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Systematic Review

Optimizing Microgrid Operation: Integration of Emerging Technologies and Artificial Intelligence for Energy Efficiency

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Abstract: Microgrids have emerged as a key element in the transition towards sustainable and resilient energy systems by integrating renewable sources and enabling decentralized energy management. This systematic review, conducted using the PRISMA methodology, analyzed 74 peer-reviewed articles from a total of 4205 studies published between 2014 and 2024. This review examines critical areas such as reinforcement learning, multi-agent systems, predictive modeling, energy storage, and optimization algorithms—essential for improving microgrid efficiency and reliability. Emerging technologies like artificial intelligence (AI), the Internet of Things, and flexible power electronics are highlighted for enhancing energy management and operational performance. However, challenges persist in integrating AI into complex, real-time control systems and managing distributed energy resources. This review also identifies key research opportunities to enhance microgrid scalability, resilience, and efficiency, reaffirming their vital role in sustainable energy solutions.

Keywords: microgrid operation; artificial intelligence; energy management; PRISMA methodology

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1. Introduction

In a context where the need for a reliable and sustainable electricity supply is more pressing than ever, microgrids (MGs) have emerged as a promising solution for energy distribution. These decentralized energy networks facilitate the integration of renewable energy sources and enhance the resilience of energy systems against disruptions and fluctuations in supply and demand [1]. The growing application of emerging technologies, such as artificial intelligence (AI) and the internet of things (IoT), has further amplified the potential of MGs by optimizing energy management and improving operational efficiency [2]. For instance, deep learning algorithms and reinforcement techniques have been shown to effectively manage the complexity of MG operations, enabling adaptive and real-time responses to changes in demand and environmental conditions [3,4]. However, despite significant advancements, critical challenges remain regarding integrating multiple technologies and managing distributed generation that require ongoing attention and innovative solutions [5]. This review article evaluates the latest emerging technologies and AI methods applied to MGs, highlighting future research opportunities to advance toward a more sustainable and efficient energy future [6,7].

Microgrids have become central to the transition towards sustainable energy systems, acting as decentralized networks that integrate distributed energy resources to enhance power system resilience and flexibility. Research underscores their potential to improve energy efficiency and reliability through advanced technologies and innovative energy management strategies. Reinforcement learning, for instance, has optimized energy scheduling amid uncertainties from extreme weather [8]. Integrating IoT with deep learning has enabled real-time decision-making and efficient load forecasting [9], and reinforcement learning has developed model-based optimization for stable MG operations [10]. Economic dispatch issues have been addressed using neural networks to manage renewable energy intermittency [11]. Hybrid meta-heuristic techniques have enhanced system reliability in distributed generation-integrated MGs. Deep reinforcement learning frameworks emphasize resilience and environmental benefits in long-term MG expansion [12], while bi-layer scheduling methods optimize day-ahead and intra-day operations [13]. Forecast-driven stochastic optimization has improved lifecycle cost management in isolated MGs using hydrogen [14], and deep reinforcement learning optimizes multi-objective dispatch models, addressing wind and solar uncertainties [1].

Industry 4.0 technologies, including AI, have revolutionized MG energy management, tackling challenges like intermittent generation and voltage harmonics [2]. AI-driven scheduling optimizes day-ahead operations, considering battery degradation and demand response [3], and reinforcement learning manages energy with renewable sources [15]. Advances in digital twin technology optimize power generation in smart building MGs, providing economic and ecological insights [16]. Stochastic optimal energy management frameworks in isolated MGs use Gaussian process regression for demand forecasting [17]. Neural networks improve battery degradation prediction accuracy, enhancing day-ahead scheduling models [18]. V2G systems foster local renewable energy consumption with hybrid learning frameworks integrating battery protection [19]. AI-based models address optimal power flow in solar MGs [4], enhancing solar radiation and wind speed forecasting for dynamic MG analysis [20]. Deep learning algorithms boost energy performance in photovoltaic-integrated MGs [21]. Multi-agent reinforcement learning facilitates energy transactions in collaborative multi-MG systems [22], and decentralized reinforcement learning adapts energy management under stochastic conditions [23]. Real-time energy management in maritime MGs uses stochastic model predictive control to manage solar energy and load uncertainties [24]. Multi-objective load dispatch models tackle the challenges of unstable renewable generation in smart grids [25]. Collaborative optimization reduces real power losses in grid-connected MGs [26], and deep neural networks with column generation techniques accelerate optimization in model predictive control-based systems [27].

Policy gradient techniques ensure reliability and reduce blackout risks in rural and islanded MGs [28]. State-of-the-art reviews emphasize advanced control strategies for networked MG systems [6]. Reinforcement learning is key in developing decentralized energy management systems for smart MGs, maximizing stakeholder benefits [7]. Robust economic dispatch models address renewable energy generation and load uncertainty [29]. Innovative energy management architectures using deep reinforcement learning improve MG scheduling and stability [30]. AI optimization techniques enhance hybrid MGs' power quality and fault management [31]. Multi-agent deep reinforcement learning supports collaboration in multi-MG systems [5], and advanced frequency control optimizes power generation in island city MGs [32]. Integral Q-learning minimizes costs and extends battery life in MGs [33]. Combining rule-based and deep learning techniques, hybrid control systems optimize MG operations under variable conditions [34]. AI optimization in hybrid electric vehicle charging reduces costs and emissions in renewable MGs [35]. Deep neural networks enhance MG operations through optimal scheduling [36]. Deep learning power control strategies reduce losses and enhance stability in MGs [37]. The transportation sector advances onboard MG energy management using AI and digital twins [38]. Reinforcement learning-based control systems improve DC MG efficiency by minimizing power losses [39]. Economic assessments of bidirectional electric vehicle charging optimize costs in workplace MGs [40]. Day-ahead scheduling models improve cost efficiency in isolated MGs [41], and real-time scheduling frameworks for EV charging stations optimize energy management [42]. Community control approaches using deep reinforcement learning balance profitability and user comfort in MGs [43], and battery scheduling control methods optimize energy trading [44]. Model predictive control-based reinforcement learning enhances residential MG energy management [45], while stochastic scheduling strategies address dependencies in campus-isolated MGs [46]. Data-driven fault tolerance methods improve frequency stability and reduce costs in islanded MGs [47]. Advanced data-driven energy management strategies based on deep reinforcement learning enhance MG stability and economy [48]. Recent advances in microgrid energy management have increasingly relied on integrating AI techniques to enhance system reliability, optimize energy distribution, and reduce operational costs. Hybrid Energy Storage Systems (HESSs) have emerged as a key solution to manage the variability of renewable energy sources, combining multiple storage technologies to achieve better performance. However, the complexity of control and power management in such systems has led to the exploration of AI-driven techniques, including fuzzy logic, neural networks, and reinforcement learning, to enhance system efficiency and adaptability [49]. AI-enhanced energy management systems (EMSs) have shown promising results in various microgrid configurations. For instance, field-programmable gate arrays (FPGAs) equipped with AI algorithms have significantly improved cost savings and reliability by dynamically adjusting to load and generation changes [50]. Predictive algorithms for energy management in DC microgrids have been successfully applied, improving overall system stability and financial outcomes by adapting to market fluctuations [51]. Furthermore, hydrogen-fueled microgrids have benefitted from novel AI-driven EMS approaches, which dynamically respond to varying conditions, enhancing system efficiency and reliability, particularly in managing renewable energy sources [52]. Recent studies have also demonstrated the feasibility of reducing carbon emissions in microgrids by optimizing cost management through AI, utilizing algorithms like the Improved Artificial Rabbits Optimization Algorithm (IAROA) and Whale Optimization Algorithm (WOA) to significantly reduce operational costs [53]. The application of deep reinforcement learning (DRL) has shown great potential in enhancing the control and management of microgrids, addressing complex challenges such as power distribution and stability in renewable energy systems [54]. Adaptive AI-based home energy management systems (HEMSs) have also been developed to improve the performance and resilience of autonomous microgrids, optimizing energy use and minimizing operational costs through advanced optimization techniques [55]. Additionally, edge-cloud computing environments have been explored to address the challenges of privacy and communication resources in centralized reinforcement learning-based microgrid management, utilizing federated deep reinforcement learning (FDRL) to optimize energy management strategies [56].

Critical research gaps remain despite significant advancements in optimizing MGs through emerging technologies such as AI and the IoT. While AI-based models, including deep learning and reinforcement learning, have proven effective in managing the operational complexity of MGs [4,8], integrating multiple technologies across diverse environments remains a major challenge [2,34]. Current research tends to focus on isolated aspects, such as energy scheduling or fault detection but lacks a holistic approach that integrates these technologies to enhance the efficiency and reliability of MGs [3,35]. Furthermore, the real-world application of AI for real-time demand prediction and distributed generation optimization is limited, and economic assessments of scalability and sustainability across different contexts remain underexplored [21,36].

This review addresses these gaps by systematically evaluating and synthesizing the challenges and opportunities of integrating emerging technologies and AI in microgrid operations, utilizing the PRISMA methodology.

The structure of this article is organized as follows. Section 2 presents the methodology used for conducting the systematic literature review, following the guidelines of the PRISMA 2020 statement. Section 3 comprehensively analyzes the selected literature, highlighting key trends, research areas, practical applications, and challenges in microgrid optimization and integrating emerging technologies. Finally, Section 4 concludes the article with a summary of key insights and directions for future research.

2. Materials and Methods

The methodology for this systematic review is grounded in the guidelines provided by the PRISMA 2020 statement [57], which structures the review process into distinct phases to ensure clarity, accuracy, and thoroughness. These phases include identification, screening, eligibility and inclusion, and synthesis, each of which plays a critical role in the systematic review process. The identification phase involves retrieving relevant items through a well-defined search strategy across selected databases. The screening phase thoroughly reviews abstracts to ensure they meet predefined inclusion and exclusion criteria. During the eligibility and inclusion phase, a meticulous approach is applied to confirm that only high-quality and relevant studies are chosen for further analysis. Finally, the synthesis phase integrates and analyzes the selected literature to form the basis for the findings and conclusions presented in the review. A simplified diagram of these phases is depicted in Figure 1.

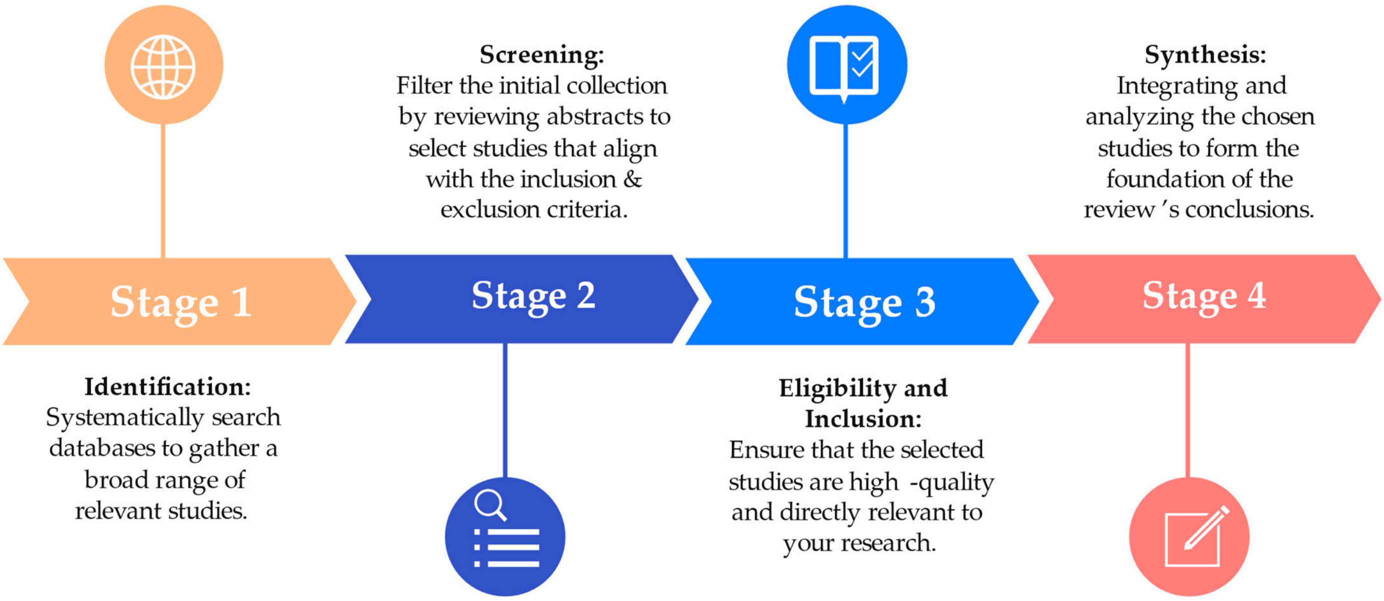

Figure 1. Simplified diagram of the PRISMA 2020 methodology phases.

2.1. Identification Phase

In the identification phase of this systematic literature review, the focus is on gathering high-quality research articles published between 2014 and 2024, specifically addressing the integration of emerging technologies and AI in optimizing microgrid operations. The search is confined to peer-reviewed journal articles written in English, with full-text access provided through institutional subscriptions or open access. The bibliographic resources for this review were sourced from Scopus and Web of Science, two databases recognized for their extensive coverage of high-impact research across various disciplines. These platforms offer access to publications from leading publishers such as Elsevier, Springer, Wiley, Taylor & Francis, MDPI, and IEEE, among others. Additionally, their advanced citation tracking features are crucial for identifying the most influential studies in the field. To align with the objectives of this research and based on the preliminary literature exploration presented in the introduction, the search terms summarized in Table 1 were employed.

The literature search conducted across the Scopus and Web of Science databases resulted in a total of 4205 documents. Specifically, Scopus returned 2285 documents, while Web of Science yielded 1920. After removing duplicates, 29 from Scopus and 1494 from Web of Science, 1523 duplicates were excluded. This process left a final sample of 2682 documents for the screening phase.

Table 1. Literature search terms and summary of database search results.

Database	Query String	N° of Returned Documents	Removal of Duplicates	Final Sample for Screening Phase
Scopus	(TITLE-ABS-KEY (“microgrid”) AND TITLE-ABS-KEY (“operation”)) AND (TITLE-ABS-KEY (“Artificial Intelligence”) OR TITLE-ABS-KEY (“Machine Learning”) OR TITLE-ABS-KEY (“IoT”) OR TITLE-ABS-KEY (“Deep Learning”) OR TITLE-ABS-KEY (“Reinforcement Learning”) OR TITLE-ABS-KEY (“Stochastic”) OR TITLE-ABS-KEY (“Meta-Heuristic”) OR TITLE-ABS-KEY (“Scheduling”)) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE, “ar”))	2285	29	2256
Web of Science	(ALL=(“microgrid”) AND ALL=(“operation”)) AND (ALL=(“Artificial Intelligence”) OR ALL=(“Machine Learning”) OR ALL=(“IoT”) OR ALL=(“Deep Learning”) OR ALL=(“Reinforcement Learning”) OR ALL=(“Stochastic”) OR ALL=(“Meta-Heuristic”)OR ALL=(“Scheduling”)) Refined By: Publication Years: 2024 or 2023 or 2022 or 2021 or 2020 or 2019 or 2018 or 2017 or 2016 or 2015 or 2014; Document Types: Article	1920	1494 *	426
	Total items	4205	1523	2682

* Scopus items were used as a reference during the duplicate identification process. Thus, our bibliographic management tool removed the Web of Science entry when a Web of Science item had a DOI identical to a Scopus item.

2.2. Screening Phase

During the Screening Phase, abstracts were carefully reviewed against the inclusion and exclusion criteria in Table 2 by two independent reviewers using a binary scoring system. Discrepancies were resolved through consensus to ensure an unbiased selection. The review focused on peer-reviewed journal articles to maintain a sample of primary literature sources, making them particularly suited for systematic reviews of this nature. Only English-language articles published between 2014 and 2024 were included to reflect recent advancements and avoid potential obsolescence. Full-text access was required to allow for a thorough evaluation of each study, with non-accessible articles excluded to maintain the review’s rigor.

The Screening process carefully evaluated 2682 items, resulting in 646 works (24% of the total) passing this phase, with the remaining 76% excluded for not meeting the inclusion and exclusion criteria. Among the selected items, *Energies* led with 55 contributions, highlighting its focus on energy systems and renewable energy research. *Applied Energy* followed with 47 items, emphasizing its role in applied research for optimizing energy systems. *IEEE Transactions on Smart Grid* contributed 38 items, reflecting the journal’s focus on smart grid technologies and their intersection with microgrid innovations. *IEEE Access* and the *Journal of Energy Storage* each provided 20 items, underscoring the importance of accessible research in engineering and the critical role of energy storage in microgrids, respectively. The journal *Energy* also added 20 items, showcasing its broad coverage of energy-related topics. The *International Journal of Electrical Power & Energy Systems* and *Sustainable Cities and Society* each contributed 17 items, highlighting their relevance in power systems research and the integration of microgrids in sustainable urban environments.

Energy Reports added 16 items, reflecting its focus on global energy challenges and the role of microgrids in sustainable energy systems. Additionally, 263 items were sourced from various other journals, demonstrating the multidisciplinary nature of research on microgrid operations.

Table 2. Inclusion and exclusion criteria for systematic literature review.

Criterion	Inclusion	Exclusion
Publication Type	Peer-reviewed journal articles	Conference papers, editorials, review articles, book chapters, theses, white papers, non-peer-reviewed materials
Language	English	Non-English
Publication Date	2014–2024	Articles published before 2014
Accessibility	Full-text access via institutional subscription or open access	Articles without full-text access
Research Focus	Studies on the integration of emerging technologies (AI, IoT, machine learning, smart grids, etc.) in microgrid operation	Articles that do not focus on microgrids, emerging technologies, or machine learning in energy management, or articles focusing solely on non-technological aspects of energy systems (e.g., policy, economics without tech analysis)

The annual progression of publications shows significant growth, starting with four items in 2014 and gradually increasing to 33 in 2019. A notable surge occurred in 2020 with 54 items, continuing to rise to 95 in 2021, 124 in 2022, peaking at 141 in 2023, and slightly decreasing to 129 in 2024, reflecting sustained interest and advancements in the field. These statistics are summarized in Figure 2, providing a visual overview of the distribution of selected items across journals and the yearly evolution of research.

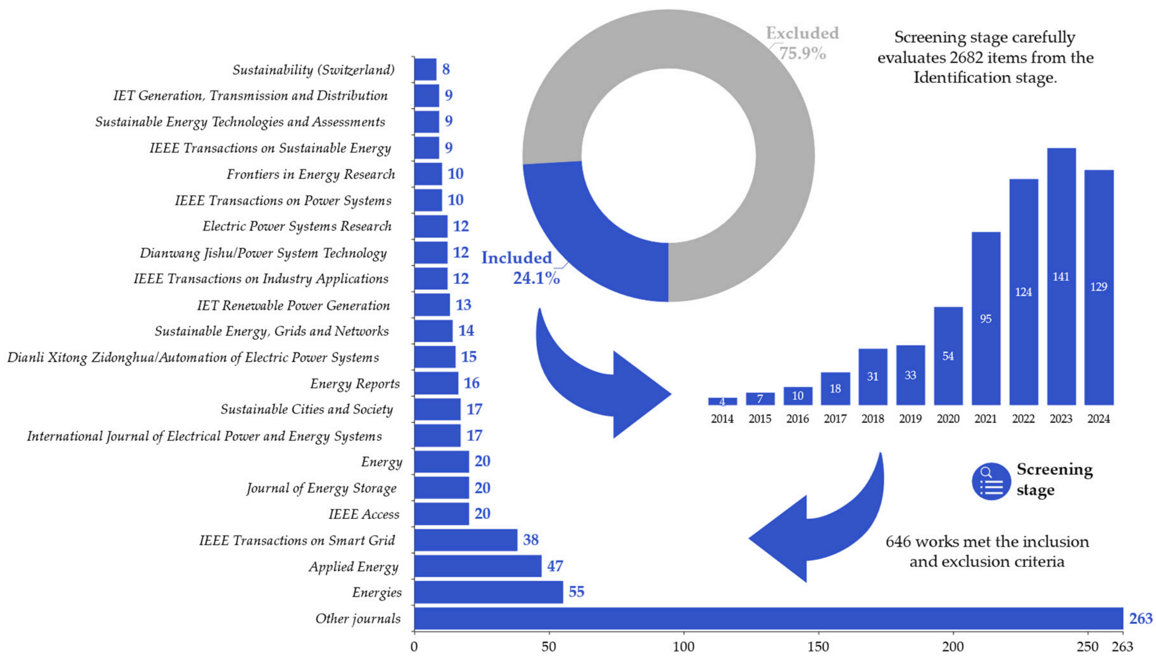

Figure 2. Outcomes of the screening phase.

2.3. Eligibility and Inclusion Phase

The eligibility and inclusion phase was crucial in selecting only the most relevant and high-quality studies for the review. Each article underwent a comprehensive full-text assessment using a three-level Likert scale based on criteria such as relevance to emerging microgrid technologies, methodological rigor, experimental validation, novelty, and clarity.

Studies were rated from one to three on each criterion, and only those that scored well were included, ensuring a focused and high-quality review of the integration of technologies like AI and IoT in microgrid operations. The detailed criteria and evaluation metrics designed by the authors for this literature review are summarized in Table 3.

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

N°	Criterion	Description and Evaluation Metrics
1	Relevance to Emerging Technologies in Microgrids	How well the study addresses the integration of emerging technologies (AI, IoT, etc.) and machine learning in microgrid operation. (1: Somewhat Relevant, 2: Relevant, 3: Central Focus)
2	Methodological Rigor	The robustness and appropriateness of the research methodology employed in the study. (1: Foundational, 2: Adequate, 3: Comprehensive)
3	Experimental Validation and Real-world Application	The extent to which the study includes experimental results, simulations, case studies, or real-world implementations. (1: Preliminary, 2: Moderate, 3: Extensive)
4	Novelty and Contribution	The originality and significance of the study's contributions to the field. (1: Incremental, 2: Significant, 3: Highly Innovative)
5	Clarity and Technical Depth	The clarity of writing, technical detail, and completeness of the information provided in the study. (1: Clear, 2: Thorough, 3: Exceptionally Detailed)

In the eligibility and inclusion phase, out of the 646 items evaluated, 74 articles (11% of the total screened items) were selected for the systematic review. This selection was based on a rigorous threshold of 11 out of 15 points, ensuring that the chosen studies exhibited a strong combination of relevance, methodological rigor, experimental validation, novelty, and clarity. Figure 3 shows the verification matrix employed for the eligibility of items, visually presenting the scoring system used in the full-text review process. After a comprehensive evaluation of each of the 646 items in the previous phase, the authors assigned scores based on the criteria outlined in Table 3. Each work was rated from one to three on five criteria: (1) relevance to emerging technologies in microgrids, which assessed how central the study was to the integration of technologies like AI, IoT, and machine learning in microgrid operations; (2) methodological rigor, which measured the robustness and appropriateness of the research methods; (3) experimental validation, which considered the extent of real-world applications, simulations, or case studies; (4) novelty and contribution, which evaluated the originality of the research; and (5) clarity and technical depth, assessing the thoroughness of the study's presentation. Studies that achieved a cumulative score of 11 points or higher across these criteria were deemed eligible for inclusion. For ease of visualization, Figure 3 only shows the ranking of items that met this minimum threshold, reflecting the systematic and objective nature of the selection process. The bibliographic information of the 74 selected items can be consulted and downloaded from the following GitHub link: https://t.ly/SrM8k (access on 18 September 2024).

2.4. Synthesis Phase

This section synthesizes the 74 articles selected during the eligibility and inclusion phase to provide a comprehensive overview of the current research on integrating emerging technologies in microgrid operations. These articles represent a carefully curated subset of the broader literature, ensuring that only the most relevant and high-quality studies are included in this analysis. The selected works span various thematic areas and have been sourced from diverse journals, reflecting the field's multidisciplinary nature.

N°	ID	Crit. 1	Crit. 2	Crit. 3	Crit. 4	Crit. 5	Total
1	S-1938	3	3	3	2	3	**14**
2	S-0626	3	2	2	3	3	**13**
3	S-0260	3	3	3	2	1	**12**
4	S-0279	3	3	3	2	1	**12**
5	S-0409	3	1	2	3	3	**12**
6	S-0426	3	2	1	3	3	**12**
7	S-0552	3	3	3	2	1	**12**
8	S-0557	3	3	3	2	1	**12**
9	S-0827	3	2	3	2	2	**12**
10	S-1126	3	2	3	3	1	**12**
11	S-1274	3	2	3	3	1	**12**
12	S-1582	3	3	1	3	2	**12**
13	S-1662	3	2	2	2	3	**12**
14	S-1844	3	2	2	2	3	**12**
15	S-1989	3	3	3	2	1	**12**
16	WoS-0298	3	2	3	3	1	**12**
17	WoS-0348	3	3	3	2	1	**12**
18	WoS-1084	3	3	3	2	1	**12**
19	WoS-1437	2	3	3	3	1	**12**
20	WoS-0650	3	2	3	2	2	**12**
21	S-0007	3	2	2	3	1	**11**
22	S-0068	3	2	1	2	3	**11**
23	S-0086	3	2	3	2	1	**11**
24	S-0090	3	2	2	3	1	**11**
25	S-0096	3	2	2	3	1	**11**
26	S-0119	3	2	2	3	1	**11**
27	S-0130	3	2	2	3	1	**11**
28	S-0181	3	2	2	3	1	**11**
29	S-0287	3	2	2	3	1	**11**
30	S-0341	3	2	2	3	1	**11**
31	S-0398	3	2	2	3	1	**11**
32	S-0493	3	2	2	3	1	**11**
33	S-0729	3	2	2	2	2	**11**
34	S-0911	3	3	1	2	2	**11**
35	S-0933	3	2	1	3	2	**11**
36	S-0969	3	3	3	1	1	**11**
37	S-1059	3	2	2	2	2	**11**
38	S-1068	3	1	2	3	2	**11**
39	S-1380	3	2	2	3	1	**11**
40	S-1412	3	3	1	3	1	**11**
41	S-1451	3	3	1	3	1	**11**
42	S-1476	3	2	3	2	1	**11**
43	S-1541	3	3	1	2	2	**11**
44	S-1573	3	2	3	2	1	**11**
45	S-1634	3	2	3	2	1	**11**
46	S-1647	2	1	2	3	3	**11**
47	S-1758	3	3	2	2	1	**11**
48	S-1811	3	2	2	3	1	**11**
49	S-1882	3	3	1	3	1	**11**
50	S-2188	3	1	3	3	1	**11**
51	S-2225	3	3	3	1	1	**11**
52	WoS-0333	3	2	3	2	1	**11**
53	WoS-1040	3	2	2	2	2	**11**
54	S-0004	3	3	2	2	1	**11**
55	S-0005	3	2	2	3	1	**11**
56	S-0008	3	3	2	2	1	**11**
57	S-0016	3	3	2	2	1	**11**
58	S-0035	3	3	2	2	1	**11**
59	S-0045	3	3	2	2	1	**11**
60	S-0069	3	3	2	2	1	**11**
61	S-0079	3	3	3	1	1	**11**
62	S-0129	3	3	2	2	1	**11**
63	S-0203	3	3	2	2	1	**11**
64	S-0213	3	2	2	3	1	**11**
65	S-0215	3	3	1	3	1	**11**
66	S-0231	3	2	1	2	3	**11**
67	S-0242	3	2	3	2	1	**11**
68	S-0293	3	2	3	2	1	**11**
69	S-0303	3	2	2	2	2	**11**
70	S-0314	3	1	3	2	2	**11**
71	S-0333	3	2	2	2	2	**11**
72	S-0345	3	2	2	3	1	**11**
73	S-0453	3	1	2	3	2	**11**
74	S-0477	3	2	2	3	1	**11**

Figure 3. Verification matrix for eligibility and inclusion.

Journal statistics in Figure 4 reveal that *Energies* led the selection with eight articles, contributing to research on microgrids, particularly in areas such as energy storage and stochastic optimization and optimal operation and power management. This journal's focus on the intersection of energy systems and cutting-edge technological integration makes it a key resource for studies aiming to enhance microgrid performance. With six articles, *Applied Energy* also plays a crucial role, particularly in intelligent control, predictive modeling, day-ahead scheduling, and optimization algorithms, which are essential for efficiently managing microgrid resources. *IEEE Transactions on Sustainable Energy* and *IEEE Transactions on Smart Grid*, each contributing four articles, highlight their emphasis on reinforcement learning and multi-agent systems real-time scheduling and multi-scale energy management, critical for advancing smart grid technologies and sustainable energy practices. The *International Journal of Electrical Power and Energy Systems*, with four articles, focuses on intelligent control and optimal operation strategies, underscoring its relevance to electrical power systems and their application in microgrid contexts.

Other journals made significant contributions as well. *IEEE Access* and *Journal of Energy Storage* each provided three articles, reflecting the importance of open-access research and energy storage solutions in the microgrid landscape. *Sustainability (Switzerland)*, with two articles, emphasizes the integration of sustainable practices with advanced technological solutions, particularly in the context of microgrid operations. Journals like *Electric Power Systems Research*, *Renewable Energy*, and *Energy Conversion and Management* contributed to areas such as energy storage and stochastic optimization, further diversifying the thematic coverage of the selected studies.

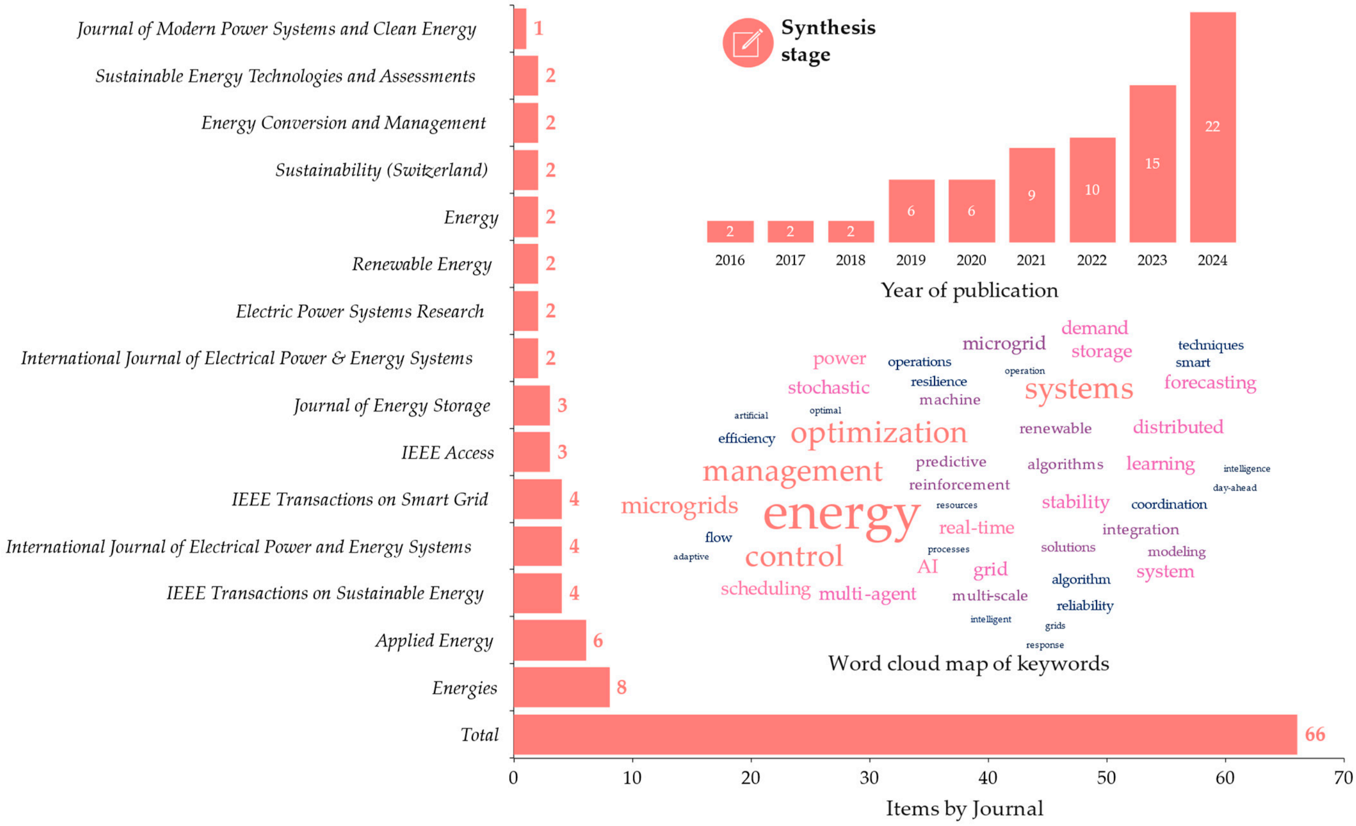

Figure 4. Synthesis of the selected articles for the literature review.

The yearly statistics provide additional insights into the evolution of research activity in this field. The selected articles reveal a clear trend of increasing research output over time, which mirrors the growing interest and advancements in microgrid technologies. In the early years, such as 2016 and 2017, the contributions were relatively modest, with only two articles each, reflecting the nascent research stage in this domain. However, as awareness of the potential of microgrids grew, the output steadily increased, with six articles each in 2019 and 2020, marking a rising focus on integrating emerging technologies into microgrid systems. The most significant growth occurred in the later years, particularly in 2023 and 2024, with 15 and 22 articles, respectively. This surge in publications highlights the accelerating pace of innovation and the critical importance of microgrids in addressing modern energy challenges, particularly in enhancing resilience and efficiency through advanced technological integration.

Figure 4 also presents a word cloud map constructed from the keywords of the selected articles. In this map, the most frequently occurring terms are visible, with prominent mentions of reinforcement learning and multi-agent systems in energy management, intelligent control and predictive modeling in microgrids, energy storage and stochastic optimization in microgrids, optimal operation, and power management using AI, real-time scheduling and multi-scale energy management, and day-ahead scheduling and optimization algorithms in microgrids.

The synthesis of the included articles provides a robust overview of the current research landscape in microgrid operations and suggests that the studies can be broadly grouped into six thematic categories:

- Reinforcement Learning and Multi-Agent Systems in Energy Management—Focus on reinforcement learning, deep learning, and multi-agent approaches in microgrid energy management.

- Intelligent Control and Predictive Modeling in Microgrids—Research on control strategies, predictive models, and intelligent systems within microgrids, including DC grid applications.
- Energy Storage and Stochastic Optimization in Microgrids—Studies involving energy management, storage solutions, renewable energy integration, and stochastic optimization in multi-microgrid systems.
- Optimal Operation and Power Management using AI—Exploration of microgrid operation, power optimization, and scheduling using AI-based approaches.
- Real-Time Scheduling and Multi-Scale Energy Management—Focus on real-time scheduling, multi-scale considerations, and energy management strategies in microgrids.
- Day-Ahead Scheduling and Optimization Algorithms in Microgrids—Investigations into day-ahead scheduling, optimal algorithms, and energy management in microgrid systems.

Section 3 presents a comprehensive analysis of the content and contributions of the articles included in this review, with the discussions organized into these six thematic groups. Finally, Figure 5 provides the standardized PRISMA 2020 flowchart [57], which outlines the steps and results obtained throughout the execution of the literature search methodology.

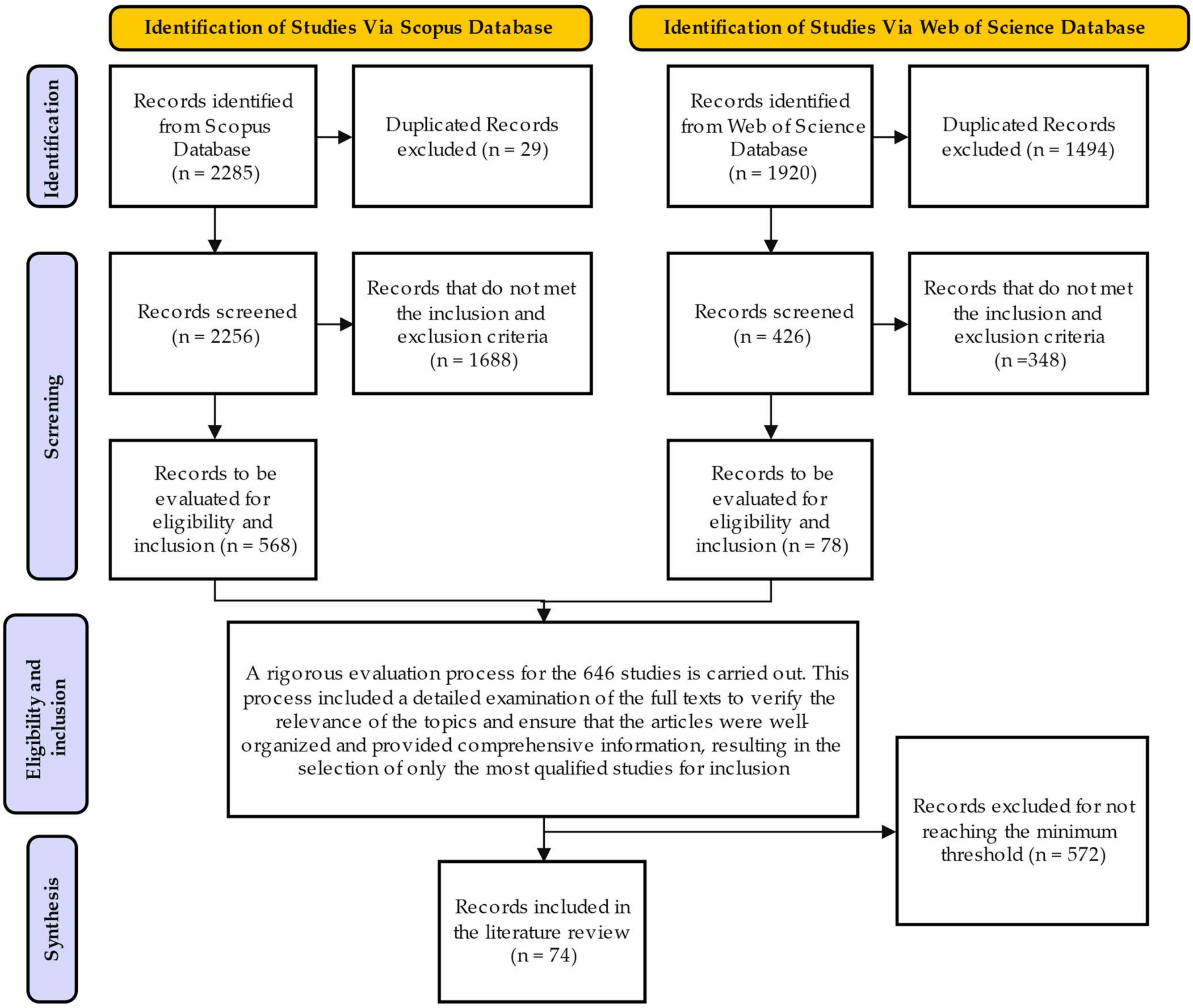

Figure 5. PRISMA 2020 flowchart of the literature review process.

3. Results and Discussions

This section provides a detailed analysis of the advancements and challenges in optimizing microgrid operations, focusing on integrating emerging technologies. The following subsections—Sections 3.1–3.6—examine critical areas shaping microgrid efficiency while addressing the shortcomings identified in current research. Section 3.1 explores the application of reinforcement learning and multi-agent systems in managing the complexities and uncertainties inherent in microgrid operations, alongside their scalability and real-world implementation limitations. In Section 3.2, attention is given to intelligent control and predictive modeling, emphasizing their role in enhancing grid stability and reliability while recognizing gaps related to real-time adaptability and the accuracy of predictive models.

Section 3.3 focuses on energy storage and stochastic optimization, highlighting their capacity to manage the variability of renewable energy sources yet noting the challenges associated with model integration and scalability. Optimal operation and power management are discussed in Section 3.4, where the benefits of current multi-criteria optimization strategies are presented, along with the limitations in balancing multiple objectives such as cost, efficiency, and sustainability. In Section 3.5, real-time scheduling and multi-scale energy management are examined, stressing the importance of flexible systems capable of adapting to real-time changes and identifying the shortcomings in managing dynamic, multi-scale grid conditions. Finally, Section 3.6 addresses day-ahead scheduling and optimization algorithms, which are crucial for resource planning but also constrained by forecasting accuracy and flexibility limitations. In each subsection, the discussion highlights technological advancements and critically evaluates the remaining gaps, providing a foundation for future research in improving microgrid operations.

3.1. Reinforcement Learning and Multi-Agent Systems

3.1.1. Current Context

Reinforcement learning (RL) and multi-agent systems (MASs) have emerged as pivotal approaches in optimizing MG operations due to their capacity to handle the inherent complexity and uncertainty of these systems [58]. The variability of renewable energy sources, such as solar and wind, introduces challenges that necessitate adaptive and rapid responses, capabilities that RL and MASs are particularly well-suited to provide. For instance, RL algorithms have been deployed to enable real-time adaptive management by continuously refining control policies based on system conditions, optimizing resource utilization, and improving grid stability [59,60]. Furthermore, MASs facilitate decentralized yet coordinated management of distributed resources, enhancing MGs' operational efficiency and resilience [61–63]. Implementing RL strategies has also been instrumental in managing extreme events and faults within microgrids, allowing systems to learn and adapt autonomously to adverse conditions without human intervention [60,64,65]. In addition, MASs have proven effective in improving the operational stability of MGs in complex and stochastic environments, which is critical for ensuring uninterrupted operation under varying conditions [66,67].

3.1.2. Research Opportunities and Future Directions

- Hybrid RL–MAS Frameworks: One promising research direction is the development of hybrid frameworks combining RL and MASs for managing distributed energy resources (DERs) within interconnected microgrids. These frameworks should consider energy price dynamics and renewable variability, optimizing internal operations and interactions between multiple microgrids [68–71]. Such systems could also focus on cooperation and controlled competition, where MAS models facilitate energy exchange and coordination among microgrids while optimizing energy flows and reducing costs [72–76].
- Electric Vehicle Integration: Another significant opportunity lies in applying RL–MAS frameworks to microgrids with high electric vehicle penetration, where energy demand is volatile and complex. RL strategies could optimize charging and discharging

patterns, ensuring better integration of electric vehicles into microgrid systems [77,78]. In addition, transfer learning techniques could be explored to accelerate the deployment of these models across different environments [79–82].

3.1.3. Shortcomings in Reinforcement Learning and Multi-Agent Systems

Despite the promise of RL and MASs in optimizing microgrid operations, current research faces significant limitations. One major challenge is the complexity of applying these methods in real-world systems, where RL algorithms' high computational demands and latency hinder real-time adaptability. Existing studies often focus on isolated aspects of RL and MASs without providing comprehensive frameworks that address internal microgrid operations and interactions between multiple microgrids. Hybrid RL–MAS frameworks that could optimize energy flows and costs through microgrid cooperation remain underexplored.

Additionally, integrating RL–MAS with electric vehicles faces challenges due to the scattered load and the unpredictable energy demand in such systems. Current research lacks scalable solutions for handling the dynamic energy demands of EVs, and transfer learning techniques that could improve model adaptability across different environments are underutilized. To overcome these limitations, further research is needed to develop more robust and scalable algorithms capable of handling the complexity and variability of modern microgrids.

3.2. Intelligent Control and Predictive Modeling

3.2.1. Current Context

Intelligent control and predictive modeling are fundamental to MGs' operation, enabling proactive management of demand and distributed generation [68]. These techniques have become increasingly important as microgrids integrate more renewable energy sources, which are inherently variable and unpredictable. AI-based predictive models allow for anticipating fluctuations in energy supply and demand, thus optimizing overall energy management and enhancing grid stability [69,70]. Additionally, these models facilitate detecting and mitigating potential faults before they escalate into critical issues, improving the system's resilience [61,71,72].

Implementing these advanced models is particularly relevant in scenarios involving high penetration of renewable energies and electric vehicles, where the variability of energy supply and demand can be challenging to manage [73,74]. For instance, predictive control systems that leverage AI can optimize the operation of microgrids by continuously adjusting operational parameters based on real-time data and historical trends, thereby ensuring a more stable and efficient energy distribution [75,76]. Moreover, the integration of stochastic predictive models has been shown to significantly improve the accuracy of forecasts in microgrids, particularly in managing uncertainties related to renewable energy sources [63,65].

3.2.2. Research Opportunities

AI-Based Predictive Control: There is a growing need to develop predictive models incorporating historical and real-time data to enhance operational stability. These models should handle the complexities introduced by renewable energy sources and electric vehicles, characterized by significant variability and unpredictability [81–83]. Leveraging deep learning techniques can significantly improve the predictive accuracy of these models in dynamic environments [74,75,80].

Real-Time Optimization Systems: Research should focus on developing real-time predictive control systems that adapt to changes in load and generation, using advanced neural networks and optimization techniques [76,81]. These systems should continuously learn from previous decisions, enhancing their effectiveness over time [67–72].

3.2.3. Shortcomings of Intelligent Control and Predictive Modeling

Although intelligent control and predictive modeling have significantly contributed to optimizing microgrid operations, several gaps remain in current research. One of the primary challenges is the difficulty in accurately forecasting real-time energy supply and demand fluctuations, particularly given the inherent variability of renewable energy sources and the unpredictable behavior of electric vehicles. While AI-driven predictive models aim to address these issues, their performance often declines when faced with rapid changes in the energy landscape, limiting their reliability for immediate decision-making.

Furthermore, real-time optimization remains an area of concern. Many existing models do not fully integrate continuous learning from historical and real-time data, making adapting to evolving microgrid conditions difficult. This limitation becomes especially pronounced in complex environments where renewable energy sources and electric vehicles interact dynamically. Despite some progress with stochastic predictive models, which improve uncertainty handling, their practical application in managing highly variable microgrid systems is still insufficiently explored. To overcome these barriers, future research must focus on developing more adaptive and flexible real-time control systems capable of consistently optimizing microgrid performance, even in volatile conditions.

3.3. Energy Storage and Stochastic Optimization

3.3.1. Current Context

Energy storage is essential for managing the intermittency of renewable energy sources in microgrids [77]. Effective energy storage solutions allow microgrids to balance supply and demand, especially when integrating variable renewable sources such as wind and solar power. Stochastic optimization plays a crucial role in the planning and operating of these storage systems by addressing the uncertainties associated with renewable energy generation and fluctuating demand [78,79]. This optimization approach ensures that energy storage resources are utilized most efficiently, accounting for degradation costs and operational reliability [80].

Given the stochastic and intermittent nature of renewable energy sources, incorporating stochastic optimization techniques is vital for enhancing the efficiency and reliability of microgrid operations [81,82]. These techniques enable the prediction and management of energy storage in a way that balances cost, availability, and system resilience [83,84]. Moreover, integrating advanced predictive models with stochastic optimization has been shown to significantly improve the performance of microgrids, especially in environments with high renewable energy penetration [85,86].

3.3.2. Research Opportunities

Optimizing Grid-Integrated Storage: Research should explore stochastic optimization techniques that address the variability of energy generation and the degradation costs of storage devices. Integrating real-time data with stochastic models can further enhance the efficiency of energy storage management [60,61]. Moreover, distributed storage solutions can be optimized using decentralized intelligence to manage local energy demands and improve overall system resilience [78–80]. The proposed work focuses on optimizing energy efficiency in urban environments by integrating renewable energy sources and the strategic role of electric vehicles in energy storage and load management. It emphasizes using technologies like solar photovoltaic and wind energy to achieve nearly zero, zero, and positive energy buildings (nZEBs, ZEBs, PEBs), while electric vehicles contribute by balancing energy fluctuations through vehicle-to-grid systems. A boundary framework is proposed to streamline energy flows within building districts, facilitating energy sharing and surplus management. Case studies from various countries illustrate the effectiveness of these strategies in reducing energy consumption and carbon emissions in urban settings [81].

3.3.3. Shortcomings of Energy Storage and Stochastic Optimization

Despite the important role of energy storage and stochastic optimization in enhancing microgrid operations, current research still faces several challenges. One key issue is the lack of comprehensive models that accurately address both the unpredictable nature of renewable energy generation and the long-term degradation costs of storage systems. While stochastic optimization techniques are essential for managing these uncertainties, many models fail to integrate real-time data effectively, limiting their ability to adapt to rapidly changing conditions in microgrid environments.

Additionally, the scalability of distributed energy storage systems is another area that remains underexplored. Existing methods often focus on centralized storage solutions, overlooking the potential benefits of decentralized intelligence that could optimize local energy demand and enhance overall system resilience. Moreover, while the combination of predictive modeling with stochastic optimization has shown promise, the current research is still insufficient in addressing the complexities of high renewable energy penetration. Models tend to oversimplify the dynamic interactions between energy generation, storage capacity, and consumption patterns, reducing the effectiveness of storage management in real-world applications.

To move beyond these limitations, future research must focus on developing more robust stochastic models that incorporate real-time data and degradation costs more seamlessly. Decentralized storage optimization, leveraging local intelligence, could also provide a more resilient and efficient approach to energy management in complex microgrid systems.

3.4. Optimal Operation and Power Management

3.4.1. Current Context

Optimal operation and power management are fundamental in maximizing efficiency and minimizing the losses in microgrids, particularly in systems with a high penetration of distributed energy resources. Microgrids, by design, aim to enhance energy resilience and flexibility, but the integration of renewable energy sources such as wind and solar introduces significant variability and unpredictability [87]. This variability can lead to stable and reliable power supply challenges, underscoring the importance of sophisticated optimization and power management strategies [88,89].

The need for optimal operation is driven by the dual goals of ensuring energy reliability and achieving sustainability targets. As microgrids incorporate more renewable energy sources, the operational complexity increases, necessitating advanced algorithms that can dynamically respond to real-time changes in both generation and demand [90]. Integrating real-time data analytics with predictive control systems has become a key approach in addressing these challenges [91]. These systems can optimize power flows by considering various factors, such as load forecasts, real-time pricing, and renewable generation profiles, enabling more stable and efficient operations even under uncertainty [61,64,92]. For instance, recent advancements have shown that incorporating AI techniques into power management systems can significantly enhance their ability to predict and adapt to changing conditions. These systems can analyze historical and real-time data to make informed decisions that optimize the distribution of power within the microgrid, reducing operational costs and enhancing system resilience [62,72]. Additionally, the use of predictive models that leverage weather forecasts and other relevant data can further improve the accuracy and efficiency of power management strategies, particularly in mitigating the impact of renewable energy variability [93,94].

3.4.2. Research Opportunities

Multi-Criteria Optimization: Research should focus on developing algorithms that optimize multiple objectives simultaneously, such as energy efficiency, cost reduction, and environmental sustainability. Integrating AI techniques into these algorithms can enhance adaptability and lead to more resilient microgrid operations [60,61]. Additionally, predictive models based on AI can improve the accuracy of power forecasts, helping microgrids to anticipate demand and supply changes [52–55,95].

3.4.3. Shortcomings of Optimal Operation and Power Management

Although optimal operation and power management in microgrids have seen significant improvements, various limitations persist in existing approaches. One major issue is the inability of current algorithms to cope efficiently with the unpredictability and variability introduced by renewable energy sources like wind and solar. While machine learning and AI techniques optimize power flow, they often struggle to accommodate real-time energy generation and demand changes. This lack of adaptability can result in inefficient operations, especially in scenarios with high penetration of distributed energy resources.

Another challenge is balancing multiple objectives, such as cost, energy efficiency, and environmental sustainability. Existing multi-criteria optimization methods focus on specific goals without considering the broader picture, limiting their effectiveness in achieving a well-rounded microgrid operational strategy. Furthermore, while predictive models anticipate demand and generation fluctuations, their accuracy is frequently compromised by incomplete real-time data integration, leading to less effective power management solutions.

Overall, the current methods lack the robustness required to address the complexities of microgrid operations. Future research needs to prioritize the development of more flexible, data-driven algorithms capable of handling the intricacies of renewable energy variability while simultaneously balancing competing operational goals to ensure efficiency, cost-effectiveness, and resilience.

3.5. Real-Time Scheduling and Multi-Scale Energy Management

3.5.1. Current Context

In the current energy management landscape, the increasing penetration of renewable energy sources into power grids has heightened the need for advanced real-time scheduling and energy management techniques. The stochastic and intermittent nature of renewables, such as solar and wind energy, poses significant challenges to grid operation and balance. This necessitates an energy management approach that is flexible, adaptable across multiple scales, and capable of real-time operation to maximize system efficiency and reliability [83]. Integrating emerging paradigms, such as distributed energy systems, has proven to be a promising solution. These paradigms enable the coordination among DERs and optimize their operation across various temporal and spatial scales [95].

In this context, real-time scheduling and management have become crucial to ensure that demand and generation are efficiently balanced, thereby reducing reliance on non-renewable sources and minimizing operational costs. Additionally, incorporating smart technologies, such as AI, has enhanced energy management systems' predictive and decision-making capabilities, allowing for quicker and more accurate responses to fluctuations in demand or generation [96].

3.5.2. Research Opportunities

- Development of Optimization Algorithms: New research opportunities arise as power grids become more complex in topology and elements and integrate more DERs. A key area of interest is the development of optimization algorithms that can efficiently manage multiple temporal and spatial scales within the energy system. These algorithms must be capable of operating under conditions of uncertainty, dynamically adapting to variations in generation and demand [83]. Research in this area could focus on improving system resilience against disturbances, such as grid failures or extreme events, ensuring the system can recover quickly and maintain operational stability.
- Internet of Things: Another significant opportunity lies in integrating emerging technologies, such as the IoT and cloud computing, into energy management systems. These technologies can offer scalable and flexible real-time data collection and analysis solutions, crucial for informed decision-making and system-wide optimization [95].

Moreover, implementing advanced energy storage systems, such as solid-state batteries or supercapacitors, can complement real-time management by enabling better integration of renewable energy sources and enhancing grid stability [81].

3.5.3. Prospective Topics for Future Research Papers of Real-Time Scheduling and Multi-Scale Energy Management

Looking forward, there are several promising topics for future research in real-time scheduling and multi-scale energy management. One area ripe for exploration is the development of multi-scale optimization algorithms that consider both temporal and spatial dimensions to enhance the operational efficiency of energy management systems. These algorithms should be capable of integrating diverse data sources and dynamically adapting to changing grid conditions, ensuring optimal performance even under fluctuating circumstances [83].

Another critical topic is advancing AI-based predictive models that accurately forecast short-term and long-term energy generation and demand. These models must be robust enough to operate under uncertainty while providing real-time recommendations that guide system operations. This is particularly important given the variable nature of renewable energy sources, which makes accurate prediction a cornerstone of effective energy management [96]. Integrating the IoT into energy management systems is also an area with significant potential. Research in this domain could focus on how IoT can enhance connectivity and control over distributed energy resources, improving the overall responsiveness and efficiency of energy systems. This includes addressing challenges related to communication protocols, data security, and the interoperability of various devices and systems [95]. Lastly, the role of emerging energy storage technologies in real-time energy management deserves considerable attention. Investigating how technologies such as solid-state batteries or supercapacitors can be integrated into energy management systems could significantly improve grid stability and facilitate the increased penetration of renewable energy. These storage solutions could provide the necessary buffering capacity to balance supply and demand in real-time, particularly during periods of peak demand or low renewable output [81].

3.5.4. Shortcomings of Real-Time Scheduling and Multi-Scale Energy Management

While real-time scheduling and multi-scale energy management are promising for optimizing energy systems, several limitations still hinder their effectiveness. One major shortcoming is the lack of truly adaptive algorithms capable of efficiently managing both temporal and spatial dimensions under the inherent uncertainty of renewable energy sources. Although current methods address the intermittent nature of solar and wind energy, many algorithms struggle to handle dynamic fluctuations in real-time, especially when operating across multiple scales and DERs. This inability to dynamically adapt to changing grid conditions weakens the overall system resilience and responsiveness.

Another critical issue is integrating emerging technologies such as IoT and cloud computing into energy management systems. While these technologies offer potential for scalable, real-time data collection and decision-making, existing research often overlooks interoperability, communication protocols, and data security challenges. Without addressing these foundational issues, the full potential of IoT in enhancing energy management remains unrealized.

Moreover, despite the increasing role of AI-based predictive models, their accuracy and robustness under uncertain and fluctuating conditions still require significant improvement. Many current models cannot provide reliable short-term and long-term predictions, crucial for maintaining grid stability and optimizing energy flows. Similarly, integrating advanced energy storage solutions, like solid-state batteries or supercapacitors, into real-time management systems is underdeveloped, with many studies failing to fully explore how these technologies can buffer supply and demand more effectively during peak periods.

3.6. Day-Ahead Scheduling and Optimization Algorithms

3.6.1. Current Context

Day-ahead scheduling and optimization algorithms are essential for effectively planning microgrid operations, ensuring the efficient use of energy resources. These processes involve forecasting energy demand and generation for the upcoming day, allowing microgrids to prepare and allocate resources accordingly [68]. Integrating renewable energy sources into microgrids adds complexity to this task due to the inherent variability and unpredictability of wind and solar power sources. Consequently, accurate day-ahead scheduling becomes crucial for maintaining operational stability and efficiency [64,72,89].

Recent advancements in predictive analytics have significantly enhanced the ability of microgrids to anticipate and manage these uncertainties. Day-ahead scheduling algorithms can optimize energy generation and storage by integrating weather forecasts, historical consumption patterns, and real-time data, reducing reliance on non-renewable sources and improving overall energy efficiency [62,73]. Moreover, developing advanced optimization algorithms has further strengthened the robustness and reliability of these scheduling processes, enabling microgrids to maintain stable operations even under highly variable conditions [65,93,97].

One of the key benefits of day-ahead scheduling is its ability to provide a framework for proactive management of energy resources, allowing microgrids to minimize operational costs while maximizing the use of available renewable energy. The scheduling process must consider a wide range of factors, including expected weather conditions, load demand forecasts, and the availability of storage resources, to ensure that energy supply matches demand as closely as possible [79,98]. This approach not only improves operational efficiency but also enhances the sustainability of microgrids by reducing their carbon footprint [60].

3.6.2. Research Opportunities

- Predictive Scheduling Algorithms: There is a growing opportunity to develop predictive scheduling algorithms that leverage AI techniques to integrate weather forecasts and consumption patterns for optimizing energy generation and storage. These algorithms can continuously improve their predictive accuracy by learning from historical and real-time data, allowing microgrids to better prepare for fluctuations in demand and renewable energy output [98–100]. For example, AI models can be trained to predict solar and wind energy generation with higher precision, enabling more effective day-ahead planning [60,79]. Additionally, these algorithms could incorporate real-time sensor data to adjust scheduling decisions dynamically, further enhancing the flexibility and resilience of microgrid operations [17].
- Robust Optimization: Another critical area of research involves developing robust optimization algorithms to handle generation and demand forecasting uncertainties. Given the stochastic nature of renewable energy sources, these algorithms must maintain effective day-ahead schedules even when actual conditions deviate significantly from predictions [85,101]. Robust optimization techniques can help microgrids mitigate the risks associated with over or under-estimating energy availability, ensuring a more reliable power supply and reducing costly backup generation [96,102]. Exploring hybrid optimization methods that combine elements of deterministic and stochastic approaches could also lead to more resilient and adaptive scheduling strategies [64,89].

3.6.3. Policy and Practical Recommendations

Based on the comprehensive review of the integration of artificial intelligence (AI) and emerging technologies in microgrid operations, several policy and practical recommendations can be made to support further advancements in this field:

- Policy Recommendations: Promote AI Integration in Microgrid Regulations: Governments and regulatory bodies should encourage incorporating AI-driven technologies within energy policies. Creating incentives for deploying AI solutions in microgrid management can enhance the efficiency of renewable energy integration, helping to meet sustainability goals [2,4].

- Standardization of Data and Interoperability: Establishing industry-wide standards for data sharing and communication between different energy systems and AI platforms will be crucial. This will enable more seamless integration of AI into microgrid operations and enhance real-time optimization of energy use [9,17].
- Support for R&D Initiatives: Policymakers should allocate funding for research and development in AI and energy storage technologies. Support for pilot projects and collaborative research initiatives between academia and industry can accelerate developing and deploying advanced microgrid systems [7,12].
- Practical Recommendations: Adoption of AI for Predictive Energy Management: Energy providers and microgrid operators should adopt AI-driven predictive control systems that can optimize demand forecasting, energy storage management, and distributed generation, particularly in areas with high penetration of renewable energy [3,8].
- Integration of Occupancy and Behavior Data: Incorporating occupancy behavior data into AI models can improve the accuracy of energy demand predictions, allowing for more responsive and adaptive microgrid operations. This can significantly enhance energy efficiency in residential and commercial buildings [15,22].
- Focus on Energy Storage Optimization: Operators should invest in advanced energy storage technologies and integrate AI-based stochastic optimization methods to manage energy variability more effectively. This will ensure better stability and resilience, especially in regions relying heavily on intermittent renewable sources [11,14].

3.6.4. Prospective Topics for Future Research Papers

A promising research direction could involve the development of a day-ahead scheduling framework that integrates deep learning with robust optimization techniques, addressing the uncertainties in renewable energy generation and fluctuating demand. This framework could utilize advanced predictive analytics to continuously refine scheduling decisions based on evolving conditions, offering a more adaptive and resilient approach to managing microgrid operations [62,72,93].

Another potential research area could focus on combining predictive algorithms with stochastic optimization methods to create a hybrid scheduling model. Such a model would balance the need for accuracy in forecasting with the flexibility to respond to unexpected changes, thereby improving the overall reliability and efficiency of microgrid operations [65,94,103]. Investigating the role of AI-driven predictive models in enhancing the robustness of day-ahead scheduling could provide valuable insights into future microgrid management practices, particularly in environments characterized by high variability and uncertainty [97,104,105]. Additionally, research could explore the integration of real-time data analytics with day-ahead scheduling algorithms to create a more dynamic and responsive scheduling process. Microgrids could achieve higher operational efficiency and reliability by continuously updating forecasts and adjusting schedules in response to new data, reducing their dependence on non-renewable energy sources and minimizing their environmental impact [60,79]. This approach would be particularly beneficial in regions with highly variable weather patterns, where quickly adapting to changing conditions is crucial [85,96,102].

3.6.5. Shortcomings of Day-Ahead Scheduling and Optimization Algorithms

Day-ahead scheduling and optimization algorithms, while critical to the efficient operation of microgrids, still face several challenges. One of the main limitations lies in the accuracy of forecasting models. Although significant advancements have been made in predictive analytics, the unpredictable nature of renewable energy sources such as wind and solar still results in large forecasting errors. Many current models are unable to fully capture the variability and intermittency of these energy sources, leading to less reliable day-ahead schedules, which in turn can affect the overall stability and efficiency of the microgrid.

Another key shortcoming is the rigidity of existing optimization algorithms. Although robust optimization techniques have been developed, they often struggle to adapt to real-time deviations from forecasts, particularly when actual energy generation or demand significantly deviates from expected values. These algorithms tend to operate under relatively fixed conditions and are not sufficiently flexible to manage dynamic, rapidly changing grid scenarios, which limits their ability to provide reliable day-ahead planning.

Furthermore, while research has explored hybrid optimization methods that combine deterministic and stochastic approaches, integrating these techniques remains underdeveloped. Current hybrid models lack the scalability needed for widespread deployment across different microgrids and often fail to account for the wide range of variables influencing energy production and consumption in real-world environments.

Finally, Table 4 summarizes the key findings, promising research areas, and challenges of optimizing and managing microgrids. This summary covers reinforcement learning, multi-agent systems, intelligent control, predictive modeling, energy storage, stochastic optimization, and day-ahead scheduling.

Table 4. Summary of key findings, promising research areas, and challenges in microgrid optimization and management.

Ref.	Key Findings/Opportunities	Promising Research Areas	Challenges
[9]	RL algorithms enable real-time adaptive management, optimizing resource utilization and improving grid stability.	Developing hybrid RL–MAS frameworks for the efficient management of distributed energy resources in interconnected microgrids.	Managing the complexity of high-dimensional and nonlinear dynamics in real-time operations.
[59]	MASs facilitate decentralized management, enhancing operational efficiency and resilience in microgrids.	Advancing DRL algorithms to handle the complexities of real-time microgrid operations, focusing on high-dimensional data management.	Balancing the need for energy resource optimization with ensuring overall system resilience and reliability.
[60]	RL strategies are effective in managing extreme events and faults within microgrids, enabling autonomous adaptation to adverse conditions.	Exploring resilient strategies for microgrid fault management under extreme conditions, utilizing autonomous learning and adaptation.	Addressing the uncertainties in renewable energy generation and demand forecasts, particularly under extreme conditions.
[61]	MASs have been shown to improve the operational stability of microgrids in complex and stochastic environments, ensuring continuous operation.	Enhancing the application of MASs in rural and isolated microgrids, addressing specific operational challenges and improving resilience.	Adapting MAS frameworks to diverse and challenging operational environments, such as rural or isolated microgrids.
[62]	Deep reinforcement learning (DRL) techniques manage high-dimensional, nonlinear dynamics, offering promising avenues for real-time interaction management.	Investigating the integration of transfer learning in EV-integrated microgrids to improve model adaptability and operational efficiency.	Improving the accuracy of predictive models, especially in the context of high variability and stochastic environments.
[63]	Cooperation among MGs using MASs can optimize energy exchange, balancing supply and demand in real-time scenarios.	Expanding the use of stochastic optimization for energy storage integration, focusing on cost efficiency and system reliability.	Reducing the costs associated with implementing advanced DRL and MAS techniques in microgrid operations.
[64]	Controlled competition among agents in MGs drives operational efficiency, reducing costs and maximizing the utilization of renewable resources.	Implementing decentralized intelligence in distributed storage systems to optimize local energy management and reduce grid dependency.	Overcoming scalability challenges in distributed storage systems, particularly in managing local energy demands efficiently.
[65]	MAS frameworks can be tailored to specific contexts, such as rural or isolated MGs, addressing unique challenges and leveraging localized benefits.	Developing AI-based robust day-ahead scheduling models that account for renewable energy variability and demand fluctuations.	Enhancing the robustness of day-ahead scheduling under variable conditions, ensuring consistent and reliable operations.
[66]	Hybrid frameworks combining RL and MASs can efficiently manage distributed energy resources in interconnected microgrids, improving system-wide stability.	Combining predictive analytics with stochastic optimization techniques to create hybrid scheduling frameworks for microgrids.	Balancing the trade-offs between forecasting accuracy and operational flexibility in hybrid scheduling models.

Table 4. *Cont.*

Ref.	Key Findings/Opportunities	Promising Research Areas	Challenges
[25]	RL strategies tailored for electric vehicles improve their integration into MGs by learning from charging and discharging patterns.	Designing dynamic real-time scheduling frameworks using AI, enhancing the flexibility and responsiveness of microgrid operations.	Ensuring the system's resilience while minimizing operational costs, particularly in real-time scheduling processes.
[67]	Transfer learning can be utilized to accelerate the deployment of RL and MAS models across different operational environments, enhancing adaptability.	Investigating MAS-based fault management in interconnected networks, focusing on improving resilience under variable conditions.	Managing the variability of renewable energy sources in fault management strategies, ensuring consistent system performance.
[94]	MASs enhance fault response in interconnected networks, allowing different microgrids to cooperate and maintain stability during adverse conditions.	AI integrated with predictive models for robust microgrid operations.	Ensuring accuracy in real-time predictive control.

4. Conclusions

This systematic review has thoroughly examined the integration of emerging technologies and AI techniques in optimizing microgrid operations, a field of growing importance as energy systems transition towards sustainability and decentralization. Using the PRISMA methodology, the review synthesized 74 high-quality studies published between 2014 and 2024, offering a thorough assessment of key research areas, including reinforcement learning, multi-agent systems, predictive modeling, energy storage, and optimization algorithms; all of which are important to improving microgrid efficiency and reliability.

The review reveals significant advancements, particularly in applying RL and MASs, which effectively manage microgrids' inherent complexity and variability. However, further research is needed to develop more advanced RL algorithms that can handle high-dimensional, nonlinear dynamics and MAS models, enhancing cooperation and competition between microgrids to maximize efficiency. Additionally, AI-based predictive models have proven critical for anticipating energy fluctuations and stabilizing microgrid operations. However, there is still a demand for more advanced real-time control systems that swiftly adapt to the dynamic nature of renewable energy and electric vehicle integration. Energy storage and stochastic optimization are essential for addressing the intermittency of renewable energy sources, but further exploration is needed in decentralized intelligence for distributed storage systems to improve resilience and efficiency. Similarly, there is a need for enhanced multi-criteria optimization algorithms that balance energy efficiency, cost reduction, and sustainability more effectively. Real-time scheduling and multi-scale energy management, supported by IoT and cloud computing, offer promising solutions for real-time data analysis and efficiently balancing supply and demand. In addition to consumption patterns, behavior patterns such as occupancy behavior play a crucial role in optimizing energy management within microgrids. Understanding how occupants interact with energy systems, particularly in residential or commercial settings, can improve demand forecasting accuracy and enhance energy management strategies' adaptability. By integrating data on occupancy behavior, AI models can make more informed decisions, leading to more efficient energy use and increased system reliability. Then, optimizing energy storage in MGs through stochastic optimization has effectively balanced supply and demand, enhancing system resilience.

Nevertheless, further exploration of multi-criteria optimization algorithms and AI-driven real-time and day-ahead scheduling is necessary to minimize operational losses and improve overall MG resilience. Then, while this review provides a comprehensive analysis of integrating emerging technologies and AI in microgrid operations, it is important to recognize that the field is rapidly evolving. As new technologies and paradigms emerge, future reviews must be updated to reflect these advancements. Continuously revisiting and expanding the scope of the review process will be essential to capture the most current and relevant developments, ensuring that the insights remain aligned with the latest trends in microgrid management.

Future work should focus on developing hybrid AI models that integrate multiple techniques, such as reinforcement learning with neural networks, to improve real-time energy management. Optimizing DERs through MAS frameworks can enhance energy exchange and system resilience, particularly in isolated or rural microgrids. Further research is needed to advance energy storage management using stochastic optimization and develop real-time and day-ahead scheduling algorithms that address renewable energy variability better. Lastly, AI-driven fault management systems should be explored to improve microgrid resilience during extreme events.

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