

Systematic Review of the Effective Integration of Storage Systems and Electric Vehicles in Microgrid Networks: Innovative Approaches for Energy Management

Paul Arévalo ^{1,2,*}, Danny Ochoa-Correa ¹ and Edisson Villa-Ávila ^{1,2}

¹ Department of Electrical Engineering, Electronics and Telecommunications (DEET), Faculty of Engineering, University of Cuenca, Balzay Campus, Cuenca 010107, Azuay, Ecuador; danny.ochoac@ucuenca.edu.ec (D.O.-C.); eava0001@red.ujaen.es (E.V.-Á.)

² Department of Electrical Engineering, University of Jaen, EPS Linares, 23700 Jaen, Spain

* Correspondence: warevalo@ujaen.es

Abstract: The increasing demand for more efficient and sustainable power systems, driven by the integration of renewable energy, underscores the critical role of energy storage systems (ESS) and electric vehicles (EVs) in optimizing microgrid operations. This paper provides a systematic literature review, conducted in accordance with the PRISMA 2020 Statement, focusing on studies published between 2014 and 2024 and sourced from Web of Science and Scopus, resulting in 97 selected works. The review highlights the potential of EVs, not only as sustainable transport solutions but also as mobile storage resources, enhancing microgrid flexibility and stability through vehicle-to-grid (V2G) systems. It also underscores the importance of advanced control strategies, such as Model Predictive Control (MPC) and hybrid AC/DC microgrids, for improving energy flow management and operational resilience. Despite these advancements, gaps remain in the comprehensive integration of ESS and EVs, particularly regarding interoperability between microgrid components and the lack of optimization frameworks that holistically address dynamic pricing, grid stability, and renewable energy integration. This paper synthesizes existing technologies and offers insights for future research aimed at advancing the sustainability, efficiency, and economic viability of microgrids.



Citation: Arévalo, P.; Ochoa-Correa, D.; Villa-Ávila, E. Systematic Review of the Effective Integration of Storage Systems and Electric Vehicles in Microgrid Networks: Innovative Approaches for Energy Management. *Vehicles* **2024**, *6*, 2075–2105. <https://doi.org/10.3390/vehicles6040102>

Academic Editor: Adolfo Dannier

Received: 15 October 2024

Revised: 20 November 2024

Accepted: 30 November 2024

Published: 3 December 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: energy management; storage system; electric vehicle; vehicle-to-grid (V2G); microgrids; renewable energy; systematic literature review

1. Introduction

1.1. Motivation and Incitement

The increasing penetration of renewable energy sources into power systems presents significant challenges, such as intermittency, grid stability, and the rising demand for efficient energy management. Microgrids have emerged as a promising solution to address these challenges by enabling localized energy generation and consumption. The integration of energy storage systems (ESS) and electric vehicles (EVs) into microgrids has become critical to mitigate these issues, facilitating more efficient energy flows, reducing operational costs, and enhancing grid resilience. Storage systems enable efficient energy management by charging during low-demand periods and discharging during peak times, thereby reducing reliance on costly and inefficient generators. This is particularly relevant in microgrids with high renewable energy penetration, where storage solutions enhance the stability and resilience of power supply.

1.2. Literature Review Including Existing Reviews and Research Gap

Extensive research has explored the integration of ESS and EVs in microgrids. Studies have shown that ESS enable efficient energy management by charging during low-demand periods and discharging during peak times, reducing reliance on costly and inefficient

generators [1,2]. By participating in demand response and frequency regulation strategies, EVs contribute to more effective resource utilization and reduce operational costs while also providing auxiliary support during peak load periods or times of grid stress [3–5]. These roles are particularly crucial for enabling greater renewable energy penetration and optimizing energy flows in distributed systems [6,7]. Simulations have validated significant improvements in grid stability and cost reduction through the integration of EVs [8]. Additionally, direct current (DC) microgrid-based EV charging stations have demonstrated higher efficiency by utilizing fuzzy logic-based controllers, improving voltage regulation and power quality [9,10]. Other research has proposed advanced control and optimization strategies, such as stochastic energy management systems, to handle variability and uncertainty in energy consumption and renewable generation [11]. Algorithms like the Manta Ray Foraging Algorithm have been applied to optimize EV integration into microgrids, reducing both operational costs and environmental impacts [12]. Fuzzy logic has also been used to manage charging stations and integrate photovoltaic systems, improving system response to variations in solar irradiation and EV charging levels [13].

The integration of distributed renewable sources and energy storage systems within microgrids has also been studied as a means to reduce dependence on thermal generators. Distributed control systems have been explored to improve frequency regulation and voltage control, demonstrating that decentralized control strategies can enhance system resilience and stability [14]. The use of second-life batteries in battery swapping stations represents another opportunity to improve sustainability and reduce operational costs in microgrids. Recent studies have analyzed the economic viability of integrating these stations into smart microgrids, showing that second-life batteries can contribute to more efficient renewable energy use and promote a circular economy [15]. Furthermore, advanced optimization strategies, such as intelligent control networks, have been developed to enhance energy and storage management in microgrids [16,17]. In autonomous microgrids, advanced controllers, such as fuzzy logic and multi-objective optimization, have shown effectiveness in improving operational efficiency and integrating energy storage and EVs [18,19]. These solutions have been experimentally validated, demonstrating improvements in system stability and battery life through the implementation of adaptive control and real-time energy management strategies [20]. Hybrid AC/DC microgrid solutions integrating energy storage have also been shown to enhance grid stability and EV integration [21].

In more complex microgrids, coordination between multiple microgrids and the use of shared energy storage systems has been studied as a strategy to improve operational efficiency and load balancing. These solutions optimize renewable energy usage and reduce load fluctuations by integrating distributed storage systems [22,23]. Additionally, microgrids incorporating intelligent technologies, such as simulation and optimization platforms based on artificial intelligence, have significantly improved energy management and operational stability [24,25]. Then, predictive strategies based on Model Predictive Control (MPC) have proven to be an effective solution for reducing the peak demand in integrated microgrids, particularly in campuses and urban environments where the use of EVs and other distributed storage systems is increasingly common [26]. These solutions highlight the critical role of integrating EVs and storage systems into microgrids as a pathway toward achieving energy sustainability and reducing operational costs. Hence, the reviewed literature underscores the importance of integrating energy storage systems and EVs into microgrids to optimize energy management, enhance stability, and reduce operational costs while facilitating the adoption of renewable energy. The application of advanced control and optimization technologies is essential to addressing the technical and economic challenges associated with operating complex microgrid systems.

Despite significant advancements in the integration of energy storage systems and EVs into microgrids, several research gaps remain that this study aims to address. Many existing studies, such as [27,28], focused on optimizing either energy storage or EVs independently, leaving a gap in the holistic optimization of both technologies within a

unified energy management system (EMS). Furthermore, while real-time control systems have been explored [9], adaptive solutions that can respond dynamically to fluctuations in renewable generation and EV demand are still underdeveloped. The existing literature reveals several critical gaps:

- The optimization of ESS and EVs is often addressed independently, lacking a holistic approach within unified EMS.
- There is a scarcity of adaptive control strategies capable of dynamically managing fluctuations in renewable generation and EV demand.
- Interoperability among distributed energy resources (DERs), including communication protocols and system coordination, is insufficiently addressed.
- Long-term economic feasibility and environmental impacts of large-scale ESS and EV integration remain underexplored, with limited quantitative analysis available.
- Hybrid AC/DC microgrid solutions, which can enhance interoperability and reduce conversion losses, are rarely analyzed in the context of ESS and EV integration.

1.3. Contributions and Paper Organization

To address these gaps, this paper introduces an advanced EMS that simultaneously optimizes energy storage and EV integration, offering a more comprehensive approach than previous work. Additionally, the issue of interoperability among communication protocols in microgrids, especially with diverse DERs, is often overlooked [4,11]. Our study addresses this gap by proposing innovative techniques to ensure seamless communication between EVs, storage systems, and other microgrid components. Moreover, while scalable solutions for integrating large EV fleets have been studied [1,10], their long-term economic viability and environmental impact have received insufficient attention. This paper extends prior research by providing long-term simulations that consider both cost reductions and environmental benefits over time.

Although the benefits of integrating EVs and ESS in microgrids have been widely discussed [29–31], the literature lacks detailed quantitative studies that demonstrate their long-term economic and environmental advantages. This paper addresses this gap by conducting a comparative analysis of emissions and operational costs under two scenarios: with and without EVs and ESS. This article explores innovative approaches for integrating energy storage systems and EVs into microgrid networks to tackle challenges like renewable energy intermittency, grid stability, and carbon emissions. The focus is on advancements that facilitate the integration of highly variable renewable resources to mitigate related challenges. Using a systematic literature review following the PRISMA 2020 guidelines, the study synthesizes recent developments in energy management, control strategies, and optimization algorithms that improve microgrid performance and efficiency. A key contribution of this work is the comprehensive evaluation of the synergies between EVs as mobile storage resources and energy storage systems, providing insights into novel solutions such as hybrid AC/DC microgrids, intelligent control strategies, and multi-objective optimization techniques. Furthermore, this review explores existing approaches, synthesizing and presenting them as a roadmap for researchers and academics in the field. It also identifies gaps in the current research, particularly concerning holistic optimization and interoperability among microgrid components, offering insights that may guide future studies focused on improving sustainability and reducing operational costs in energy systems. In the interest of simplicity, the contributions are summarized as follows:

- Development of a unified EMS that simultaneously optimizes the integration of ESS and EVs.
- Proposal of adaptive and predictive control strategies tailored to manage dynamic energy flows and fluctuations in renewable energy generation and EV demand.
- Evaluation of hybrid AC/DC microgrid solutions to enhance interoperability and reduce conversion losses.
- Quantitative analysis of long-term economic and environmental impacts, demonstrating cost reductions and CO₂ emission savings through ESS and EV integration.

- Introduction of innovative techniques to improve interoperability among microgrid components, ensuring seamless communication and coordination.
- Advancement of multi-objective optimization frameworks that balance operational efficiency, economic sustainability, and environmental benefits.

The paper is structured as follows: Section 2 outlines the methodology, providing a detailed account of the systematic review process conducted in accordance with the PRISMA 2020 guidelines. Section 3 presents the results, organized into thematic areas including energy management strategies, optimization techniques, and hybrid microgrid solutions. Finally, Section 4 concludes with a synthesis of key insights and a discussion of future research directions to advance the integration of energy storage systems and electric vehicles in microgrid networks.

2. Methodology for Selecting Studies

This review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines [32], which ensures a rigorous and transparent approach to conducting and reporting systematic reviews. The primary objective of this review is to address critical gaps in the existing literature, including the lack of holistic optimization frameworks that simultaneously integrate ESS and EVs, the limited application of adaptive and predictive control strategies to manage dynamic energy flows, the insufficient focus on interoperability challenges among DERs, and the scarcity of long-term economic and environmental analyses for large-scale ESS and EV integration. The process begins with the Identification phase, where relevant studies are systematically searched for in multiple databases, followed by the Screening phase, where abstracts and titles are reviewed to eliminate studies that do not meet the inclusion criteria. Next, the Eligibility phase involves a more detailed evaluation of the full texts to ensure that only high-quality and pertinent studies are selected. Finally, the Synthesis phase integrates the chosen studies, analyzing and summarizing their findings to draw meaningful conclusions. Figure 1 offers a simplified visual representation of this systematic approach, encapsulating each stage's role in the overall review process.

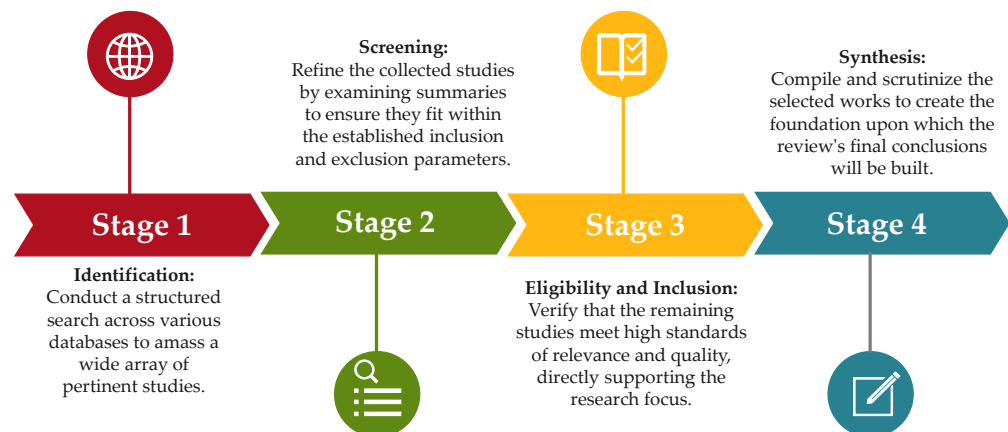


Figure 1. Literature review methodology.

2.1. Identification Phase: Database Selection, Definition of Search Terms, and Removal of Duplicates

For the Identification Phase, a comprehensive search was conducted over ten years (2014–2024), focusing on journal articles and conference papers. These sources complement one another, with journals providing peer-reviewed, in-depth studies that establish theoretical and methodological foundations, while conference papers showcase cutting-edge developments and emerging trends in areas like microgrids, energy storage systems, and electric vehicles. By combining these two types of publications, this review ensures that both established research and the latest innovations are captured. Non-peer-reviewed

materials such as editorials, opinion pieces, and book chapters were excluded due to their lack of empirical rigor. The literature search was performed using two digital databases, Web of Science (WoS) and Scopus, selected for their extensive coverage and inclusion of reputable publishers like IEEE, Elsevier, Springer, Taylor & Francis, Wiley, and MDPI. These databases offer a broad and high-quality range of literature, facilitating a transparent and objective review process. The search terms “energy storage systems” AND “electric vehicles” AND “microgrid” were applied across titles, abstracts, and keywords to ensure relevance to the topic. The results of this initial search are summarized in Table 1, detailing the search terms and findings.

Table 1. Search terms for the literature review, and summary of the results from the database queries.

Database Source	Search Query	Total Documents Retrieved	Duplicates Eliminated	Final Set for Screening
Web of Science	ALL = (“energy storage system”) AND ALL = (“electric vehicles”) AND ALL = (“microgrid”) 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, Proceeding Paper or Article	157	0	157
Scopus	TITLE-ABS-KEY (“energy storage systems” AND “electric vehicles” AND “microgrid”) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE, “cp”) OR LIMIT-TO (DOCTYPE, “ar”))	618	134	484
Total items		775	134	641

The initial search yielded a total of 775 items: 157 from WoS and 618 from Scopus. Since these databases often share items from the same publishers and conferences, it is common to encounter duplicate entries. Using bibliographic management tools, 134 duplicate items were identified and removed. This left a final sample of 641 items, with 157 from WoS and 484 from Scopus. Of these records, 67% were journal articles, and 33% were conference proceedings. These identified documents underwent further analysis in the Screening Phase to ensure they met the criteria for inclusion in this review.

2.2. Screening Phase: Evaluation of Inclusion Criteria—Review of Titles and Abstracts

In the Screening Phase, the team initially filtered 641 items from the Identification Phase by reviewing their titles and abstracts. The goal was to select only the studies directly aligned with the research objectives for further analysis. The research team rigorously designed the filtering process to exclude irrelevant or redundant studies at this stage. They focused on capturing the latest developments in energy management for microgrids, particularly those integrating storage systems and electric vehicles. To maintain relevance and quality, the team applied the following inclusion criteria during the screening:

1. **Criteria 1—Publication Date:** Only articles published between 2014 and 2024 were included to ensure that the review covers the latest advancements and trends in the field. Studies published prior to 2014 were excluded to avoid outdated information.
2. **Criteria 2—Publication Type:** The review focused exclusively on peer-reviewed journal articles and conference papers, as these formats provide original research and technical contributions. Other publication types, such as review articles, editorials, book chapters, theses, white papers, and non-peer-reviewed materials, were excluded to ensure that only primary research and innovative findings were considered.

3. **Criteria 3—Language:** Only studies written in English were included, ensuring uniformity in language and ease of accessibility. Articles in other languages were excluded to maintain consistency in the review process.
4. **Criteria 4—Access:** Full-text availability was a mandatory criterion. Only studies with full-text access, either through institutional subscriptions or as open access, were included. This criterion was essential for allowing a comprehensive analysis of the study’s methodology, findings, and conclusions. Articles without full-text access were excluded from the review.
5. **Criteria 5—Focus:** The screening specifically targeted studies related to innovative energy management approaches that facilitate the effective integration of storage systems and electric vehicles within microgrid networks. This includes topics such as optimization strategies, control mechanisms, and the role of renewable energy grid-friendly integration. Only studies closely aligned with this focus area were selected for further consideration.

During this phase, each study underwent a binary evaluation, where the title and abstract were reviewed to assess whether they met all predefined inclusion criteria. After screening the 641 identified items, 611 (95.3%) met all the refined inclusion criteria. These items, relevant to the research focus, were filtered based on factors such as publication date, type, language, access, and relevance. The distribution of the approved items, as shown in Figure 2, reveals the dominance of seven key publishers. *IEEE* leads with 264 items (43.2%), highlighting its authority in technological research, especially in areas like microgrids and energy management. Elsevier follows with 122 items (20%), contributing significantly to energy management and optimization strategies. *MDPI* provided 67 items (11%), reflecting its influence on renewable energy integration and control strategies. Springer contributed 17 items (2.8%), focusing on optimization and control for microgrids. Pergamon-Elsevier Science Ltd. added 15 items (2.5%), aligned with Elsevier’s broader scope. John Wiley and Sons Inc. contributed 12 items (2%), known for work in optimization in energy systems, while the Institution of Engineering and Technology (*IET*) provided 10 items (1.6%), focusing on innovative solutions in energy management.

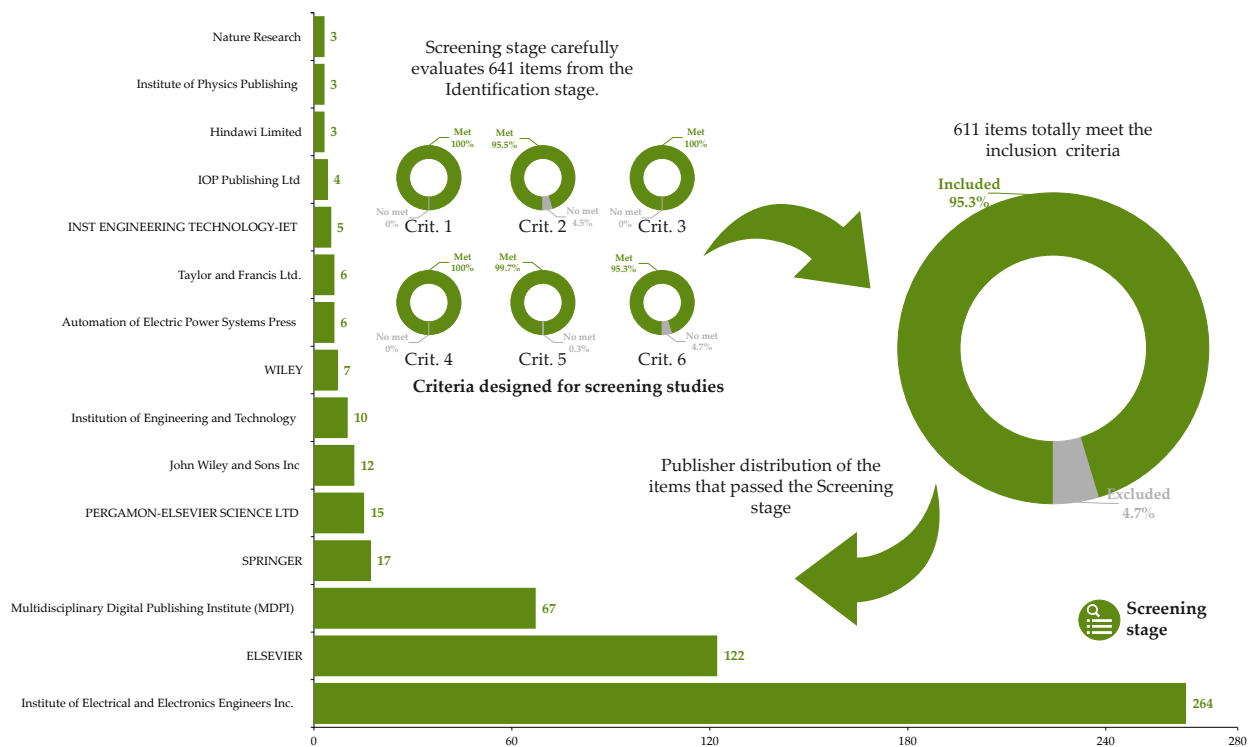


Figure 2. Summary of the results from the screening phase.

Although a selective sample of articles has been obtained at this stage, a more thorough evaluation of the content is required. A comprehensive full-text review will allow for a deeper assessment, enabling a further narrowing of the selection to ensure that only the most relevant and high-quality studies are included in the final analysis.

2.3. Eligibility and Inclusion Phase: Comprehensive Full-Text Evaluation

At this stage of the systematic review, a full-text evaluation of the selected items is conducted to ensure that the studies meet a higher standard of relevance and quality. The objective of this phase is to ensure that only the most pertinent and high-quality works are included in the final synthesis. For this purpose, five eligibility criteria have been defined, each assessed on a three-level scale:

1. Eligibility Criteria 1—Relevance to Research Objectives: How well the study addresses the integration of energy storage systems and electric vehicles within microgrid networks, particularly in terms of innovation and energy management.
(1: Peripheral, 2: Related, and 3: Highly Relevant)
2. Eligibility Criteria 2—Methodological Rigor: The robustness and appropriateness of the research design and methodology employed in the study, focusing on how well it supports the study's conclusions.
(1: Needs Improvement, 2: Acceptable, and 3: Strong)
3. Eligibility Criteria 3—Innovation and Originality: The degree of originality in proposing new solutions, algorithms, or control strategies for optimizing the integration of storage systems and electric vehicles in microgrids.
(1: Minor, 2: Moderate, and 3: Major)
4. Eligibility Criteria 4—Data Quality and Analysis: The quality and reliability of the data presented, as well as the depth and thoroughness of the analysis performed.
(1: Satisfactory, 2: Good, and 3: Excellent)
5. Eligibility Criteria 5—Impact on the Field: Impact of the manuscript to the scientific community.
(1: Low cited, 2: Moderate cited, and 3: High cited)

For the selection of studies, the researchers have defined a threshold of 12 out of 15 points. Setting a threshold of 12 out of 15 for study selection ensures that only high-quality, relevant research is included in the review. For relevance (Crit. 1), studies must address the integration of energy storage systems and electric vehicles in microgrids, scoring at least 2, indicating a precise alignment with the review's goals. In terms of methodological rigor (Crit. 2), studies must use robust methods like modeling or simulations, ensuring at least an acceptable level with a score of 2. For innovation (Crit. 3), studies should offer new or moderately novel contributions, justifying a minimum score of 2. Regarding data quality (Crit. 4), studies need reliable data and thorough analysis, meriting at least 2 points. Finally, impact (Crit. 5) is measured by citation counts, with a score of 2 indicating moderate influence within the field.

Two researchers independently reviewed all the selected items, carefully evaluating them based on the five eligibility criteria defined above. Figure 3 shows the evaluation sheet used during this process. It illustrates the 118 items that surpassed the minimum threshold, confirming their inclusion for further analysis.

2.4. Synthesis Phase: Bibliometric Analysis and Topic Clustering of the Selected Studies

The distribution of the 118 selected articles across different journals is detailed in Figure 4. The journal *Applied Energy* leads with nine articles, emphasizing its significant role in publishing cutting-edge research on energy systems, particularly in energy storage and microgrid management. The *Journal of Energy Storage* closely follows, with seven articles reflecting the increasing focus on technologies related to energy storage systems. *IEEE Access and Sustainability* contributed five articles, each highlighting key advancements in sustainable energy solutions and the integration of renewable sources within energy systems. The specialized journal, *IEEE Transactions on Sustainable Energy*, offers four.

IEEE Access, Electric Power Systems Research, Journal of Cleaner Production, Energies, Sensors, Energy, and Energy Conversion and Management each contributed three articles, signifying a broad interest in diverse aspects of energy management, renewable energy integration, and sensor technology.

Nº	ID	Crit. 1	Crit. 2	Crit. 3	Crit. 4	Crit. 5	Total	Nº	ID	Crit. 1	Crit. 2	Crit. 3	Crit. 4	Crit. 5	Total	Nº	ID	Crit. 1	Crit. 2	Crit. 3	Crit. 4	Crit. 5	Total
1	WoS-057	3	3	3	3	3	15	41	WoS-087	2	2	3	3	2	12	81	S-433	3	3	3	2	1	12
2	S-460	3	3	3	3	3	15	42	WoS-091	2	3	3	3	1	12	82	S-436	3	3	3	1	2	12
3	WoS-099	3	3	3	3	2	14	43	WoS-094	3	3	3	1	2	12	83	S-452	2	3	3	3	1	12
4	S-108	3	3	3	3	2	14	44	WoS-100	3	3	3	1	2	12	84	S-455	3	2	3	3	1	12
5	WoS-002	3	3	3	3	1	13	45	WoS-115	3	3	3	1	2	12	85	S-473	3	3	3	1	2	12
6	WoS-014	3	3	3	2	2	13	46	WoS-120	2	3	3	3	1	12	86	S-482	3	3	3	2	1	12
7	WoS-021	3	3	3	2	2	13	47	WoS-124	3	3	3	2	1	12	87	S-496	3	3	3	1	2	12
8	WoS-031	3	3	3	3	1	13	48	WoS-130	3	3	3	2	1	12	88	S-601	3	2	3	3	1	12
9	WoS-040	3	1	3	3	3	13	49	WoS-131	3	2	3	3	1	12	89	S-607	2	3	3	3	1	12
10	WoS-051	3	3	3	3	1	13	50	WoS-134	2	3	3	3	1	12	90	WoS-035	3	3	3	1	2	12
11	WoS-056	3	3	3	3	1	13	51	WoS-136	1	3	3	3	2	12	91	WoS-044	3	3	3	1	2	12
12	WoS-074	3	2	3	3	2	13	52	WoS-141	2	3	3	3	1	12	92	WoS-053	3	3	3	1	2	12
13	WoS-079	2	2	3	3	3	13	53	WoS-146	1	3	3	3	2	12	93	WoS-089	3	2	3	2	2	12
14	WoS-101	3	3	3	3	1	13	54	S-008	2	3	3	3	1	12	94	S-106	2	2	3	3	2	12
15	WoS-109	2	3	3	3	2	13	55	S-011	3	3	3	1	2	12	95	S-255	2	2	3	3	2	12
16	WoS-142	2	3	3	3	2	13	56	S-045	2	3	3	3	1	12	96	S-434	2	2	3	3	2	12
17	S-094	3	3	3	3	1	13	57	S-084	3	3	3	2	1	12	97	WoS-113	3	3	3	1	2	12
18	S-128	2	3	3	3	2	13	58	S-102	3	3	3	2	1	12	98	S-518	2	2	3	3	2	12
19	S-132	3	3	3	3	1	13	59	S-104	2	2	3	3	2	12	99	S-290	2	3	3	3	1	12
20	S-152	2	3	3	3	2	13	60	S-109	3	3	3	2	1	12	100	WoS-049	2	2	3	3	2	12
21	S-184	3	3	3	3	1	13	61	S-115	3	3	3	2	1	12	101	S-180	3	3	3	1	2	12
22	S-186	3	3	3	3	1	13	62	S-203	3	3	3	1	2	12	102	S-310	3	3	3	2	1	12
23	S-221	3	3	3	3	1	13	63	S-211	2	3	3	3	1	12	103	WoS-023	2	3	3	2	2	12
24	S-299	3	3	3	3	1	13	64	S-227	3	2	3	3	1	12	104	WoS-137	2	2	3	3	2	12
25	S-307	3	3	3	3	1	13	65	S-256	2	2	3	3	2	12	105	S-096	2	3	2	3	2	12
26	S-350	3	3	3	3	1	13	66	S-260	3	3	3	2	1	12	106	S-489	2	2	3	3	2	12
27	S-416	3	3	3	3	1	13	67	S-282	2	3	3	3	1	12	107	S-560	2	3	3	2	2	11
28	S-443	3	3	3	3	1	13	68	S-304	3	3	3	2	1	12	108	WoS-156	2	3	3	2	2	12
29	S-486	3	3	3	3	1	13	69	S-314	3	3	3	2	1	12	109	S-024	3	2	3	2	2	12
30	S-558	3	3	3	3	1	13	70	S-317	2	3	3	3	1	12	110	S-124	3	2	3	2	2	12
31	S-579	3	3	3	3	1	13	71	S-319	3	3	3	2	1	12	111	S-372	3	2	3	2	2	12
32	S-598	3	3	3	3	1	13	72	S-322	3	3	3	1	2	12	112	S-528	2	2	3	3	2	12
33	S-609	3	3	3	3	1	13	73	S-361	3	2	3	3	1	12	113	S-380	2	2	3	3	2	12
34	WoS-006	3	3	3	1	2	12	74	S-367	2	3	3	3	1	12	114	S-399	2	3	2	2	3	12
35	WoS-013	3	3	3	1	2	12	75	S-373	3	3	3	1	2	12	115	S-425	2	3	3	1	3	12
36	WoS-016	3	3	3	2	1	12	76	S-411	1	3	3	3	2	12	116	S-468	3	2	3	3	1	12
37	WoS-050	3	2	3	3	1	12	77	S-417	2	3	3	3	1	12	117	WoS-154	3	2	2	2	3	12
38	WoS-061	3	1	3	3	2	12	78	S-420	3	3	3	2	1	12	118	S-574	3	2	2	2	3	12
39	WoS-065	2	3	3	3	1	12	79	S-421	2	3	3	1	3	12								
40	WoS-068	3	2	3	3	1	12	80	S-432	2	3	3	3	1	12								



Figure 3. Matrix for verifying the eligibility and inclusion criteria during full-text evaluation.

Other journals such as IEEE Transactions on Industrial Informatics, International Journal of Electrical Power & Energy Systems, IEEE Transactions on Industry Applications, Journal of Modern Power Systems and Clean Energy, Energy and Buildings, and IET Renewable Power Generation each contributed between two to three articles, providing valuable insights into energy optimization, hybrid systems, and power management in industrial applications.

The selected conference papers were distributed across multiple international events. Notably, the second and fifth IEEE Conference on Energy Internet and Energy System Integration (2018, 2021) contributed to research on integrating energy systems to achieve carbon neutrality, addressing both technical and policy challenges in energy systems.

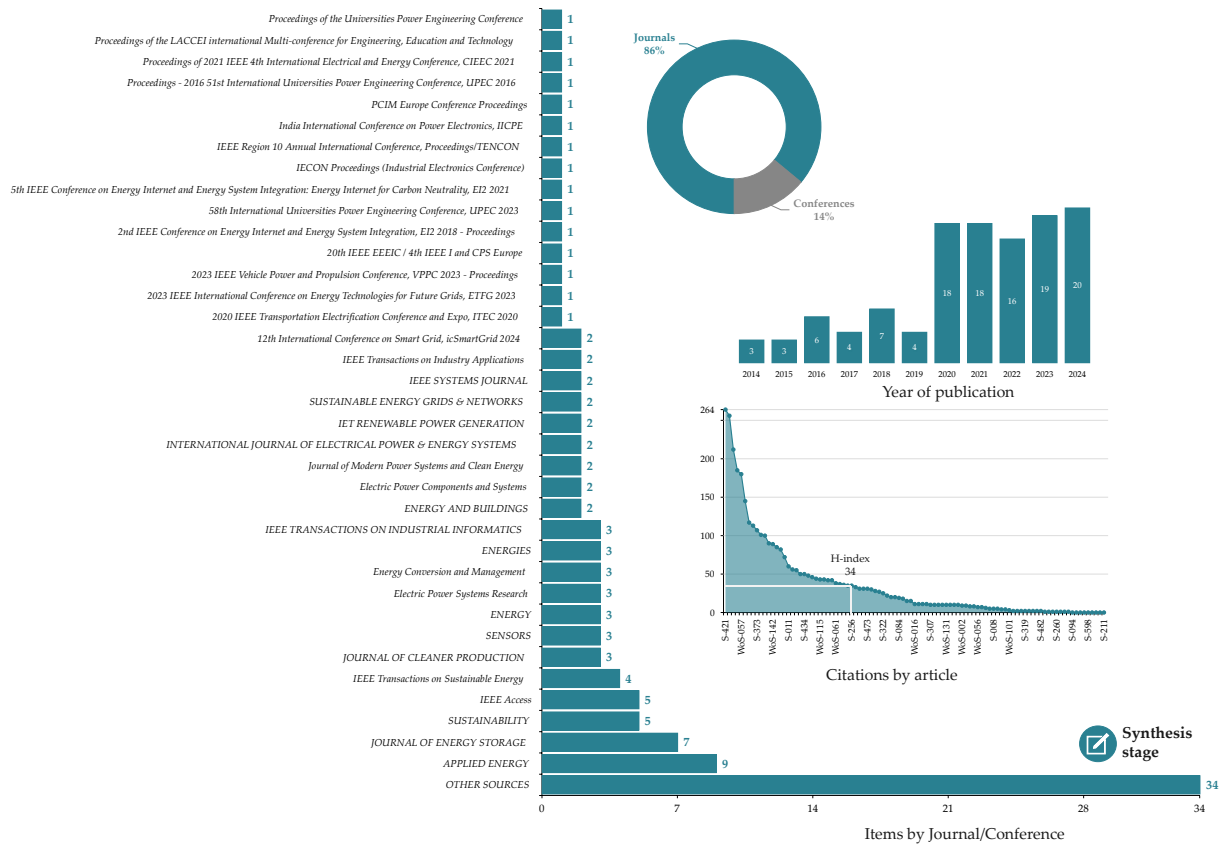


Figure 4. Bibliometric analysis of the selected articles.

Other key contributions came from the IEEE Transportation Electrification Conference (ITEC 2020), the IEEE International Conference on Environment and Electrical Engineering (EEEIC 2020), and the 12th International Conference on Smart Grid (icSmartGrid 2024). These conferences focus on advancements in smart grids, electrification of transportation, and energy system sustainability.

Additionally, the IEEE Region 10 Annual International Conference (TENCON), India International Conference on Power Electronics (IICPE), PCIM Europe Conference, and the Universities Power Engineering Conference (UPEC) provided essential discussions on power electronics, grid integration, and energy systems education.

The temporal evolution of the selected publications shows steady growth in research on energy storage, electric vehicles, and microgrids over the past decade. In 2014 and 2015, only three articles were published each year, indicating early interest in integrating renewable energy and storage systems, with limited attention to algorithms and optimization. A gradual rise occurred in 2016 with six publications, increasing to seven in 2018, reflecting advancements in storage technologies and electric vehicle integration. The most notable surge came in 2020 and 2021 with 18 publications, likely driven by the global focus on renewable energy solutions. This momentum continued in 2022, with 16 publications. In 2023 and 2024, research output remains strong, with 19 publications in 2023 and 20 expected in 2024, emphasizing the ongoing focus on multi-objective optimization, advanced algorithms, and hybrid systems for energy storage and grid integration.

This upward trend confirms the relevance of this review’s topic. The growing focus on integrated energy systems, control strategies, and optimization techniques highlights the need to address challenges in renewable energy integration and demand response in modern grids. The significant impact of the selected works, with 3715 citations over the past decade (H-index 34), underscores their role in advancing research and innovation in energy storage, electric vehicles, and microgrids.

particularly when integrated with energy storage systems [34]. Studies have shown that EVs, functioning as mobile energy units, can significantly enhance the overall stability of microgrids by providing auxiliary support during peak load periods or times of grid stress [29,35–37].

The coordination between ESS and EVs is crucial for enhancing the reliability and resilience of microgrids, especially as the penetration of intermittent renewable energy sources increases. As EVs can function as both consumers and suppliers of energy, they help mitigate fluctuations caused by renewable energy generation [38–40]. This bidirectional flow of energy—where EVs can absorb excess energy from the grid during off-peak hours and supply energy back during high-demand periods—enables more effective energy management [41–43]. Advanced control strategies for optimizing the dispatch of EVs and ESS in tandem can thus prevent grid overloads and improve the overall reliability of microgrids [44–46].

3.1.2. Energy Flow Optimization in Microgrids with High Penetration of Storage

Optimizing the energy flow is a central challenge in microgrids, mainly when the system includes a high penetration of renewable energy sources and energy storage systems. During periods of low demand, excess energy generated by renewable sources can be stored in ESS or EVs, reducing the need for thermal generation and lowering operational costs [30,47,48]. This energy can then be dispatched when demand peaks, improving the operational efficiency of the microgrid [49–51]. Several optimization algorithms and control strategies have been proposed to manage energy flow efficiently. These strategies aim to maximize the use of renewable energy while minimizing the reliance on fossil fuel-based generators. One of the key benefits of integrating EVs into this system is their ability to act as both loads and energy providers. EVs can be charged when renewable energy generation exceeds demand, effectively storing this excess energy. Conversely, when demand rises, EVs can discharge energy back into the microgrid, serving as an additional energy source that enhances grid stability [52,53].

Furthermore, EVs are increasingly being seen as a solution to the intermittency problem posed by renewable energy sources such as wind and solar. Since these sources are variable, EVs provide a buffer that absorbs the excess energy generated when these renewables produce more energy than is needed [54–56]. In this way, the use of EVs helps smooth out fluctuations in the energy supply, allowing microgrids to operate more efficiently and with greater reliability [57–59]. Research has shown that systems that integrate both ESS and EVs into their operational frameworks are more resilient and efficient, especially in scenarios with high renewable energy penetration [60–62].

3.1.3. Impact of EVs on Operational Stability and Efficiency in Microgrids

Electric vehicles have a substantial impact on the operational stability and efficiency of microgrids. When integrated into microgrid systems, EVs serve as mobile energy storage units and contribute to grid stability by helping balance supply and demand in real-time via the vehicle-to-grid concept (V2G) [31,37,55]. This capacity is especially critical in microgrids with high renewable energy penetration, where the variability of energy supply can lead to imbalances [29,44,63]. One of the primary advantages of EVs in microgrid applications is their ability to function as DERs. This means that EVs can store energy during periods of low demand or high renewable generation and release it back into the grid during periods of high demand or low generation [43,47,53]. This dual functionality increases the flexibility of the energy system, allowing for more efficient management of energy flows and reducing the reliance on traditional thermal generation [58,61,64]. Moreover, the ability of EVs to provide grid services such as peak shaving, load shifting, and frequency regulation makes them invaluable for improving the overall efficiency and stability of microgrids [50,57]. By participating in these ancillary services, EVs enhance the operational performance of microgrids and contribute to reducing operational costs and environmental impact [42,48,52].

3.1.4. Quantitative Analysis of Environmental and Economic Impacts

The integration of EVs and ESS within microgrids not only enhances operational stability but also provides significant environmental and economic benefits. A quantitative analysis was conducted to evaluate these advantages under two scenarios: (1) a traditional model without EVs/ESS and (2) a model incorporating EVs and ESS. The results demonstrate that the inclusion of EVs and ESS reduces CO₂ emissions by 57% over a 10-year period, primarily due to decreased reliance on fossil fuels and improved utilization of renewable energy surplus [29,30,44]. From an economic perspective, cumulative operational costs are reduced by 21% with the integration of EVs and ESS. An additional 20% cost reduction is achieved by reusing second-life batteries in stationary applications, further enhancing economic sustainability [31,48,50]. The key results include cumulative CO₂ emissions reductions of approximately 450 tons over 10 years [29,44,63], underscoring the feasibility and effectiveness of these technologies in advancing sustainable energy systems.

3.1.5. AI and Deep Learning Techniques in Energy Management Systems

The integration of AI and deep learning techniques is revolutionizing energy management systems (EMS) in microgrids, especially in scenarios involving renewable energy sources and EVs. These approaches enhance operational efficiency, optimize power utilization, and address the challenges posed by the variability of renewable energy generation. AI-driven forecasting models significantly outperform traditional techniques such as ARIMA in predicting renewable energy generation for EV charging stations. By incorporating solar and wind energy data, these models achieve a higher R-squared value (0.92), demonstrating their ability to navigate the complexities of renewable energy fluctuations. This precision reduces grid reliance during peak hours, ensuring grid stability and supporting sustainable energy goals [65]. Similarly, advanced AI-based methods optimize the energy supply and demand in EV charging stations connected to microgrids. These systems compensate for peak demand and enhance the energy distribution efficiency, making them indispensable for modern demand-side management strategies [66].

AI-based solutions such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been effectively employed in V2G-integrated microgrids to determine the optimal power generated or stored in EV batteries. These systems dynamically consider factors like state of charge, rated capacity, and departure times for EVs. Comparisons with traditional fuzzy logic controllers reveal superior performance under varying system uncertainties, ensuring better resource allocation [67]. Moreover, reinforcement learning (RL) has been applied to real-time control in high-renewable-penetration microgrids, dynamically adjusting ESS and EV charging schedules to address load and generation uncertainties. This approach improves energy utilization efficiency, reduces power losses by 61%, and lowers peak demand by 17%, showcasing the adaptability of AI in real-world energy systems [68].

Deep learning techniques play a critical role in improving the reliability of microgrid operations. For example, machine learning models for a lithium-ion battery state of health (SOH) estimation enable precise, data-driven predictions of battery conditions using patterns observed in voltage, current, and temperature profiles. These models achieve coefficients of determination between 0.896 and 0.992, providing reliable insights for battery-based energy storage systems in microgrids [69]. Additionally, hybrid energy storage systems (HESS) with AI-based controls, such as predictive-flex smoother methods, mitigate power fluctuations in grid-connected PV systems while optimizing energy management for EV charging stations. This approach leverages supercapacitors and vanadium redox flow batteries to ensure grid stability and reduce costs, with real-time response times under 500 ms [70].

Emerging platforms combining AI, blockchain, and IoT technologies have enabled innovative energy management solutions, such as vehicle-to-everything (V2X) blockchain power trading. These platforms facilitate decentralized green power transactions across microgrids, bidirectional power flows, and demand response bidding, enhancing the flexibility and security of energy systems. The integration of smart contracts and distributed

ledgers ensures fairness and reliability in power transactions while optimizing charging and discharging schedules for EVs [71]. Furthermore, concepts like the smart mobile power bank (SMPB) leverage hybrid energy storage systems and virtual inertia control to improve grid reliability and support cost-effective energy management in grids with high renewable penetration [72].

3.1.6. Battery Management and Lifespan Optimization

Battery management and lifespan optimization have become critical aspects of ESS in microgrids and EVs. Effective strategies in this domain extend the operational life of batteries and improve the efficiency, reliability, and sustainability of the overall energy system, addressing challenges such as degradation, imbalances, and operational costs. One significant advancement in battery management involves modular reconfigurable battery energy storage systems (MR-BESS). These systems tackle issues of imbalance, which often reduce reliability and capacity utilization, by employing fast battery balancing methods without the need for additional equalizers. This approach enhances the battery lifespan while ensuring fault tolerance and operational flexibility [73]. To further address battery degradation, optimization models such as mixed-integer linear programming (MILP) have been applied to microgrids to maintain full SoC conditions. By preventing partial SoC operations and ensuring safe charging and discharging dynamics, these strategies significantly prolong battery life in microgrids with renewable energy integration [74]. Additionally, studies on vehicle-to-grid (V2G) systems reveal that bidirectional power flow, while beneficial for grid stability, can accelerate battery degradation under certain conditions. By analyzing the effects of depth of discharge (DoD), charging regimes, and battery capacity, researchers have developed models to mitigate capacity fading and optimize charging to preserve battery lifespan [75].

Advanced control strategies have proven highly effective in improving battery health and operational efficiency. For example, multiagent reinforcement learning (MARL) techniques enable real-time synchronized charging and discharging of ESS in microgrids, balancing power flows and minimizing degradation. These methods dynamically adapt to changing loads and environmental factors, providing robust solutions for diverse microgrid applications [76]. Similarly, reinforcement learning-based EMS optimize power distribution while treating battery degradation as a cost to be minimized. This not only improves battery lifespan but also increases profitability and energy efficiency in high-renewable penetration microgrids [77]. Smart charging strategies also play an important role in maximizing battery lifespan. For instance, advanced power management schemes for plug-in hybrid electric vehicles (PHEVs) in AC microgrids reduce energy drawn from utility grids, maximize the use of DERs, and extend the battery lifetime. Multi-objective optimization algorithms ensure efficient PHEV charging while minimizing the adverse effects of uncoordinated charging on microgrid performance [78]. Moreover, optimization techniques for EV charging stations incorporating vehicle-to-everything (V2X) capabilities combine solar power and battery storage to mitigate peak demand, reduce operational costs, and enhance grid stability. These systems demonstrate how effective integration of renewable energy sources and ESS can significantly benefit both the grid and battery longevity [79].

3.1.7. Battery Life and Storage Capabilities in Microgrid Systems

Battery life and storage capabilities are critical to the successful integration of ESS in microgrids, particularly with the increasing adoption of EVs and renewable energy sources. Batteries play a pivotal role in ensuring energy resilience, grid stability, and the efficient utilization of renewable energy, but their performance and longevity must be carefully managed to address challenges such as degradation, demand fluctuations, and storage limitations. Microgrids integrating renewable energy sources, such as photovoltaic (PV) systems, have demonstrated the potential to enhance energy independence while supporting EV adoption. Studies have shown that residential microgrids equipped with PV

systems and lithium-ion batteries can meet a significant portion of EV charging demands. For instance, a microgrid with 6 kWp PV capacity and 20 kWh battery storage allows 23% of daily BEV charging and 68% of PHEV charging to be supplied entirely by renewable energy, highlighting the importance of scaling PV capacity and battery storage to support future EV penetration [80].

Beyond energy independence, cost optimization is a key factor in battery storage integration. Innovative strategies combining vehicle-to-grid (V2G) technology and demand response programs enable more efficient energy utilization. These approaches leverage energy credit mechanisms to store excess PV energy in shared ESS for later use, reducing peak demand and total energy costs for both EV fleets and residential users. By accounting for battery degradation costs and user behavior, such systems ensure a realistic and economically viable integration of EV batteries into microgrids [81]. To optimize the interaction between ESS, EVs, and interconnected microgrids, advanced control strategies have been developed. Model Predictive Control (MPC) techniques address the complexities of energy exchange, particularly under scenarios involving uni- and bidirectional flows. These strategies ensure efficient energy management, adapting to variable renewable generation and EV charging demands while maintaining grid stability and extending the battery lifespan. Such control methodologies provide the necessary flexibility to accommodate the increasing number of interconnected microgrids and EVs [82].

Hybrid energy storage systems (HESS), which combine high-power density supercapacitors with high-energy density battery units, offer additional solutions to enhance performance. These systems address both transient and average power demands in EV charging stations while stabilizing the grid during periods of high demand. For instance, hybrid systems store excess renewable energy for later use and employ advanced charging strategies, such as stepwise constant current control, to optimize EV battery charging. This method reduces battery degradation by adjusting charging currents to the state of charge, thereby extending battery life and improving the overall system performance [83]. As the penetration of renewable energy and EVs continues to grow, the effective integration of advanced storage technologies and control strategies is essential for ensuring grid stability and economic sustainability. Enhancing battery life and storage capabilities addresses the challenges of renewable energy variability and contributes to the broader goals of decarbonization and energy efficiency. Continued research into innovative battery architectures, scalable storage solutions, and predictive control systems will be vital to meeting the demands of future energy systems.

3.2. Algorithms and Control Strategies for Energy Optimization

3.2.1. Advanced Algorithms for Optimizing Storage and Electric Vehicles

The integration of advanced algorithms is fundamental for the optimization of ESS and EVs within microgrids [84,85]. Research has consistently demonstrated that various algorithmic approaches, such as fuzzy logic, genetic algorithms, and stochastic methods, can significantly enhance the management of DERs [31,35]. These advanced methodologies facilitate efficient energy dispatch and operational flexibility, particularly in the context of the increased penetration of renewable energy [86]. Fuzzy logic, in particular, has proven effective in managing the uncertainties inherent in renewable energy generation, as well as the variability of energy demand [87]. This approach allows for dynamic decision-making, making it highly applicable for managing EVs as mobile storage units in microgrids [30,60]. Genetic algorithms further contribute to optimal scheduling, allowing energy systems to balance load forecasting, energy pricing, and renewable energy generation, all while minimizing operational costs [36,37,49]. Stochastic optimization has gained prominence for addressing the variability of renewable energy sources [88,89]. Studies show that these algorithms enhance energy dispatch by maximizing the use of renewable energy during periods of low demand and optimizing the participation of EVs, effectively reducing the reliance on thermal generators [41,52,54]. These advanced algorithms collectively improve

the overall sustainability and efficiency of microgrid operations, contributing to lower greenhouse gas emissions and increased system reliability [29,47,61].

Advanced algorithms, such as fuzzy logic, genetic algorithms, and stochastic methods, are essential in optimizing ESS and EVs within microgrids. These methodologies enhance energy dispatch, operational flexibility, and sustainability, particularly under high renewable energy penetration. To better understand the capabilities and limitations of these approaches, Table 2 compares the key algorithmic methods, highlighting their respective merits and demerits. These algorithms collectively contribute to reducing greenhouse gas emissions and minimizing the reliance on thermal generators, ensuring sustainable microgrid operations [29,31,36–41,47].

Table 2. Comparison of advanced algorithms for optimizing ESS and EVs.

Algorithm	Merits	Demerits
Fuzzy Logic	Effective in handling uncertainty in energy generation and demand.	Relies heavily on expert knowledge for rule creation, limiting scalability.
Genetic Algorithms	Optimal scheduling, balancing energy pricing, load forecasting, and renewables.	Computationally intensive, especially for large-scale systems.
Stochastic Methods	Robust against variability of renewable energy, enhancing reliability.	Requires high-quality probabilistic models; sensitive to input inaccuracies.

3.2.2. Predictive Control Strategies for Dynamic Renewable Integration

Predictive control strategies have emerged as critical tools for managing the integration of renewable energy within microgrids [90]. These strategies leverage real-time data from sources such as weather forecasts and historical energy generation patterns to predict changes in energy supply and demand, ensuring a more stable and reliable grid [53,55,58]. Predictive control strategies are precious in handling the intermittent nature of renewable energy sources, such as solar and wind power. By dynamically adjusting system operations in response to predicted fluctuations, microgrids can better manage energy storage and the charging or discharging of EVs [44,51]. This capability is essential for minimizing the need for backup energy from fossil fuels and maintaining a high level of renewable energy utilization [59,63].

One of the key benefits of predictive control models is their ability to anticipate short-term changes in energy generation, enabling microgrids to adjust power output in real-time. This improves both the operational efficiency and the economic viability of microgrid systems, particularly in environments with high renewable energy penetration [46,64]. As the role of artificial intelligence (AI) in predictive modeling continues to evolve, these strategies are expected to enhance further the adaptability and efficiency of microgrids [91,92].

Predictive control strategies leverage real-time and historical data to anticipate fluctuations in renewable energy generation, enabling dynamic adjustments to microgrid operations. These approaches excel in maintaining grid stability and maximizing renewable energy utilization. To illustrate their advantages and limitations, Table 3 compares predictive control strategies with traditional control methods. As predictive control strategies evolve with advancements in artificial intelligence (AI), they are expected to offer enhanced adaptability and efficiency, further solidifying their role in managing renewable energy variability [44,46,51–65].

Table 3. Comparison of predictive and traditional control strategies.

Control Strategy	Merits	Demerits
Traditional Control	Simpler implementation and lower computational requirements.	Limited responsiveness to renewable variability and demand changes.
Predictive Control	Proactive management; enhances operational efficiency and grid stability.	Dependent on accurate forecasts; vulnerable to forecasting errors and delays.

3.2.3. Adaptive Algorithmic Solutions for Generation and Demand Variability

The inherent variability of both energy generation from renewable sources and energy demand poses significant challenges for microgrid operations. Adaptive algorithms provide a robust solution to these challenges by continuously monitoring and adjusting system operations based on real-time conditions [93–95]. These algorithms offer the flexibility needed to respond to sudden changes in energy generation or consumption, ensuring that microgrids maintain a stable energy supply [96–98]. Recent studies have highlighted the role of adaptive algorithms in managing the unpredictability of renewable energy sources, such as wind and solar power [99,100]. By dynamically optimizing the charging and discharging cycles of EVs, these algorithms improve the grid’s ability to balance supply and demand [101–103]. This adaptability is crucial in regions with high levels of renewable energy penetration, where sudden fluctuations in energy generation can lead to instability if not properly managed [104–106].

Moreover, adaptive algorithms enhance the resilience of microgrids by reducing their dependence on thermal generation, enabling the system to maximize the use of renewable energy sources and energy storage systems [107–109]. The development of more advanced adaptive algorithms, which incorporate machine learning and AI, is expected to improve further the efficiency and reliability of microgrids, particularly as renewable energy becomes an increasingly dominant source of power [110–112]. These advances in algorithmic solutions, ranging from fuzzy logic and stochastic optimization to predictive and adaptive control strategies, underscore the importance of innovative approaches to managing energy in microgrids [113]. As the energy landscape continues to evolve, the role of these algorithms will become even more critical in ensuring the successful integration of renewable energy and the efficient management of EVs and energy storage systems [114–118].

Adaptive algorithms address the unpredictability of renewable energy generation and fluctuating demand by continuously adjusting system operations based on real-time conditions. These solutions are vital for ensuring microgrid resilience and maximizing renewable resource utilization. Table 4 presents a comparison between adaptive and static algorithms, outlining their respective merits and demerits. By integrating machine learning and artificial intelligence, adaptive algorithms are expected to improve further, enabling efficient and reliable microgrid operations while addressing the dynamic nature of renewable energy systems [94–113].

Table 4. Comparison of adaptive and static algorithms.

Approach	Merits	Demerits
Static Algorithms	Simpler design and lower computational demands.	Ineffective under rapidly changing conditions; lacks responsiveness.
Adaptive Algorithms	Flexible and responsive to real-time changes in generation and demand.	High computational complexity; requires precise tuning for optimal operation.

3.3. Renewable Energy Integration and Grid-Friendly Solutions

3.3.1. Grid-Friendly Integration of Renewable Energies in Microgrids

Integrating renewable energy sources such as solar and wind into microgrids introduces notable challenges, especially concerning grid stability [119]. The inherent intermittency of these renewable sources often leads to unpredictable fluctuations in energy generation [120,121]. When the generation surpasses the demand, excess energy needs to be stored or redirected, and when generation is lower than the demand, supplementary energy is required to maintain stability. Several studies emphasize that the use of ESS and EVs offers promising solutions to address these challenges by enhancing the operational resilience of microgrids [35]. One key aspect of integrating renewables into microgrids is the role of energy storage systems, which are essential for balancing the variability of renewable energy. These storage systems can absorb excess energy during periods of high production, such as when solar panels generate surplus electricity on sunny days. This stored energy can then be used during periods of low production, like cloudy days or nighttime. By managing these fluctuations, energy storage systems help maintain grid stability, ensuring a smooth and reliable energy supply to consumers [30,31].

Additionally, the integration of EVs into microgrids has garnered significant attention due to their ability to function as mobile energy storage units. EVs can not only absorb excess energy during off-peak times but also discharge stored energy back into the grid during peak demand. This flexibility enhances the overall energy management of the microgrid and allows for the better utilization of renewable resources. Research has demonstrated that EVs, when adequately integrated, provide an effective mechanism for stabilizing microgrids, especially those with a high penetration of renewables like solar and wind energy [36,37]. Moreover, smart energy management systems, which incorporate advanced control algorithms, play a crucial role in coordinating the flow of energy between renewable sources, storage systems, and EVs. These algorithms monitor energy production and consumption patterns in real-time, dynamically adjusting energy flows to ensure stability. For instance, during periods of peak renewable energy generation, these systems can optimize the use of storage and direct energy to EVs, which act as flexible loads [41]. This dynamic coordination is key to achieving a grid-friendly integration of renewable energy sources, and multiple studies underscore the importance of these intelligent systems in managing energy flow and enhancing the resilience of microgrids [42,57].

3.3.2. Role of Storage Systems and EVs in Stabilizing Microgrids

Energy storage systems and electric vehicles are essential in stabilizing microgrids, particularly those with a high reliance on intermittent renewable energy sources. Storage systems, such as batteries, are essential for smoothing out the fluctuations that arise from renewable energy generation. By storing energy during periods of excess generation and discharging it during periods of low generation, these systems help balance supply and demand, ensuring a steady and reliable power supply [29]. Studies have shown that, without adequate energy storage solutions, microgrids with significant renewable energy penetration would struggle to maintain stability, leading to frequent energy imbalances and potential blackouts [61]. In addition to traditional stationary energy storage systems, the integration of EVs into microgrids provides a novel approach to enhancing grid stability. Electric vehicles, equipped with bidirectional charging capabilities, can function both as energy consumers and providers. During times of excess energy production, EVs can be charged, effectively acting as distributed energy storage units. When the energy demand rises, these vehicles can discharge their stored energy back into the grid, helping to mitigate supply shortages and reduce the strain on conventional generation systems [43]. This capability significantly improves the flexibility and adaptability of microgrids, as EVs can be deployed strategically to balance energy loads across the network [48,50].

Moreover, the ability of EVs to act as mobile energy storage solutions adds another layer of flexibility to microgrid operations. This mobility allows for energy to be stored in one location and discharged in another, providing greater flexibility for energy distribution.

For instance, EVs can be charged at a workplace during the day when solar energy is abundant and then discharge energy at home during the evening when demand is higher. This mobility, coupled with the ability to operate in conjunction with stationary storage systems, ensures a more stable and reliable operation of microgrids, especially under conditions of high renewable energy penetration [53,58].

3.3.3. Minimizing Dependence on Traditional Generators

One of the most significant advantages of integrating renewable energy sources into microgrids is the potential to reduce dependence on traditional, fossil-fuel-based generators. Studies have shown that the strategic use of energy storage systems and EVs can minimize the need for conventional thermal generators, which are typically used to provide backup power during periods of low renewable generation [44]. By effectively storing and redistributing renewable energy, microgrids can rely more heavily on sustainable energy sources, thus reducing greenhouse gas emissions and promoting long-term sustainability [51]. Energy storage systems, in particular, play a vital role in reducing reliance on traditional generators. By storing surplus renewable energy and discharging it during peak demand, these systems decrease the need for fossil fuel-based generators to fill the gap when renewable generation is low [56]. Furthermore, EVs contribute to this effort by providing additional storage capacity and reducing the overall energy demand from the grid. Research indicates that, with high levels of energy storage and EV integration, microgrids can operate with minimal effort.

3.4. Microgrid Management and Demand Response Systems

3.4.1. Demand Response Solutions to Optimize Consumption in Microgrids

Demand response (DR) solutions are attractive in enhancing energy efficiency and optimizing the use of resources in microgrids [122]. These systems allow for the dynamic adjustment of energy consumption based on real-time conditions in the grid, improving the flexibility and adaptability of microgrids, especially those integrating renewable energy sources [123]. Renewable energy systems such as solar and wind are inherently intermittent, and the balance between energy generation and consumption can shift rapidly. To address this, DR mechanisms are designed to modify energy usage patterns by either reducing or shifting loads during peak times, which helps maintain stability within the microgrid [35,36].

The flexibility offered by DR is often implemented through pricing mechanisms like real-time pricing (RTP), critical peak pricing (CPP), and time-of-use (ToU) tariffs. These mechanisms incentivize consumers to adjust their energy consumption during off-peak periods, where the grid is less stressed and energy is cheaper compared to peak times. Studies have shown that consumers respond positively to these incentives, contributing to reduced peak demand and an overall smoother load profile across the day [42]. This is particularly useful in microgrids, where supply from renewable sources can vary significantly. Additionally, DR solutions can be automated with advanced systems that utilize AI to monitor and control energy use in real time, adjusting consumption according to grid needs [29,57].

The integration of ESS and EVs into DR programs further enhances their potential. ESS and EVs act as controllable loads that can absorb excess energy during times of surplus generation and release it during peak demand. This capability provides an additional layer of flexibility, allowing microgrids to respond dynamically to fluctuations in both energy supply and demand [43]. Research has demonstrated that the combination of DR and storage systems can reduce reliance on conventional fossil fuel generators, lowering greenhouse gas emissions and operational costs [48,58]. Furthermore, predictive algorithms incorporated into DR systems can forecast energy demand and generation trends, allowing for proactive adjustments that improve the efficiency of the microgrid.

3.4.2. Load Management Strategies and Peak Reduction

Effective load management strategies are crucial in reducing peak demand and ensuring the efficient operation of microgrids. Peak demand periods put significant strain on the energy system, requiring additional resources that can increase operational costs and reduce the lifespan of grid components. Load management involves shifting or reducing energy demand during these high-demand periods, smoothing out the consumption curve, and improving the overall stability and efficiency of the microgrid. One of the most effective methods for achieving this is through the coordination of energy storage systems and electric vehicles, which can store energy during off-peak periods and release it during peak times [45,56,62].

Several studies have explored advanced load management strategies that use predictive control systems to anticipate the peak demand and adjust energy usage accordingly. These systems analyze real-time data on energy consumption patterns and use machine learning algorithms to forecast future demand, allowing for preemptive load shifting or demand reduction [64]. For example, during periods of high renewable energy generation, energy storage systems can store the surplus energy for later use. EVs, when integrated into these systems, add another dimension of flexibility. They can absorb energy when demand is low, such as overnight when electricity prices are lower, and discharge energy back into the grid during peak demand, reducing the strain on the system [98,100].

Incorporating EVs into load management strategies is particularly beneficial in reducing peak loads. When managed intelligently, EV charging can be coordinated to occur during periods of low demand, helping to flatten the overall load curve and prevent spikes in energy usage. This reduces the need for additional generation capacity during peak times, which is often provided by less efficient and more expensive fossil fuel generators [101,124]. Moreover, this approach helps optimize the use of renewable energy sources, as the excess energy generated during peak production periods can be stored and used when needed, further reducing the reliance on traditional power generation methods [103].

3.4.3. EV and Storage Participation in Dynamic Demand Response

EVs and ESS are crucial in improving the effectiveness of dynamic DR strategies within microgrids. By functioning as both energy consumers and distributed storage units, EVs provide unique flexibility that can be utilized to optimize real-time energy flows. With bidirectional charging capabilities, EVs can store excess energy during periods of low demand or high renewable generation and discharge it back into the grid during peak demand, providing a dynamic resource for balancing supply and demand [105,107].

The incorporation of ESS, such as batteries, into dynamic DR systems adds another layer of flexibility to microgrid operations. These systems act as buffers, absorbing excess energy during periods of surplus generation and releasing it when demand rises. This capability is beneficial in microgrids with high renewable energy penetration, where the variability of solar and wind generation can lead to fluctuations in energy supply [108,109]. By providing a stable source of energy during periods of low generation, ESS helps maintain grid stability and ensures a consistent power supply to meet demand [110].

In dynamic DR programs, the combined use of EVs and ESS enables more responsive and flexible microgrid operations. Studies have shown that, when EVs and storage systems are integrated into DR strategies, they significantly enhance the grid's ability to respond to real-time changes in demand and generation. This improves the operational efficiency of the microgrid and reduces the reliance on fossil fuel-based generation during peak demand [112,125]. Moreover, the ability of EVs to act as mobile storage units allows for greater adaptability in energy distribution. For instance, EVs can be charged at work during the day when solar energy generation is high and discharge energy at home during peak evening demand [27,116]. This flexibility makes EVs and storage systems critical components of dynamic DR strategies, contributing to a more resilient and sustainable energy system [126,127].

The role of predictive algorithms and AI-based control systems in managing the participation of EVs and ESS in DR programs cannot be overstated. These advanced systems allow for real-time monitoring and adjustment of energy flows, optimizing the use of storage and EVs to balance supply and demand dynamically [128]. Predictive models can forecast demand trends and renewable energy generation, enabling the microgrid to proactively adjust energy usage and minimize disruptions [129,130]. This level of automation and intelligence in DR systems is key to maximizing the potential of EVs and ESS, ensuring that microgrids operate efficiently and sustainably even under fluctuating conditions [131–133]. Then, the integration of advanced demand response solutions, coupled with the dynamic participation of EVs and energy storage systems, represents a significant advancement in microgrid management. These technologies enable microgrids to handle the variability of renewable energy sources better, reduce reliance on traditional power generation, and optimize energy use, leading to a more resilient, efficient, and sustainable energy infrastructure [134–138].

3.5. Multi-Objective Optimization and Hybrid Systems in Microgrids

3.5.1. Multi-Objective Optimization in Microgrid Operations

Multi-objective optimization has become a key tool in enhancing microgrid performance by balancing multiple factors, such as operational costs, grid stability, and environmental sustainability. The reviewed studies indicate that these optimization models can maximize energy efficiency while simultaneously minimizing carbon emissions and operational expenses. By considering multiple objectives, such as reducing reliance on fossil fuels and optimizing renewable energy integration, these models allow for more resilient and adaptive energy management systems [52]. One common approach involves the use of Pareto-based optimization methods, which enable decision makers to choose the most optimal trade-offs based on their specific needs [47]. These optimization methods are also crucial for ensuring that microgrids can efficiently handle the fluctuating demand and renewable energy supply, improving the overall system reliability and sustainability [103].

3.5.2. Integration of AC/DC Hybrid Systems for Improved Interoperability

The integration of AC/DC hybrid systems in microgrids has shown to improve operational flexibility and interoperability between different energy technologies. Hybrid systems are particularly beneficial in optimizing the distribution and consumption of energy between alternating current (AC) and direct current (DC) systems, which are both prevalent in modern microgrids [109]. Studies highlight that such systems increase energy efficiency and facilitate a better integration of renewable energy sources such as solar and wind, which often require DC connections to function optimally [110]. This improved interoperability allows for seamless energy flow between AC and DC technologies, reducing conversion losses and enhancing the overall system performance [127].

Hybrid systems also provide greater versatility in microgrids by accommodating different energy storage technologies. For example, DC-based storage systems, such as batteries, can work in tandem with AC grids to store and discharge energy as needed, thereby smoothing out fluctuations in renewable energy generation [129]. The dual nature of AC/DC systems also enhances the robustness of microgrids, enabling them to adapt more easily to dynamic changes in energy supply and demand [133].

3.5.3. Comparative Analysis with Traditional Energy Models

The comparison of the two models (with and without EVs/ESS) underscores the advantages of integrating multi-objective optimization strategies in microgrid design. Traditional models prioritize minimizing operational costs, often relying heavily on fossil fuel-based generation and neglecting the environmental and long-term sustainability benefits. While effective in the short term, these models fail to leverage the flexibility and efficiency improvements provided by modern technologies. In contrast, the model incorporating EVs and ESS achieves a 21% reduction in operational costs over a 10-year period.

Additionally, reusing second-life EV batteries in stationary applications further enhances economic performance, yielding a 20% additional cost reduction [30,31]. This dual use of EV batteries extends their lifecycle and helps address growing concerns about battery waste, contributing to a circular economy in the energy sector.

Environmentally, the proposed model reduces CO₂ emissions by 57%, avoiding approximately 450 tons of CO₂ over a decade [29,44,63]. These reductions are primarily driven by better utilization of renewable energy sources and the bidirectional capabilities of EVs, which store surplus renewable energy during off-peak periods and discharge it during peak demand. Such flexibility also enhances the stability of the microgrid by mitigating the intermittency of renewable energy generation [30,31]. These findings emphasize the importance of adopting sustainable and integrated approaches in microgrid design. By balancing economic, environmental, and operational goals, the model with EVs and ESS demonstrates a viable pathway toward achieving clean, reliable, and cost-effective energy systems [29,48,50].

3.5.4. Scalability Strategies for EV and ESS Integration into Larger Grids

Scaling the integration of EVs and ESS from microgrids to larger, more complex grids introduces significant challenges, such as managing low inertia, maintaining voltage regulation, and implementing effective control mechanisms. Addressing these issues requires scalable strategies that extend the benefits observed in microgrid applications—such as grid stability and renewable energy optimization—to larger grid systems. One critical challenge in scaling is the management of low grid inertia, especially in systems with high renewable energy penetration. Hybrid energy storage systems (HESS), which combine supercapacitors for rapid response with batteries for sustained energy needs, play a key role in mitigating power fluctuations and ensuring frequency stability as EV fleets expand. These systems have proven effective in addressing transient stability while supporting long-term grid operations [46,47]. Voltage regulation emerges as another pivotal issue in larger grids. Advanced control strategies, such as model predictive control provide real-time optimization of power flows, ensuring stable voltage profiles across interconnected grid systems. By enabling precise energy dispatch between microgrids and the main grid, MPC addresses the variability in renewable energy output and fluctuating EV charging demands [50]. Distributed control techniques further enhance scalability by decentralizing decision-making, reducing computational complexity, and improving system adaptability [45,49].

Interoperability between microgrid solutions and larger grid infrastructures is essential for seamless scaling. Hybrid AC/DC systems facilitate efficient energy transfer, reducing conversion losses and ensuring compatibility across different grid architectures. Additionally, vehicle-to-grid (V2G) and vehicle-to-everything (V2X) technologies provide critical support during peak demand periods by enabling bidirectional energy flows, allowing EV fleets to act as dynamic grid stabilizers [43,47]. Economic considerations also highlight the importance of scalability strategies. Although initial investments in infrastructure and technology may be substantial, long-term benefits, including reduced operational costs, enhanced grid resilience, and lower reliance on fossil fuels, make these solutions viable for large-scale implementation. Dynamic pricing models and fleet-wide energy management systems ensure that EV and ESS integration remains cost-effective as the grids grow in size and complexity [48].

3.5.5. Economic and Environmental Viability Analysis of Hybrid Systems

The economic and environmental viability of AC/DC hybrid systems in microgrids has been extensively analyzed in the reviewed literature. Studies suggest that while the initial investment costs for hybrid systems may be higher compared to traditional microgrids, the long-term economic benefits far outweigh these costs [17]. The use of hybrid systems reduces operational expenses by optimizing energy use, minimizing conversion losses, and

integrating renewable energy sources more effectively, which can lead to significant cost savings over time [139].

From an environmental perspective, the integration of hybrid systems has the potential to reduce greenhouse gas emissions drastically. By facilitating the use of renewable energy and reducing the reliance on traditional thermal generators, hybrid microgrids contribute to lower carbon footprints and greater sustainability [140]. These findings suggest that hybrid AC/DC systems represent a promising path forward for developing more efficient and environmentally friendly microgrids [52,110,129]. Then, the combination of multi-objective optimization and AC/DC hybrid systems offers a comprehensive solution to the challenges faced by modern microgrids. These systems improve operational efficiency and flexibility and contribute to economic savings and environmental sustainability in the long run.

Table 5 provides an overview of the key topics and innovations identified in the reviewed studies, highlighting the most novel contributions to microgrid optimization, energy management, and the integration of renewable energy sources. The table also outlines the future challenges and research directions associated with each contribution. By consolidating multiple studies, this table illustrates the current state of knowledge and the remaining gaps in the field, particularly in areas such as multi-objective optimization, hybrid systems, demand response strategies, and storage integration. The synthesized findings serve as a foundation for proposing future improvements to enhance the operational efficiency and sustainability of microgrids.

Table 5. Key findings and future challenges in microgrid optimization and renewable energy integration.

Ref.	Main Novel Idea	Future Challenges
[30,31,35,41]	Role of energy storage in balancing renewable integration	Improving the efficiency and reducing the cost of large-scale storage systems
[36,37,43,50]	Integration of EVs as mobile energy storage	Enhancing EV charging infrastructure to maximize their role in grid stabilization
[41,42,53,57]	Smart energy management systems for dynamic energy flow	Development of more advanced algorithms for real-time coordination
[29,48,61]	Stationary storage systems for smoothing renewable fluctuations	Scaling up deployment in microgrids with high renewable penetration
[43,44,48,50]	Bidirectional EV charging for grid support	Further research on V2G (Vehicle-to-Grid) technologies to ensure grid resilience
[44,53,58]	Reducing reliance on fossil-fuel generators	Achieving reliable microgrid operations during extreme weather or demand spikes
[56,63]	Viability of renewable storage systems in microgrids	Lowering the financial and environmental costs of integrating renewables
[45,63,64]	Multi-objective optimization in microgrid management	Developing models that balance economic, environmental, and operational goals
[91,97]	Hybrid AC/DC systems for better flexibility and interoperability	Ensuring seamless integration of hybrid systems with existing infrastructure
[98,103]	Economic and environmental analysis of hybrid systems	Reducing upfront costs and improving the long-term sustainability of hybrid solutions
[109,110,129]	Real-time predictive control strategies for energy flow	Achieving more accurate predictive models for renewable energy integration
[127,133,141]	Use of AI in optimizing microgrid operations	Addressing computational complexity and scalability of AI-driven systems
[17,139,140]	Dynamic demand response with EVs and storage systems	Increasing consumer participation and responsiveness in demand-side management

4. Conclusions

This paper presents a comprehensive review of the integration of ESS and EVs into microgrid networks, employing the PRISMA methodology to analyze relevant research published between 2014 and 2024. Using Web of Science and Scopus databases, an initial search yielded 775 studies, which were screened and narrowed down to 118 relevant works through title, abstract, and full-text evaluations. The review emphasizes innovative technologies and approaches aimed at enhancing the operational efficiency of microgrids, particularly in contexts with high penetration of RES. A key finding is the critical role EVs play as sustainable transportation solutions and mobile storage units, enhancing grid flexibility and stability through vehicle-to-grid systems. Their ability to function as both energy consumers and providers allows EVs to support grid stability during peak periods and mitigate fluctuations in renewable generation. The integration of advanced control strategies, such as MPC and stochastic optimization, is highlighted for improving the dynamic management of energy flows, reducing operational costs, and enhancing overall microgrid resilience.

Hybrid AC/DC microgrids also emerge as promising solutions for minimizing conversion losses and improving operational flexibility, particularly in both grid-connected and islanded environments. These systems optimize the use of alternating and direct current, improving energy efficiency and facilitating better integration of renewable sources. Furthermore, energy flow optimization, especially with high RES penetration, relies on the coordinated dispatch of ESS and EVs to smooth out fluctuations and store excess energy during periods of low demand, which can later be used during peak loads. Despite these technological advances, the review identifies several research gaps, such as the lack of comprehensive multi-objective optimization frameworks that address ESS sizing, EV scheduling, and renewable energy integration while considering dynamic pricing, grid stability, and carbon emissions reduction. Additionally, the long-term economic feasibility and lifecycle analysis of large-scale ESS and EV integration remain underexplored, requiring further investigation.

The identified research gaps highlight critical challenges, including the need for adaptive control strategies capable of managing fluctuations in renewable generation and EV demand, enhanced interoperability among distributed energy resources, and scalable hybrid AC/DC microgrid solutions to reduce conversion losses and support seamless communication among components. Future research directions include developing unified EMS that optimize ESS and EV integration, leveraging machine learning and AI-driven predictive algorithms to enhance real-time energy management and predictive maintenance, and conducting detailed economic and environmental impact analyses over longer timeframes. Furthermore, advancements in cost-effective technologies and market mechanisms to incentivize prosumer participation will be essential for fostering a more sustainable and economically viable energy ecosystem.

Interoperability challenges between microgrid components, particularly in communication protocols and data management systems, also persist and require further development to ensure the effective coordination of distributed energy resources. Future research should focus on developing scalable and robust energy management systems that seamlessly integrate ESS and EVs, particularly as RES penetration increases. The application of advanced machine learning techniques for predictive maintenance, real-time optimization, and fault detection within microgrids also holds significant potential for enhancing system efficiency and reliability. Moreover, the development of cost-effective technologies and market mechanisms to incentivize prosumer participation will be key to enhancing the economic viability and long-term sustainability of microgrid operations.

Author Contributions: Conceptualization, D.O.-C. and P.A.; methodology, D.O.-C. and E.V.-Á.; software, P.A.; validation, D.O.-C. and P.A.; formal analysis, D.O.-C.; investigation, P.A.; resources, D.O.-C. and E.V.-Á.; data curation, P.A.; writing—original draft preparation, D.O.-C.; writing—review and editing, P.A.; visualization, D.O.-C. and E.V.-Á.; supervision, P.A.; project administration, D.O.-C.; funding acquisition, D.O.-C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data will be made available on request.

Acknowledgments: The authors thank Universidad de Cuenca (UCUENCA), Ecuador, for easing access to the facilities of the Micro-Grid Laboratory, Faculty of Engineering, for allowing the use of its equipment to provide the technical support for the descriptive literature analysis included in this article. The author Edisson Villa Ávila expresses his sincere gratitude for the opportunity to partially present his research findings as part of his doctoral studies in the Ph.D. program in Advances in Engineering of Sustainable Materials and Energies at the University of Jaen, Spain. This review paper is part of the research activities of the project titled: “Promoviendo la sostenibilidad energética: Transferencia de conocimientos en generación solar y micromovilidad eléctrica dirigida a la población infantil y adolescente de la parroquia Cumbe”, winner of the XI Convocatoria de proyectos de servicio a la comunidad organized by Dirección de Vinculación con la Sociedad (DVS) of UCUENCA, under the direction of the author Danny Ochoa-Correa. Finally, the results of this research will serve as input for developing the project titled “Planeamiento conjunto de la expansión óptima de los sistemas eléctricos de generación y transmisión”, Proj. code: VI-UC_XX_2024_3_TORRES_SANTIAGO, winner of the XX Concurso Universitario de Proyectos de Investigación, promoted by the Vicerrectorado de Investigación of UCUENCA, a department to which the authors also wish to express their gratitude.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The systematic review process strictly followed the PRISMA 2020 Statement [32], ensuring transparency and rigor throughout the research. The standardized PRISMA flow diagram, presented in Figure A1, was used to guide the review process.

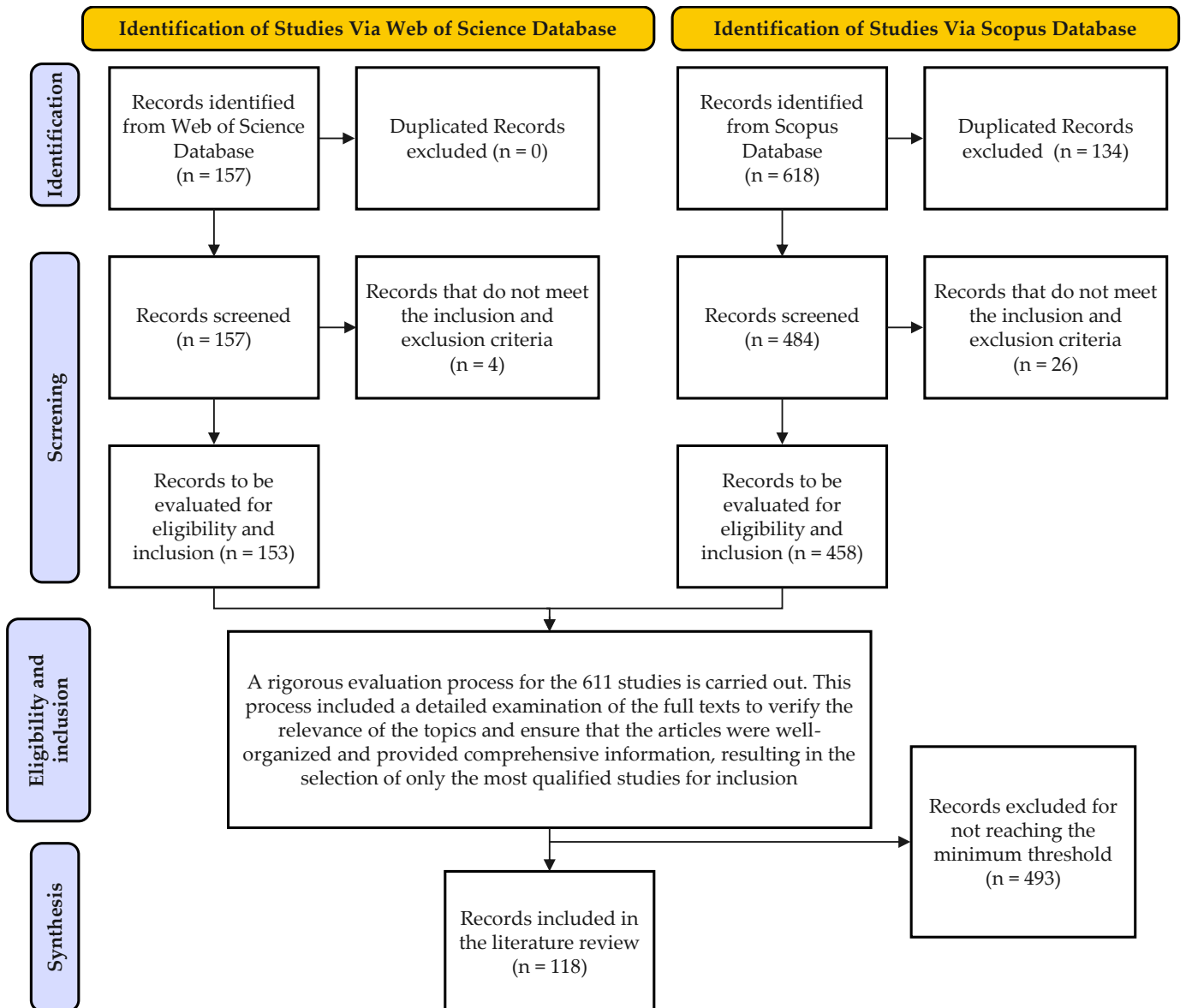


Figure A1. PRISMA methodology flowchart for the studies selection.

References

1. Hadero, M.; Khan, B. Development of DC Microgrid Integrated Electric Vehicle Charging Station with Fuzzy Logic Controller. *Front. Energy Res.* **2022**, *10*, 922384. [[CrossRef](#)]
2. Alizadeh, M.; Tighiz, L.; Nasab, M.A. Providing an Intelligent Frequency Control Method in a Microgrid Network in the Presence of Electric Vehicles. *World Electr. Veh. J.* **2024**, *15*, 276. [[CrossRef](#)]
3. Arévalo, P.; Ochoa-Correa, D.; Villa-Ávila, E.; Arévalo, P.; Ochoa-Correa, D.; Villa-Ávila, E. A Systematic Review on the Integration of Artificial Intelligence into Energy Management Systems for Electric Vehicles: Recent Advances and Future Perspectives. *World Electr. Veh. J.* **2024**, *15*, 364. [[CrossRef](#)]
4. Sepasi, S.; Talichet, C.; Pramanik, A. Power Quality in Microgrids: A Critical Review of Fundamentals, Standards, and Case Studies. *IEEE Access* **2023**, *11*, 108493–108531. [[CrossRef](#)]
5. Elkholy, M.; Elymany, M.; Metwally, H.; Farahat, M.; Senjyu, T.; Lotfy, M. Design and Implementation of a Real-Time Energy Management System for an Isolated Microgrid: Experimental Validation. *Appl. Energy* **2022**, *327*, 120105. [[CrossRef](#)]
6. Seyedeh-Barhagh, S.; Abapour, M.; Mohammadi-Ivatloo, B.; Shafie-Khah, M.; Laaksonen, H. Optimal Scheduling of a Microgrid Based on Renewable Resources and Demand Response Program Using Stochastic and IGDT-Based Approach. *J. Energy Storage* **2024**, *86*, 111306. [[CrossRef](#)]
7. Battula, A.; Vuddanti, S. Distributed Control Strategy for Secondary Frequency Regulation with EV Demand Aggregation and Delay Compensation in AC Unbalanced Microgrid. *Electr. Power Syst. Res.* **2023**, *225*, 109782. [[CrossRef](#)]

8. Lipu, M.; Bhuiyan, M.; Islalm, M.; Ghosh, S.; Rahman, M.; Amin, M. A Review of Controllers and Optimizations Based Scheduling Operation for Battery Energy Storage System towards Decarbonization in Microgrid: Challenges and Future Directions. *J. Clean. Prod.* **2022**, *360*, 132188. [[CrossRef](#)]
9. Aatabe, M.; El Abbadi, R.; Vargas, A.; Bouzid, A.; Bawayan, H.; Mosaad, M. Stochastic Energy Management Strategy for Autonomous PV-Microgrid under Unpredictable Load Consumption. *IEEE Access* **2024**, *12*, 84401–84419. [[CrossRef](#)]
10. Abraham, D.; Elumala, S.; Sharma, K.; Banerjee, R.; Swain, R. Fuzzy-Based Efficient Control of DC Microgrid Configuration for PV-Energized EV Charging Station. *Energies* **2023**, *16*, 2753. [[CrossRef](#)]
11. Chakraborty, A.; Ray, S. Microgrid Operational Energy Management with Plug-in Hybrid Electric Vehicles Charging Demand. *Electr. Eng.* **2024**, *106*, 2245–2263. [[CrossRef](#)]
12. Satheesan, J.; Nair, R. An Adaptive Energy Management Strategy for Supercapacitor Supported Solar-Powered Electric Vehicle Charging Station. *Int. J. Emerg. Electr. Power Syst.* **2023**, *24*, 705–716. [[CrossRef](#)]
13. Akarne, Y.; Essadki, A.; Nasser, T.; El Bhiri, B. Experimental Analysis of Efficient Dual-Layer Energy Management and Power Control in an AC Microgrid System. *IEEE Access* **2024**, *12*, 30577–30592. [[CrossRef](#)]
14. Hou, H.; Wang, Z.; Hou, T.; Fang, R.; Tang, J.; Xie, C. Optimal Schedule of 100% Renewable Energy Microgrid Considering Demand Response of EVs. *Energy Rep.* **2023**, *9*, 1743–1750. [[CrossRef](#)]
15. Ali, A.; Muqet, H.; Khan, T.; Hussain, A.; Waseem, M.; Niazi, K. IoT-Enabled Campus Prosumer Microgrid Energy Management, Architecture, Storage Technologies, and Simulation Tools: A Comprehensive Study. *Energies* **2023**, *16*, 1863. [[CrossRef](#)]
16. Lee, J.; Razeghi, G.; Samuelsen, S. Utilization of Battery Electric Buses for the Resiliency of Islanded Microgrids. *Appl. Energy* **2023**, *347*, 121295. [[CrossRef](#)]
17. Elkholy, M.; Elymany, M.; Metwally, H.; Farahat, M.; Senjyu, T.; Lotfy, M. Optimal Resilient Operation and Sustainable Power Management within an Autonomous Residential Microgrid Using African Vultures Optimization Algorithm. *Renew. Energy* **2024**, *224*, 120247. [[CrossRef](#)]
18. Lu, J.; Zheng, W.; Yu, Z.; Xu, Z.; Jiang, H.; Zeng, M. Optimizing Grid-Connected Multi-Microgrid Systems with Shared Energy Storage for Enhanced Local Energy Consumption. *IEEE Access* **2024**, *12*, 13663–13677. [[CrossRef](#)]
19. Sraidi, S.; Maaroufi, M. Energy Management in the Microgrid and Its Optimal Planning for Supplying Wireless Charging Electric Vehicle. *J. Electr. Comput. Eng.* **2022**, *2022*, 5923568. [[CrossRef](#)]
20. Marchesano, M.G.; Guizzi, G.; Vespoli, S.; Ferruzzi, G. Battery Swapping Station Service in a Smart Microgrid: A Multi-Method Simulation Performance Analysis. *Energies* **2023**, *16*, 6576. [[CrossRef](#)]
21. Sadoudi, S.; Boudour, M.; Kouba, N. Multi-Microgrid Intelligent Load Shedding for Optimal Power Management and Coordinated Control with Energy Storage Systems. *Int. J. Energy Res.* **2021**, *45*, 15857–15878. [[CrossRef](#)]
22. Chen, W.; He, Y.; Li, N.; Wang, Z.; Peng, J.; Xiang, X. A Smart Platform (BEVPro) for Modeling, Evaluating, and Optimizing Community Microgrid Integrated with Buildings, Distributed Renewable Energy, Electricity Storage, and Electric Vehicles. *J. Build. Eng.* **2024**, *87*, 109077. [[CrossRef](#)]
23. Achour, Y.; Ouammi, A.; Zejli, D. Model Predictive Control Based Demand Response Scheme for Peak Demand Reduction in a Smart Campus Integrated Microgrid. *IEEE Access* **2021**, *9*, 162765–162778. [[CrossRef](#)]
24. Abdelsattar, M.; Ismeil, M.; Aly, M.; Abu-Elwfa, S. Analysis of Renewable Energy Sources and Electrical Vehicles Integration into Microgrid. *IEEE Access* **2024**, *12*, 66822–66832. [[CrossRef](#)]
25. Perez, F.; Iovine, A.; Damm, G.; Galai-Dol, L.; Ribeiro, P. Stability Analysis of a DC Microgrid for a Smart Railway Station Integrating Renewable Sources. *IEEE Trans. Control Syst. Technol.* **2020**, *28*, 1802–1816. [[CrossRef](#)]
26. Cleenwerck, R.; Azaïoud, H.; Vafaiepour, M.; Coosemans, T.; Desmet, J. Impact Assessment of Electric Vehicle Charging in an AC and DC Microgrid: A Comparative Study. *Energies* **2023**, *16*, 3205. [[CrossRef](#)]
27. Rasoulinezhad, H.; Abapour, M.; Sadeghian, O.; Zare, K. The Role of Risk-Based Demand Response in Resource Management of a Grid-Connected Renewable-Based Large-Scale Microgrid with Stationary and Mobile Energy Storage Systems and Emission Tax. *Comput. Ind. Eng.* **2023**, *183*, 109555. [[CrossRef](#)]
28. Abed, A.; Rahimi, M.; Rezaei, F.; Farhadi, S.; Bouzid, A.; Dadkhah, M.; Chatterjee, K. Optimizing Energy and Reserve Minimization in a Sustainable Microgrid with Electric Vehicle Integration: Dynamic and Adjustable Manta Ray Foraging Algorithm. *Processes* **2023**, *11*, 2848. [[CrossRef](#)]
29. Satheesan, J.; Nair, R.T. An Adaptive Two-Level Hierarchical Controller for Universal Power Sharing and Performance Enhancement of Hybrid Energy Storage-Supported AC/DC Microgrids. *Int. J. Circ. Theory Appl.* **2023**, *51*, 2122–2140. [[CrossRef](#)]
30. Ali, H.; Magdy, G.; Xu, D. A New Optimal Robust Controller for Frequency Stability of Interconnected Hybrid Microgrids Considering Non-Inertia Sources and Uncertainties. *Int. J. Electr. Power Energy Syst.* **2021**, *128*, 106651. [[CrossRef](#)]
31. Khooban, M.-H.; Niknam, T.; Shasadeghi, M.; Dragicevic, T.; Blaabjerg, F. Load Frequency Control in Microgrids Based on a Stochastic Noninteger Controller. *IEEE Trans. Sustain. Energy* **2018**, *9*, 853–861. [[CrossRef](#)]
32. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *BMJ* **2021**, *372*, n71. [[CrossRef](#)] [[PubMed](#)]
33. Tepe, I.F.; Irmak, E. Design and Model Predictive Control of a Bidirectional EV Fast Charging Station Operating in a DC Microgrid. In Proceedings of the 2024 12th International Conference on Smart Grid (icSmartGrid), Setubal, Portugal, 27–29 May 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 521–529. [[CrossRef](#)]

34. Roy, N.B.; Das, D. Stochastic Power Allocation of Distributed Tri-Generation Plants and Energy Storage Units in a Zero Bus Microgrid with Electric Vehicles and Demand Response. *Renew. Sustain. Energy Rev.* **2024**, *191*, 114170. [[CrossRef](#)]
35. Liu, Z.; Chen, Y.; Zhuo, R.; Jia, H. Energy Storage Capacity Optimization for Autonomy Microgrid Considering CHP and EV Scheduling. *Appl. Energy* **2018**, *210*, 1113–1125. [[CrossRef](#)]
36. Yang, A.; Wang, H.; Li, B.; Tan, Z. Capacity Optimization of Hybrid Energy Storage System for Microgrid Based on Electric Vehicles' Orderly Charging/Discharging Strategy. *J. Clean. Prod.* **2023**, *411*, 137346. [[CrossRef](#)]
37. Ali, A.Y.; Hussain, A.; Baek, J.-W.; Kim, H.-M. Optimal Operation of Networked Microgrids for Enhancing Resilience Using Mobile Electric Vehicles. *Energies* **2020**, *14*, 142. [[CrossRef](#)]
38. Abdelghany, M.; Al-Durra, A.; Gao, F. A Coordinated Optimal Operation of a Grid-Connected Wind-Solar Microgrid Incorporating Hybrid Energy Storage Management Systems. *IEEE Trans. Sustain. Energy* **2024**, *15*, 39–51. [[CrossRef](#)]
39. Moradi, S.; Tinajero, G.D.A.; Vasquez, J.C.; Zizzo, G.; Guerrero, J.M.; Sanseverino, E.R. Hierarchical-Power-Flow-Based Energy Management for Alternative/Direct Current Hybrid Microgrids. *Sustain. Energy Grids Netw.* **2024**, *38*, 101384. [[CrossRef](#)]
40. Ahmadi, M.; Jafari Kaleybar, H.; Brenna, M.; Castelli-Dezza, F.; Carmeli, M.S. Integration of Distributed Energy Resources and EV Fast-Charging Infrastructure in High-Speed Railway Systems. *Electronics* **2021**, *10*, 2555. [[CrossRef](#)]
41. Wen, L.; Zhou, K.; Yang, S.; Lu, X. Optimal Load Dispatch of Community Microgrid with Deep Learning Based Solar Power and Load Forecasting. *Energy* **2019**, *171*, 1053–1065. [[CrossRef](#)]
42. Colombo, P.; Saeedmanesh, A.; Santarelli, M.; Brouwer, J. Dynamic Dispatch of Solid Oxide Electrolysis System for High Renewable Energy Penetration in a Microgrid. *Energy Convers. Manag.* **2020**, *204*, 112322. [[CrossRef](#)]
43. Baghaee, H.R.; Mlakic, D.; Nikolovski, S.; Dragicevic, T. Anti-Islanding Protection of PV-Based Microgrids Consisting of PHEVs Using SVMs. *IEEE Trans. Smart Grid* **2020**, *11*, 483–500. [[CrossRef](#)]
44. Arunkumar, C.R.; Manthathi, U.B. Design and Small Signal Modelling of Battery-Supercapacitor HESS for DC Microgrid. In Proceedings of the TENCON 2019—2019 IEEE Region 10 Conference (TENCON), Kochi, India, 17–20 October 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 2216–2221. [[CrossRef](#)]
45. Wang, C.; Qu, X.; Mai, R.; Zhang, P.; Chai, W.; Wu, S. Research on Low-Carbon Operation of Substation Power Supply System Based on Microgrids. In Proceedings of the 2023 International Conference on Wireless Power Transfer (ICWPT2023), Singapore, 21–23 June 2023; Springer Nature: Singapore, 2023; pp. 472–480.
46. Ur Rahman, A.; Campagna, N.; Pellitteri, F.; Di Tommaso, A.O.; Miceli, R. Stability-Centric Design of a Droop-Mounted Adaptive Nonlinear Control for EV Charging in DC Microgrid. *IEEE Access* **2024**, *12*, 123362–123375. [[CrossRef](#)]
47. Mehrasa, M.; Sheikholeslami, A.; Rezanejad, M.; Alipoor, J. Inertia Augmentation-Based Optimal Control Strategy of a Weak Grid-Connected Microgrid with PV Unit and Energy Storage System. *J. Energy Storage* **2023**, *62*, 106874. [[CrossRef](#)]
48. Paredes, L.A.; Pozo, M. Energy Management Model for an Electric Vehicle Charging Station in the Environment of a Microgrid. In Proceedings of the 2020 IEEE ANDESCON, Quito, Ecuador, 13–15 October 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1–7. [[CrossRef](#)]
49. García-Triviño, P.; Torreglosa, J.P.; Fernández-Ramírez, L.M.; Jurado, F. Control and Operation of Power Sources in a Medium-Voltage Direct-Current Microgrid for an Electric Vehicle Fast Charging Station with a Photovoltaic and a Battery Energy Storage System. *Energy* **2016**, *115*, 38–48. [[CrossRef](#)]
50. Jacome-Ruiz, P.; Hidalgo-Leon, R.; Sanchez-Zurita, C.; Muñoz-Jadan, Y.; Soriano-Idrovo, G. A Model for Electric Vehicle Integration in a Connected Microgrid Considering Greenhouse Gas Emissions. In Proceedings of the 15th LACCIE International Multi-Conference for Engineering, Education, and Technology: Global Partnership for Development and Engineering Education, Boca Raton, FL, USA, 19–21 July 2017. [[CrossRef](#)]
51. Lu, Z.; Xu, X.; Yan, Z.; Wang, H. Density-Based Global Sensitivity Analysis of Islanded Microgrid Loadability Considering Distributed Energy Resource Integration. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 94–101. [[CrossRef](#)]
52. Han, X.; Li, X.; Wang, Z. An Optimal Control Method of Microgrid System with Household Load Considering Battery Service Life. *J. Energy Storage* **2022**, *56*, 106002. [[CrossRef](#)]
53. Olatunde, O.; Hassan, M.Y.; Abdullah, M.P.; Rahman, H.A. Hybrid Photovoltaic/Small-Hydropower Microgrid in Smart Distribution Network with Grid Isolated Electric Vehicle Charging System. *J. Energy Storage* **2020**, *31*, 101673. [[CrossRef](#)]
54. Sharma, P.; Mishra, P.; Mathur, H.D. Optimal Energy Management in Microgrid Including Stationary and Mobile Storages Based on Minimum Power Loss and Voltage Deviation. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e13182. [[CrossRef](#)]
55. Khokhar, B.; Dahiya, S.; Parmar, K.P.S. A Robust Cascade Controller for Load Frequency Control of a Standalone Microgrid Incorporating Electric Vehicles. *Electr. Power Compon. Syst.* **2020**, *48*, 711–726. [[CrossRef](#)]
56. Haffaf, A.; Lakdja, F.; Abdeslam, D.O. Experimental Performance Analysis of an Installed Microgrid-Based PV/Battery/EV Grid-Connected System. *Clean Energy* **2022**, *6*, 599–618. [[CrossRef](#)]
57. Thomas, D.; Deblecker, O.; Ioakimidis, C.S. Optimal Operation of an Energy Management System for a Grid-Connected Smart Building Considering Photovoltaics' Uncertainty and Stochastic Electric Vehicles' Driving Schedule. *Appl. Energy* **2018**, *210*, 1188–1206. [[CrossRef](#)]
58. Wang, B.; Wang, D.; Yin, R.; Black, D.; Chan, C. Predictive Management of Electric Vehicles in a Community Microgrid. In Proceedings of the 2020 IEEE Transportation Electrification Conference & Expo (ITEC), Chicago, IL, USA, 24–26 June 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 773–778. [[CrossRef](#)]

59. Papari, B.; Edrington, C.S.; Ghadamyari, M.; Ansari, M.; Ozkan, G.; Chowdhury, B. Metrics Analysis Framework of Control and Management System for Resilient Connected Community Microgrids. *IEEE Trans. Sustain. Energy* **2022**, *13*, 704–714. [[CrossRef](#)]
60. Rahman, M.S.; Hossain, M.J.; Lu, J. Coordinated Control of Three-Phase AC and DC Type EV-ESSs for Efficient Hybrid Microgrid Operations. *Energy Convers. Manag.* **2016**, *122*, 488–503. [[CrossRef](#)]
61. Aslam, S.; Javaid, N.; Khan, F.A.; Alamri, A.; Almogren, A.; Abdul, W. Towards Efficient Energy Management and Power Trading in a Residential Area via Integrating a Grid-Connected Microgrid. *Sustainability* **2018**, *10*, 1245. [[CrossRef](#)]
62. Wang, L.; Lu, X.; Zhang, Y.; Zhou, X.; Xiong, X.; Ma, H.; Li, X.; Chen, M.; Fu, X. Stability Analysis of a Grid-Connected DC Microgrid with Hybrid Renewable-Energy Systems and EV Loads. In Proceedings of the 2023 IEEE Industry Applications Society Annual Meeting (IAS), Nashville, TN, USA, 29 October–2 November 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–9. [[CrossRef](#)]
63. Diaz-Cachinero, P.; Munoz-Hernandez, J.I.; Contreras, J. A Microgrid Model with EV Demand Uncertainty and Detailed Operation of Storage Systems. *IEEE Trans. Ind. Appl.* **2022**, *58*, 2497–2511. [[CrossRef](#)]
64. Shu, Y.; Dong, W.; Yang, Q.; Wang, Y. Microgrid Energy Management Using Improved Reinforcement Learning with Quadratic Programming. In Proceedings of the 2021 IEEE 5th Conference on Energy Internet and Energy System Integration (EI2), Taiyuan, China, 22–24 October 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 2015–2020. [[CrossRef](#)]
65. Shetty, N.; Smith, A.; Kumar, R.; Patel, S. AI-Driven Energy Forecasting for Electric Vehicle Charging Stations Powered by Solar and Wind Energy. In Proceedings of the 2024 12th International Conference on Smart Grid (icSmartGrid), Setubal, Portugal, 27–29 May 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 336–339. [[CrossRef](#)]
66. Hafeez, A.; Alammari, R.; Iqbal, A. Utilization of EV Charging Station in Demand Side Management Using Deep Learning Method. *IEEE Access* **2023**, *11*, 8747–8760. [[CrossRef](#)]
67. Shakeel, F.M.; Malik, O.P. ANFIS-Based Energy Management System for V2G Integrated Micro-Grids. *Electr. Power Compon. Syst.* **2022**, *50*, 584–599. [[CrossRef](#)]
68. Lin, Y.-J.; Chen, Y.-C.; Hsieh, S.-F.; Liu, H.-Y.; Chiang, C.-H.; Yang, H.-T. Reinforcement Learning-Based Energy Management System for Microgrids with High Renewable Energy Penetration. In Proceedings of the 2023 IEEE International Conference on Energy Technologies for Future Grids (ETFGE), Wollongong, Australia, 8–10 November 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–6. [[CrossRef](#)]
69. Driscoll, L.; de la Torre, S.; Gomez-Ruiz, J.A. Feature-Based Lithium-Ion Battery State of Health Estimation with Artificial Neural Networks. *J. Energy Storage* **2022**, *50*, 104584. [[CrossRef](#)]
70. Benavides, D.; Arévalo, P.; Villa-Ávila, E.; Aguado, J.A.; Jurado, F. Predictive Power Fluctuation Mitigation in Grid-Connected PV Systems with Rapid Response to EV Charging Stations. *J. Energy Storage* **2024**, *86 Pt A*, 111230. [[CrossRef](#)]
71. Lin, Y.-J.; Chen, Y.-C.; Zheng, J.-Y.; Chu, D.; Shao, D.-W.; Yang, H.-T. Blockchain Power Trading and Energy Management Platform. *IEEE Access* **2022**, *10*, 75932–75948. [[CrossRef](#)]
72. Wan, Y.; Wang, Y.; Yu, H.; Zhang, H.; Chen, Z. Smart Mobile Power Bank: A Novel Grid-Friendly Mobile Microgrid for Power Grid with High Penetration of Renewable Vehicles. *IEEE Trans. Transp. Electr.* **2024**, *1*. [[CrossRef](#)]
73. Huang, H.; Ghias, A.M.Y.M.; Acuna, P.; Dong, Z.; Zhao, J.; Reza, M.S. A Fast Battery Balance Method for a Modular-Reconfigurable Battery Energy Storage System. *Appl. Energy* **2024**, *356*, 122470. [[CrossRef](#)]
74. Kailasa Gounder, Y.; Subramanian, S. Enhancement of Battery Life in Microgrid Energy Management Using Mixed Integer Linear Programming and Hybrid Knapsack. *Int. J. Energy Res.* **2022**, *46*, 8158–8174. [[CrossRef](#)]
75. Wang, L.; Chen, B. *Model-Based Analysis of V2G Impact on Battery Degradation*; SAE Technical Paper; SAE International: Warrendale, PA, USA, 2017. [[CrossRef](#)]
76. Al-Saadi, M.; Short, M. Multiagent Power Flow Control for Plug-and-Play Battery Energy Storage Systems in DC Microgrids. In Proceedings of the 2023 58th International Universities Power Engineering Conference (UPEC), Dublin, Ireland, 29 August–1 September 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–6. [[CrossRef](#)]
77. Célié, N.; Sari, A.; Gaetani-Liseo, M.; Lahyani, A. Optimal Multi-Criteria Management of Energy Storage Systems in a Micro-Grid. In Proceedings of the 2023 IEEE Vehicle Power and Propulsion Conference (VPPC), Milan, Italy, 30 October–2 November 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–6. [[CrossRef](#)]
78. Fouladi, E.; Baghaee, H.R.; Bagheri, M.; Gharehpetian, G.B. Smart V2G/G2V Charging Strategy for PHEVs in AC Microgrids Based on Maximizing Battery Lifetime and RER/DER Employment. *IEEE Syst. J.* **2021**, *15*, 4907–4917. [[CrossRef](#)]
79. Šolić, A.J.; Jakus, D.; Vasilj, J.; Jolevski, D. Electric Vehicle Charging Station Power Supply Optimization with V2X Capabilities Based on Mixed-Integer Linear Programming. *Sustainability* **2023**, *15*, 16073. [[CrossRef](#)]
80. Pelosi, D.; Barelli, L.; Longo, M.; Zaninelli, D. Assessment Analysis of BEV/PHEV Recharge in a Residential Micro-Grid Based on Renewable Generation. In *Sustainability in Energy and Buildings 2022*; Littlewood, J., Howlett, R.J., Jain, L.C., Eds.; SEB 2022. Smart Innovation, Systems and Technologies; Springer: Singapore, 2023; Volume 336. [[CrossRef](#)]
81. Beyazıt, M.A.; Taşçıkaraoğlu, A.; Catalão, J.P.S. Cost Optimization of a Microgrid Considering Vehicle-to-Grid Technology and Demand Response. *Sustain. Energy Grids Netw.* **2022**, *32*, 100924. [[CrossRef](#)]
82. Bordons, C.; Garcia-Torres, F.; Ridao, M. Control Predictivo en Microrredes Interconectadas y con Vehículos Eléctricos. *Rev. Iberoam. Autom. Inf. Ind.* **2020**, *17*, 239–253. [[CrossRef](#)]
83. Yadav, A.K.; Bharatee, A.; Ray, P.K. Solar Powered Grid-Integrated Charging Station with Hybrid Energy Storage System. *J. Power Sources* **2023**, *582*, 233545. [[CrossRef](#)]

84. Ouramdane, O.; Elbouchikhi, E.; Amirat, Y.; Le Gall, F.; Gooya, E.S. Home Energy Management Considering Renewable Resources, Energy Storage, and an Electric Vehicle as a Backup. *Energies* **2022**, *15*, 2830. [[CrossRef](#)]
85. Ibrahim, M.M.; Hasanien, H.M.; Farag, H.E.Z.; Omran, W.A. Energy Management of Multi-Area Islanded Hybrid Microgrids: A Stochastic Approach. *IEEE Access* **2023**, *11*, 101409–101424. [[CrossRef](#)]
86. Wang, S.; Lu, L.; Han, X.; Ouyang, M.; Feng, X. Virtual-Battery Based Droop Control and Energy Storage System Size Optimization of a DC Microgrid for Electric Vehicle Fast Charging Station. *Appl. Energy* **2020**, *259*, 114146. [[CrossRef](#)]
87. De Oliveira-Assis, L.; Santana, D.C.; Araújo, A.A.; Santos, D.M.; Morais, T.L.; Muniz, L.B. Optimal Energy Management System Using Biogeography Based Optimization for Grid-Connected MVDC Microgrid with Photovoltaic, Hydrogen System, Electric Vehicles and Z-Source Converters. *Energy Convers. Manag.* **2021**, *248*, 114808. [[CrossRef](#)]
88. Tushar, M.H.K.; Zeineddine, A.W.; Assi, C. Demand-Side Management by Regulating Charging and Discharging of the EV, ESS, and Utilizing Renewable Energy. *IEEE Trans. Ind. Inform.* **2018**, *14*, 117–126. [[CrossRef](#)]
89. Kaewdornhan, N.; Chatthaworn, R. Model-Free Data-Driven Approach Assisted Deep Reinforcement Learning for Optimal Energy Management in MicroGrid. *Energy Rep.* **2023**, *9*, 850–858. [[CrossRef](#)]
90. Savic, N.; Katic, V.; Dumnic, B.; Milicevic, D.; Corba, Z.; Katic, N. The Investment Justification Estimate and Techno-Economic and Ecological Aspects Analysis of the University Campus Microgrid. *Electron. ETF* **2019**, *23*, 26. [[CrossRef](#)]
91. Knežević, S.; Šošić, D. Isolated Work of a Multi-Energy Carrier Microgrid. *Energies* **2024**, *17*, 2948. [[CrossRef](#)]
92. Gupta, A.; Suhag, S. Hybrid Structure Integrating Multiple Battery and Hydrogen Charging Stations in an Autonomous Microgrid for Customized Energy and Voltage Control. *Sustain. Mater. Technol.* **2024**, *41*, e01116. [[CrossRef](#)]
93. Chen, C.; Duan, S. Optimal Integration of Plug-In Hybrid Electric Vehicles in Microgrids. *IEEE Trans. Ind. Inform.* **2014**, *10*, 1917–1926. [[CrossRef](#)]
94. Serban, I.; Marinescu, C. Battery Energy Storage System for Frequency Support in Microgrids and with Enhanced Control Features for Uninterruptible Supply of Local Loads. *Int. J. Electr. Power Energy Syst.* **2014**, *54*, 432–441. [[CrossRef](#)]
95. Mesarić, P.; Krajcar, S. Home Demand Side Management Integrated with Electric Vehicles and Renewable Energy Sources. *Energy Build.* **2015**, *108*, 1–9. [[CrossRef](#)]
96. Chen, C.; Duan, S. Microgrid Economic Operation Considering Plug-In Hybrid Electric Vehicles Integration. *J. Mod. Power Syst. Clean Energy* **2015**, *3*, 221–231. [[CrossRef](#)]
97. Sedighzadeh, M.; Fazlhashemi, S.S.; Javadi, H.; Taghvaei, M. Multi-Objective Day-Ahead Energy Management of a Microgrid Considering Responsive Loads and Uncertainty of the Electric Vehicles. *J. Clean. Prod.* **2020**, *267*, 121562. [[CrossRef](#)]
98. Chae, S.H.; Kim, G.H.; Choi, Y.-J.; Kim, E.-H. Design of Isolated Microgrid System Considering Controllable EV Charging Demand. *Sustainability* **2020**, *12*, 9746. [[CrossRef](#)]
99. Abadi, S.A.G.K.; Choi, J.; Bidram, A. A Method for Charging Electric Vehicles with Battery-Supercapacitor Hybrid Energy Storage Systems to Improve Voltage Quality and Battery Lifetime in Islanded Building-Level DC Microgrids. *IEEE Trans. Sustain. Energy* **2023**, *14*, 1895–1908. [[CrossRef](#)]
100. Dagdougui, H.; Ouammi, A.; Dessaint, L.A. Peak Load Reduction in a Smart Building Integrating Microgrid and V2B-Based Demand Response Scheme. *IEEE Syst. J.* **2019**, *13*, 3274–3282. [[CrossRef](#)]
101. Yang, Q.; An, D.; Yu, W.; Tan, Z.; Yang, X. Towards Stochastic Optimization-Based Electric Vehicle Penetration in a Novel Archipelago Microgrid. *Sensors* **2016**, *16*, 907. [[CrossRef](#)]
102. Yang, Q.; Tan, Z.; Yu, W.; An, D.; Li, X. An Improved Vehicle to the Grid Method with Battery Longevity Management in a Microgrid Application. *Energy* **2020**, *198*, 117374. [[CrossRef](#)]
103. Sankaran, K.S.; El-Bayeh, C.Z.; Eicker, U. Design of Multi-Renewable Energy Storage and Management System Using RL-ICSO Based MPPT Scheme for Electric Vehicles. *Sustainability* **2022**, *14*, 4826. [[CrossRef](#)]
104. Nasir, T.; Jamil, M.; Khan, A.; Hashmi, S.R.; Jamil, M.; Iqbal, S. Optimal Scheduling of Campus Microgrid Considering the Electric Vehicle Integration in Smart Grid. *Sensors* **2021**, *21*, 7133. [[CrossRef](#)]
105. Dini, A.; Pirouzi, S.; Norouzi, M.; Lehtonen, M. Hybrid Stochastic/Robust Scheduling of the Grid-Connected Microgrid Based on the Linear Coordinated Power Management Strategy. *Sustain. Energy Grids Netw.* **2020**, *24*, 100400. [[CrossRef](#)]
106. Rezaei, E.; Dagdougui, H. Optimal Real-Time Energy Management in Apartment Building Integrating Microgrid with Multizone HVAC Control. *IEEE Trans. Ind. Inform.* **2020**, *16*, 6848–6856. [[CrossRef](#)]
107. Gupta, R.K.; Kumar, A. Synergistic Frequency Regulation in Microgrids: Pioneering a Controller for Seamless Integration of Wave Energy Conversion Systems. *Electr. Eng.* **2024**. [[CrossRef](#)]
108. Manoharan, P.; Chandrasekaran, K.; Chandran, R.; Ravichandran, S.; Mohammad, S.; Jangir, P. An Effective Strategy for Unit Commitment of Microgrid Power Systems Integrated with Renewable Energy Sources Including Effects of Battery Degradation and Uncertainties. *Environ. Sci. Pollut. Res.* **2024**, *31*, 11037–11080. [[CrossRef](#)]
109. Hussain, A.; Kim, H.-M. Goal-Programming-Based Multi-Objective Optimization in Off-Grid Microgrids. *Sustainability* **2020**, *12*, 8119. [[CrossRef](#)]
110. Abid, M.S.; Ahshan, R.; Al Abri, R.; Al-Badi, A.; Albadi, M. Techno-Economic and Environmental Assessment of Renewable Energy Sources, Virtual Synchronous Generators, and Electric Vehicle Charging Stations in Microgrids. *Appl. Energy* **2024**, *353*, 122028. [[CrossRef](#)]
111. Lakshmi, S.E.; Singh, S.P.; Padmanaban, S.; Leonowicz, Z.; Holm-Nielsen, J. Prosumer Energy Management for Optimal Utilization of Bid Fulfillment with EV Uncertainty Modeling. *IEEE Trans. Ind. Appl.* **2022**, *58*, 599–611. [[CrossRef](#)]

112. Dhingra, K.; Singh, M. Frequency Support in a Microgrid Using Virtual Synchronous Generator Based Charging Station. *IET Renew. Power Gener.* **2018**, *12*, 1034–1044. [[CrossRef](#)]
113. Gonzalez-Rivera, E.; Garcia-Trivino, P.; Sarrias-Mena, R.; Torreglosa, J.P.; Jurado, F.; Fernandez-Ramirez, L.M. Model Predictive Control-Based Optimized Operation of a Hybrid Charging Station for Electric Vehicles. *IEEE Access* **2021**, *9*, 115766–115776. [[CrossRef](#)]
114. Koseoglou, M.; Tsioumas, E.; Papagiannis, D.; Jabbour, N.; Mademlis, C. A Novel On-Board Electrochemical Impedance Spectroscopy System for Real-Time Battery Impedance Estimation. *IEEE Trans. Power Electron.* **2021**, *36*, 10776–10787. [[CrossRef](#)]
115. Zecchino, A.; Rezkalla, M.; Marinelli, M. Grid Frequency Support by Single-Phase Electric Vehicles: Fast Primary Control Enhanced by a Stabilizer Algorithm. In Proceedings of the 2016 51st International Universities Power Engineering Conference (UPEC), Coimbra, Portugal, 6–9 September 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–6. [[CrossRef](#)]
116. Li, Y.; Mohammed, S.Q.; Nariman, G.S.; Aljojo, N.; Rezvani, A.; Dadfar, S. Energy Management of Microgrid Considering Renewable Energy Sources and Electric Vehicles Using the Backtracking Search Optimization Algorithm. *J. Energy Resour. Technol.* **2020**, *142*, 052103. [[CrossRef](#)]
117. Zhao, T.; Xiao, J.; Koh, L.H.; Wang, P.; Ding, Z. Strategic Day-Ahead Bidding for Energy Hubs with Electric Vehicles. In Proceedings of the 2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2), Beijing, China, 20–22 October 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6. [[CrossRef](#)]
118. Mistry, R.D.; Eluyemi, F.T.; Masaud, T.M. Impact of Aggregated EVs Charging Station on the Optimal Scheduling of Battery Storage System in Islanded Microgrid. In Proceedings of the 2017 North American Power Symposium (NAPS), Morgantown, WV, USA, 17–19 September 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–5. [[CrossRef](#)]
119. Azarhooshang, A.; Sedighizadeh, D.; Sedighizadeh, M. Two-Stage Stochastic Operation Considering Day-Ahead and Real-Time Scheduling of Microgrids with High Renewable Energy Sources and Electric Vehicles Based on Multi-Layer Energy Management System. *Electr. Power Syst. Res.* **2021**, *201*, 107527. [[CrossRef](#)]
120. Wang, Y.; Wang, B.; Chu, C.-C.; Pota, H.; Gadh, R. Energy management for a commercial building microgrid with stationary and mobile battery storage. *Energy Build.* **2016**, *116*, 141–150. [[CrossRef](#)]
121. Silva, J.A.A.; López, J.C.; Arias, N.B.; Rider, M.J.; Da Silva, L.C.P. An optimal stochastic energy management system for resilient microgrids. *Appl. Energy* **2021**, *300*, 117435. [[CrossRef](#)]
122. Wang, Q.-Y.; Lv, X.-L.; Zeman, A. Optimization of a multi-energy microgrid in the presence of energy storage and conversion devices by using an improved gray wolf algorithm. *Appl. Therm. Eng.* **2023**, *234*, 121141. [[CrossRef](#)]
123. Balasubramaniam, K.; Saraf, P.; Hadidi, R.; Makram, E.B. Energy management system for enhanced resiliency of microgrids during islanded operation. *Electr. Power Syst. Res.* **2016**, *137*, 133–141. [[CrossRef](#)]
124. Vijayan, M.; Udumula, R.R.; Mahto, T.; KM, R.E. A novel multi-port high-gain bidirectional DC–DC converter for energy storage system integration with DC microgrids. *J. Energy Storage* **2024**, *87*, 111431. [[CrossRef](#)]
125. Spiliotis, K.; Gonçalves, J.E.; Saelens, D.; Baert, K.; Driesen, J. Electrical system architectures for building-integrated photovoltaics: A comparative analysis using a modelling framework in Modelica. *Appl. Energy* **2020**, *261*, 114247. [[CrossRef](#)]
126. Fei, L.; Shahzad, M.; Abbas, F.; Muqet, H.A.; Hussain, M.M.; Bin, L. Optimal Energy Management System of IoT-Enabled Large Building Considering Electric Vehicle Scheduling, Distributed Resources, and Demand Response Schemes. *Sensors* **2022**, *22*, 7448. [[CrossRef](#)]
127. Zhu, W.; Guo, J.; Zhao, G. Multi-Objective Dispatching Optimization of an Island Microgrid Integrated with Desalination Units and Electric Vehicles. *Processes* **2021**, *9*, 798. [[CrossRef](#)]
128. Farinis, G.K.; Kanellos, F.D. Integrated energy management system for Microgrids of building prosumers. *Electr. Power Syst. Res.* **2021**, *198*, 107357. [[CrossRef](#)]
129. Coelho, V.N.; Coelho, I.M.; Coelho, B.N.; de Oliveira, G.C.; Barbosa, A.C.; Pereira, L.; de Freitas, A.; Santos, H.G.; Ochi, L.S.; Guimarães, F.G. A communitarian microgrid storage planning system inside the scope of a smart city. *Appl. Energy* **2017**, *201*, 371–381. [[CrossRef](#)]
130. Zheng, Y.; Xue, X.; Xi, S.; Xin, W. Enhancing microgrid sustainability: Dynamic management of renewable resources and plug-in hybrid electric vehicles. *J. Clean. Prod.* **2024**, *450*, 141691. [[CrossRef](#)]
131. Stone, D. Modelling and Sizing Sensitivity Analysis of a Fully Renewable Energy-based Electric Vehicle Charging Station Microgrid. In Proceedings of the PCIM Europe 2024—International Exhibition and Conference for Power Electronics, Intelligent Motion, Renewable Energy and Energy Management, Nürnberg, Germany, 11–13 June 2024; VDE VERLAG GMBH: Berlin, Germany, 2024.
132. Muhssin, M.T.; Cipcigan, L.M.; Obaid, Z.A. Small Microgrid stability and performance analysis in isolated island. In Proceedings of the 2015 50th International Universities Power Engineering Conference (UPEC), Stoke on Trent, UK, 1–4 September 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 1–6. [[CrossRef](#)]
133. Abdunnasser, G.; Ali, A.; Shaaban, M.F.; Mohamed, E.E.M. Stochastic multi-objectives optimal scheduling of energy hubs with responsive demands in smart microgrids. *J. Energy Storage* **2022**, *55*, 105536. [[CrossRef](#)]
134. Chouaf, W.; Abbou, A.; Bouaddi, A. Energy management for an AC island microgrid using dynamic programming. *Int. J. Renew. Energy Res.* **2022**, *12*, 2223–2236. [[CrossRef](#)]
135. Guo, S.; Li, P.; Ma, K.; Yang, B.; Yang, J. Robust energy management for industrial microgrid considering charging and discharging pressure of electric vehicles. *Appl. Energy* **2022**, *325*, 119846. [[CrossRef](#)]

136. Kumar, P.; Pawar, R. Robust control strategy for power/frequency regulation in autonomous microgrid system. *Energy Sources Part A* **2023**, *45*, 6834–6855. [[CrossRef](#)]
137. Elizabeth Michael, N.; Hasan, S.; Mishra, S. Virtual inertia provision through data centre and electric vehicle for ancillary services support in microgrid. *IET Renew. Power Gener.* **2020**, *14*, 3792–3801. [[CrossRef](#)]
138. Mahmud, M.A.; Hossain, M.J.; Pota, H.R.; Oo, A.M.T. Robust Nonlinear Distributed Controller Design for Active and Reactive Power Sharing in Islanded Microgrids. *IEEE Trans. Energy Convers.* **2014**, *29*, 893–903. [[CrossRef](#)]
139. Datta, J.; Das, D. Energy Management of multi-microgrids considering impacts of plug-in hybrid vehicles uncertainties and demand response. In Proceedings of the 2021 47th Annual Conference of the IEEE Industrial Electronics Society (IECON), Toronto, ON, Canada, 13–16 October 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 1–6. [[CrossRef](#)]
140. Hosseini, S.M.; Carli, R.; Dotoli, M. Robust Optimal Energy Management of a Residential Microgrid Under Uncertainties on Demand and Renewable Power Generation. *IEEE Trans. Autom. Sci. Eng.* **2021**, *18*, 618–637. [[CrossRef](#)]
141. Gupta, V.; Maurya, A.K.; Ahuja, H. Vehicle to Grid Technologies Resolving Micro Grid Power Intermittencies Issues. In Proceedings of the 2023 9th IEEE India International Conference on Power Electronics (IICPE), Sonipat, India, 28–30 November 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–5. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.