analysis tools are used to optimize real-time microgrid operations [63,73,83].	Develop more advanced methods for predictive analysis and real-time data management. Improve the accuracy and speed of analysis algorithms [69,89,94].
Urban and Rural Energy Solutions	Implementation of autonomous microgrids in rural areas. Use of affine arithmetic-based energy management schemes for multi-microgrid networks in urban settings [26,40,97].	Foster the integration of urban and rural energy solutions to optimize resource use. Promote sustainable development through the adoption of clean and efficient technologies [42,69,97].

3.7. Quantitative Analysis of Optimization Strategies

A detailed descriptive analysis of the quantitative data available in the reviewed studies revealed several significant trends in the performance of microgrid optimization strategies. Strategies based on artificial intelligence, such as machine learning, have proven particularly effective in enhancing energy efficiency and operational stability. Studies that applied deep learning techniques reported average improvements of 20% in energy efficiency, attributed to these algorithms' ability to anticipate demand and adjust energy production in real time [35,42,89]. Furthermore, studies that integrated advanced storage technologies, such as redox flow batteries and supercapacitors, along with predictive control systems, reported reductions in operational costs between 15% and 35%, underscoring the effectiveness of these approaches in managing the intermittency of renewable energy sources [26,28,70]. A notable improvement in system resilience was also observed; in microgrids that utilized advanced controllers and real-time simulations, a 30% reduction in fault recovery time and a 25% increase in the capacity to respond to extreme events were documented [63,76,94]. These quantitative findings underscore the effectiveness of innovative strategies and highlight the need for a more systematic and quantitative approach in evaluating the benefits of microgrid optimization, considering both operational and economic aspects.

3.8. Comprehensive Analysis of Microgrid Planning Components

Microgrid planning requires a holistic approach, encompassing various components to ensure efficient and sustainable operation. Key elements include the selection and sizing of RES, such as PV, WT, and hydropower, and the appropriate selection and sizing of ESS, like batteries, fuel cells, hydro-pumped storage, flywheels, and supercapacitors.

3.8.1. Renewable Energy Source Selection and Sizing

The selection of RESs for microgrids is critical in determining their overall performance and sustainability. Technologies, such as PV systems, wind turbines, and hydropower, have unique characteristics that affect their integration into microgrids. For instance, PV systems are well suited for regions with high solar irradiance, while wind turbines are effective in areas with consistent wind patterns. Although less common in microgrids, hydropower can provide a stable and reliable energy source, especially in water-abundant regions [99]. Accurate sizing of these RESs is essential to balance energy supply and demand while minimizing costs and maximizing efficiency. Mathematical optimization, including techniques like MILP and dynamic programming, helps determine the optimal capacity of RESs to install in a microgrid, considering factors, such as peak demand, generation variability, and cost constraints [35,37].

3.8.2. Energy Storage System Selection and Sizing

Energy storage systems play a vital role in managing the variability and intermittency of renewable energy sources. The selection of ESSs depends on the specific needs of the microgrid, such as storage capacity, discharge rate, lifespan, and cost. Common types of ESSs include batteries, fuel cells, hydro-pumped storage, flywheels, and supercapacitors. Each technology has its advantages and limitations; for example, batteries are ideal for short-term storage due to their fast response times, while hydro-pumped storage is better suited for long-term energy storage due to its high capacity [99]. Proper sizing of ESSs is crucial to ensure that the microgrid can store excess energy generated during periods of low demand and release it during peak demand. Optimization methodologies such as metaheuristics and heuristics, including genetic algorithms and particle swarm optimization, are widely used to determine the optimal size and placement of ESSs within a microgrid, ensuring cost-effectiveness and reliability [28,42].

3.8.3. Microgrid Topologies and Load Forecasting

Microgrid topologies, which define the arrangement of RESs and ESSs, significantly impact the efficiency and reliability of the system. Traditional AC microgrids have been the most common configuration; however, the integration of DC components is gaining traction due to the increasing number of DC loads and the inherent efficiency of DC power distribution. Hybrid AC/DC microgrids combine the benefits of both AC and DC systems, offering flexibility and efficiency advantages, especially in systems that incorporate a mix of generation sources and loads [100]. Load forecasting is another crucial component of microgrid planning. Accurate load forecasts enable better planning and operation, ensuring that the microgrid can meet future energy demands without over-sizing or under-sizing its components. Techniques such as machine learning and artificial neural networks are increasingly used to improve the accuracy of load forecasts by analyzing historical consumption data and predicting future trends [37,70].

3.8.4. Integration of Emerging Technologies and Sector Coupling

Integrating emerging technologies such as EV charging stations, heat pumps, and solid-state transformers is becoming increasingly important in microgrid planning. EV charging stations, for example, add a new dimension to energy demand, requiring careful planning to avoid overloading the grid while optimizing the use of renewable energy. Heat pumps provide a means to use electricity for heating and cooling efficiently, contributing to sector coupling by linking the electricity sector with the heating and cooling sectors [101]. Solid-state transformers offer significant advantages in AC/DC conversion, providing greater flexibility and efficiency in managing power flows between different parts of the microgrid. When integrated effectively, these technologies enhance microgrids' functionality and resilience, making them more adaptable to future energy landscapes [26,70,89].

3.8.5. Optimization Methodologies

Optimization methodologies play a pivotal role in microgrid planning, helping to balance costs, performance, and sustainability. Mathematical optimization methods, such as linear programming, mixed-integer linear programming, and dynamic programming, provide precise solutions for optimizing RES and ESS capacities and developing efficient operational strategies [35,37]. Metaheuristics and heuristics, including genetic algorithms and particle swarm optimization, offer flexible and robust solutions for complex optimization problems where traditional methods may fall short [28,42].

4. Conclusions

This review systematically synthesized the advancements, challenges, and future directions in microgrid (MG) planning and optimization for renewable integration, utilizing the PRISMA methodology to ensure a thorough and unbiased analysis. The literature review encompassed an extensive search across multiple databases, including Scopus, IEEE Xplore, and MDPI, ensuring a broad coverage of high-quality, peer-reviewed studies. After removing duplicates, the review identified a total of 1929 articles, with 1892 unique items. These articles were rigorously screened against predefined inclusion and exclusion criteria, ultimately resulting in 617 studies that were included for detailed analysis. After the eligibility and inclusion phase, 81 articles were selected based on a minimum threshold of 3.85 out of 5, as validated in an eligibility and inclusion matrix, constituting the sample for the literature review synthesis.

The selected articles were published between 2013 and 2024, reflecting the most recent advancements and trends in MG research. A significant portion of the literature was sourced from reputable journals, with notable contributions from *IEEE Access*, *Energies*, *IEEE Transactions on Smart Grid*, and *IEEE Transactions on Sustainable Energy*, among others. The distribution of articles over the years highlighted a growing interest in MGs, with a notable increase in publications from 2017 onwards, peaking in 2023. This trend underscores the expanding focus on sustainable energy solutions and the critical role of MGs in modern energy systems.

The literature synthesis revealed significant advancements and challenges in microgrid planning and optimization across six key areas. Historical narratives show the evolution from early independent systems to sophisticated, integrated microgrids with enhanced resilience and efficiency through advanced energy management systems and stochastic optimization techniques. Innovative methods, including AI and machine learning, offer adaptive solutions that improve operational efficiency and resilience by predicting and responding to demand and environmental changes in real time. Innovations in energy storage, particularly lithium-ion and redox flow batteries, have enhanced energy density, safety, and recyclability, which are critical for managing the intermittency of renewable energy sources and improving MG sustainability. Implementing real-time simulations, hardware-in-the-loop testing, and dynamic power electronic converters has significantly enhanced MG operational efficiency and stability, ensuring the effective integration of renewable energies while maintaining reliability. AI and machine learning applications for data analysis have optimized real-time MG operations, with advanced data-driven methods improving predictive analysis, fault tolerance, and overall system stability, leading to more efficient energy management. Customized energy solutions for urban and rural communities show great promise, with autonomous MGs in rural areas and advanced energy management schemes in urban settings demonstrating the potential to enhance sustainability and operational efficiency, optimizing resource use and promoting sustainable development.

Specifically, this review seeks to answer key questions: What are the most effective strategies for planning and optimizing MG clusters? How can renewable energy integration and storage solutions be improved to enhance MG's efficiency and resilience? What are the critical challenges in simulation accuracy and energy storage sustainability that need to be addressed? The findings indicate that integrating AI, IoT, and advanced energy

storage systems into MGs significantly enhances efficiency, reliability, and resilience. Advanced modeling and simulation techniques, such as stochastic optimization and genetic algorithms, are crucial for managing renewable energy variability. However, the critical challenges identified include developing self-optimization technologies for MGs, improving simulation accuracy, enhancing the sustainability of energy storage technologies, and conducting comprehensive economic assessments of MG scalability.

Despite these advancements, several challenges require further research and innovation: developing technologies that allow for the self-optimization and autonomous management of MGs is crucial, as efficiently integrating new renewable energy sources into existing MG frameworks remains a significant challenge that needs innovative solutions. Improving simulations' accuracy and efficiency to predict and manage energy generation and demand fluctuations is essential, as enhanced simulation techniques will provide more reliable data for optimizing MG operations. Increasing the sustainability and recyclability of energy storage technologies, while reducing production costs and improving lifespan, is necessary for the broader adoption of MGs, with research into new materials and storage solutions being vital in achieving these goals. Enhancing the resilience of MGs against faults and disturbances and optimizing the integration of renewable energies to maintain system stability are ongoing challenges that require advanced control strategies and fault-tolerant designs. Comprehensive economic assessments of MG scalability and sustainability across different contexts are underexplored, and future research should focus on the economic viability and long-term benefits of MGs to ensure they are both cost-effective and scalable. The current literature often isolates aspects like scheduling or fault detection, lacking a holistic approach that integrates machine learning for efficiency and reliability; thus, future studies should adopt more integrated methodologies to comprehensively address the multifaceted challenges of MGs.

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