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Systematic Review

A Systematic Review of Model Predictive Control for Robust and Efficient Energy Management in Electric Vehicle Integration and V2G Applications

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Abstract: The increasing adoption of electric vehicles has introduced challenges in maintaining grid stability, energy efficiency, and economic optimization. Advanced control strategies are required to ensure seamless integration while enhancing system reliability. This study systematically reviews predictive control applications in energy systems, particularly in electric vehicle integration and bidirectional energy exchange. Using the PRISMA 2020 methodology, 101 high-quality studies were selected from an initial dataset of 5150 records from Scopus and Web of Science. The findings demonstrate that predictive control strategies can significantly enhance energy system performance, achieving up to 35% reduction in frequency deviations, 20–30% mitigation of harmonic distortion, and a 15–20% extension of battery lifespan. Additionally, hybrid approaches combining predictive control with adaptive learning techniques improve system responsiveness by 25% under uncertain conditions, making them more suitable for dynamic and decentralized networks. Despite these advantages, major barriers remain, including high computational demands, limited scalability for large-scale electric vehicle integration, and the absence of standardized communication frameworks. Future research should focus on integrating digital modeling, real-time optimization, and machine learning techniques to improve predictive accuracy and operational resilience. Additionally, the development of collaborative platforms and regulatory frameworks is crucial for large-scale implementation.

Keywords: model predictive control; energy management; V2G; frequency stability; AI; fuzzy logic; distributed energy resource; microgrids

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1. Introduction

The urgent need to reduce greenhouse gas emissions and transition toward cleaner energy solutions has accelerated the adoption of electric vehicles (EVs) and renewable energy sources (RES). EVs offer a promising solution for decarbonizing the transportation sector while also serving as flexible energy storage units. However, their large-scale integration into power grids introduces significant operational challenges, including grid instability, frequency deviations, and increased energy management complexity due to the intermittent nature of RES and the variability in EV charging behaviors. To address these challenges, advanced control strategies are required to optimize energy flow, enhance grid stability, and improve overall efficiency. Predictive control methodologies have gained attention for their ability to anticipate fluctuations and dynamically manage energy resources. Among these, Model Predictive Control (MPC) stands out as an effective approach, offering real-time optimization and adaptability to uncertain conditions. By leveraging system models under specific constraints, MPC enables frequency and voltage stabilization, power quality improvements, and efficient energy scheduling in EV-integrated networks. Despite its advantages, several barriers hinder the large-scale adoption of predictive control in EV-grid integration, including computational complexity, scalability limitations, and interoperability challenges. Given these issues, there is a critical need to systematically analyze and evaluate the role of predictive control methodologies in this domain. This study aims to provide a comprehensive review of MPC applications in EV energy systems, identifying key advancements, limitations, and future research directions to enhance its effectiveness and facilitate its widespread implementation.

Optimizing the operation of isolated microgrids is of critical importance; for instance, as noted in [1], a two-layer MPC leveraging a seasonal autoregressive integrated moving average (SARIMA) model is adopted for power flow optimization. Numerous studies have analyzed the bidirectional energy transmission capabilities of EV chargers, which allow them to serve dual functions of consumption and supply [2–4]. However, despite the significant advancements in MPC-based energy management, a systematic and structured synthesis of its role, limitations, and future potential in V2G systems and microgrids remains lacking. This capability enables efficient energy management during peak demand hours through discharging and recharging during low-demand periods. Furthermore, EVs can be utilized as distributed energy storage units [5]. The reliability of management and control systems in microgrids (MGs) is closely linked to the communication networks employed [6]. Therefore, it is essential to have effective communication tools that facilitate information exchange among MG participants and the grid. The V2G approach provides various services, such as reactive power compensation, voltage regulation, harmonic filtering, and primary frequency control. These services require a robust connection to enable seamless communication between the charging infrastructure and EVs. The V2G concept also offers numerous advantages. For example, a household can utilize the energy stored in an EV battery during peak hours when electricity prices are high to power home appliances. Conversely, the EV battery can be recharged at night when energy prices are lower. It is important to note that this scenario is only feasible in countries where energy prices vary according to consumption periods [7]. According to [8], the satisfaction level of EV owners after participating in V2G applications is a crucial factor that will directly influence future participation. Since V2G operations impact vehicle battery health, this approach remains somewhat controversial. For this reason, the discharge rate is a critical area of study, as high discharge rates can negatively affect battery degradation. It is essential to consider this parameter because EV batteries can participate in frequency regulation analysis via V2G technology. In this regard, ref. [9] estimates that EVs with a state of charge (SoC) below 80% or above 90% are not controlled and, therefore, cannot participate in V2G control schemes.

Meanwhile, EV user behavior is becoming increasingly significant. Thus, there is a pressing need to develop an energy management model for MGs that incorporates EV interaction with the grid, considering user behaviors to adapt to an environment of uncertainties with higher penetration of renewable energy sources (RES). Consequently, ref. [10,11] suggest that establishing an EV aggregator is necessary, as the aggregator's role is to facilitate EV integration into the electricity market. The assistance framework analyzed in [12], such as ancillary services provided at both transmission and distribution levels, is of interest as it helps maintain the reliability of power system operations. For EVs integrated into V2G, these ancillary services (Electric Vehicle Ancillary Services, EVAS) provide support in frequency regulation, frequency contingencies, inertia, voltage regulation, and more. Therefore, it is essential to address gaps in control and optimization strategies to ensure the practical application of these services without introducing significant computational burdens or requiring substantial economic investment. Regarding the Sizing of Energy Storage Systems (ESS), ref. [7] highlights certain advantages and disadvantages of optimization methodologies for ESS. For instance, with linear programming (LP), the objective function must always be linear, which can be challenging to achieve in MG systems. Nonlinear programming (NLP), on the other hand, involves iterative calculations, making it computationally expensive. Heuristic methods do not guarantee an optimal solution, which may lead to inaccuracies in decision-making and insufficient data selection. Stochastic methods may rely on overly simplistic and unrealistic assumptions, and their models are often too complex from a computational perspective, requiring more advanced statistical and computational knowledge than simpler deterministic models [13]. Dynamic programming, which solves problems recursively, increases process complexity. Fuzzy logic produces results that are not always precise, leading to potential confusion with probability hypotheses. Lastly, neural networks require processors with parallel processing capabilities [7], increasing the complexity of iteration and processing.

On the other hand, the large number of control variables for different network elements and control timescales necessitate the development of new optimal control techniques. Among these, the Model Predictive Control (MPC) approach has gained popularity in recent research. As noted in [14], MPC enables superior performance optimization with multivariable constraints across various applications, such as industrial automation and plug-in electric vehicles [15]. Furthermore, ref. [16] states that conventional control methods may no longer be effective given the fluctuating output of renewable energy sources. Hence, MPC, with its fast transient characteristics, emerges as a viable solution to these challenges. MPC techniques are applied at both the converter and grid levels of the microgrid. The predictive model, cost function, and resolution algorithm are the three critical components of MPC. The predictive model generates signals for power converters, while the cost function provides dispatch instructions for distributed generators. At the grid level, MPC designs predictive models, cost functions, and resolution algorithms to control, for example, the capacity of energy storage systems within the microgrid and the power flows among distributed energy resources (DERs), offering forecasts of future states based on current and historical states [1,17]. The authors in [18] suggest that adopting MPC with a receding horizon strategy is appropriate for real-time scheduling and energy management. Given the uncertainty in renewable energy production, stochastic model predictive control (SMPC) is recommended as it enables cost-efficient energy management for microgrids. To leverage MPC's predictive advantage and address communication delays in distributed control, while ref. [2] propose the development of Distributed Model Predictive Control (DMPC). This strategy enables EV chargers to exploit V2G reactive power capabilities and participate in real-time voltage regulation for both balanced and unbalanced distributed networks without interfering with active power exchange. The authors in [19] propose a frequency regulation method for an isolated MG comprising RES, diesel generators, and consumers, employing two independent control techniques: MPC and Adaptive Droop Control (ADC). These techniques mitigate power imbalances in the MG through effective control of RES and EV battery charging/discharging. In [20], the authors present a robust MPC algorithm with a Linear Quadratic Regulator (LQR-RMPC) to design a frequency controller for a group of MGs.

The method uses dynamic state feedback gain to enhance system robustness, while the quadratic linear regulator optimizes control variables under constraints, improving system stability. In [21], the authors introduce a two-layer MPC approach that optimizes the charging and discharging of aggregated EVs while simultaneously distributing energy across the upper and lower layers. On the other hand, ref. [22] proposes a two-layer multiple

Model Predictive Control (TLMMPC) method comprising nominal and auxiliary predictive models to send effective control signals to energy storage systems, enhancing system frequency performance. The authors in [23] explore the use of fuzzy logic controllers (FLC), a type of AI, for hybrid MG (HMG) operations. However, their application is limited due to higher memory requirements and additional parameter demands. Several authors suggest metaheuristic strategies to adjust controller gains. The study [24] proposes implementing an intelligent charge and discharge management system based on fuzzy logic for EV batteries to improve V2G and G2V performance. Meanwhile, in [25] the authors integrate Gaussian processes into a learning-based MPC to demonstrate how model learning enhances overall control performance by improving MPC predictions. Meanwhile, ref. [26] introduce a novel approach combining robust and stochastic MPC (RS-MPC) with granular models to address online dispatch problems effectively, tackling uncertainties in RES output and load demand. Additionally, ref. [27] examines a robust optimization algorithm designed to handle uncertainties in RES generation and industrial loads, analyzing the impact of various scenarios on stable MG operations. Finally, ref. [28] compares PID controllers with MPC through simulations, employing a battery discharging into a resistive load, concluding that synchronous reinforcement configuration is required.

Despite its numerous advantages, the MPC approach has certain limitations that may hinder optimal performance. These include the lack of scalable solutions for managing large EV fleets and distributed networks, as well as robust optimization strategies for MGs with high renewable energy penetration. Advanced techniques incorporating AI and fuzzy logic to address challenges such as computational costs, battery health, and user behavior also remain underdeveloped [29]. Modeling under these uncertainties becomes increasingly complex, and the choice of control models depends heavily on the quality and availability of data for analysis.

To address this gap, this study provides a systematic review of MPC applications in EV integration and V2G technologies, structured under the PRISMA 2020 methodology to ensure transparency and reproducibility. The main contributions of this research are as follows:

- Comprehensive Classification of MPC Strategies: The study categorizes MPC applications into four key areas: (i) energy management in V2G applications, (ii) frequency control in renewable-dominated networks, (iii) advanced control techniques using AI and fuzzy logic, and (iv) microgrid optimization, providing a structured framework for future research [1,17].
- Quantitative Impact Assessment: This review consolidates empirical findings from recent studies, highlighting key performance metrics such as a 35% reduction in frequency deviations, 20–30% mitigation of total harmonic distortion (THD), and 15–20% extension of battery lifespan when MPC is applied in EV-grid integration [9,19]. These insights offer a data-driven foundation for evaluating MPC's effectiveness.
- Emerging Trends and Research Gaps: The study identifies critical barriers to MPC implementation, such as computational complexity, scalability issues, and interoperability challenges in V2G systems. Additionally, it highlights the potential of hybrid approaches, such as the integration of MPC with AI-based learning models and digital twins, to enhance predictive accuracy and system adaptability [25,26].
- Decision-Support Framework for Policymakers and Researchers: By systematically analyzing over 100 high-quality studies, this work serves as a decision-support tool for researchers, grid operators, and policymakers aiming to optimize renewable energy integration and smart grid stability through predictive control mechanisms [28,29].

This article is structured into four sections: Section 2 specifies the review methodology employed, PRISMA 2020, divided into four phases: Phase 1 (Identification), Phase 2

(Screening), Phase 3 (Eligibility), and Phase 4 (Synthesis). Section 3 presents the results and discussion based on the different phases of the MPC approaches for MGs with EV and V2G integration. Section 4 provides a critical discussion of the reviewed MPC techniques guided by the PRISMA methodology. Finally, Section 5 concludes the study.

2. Methodology for Selecting Studies

The methodology for this systematic review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). PRISMA Statement 2020 provides a detailed checklist and flow diagram to guide researchers in systematically identifying, screening, and including studies, ensuring reproducibility and methodological integrity. Its adaptability across disciplines makes it particularly well-suited for interdisciplinary topics like energy systems and engineering, where diverse methodologies and findings need to be synthesized. Unlike domain-specific frameworks such as MOOSE or GRADE, PRISMA offers a flexible structure applicable across a variety of scientific domains, making it an ideal choice for exploring the application of Model Predictive Control in EV integration and V2G technologies. The methodology begins with the Identification phase, during which relevant studies are retrieved from multiple academic databases using predefined search strategies to capture a comprehensive dataset. Subsequently, the Screening phase evaluates titles and abstracts to exclude studies that fail to align with established inclusion criteria, such as relevance, document type, and publication language. The process then progresses to the Eligibility phase, involving a meticulous review of the full texts to verify their methodological quality, data reliability, and thematic relevance. Finally, the Synthesis phase integrates the selected studies, conducting detailed analyses to summarize their findings and derive conclusions that address the review objectives. Figure 1 provides a streamlined visual representation of these phases.

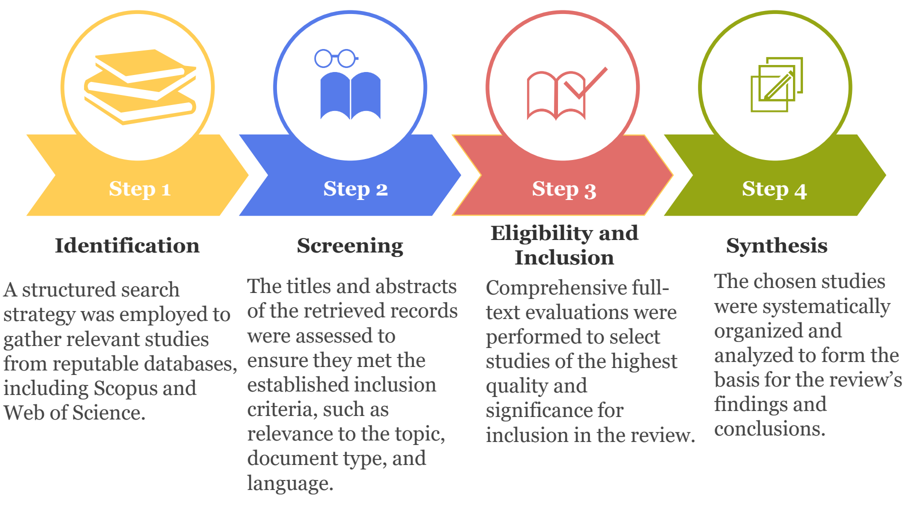

Figure 1. PRISMA 2020-based workflow for systematic review: A step-by-step representation of the study selection process, detailing the sequential phases of Identification, Screening, Eligibility, and Synthesis.

The systematic review methodology designed in this study aims to answer four research questions:

RQ1—How has Model Predictive Control been applied in energy management for power systems integrating electric vehicles (EVs) and Vehicle-to-Grid (V2G) technologies in the recent literature?

This question guides the identification of relevant studies that explore MPC's role in enhancing grid stability, energy quality, and operational efficiency in systems with high EV and V2G penetration.

RQ2—What are the key technological advancements and optimization strategies in MPC that have demonstrated improvements in grid stability, uncertainty management, and economic efficiency in EV and V2G-integrated systems?

This addresses the major findings on how MPC helps mitigate frequency fluctuations, total harmonic distortion, and battery degradation, as well as the integration of hybrid approaches with artificial intelligence and fuzzy logic.

RQ3—What are the current barriers and limitations in the large-scale implementation of MPC for EV integration in power systems, and how can they be overcome?

This question analyzes the challenges identified in the literature, such as computational complexity, scalability for large EV fleets, and the lack of global standards for V2G interoperability.

RQ4—How can emerging technologies such as digital twins, deep learning, and distributed optimization enhance the predictive accuracy and operational resilience of MPC in decentralized power networks?

This question connects the study's findings with future research directions, exploring how new technological tools can strengthen MPC's capabilities and facilitate its more effective implementation in modern energy systems.

2.1. Identification Stage (Database Search and Removal of Duplicated)

The identification stage involved a systematic search in two prominent bibliographic databases: Scopus and Web of Science (WoS). These platforms were selected for their broad coverage of peer-reviewed literature, encompassing diverse fields such as engineering, energy systems, and control theory. Scopus, recognized for its advanced search capabilities and extensive index of journals and conference proceedings, offers access to publications from leading publishers, including IEEE, Elsevier, and Springer. WoS complements this with its curated collection of high-impact journals and conference materials, ensuring a comprehensive retrieval of relevant studies.

The search strategy targeted publications from 2019 to 2024, focusing on recent advancements in Model Predictive Control for electric vehicle integration and Vehicle-to-Grid systems. Inclusion criteria limited the dataset to original research articles and conference papers published in English, ensuring consistency and accessibility. Excluded document types comprised editorials, review articles, letters, policy briefs, theses, books, and book chapters. Additionally, only studies with full-text availability, either via institutional subscriptions or open access, were eligible for further consideration.

Database-specific queries were carefully tailored to maximize relevance. The Scopus query was as follows:

TITLE-ABS-KEY ((“predictive control”) AND ((“electric vehicle”) OR (“v2g”))) AND PUBYEAR > 2018 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE, “cp”) OR LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO (LANGUAGE, “English”))

The Web of Science query used a similar structure, targeting relevant fields while applying refinement filters:

(ALL = (predictive control)) AND (ALL = (electric vehicle)) OR (ALL = (v2g))
Refined by: Publication year range: 2019–2024, Document Type: Article or Proceeding Paper, Language: English

The initial search retrieved 1739 records from Scopus and 4484 from WoS. To facilitate bibliographic management, records from Scopus were labeled with the prefix S-XXXX, while those from Web of Science were marked as WoS-XXXX, ensuring clear source identification throughout the review process. A bibliographic reference manager was then used to identify and remove 1073 duplicates, yielding a refined dataset of 5150 unique records. The final dataset comprised 33.5% Scopus entries and 66.5% WoS entries, with 89.5% classified as journal articles and 10.5% as conference papers.

2.2. Screening Phase (Title and Abstract Filtering)

In the Screening Phase, 5150 records identified during the previous stage were filtered by reviewing their titles and abstracts to assess their alignment with the research objectives. This process aimed to retain studies that directly addressed advancements in energy management for microgrids, particularly those integrating storage systems and electric vehicles, while systematically excluding irrelevant or redundant entries. The screening procedure was meticulously designed to ensure consistency and rigor, relying on a set of predefined inclusion criteria to evaluate each record

The inclusion criteria applied during this phase were as follows:

1. **Publication Year:** Only studies published between 2019 and 2024 were included, ensuring that the review captured recent developments in the rapidly evolving fields of energy management and EV integration.
2. **Document Type:** The dataset was restricted to original research articles and conference proceedings, excluding review articles, editorials, letters, and opinion pieces that lack primary data or empirical methodologies.
3. **Language:** Only English-language studies were considered, as English serves as the predominant language in global academic communication, ensuring accessibility to a wide research audience.
4. **Full-Text Availability:** Full-text access was a prerequisite for inclusion, allowing for a comprehensive evaluation of each study's methodology, results, and conclusions.
5. **Thematic Relevance:** Studies had to explicitly focus on the application, design, optimization, or development of MPC in EV integration and V2G technologies to ensure relevance to the review objectives.

During this phase, each study underwent a binary evaluation, where the title and abstract were carefully reviewed to determine whether they met all predefined inclusion criteria. Of the 5150 items initially identified, 443 studies (8.6%) fulfilled the refined criteria, which included publication year, document type, language, full-text availability, and thematic relevance. This rigorous screening ensured the retention of high-quality studies directly aligned with the research objectives.

The bibliometric analysis of the screened dataset revealed a strong concentration of studies published by specific leading publishers. The distribution of studies among major publishers is as follows:

- **Institute of Electrical and Electronics Engineers (IEEE):** 192 studies (43.4%)
- **Multidisciplinary Digital Publishing Institute (MDPI):** 64 studies (14.4%)
- **Elsevier Science LTD:** 54 studies (12.2%)
- **Other significant contributors:** WILEY, SPRINGER, and the IEEE Computer Society

Regarding the publication timeline, the dataset exhibited a steady increase in relevant studies over time, reflecting growing interest in the field:

- **2019:** 51 studies
- **2020:** 47 studies
- **2021:** 60 studies
- **2022:** 79 studies (notable rise)
- **2023:** 100 studies (peak)
- **2024:** 106 studies (continuing the upward trend)

These 443 studies will advance to the next stage, Eligibility and Inclusion, where they will undergo a more comprehensive evaluation. The bibliometric statistics resulting from this screening phase are illustrated in Figure 2, providing a visual representation of publisher contributions and temporal trends in the selected studies.

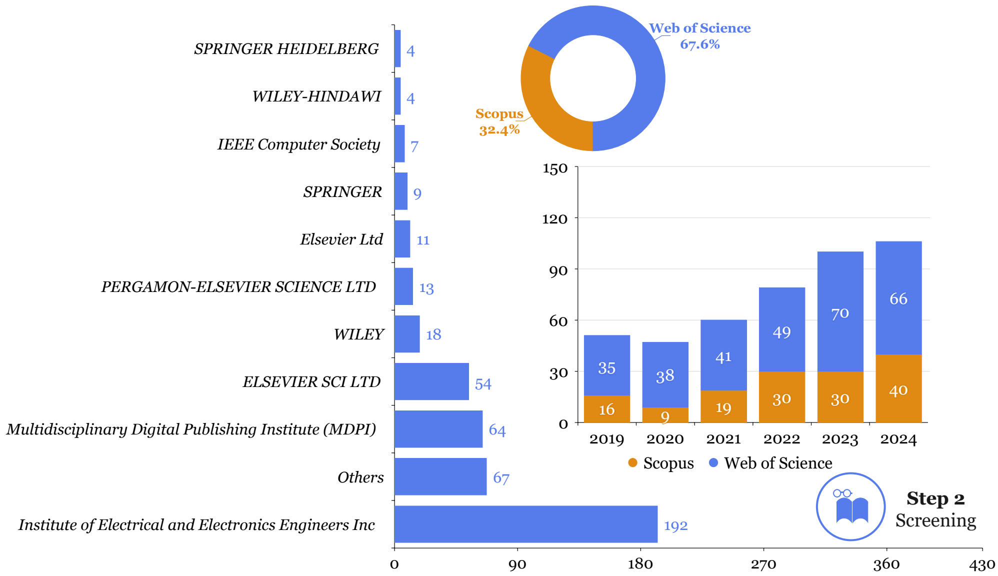

Figure 2. Bibliometric analysis of screened studies: distribution of studies by publisher and publication year.

2.3. Eligibility and Inclusion (Full-Text Evaluation)

The Eligibility and Inclusion phase involves a detailed full-text evaluation of the studies that passed the screening phase to ensure their relevance, quality, and alignment with the research objectives. This stage refines the dataset further, retaining only those studies that demonstrate methodological rigor and provide a substantial contribution to the application of MPC in EVs and V2G technologies. To achieve this, five eligibility criteria were applied, each assessed on a three-level scale to ensure a comprehensive and objective evaluation.

Eligibility Criterion 1—Alignment with Research Objectives: This criterion evaluates the extent to which a study addresses the development, optimization, or application of MPC in EV integration and V2G technologies. Studies are assessed on their focus on predictive control strategies for energy management and grid stability enhancement, with scores ranging from peripheral (1) to highly relevant (3).

Eligibility Criterion 2—Methodological Rigor: This criterion examines the robustness and appropriateness of the study's methodology, including its experimental design, simulation accuracy, and validation techniques. The assessment ensures that the methods substantiate the study's conclusions, with scores ranging from needs improvement (1) to strong (3).

Eligibility Criterion 3—Originality and Innovation: This criterion considers the novelty of the proposed solutions, control strategies, or algorithms, particularly in addressing challenges associated with predictive control and V2G systems. The scoring scale ranges from minor (1) to major (3) levels of originality and innovation.

Eligibility Criterion 4—Data Quality and Analysis: This criterion assesses the quality, reliability, and depth of the data analysis, including the clarity and reproducibility of the results presented. Studies are evaluated on a scale from satisfactory (1) to excellent (3), ensuring robust and reliable findings.

Eligibility Criterion 5—Scientific Contribution: This criterion evaluates the potential impact of the study on the field, as indicated by its contribution to advancing knowledge and its influence within the scientific community. Impact levels are scored from low (1) to high (3) based on potential scientific relevance.

Each study was rigorously evaluated against the five eligibility criteria, scored on a three-level scale (1 to 3 points), for a maximum of 15 points. To ensure the inclusion of high-quality and impactful research, a threshold of 13 out of 15 points (approximately 87%) was established. Studies scoring highest in relevance focused on MPC applications in EV and V2G scenarios or frequency regulation. Methodological rigor required robust experimental designs backed by validated simulations or empirical data. Originality and innovation were assessed based on novel control algorithms and unique strategies. Data quality and analysis emphasized reproducibility and transparency, while scientific contribution considered citation impact and influence on future research.

Requiring 13 points ensured that selected studies met high standards of quality and relevance, excelling in at least three criteria while performing strongly in others. The evaluation was conducted independently by two reviewers, adding reliability to the process. Ultimately, 101 studies surpassed the threshold, forming a methodologically sound and influential dataset. This rigorous selection process ensures that the analysis and synthesis draw upon highly relevant literature that advances MPC applications in EV and V2G technologies. Figure 3 presents the completed evaluation form, including entries from both reviewers after a thorough assessment, highlighting the items that successfully progressed through this stage. A more detailed discussion of the bibliometric analysis of the 101 studies that surpassed the eligibility threshold is discussed more deeply in the next subsection. Finally, for transparency purposes, the complete metadata of the studies selected for this systematic review can be accessed at the following GitHub repository: https://github.com/dannyochoa87/MDPI-Modelling/archive/refs/heads/main.zip (accessed on 10 February 2025).

2.4. Synthesis (Bibliometric Analysis of the Selected Studies)

The bibliometric analysis of the 101 selected studies provides key insights into their sources, temporal distribution, and academic impact (Figures 4 and 5). The dataset exhibits an H-index of 33, reflecting significant citation influence and highlighting its relevance in predictive control, energy management, and EV/V2G integration. This high H-index underscores the quality and alignment of the selected studies with cutting-edge research trends. Figure 4 visually represents their contribution to the academic discourse.

Figure 5 expands on this analysis, showcasing highlighting the dataset's robustness and relevance.

The selected studies are concentrated in high-impact IEEE journals, with *IEEE Access* leading (9 studies), followed by *Applied Energy and Energies* (8 each), *the International Journal of Electrical Power & Energy Systems* (6), *and IEEE Transactions on Transportation Electrification and Vehicular Technology* (5 each). A significant portion (25 studies) comes from other journals, reflecting interdisciplinary contributions. While most selected studies are journal articles, 10 originate from leading conferences, including SGRE 2024, the IEEE International Conference on Industrial Technology, and the ECCE, showcasing cutting-edge developments and experimental research. The temporal distribution shows dynamic growth in research interest, with 2019 having the highest contribution (26 studies), a decline in 2020 (15 studies) likely due to the global pandemic, a resurgence in 2021–2022 (22 and 15 studies), and a declining trend in 2023–2024 (13 and 10 studies), possibly due to a narrowing research focus or publication cycle lag. These trends indicate an initial expansion phase, followed by stabilization as the field matures.

N°	ID	Crit. 1	Crit. 2	Crit. 3	Crit. 4	Crit. 5	Total Score
1	S-0029	3	3	3	3	3	15
2	WoS-1597	3	3	3	3	3	15
3	WoS-3374	3	3	3	3	3	15
4	WoS-3415	3	3	3	3	3	15
5	WoS-4062	3	3	3	3	3	15
6	WoS-4416	3	3	3	3	3	15
7	S-0013	3	3	2	3	3	14
8	S-0022	3	3	2	3	3	14
9	S-0081	3	3	2	3	3	14
10	S-0286	3	3	2	3	3	14
11	S-0854	3	3	2	3	3	14
12	S-0859	3	3	2	3	3	14
13	S-1090	3	3	3	2	3	14
14	S-1277	3	3	2	3	3	14
15	S-1337	3	3	2	3	3	14
16	WoS-1950	3	3	2	3	3	14
17	WoS-2352	3	3	3	3	2	14
18	WoS-2721	3	3	2	3	3	14
19	WoS-2930	3	3	2	3	3	14
20	WoS-3186	3	3	2	3	3	14
21	WoS-3369	3	3	2	3	3	14
22	WoS-3400	3	3	2	3	3	14
23	WoS-3435	3	3	2	3	3	14
24	WoS-3506	3	3	3	3	2	14
25	WoS-3544	3	3	2	3	3	14
26	WoS-3605	3	3	3	2	3	14
27	WoS-3662	3	3	3	3	2	14
28	WoS-3673	3	3	2	3	3	14
29	WoS-3954	3	3	2	3	3	14
30	WoS-3966	3	3	2	3	3	14
31	WoS-4109	3	3	2	3	3	14
32	WoS-4215	3	3	3	3	2	14
33	WoS-4320	3	3	3	3	2	14
34	WoS-4346	3	3	3	3	2	14
35	WoS-4424	3	3	2	3	3	14
36	S-0003	3	3	2	3	2	13
37	S-0056	3	3	3	3	1	13
38	S-0090	2	3	2	3	3	13
39	S-0098	3	3	3	3	1	13
40	S-0185	3	3	3	3	1	13
41	S-0326	3	3	3	3	1	13
42	S-0446	3	3	2	3	2	13
43	S-0464	3	3	2	3	2	13
44	S-0466	3	3	3	3	1	13
45	S-0607	3	3	3	3	1	13
46	S-0640	3	3	3	3	1	13
47	S-0650	3	3	2	3	2	13
48	S-0676	3	3	3	3	1	13
49	S-0677	2	3	2	3	3	13
50	S-0716	3	3	3	3	1	13
51	S-0844	3	3	2	3	2	13
52	S-1008	3	3	2	3	2	13
53	S-1024	3	2	3	3	2	13
54	S-1113	3	3	3	3	1	13
55	S-1497	3	3	3	3	1	13
56	S-1523	3	3	2	3	2	13
57	WoS-0704	3	3	3	3	1	13
58	WoS-1450	2	3	2	3	3	13
59	WoS-1456	3	3	2	3	2	13
60	WoS-1636	3	3	3	3	1	13
61	WoS-1943	3	3	2	3	2	13
62	WoS-1979	3	3	2	3	2	13
63	WoS-2028	3	3	2	3	2	13
64	WoS-2081	3	3	3	3	1	13
65	WoS-2152	3	3	3	3	1	13
66	WoS-2199	3	3	1	3	3	13
67	WoS-2430	3	3	3	3	1	13
68	WoS-2443	3	3	3	1	3	13
69	WoS-2591	3	3	1	3	3	13
70	WoS-2636	3	3	1	3	3	13
71	WoS-2723	3	3	2	3	2	13
72	WoS-2907	3	3	2	3	2	13
73	WoS-3034	3	3	2	3	2	13
74	WoS-3231	3	3	3	3	1	13
75	WoS-3259	3	3	1	3	3	13
76	WoS-3306	3	3	3	1	3	13
77	WoS-3433	3	3	3	3	1	13
78	WoS-3468	3	3	3	3	1	13
79	WoS-3484	3	3	2	3	2	13
80	WoS-3509	3	3	2	2	3	13
81	WoS-3528	3	3	2	3	2	13
82	WoS-3567	3	3	3	1	3	13
83	WoS-3570	3	3	2	3	2	13
84	WoS-3573	3	3	2	3	2	13
85	WoS-3613	3	3	2	3	2	13
86	WoS-3622	3	3	2	3	2	13
87	WoS-3646	3	3	3	3	1	13
88	WoS-3902	3	3	3	3	1	13
89	WoS-3903	3	3	3	3	1	13
90	WoS-4029	3	3	3	3	1	13
91	WoS-4124	3	3	1	3	3	13
92	WoS-4125	3	3	2	3	2	13
93	WoS-4129	3	3	2	3	2	13
94	WoS-4208	3	3	3	3	1	13
95	WoS-4233	3	3	2	2	3	13
96	WoS-4289	3	3	2	2	3	13
97	WoS-4298	3	3	2	3	2	13
98	WoS-4306	3	3	3	3	1	13
99	WoS-4312	3	3	3	3	1	13
100	WoS-4397	3	3	3	1	3	13
101	WoS-4458	3	3	2	2	3	13

Step 3
Eligibility and Inclusion

Figure 3. Completed evaluation form for eligibility and inclusion.

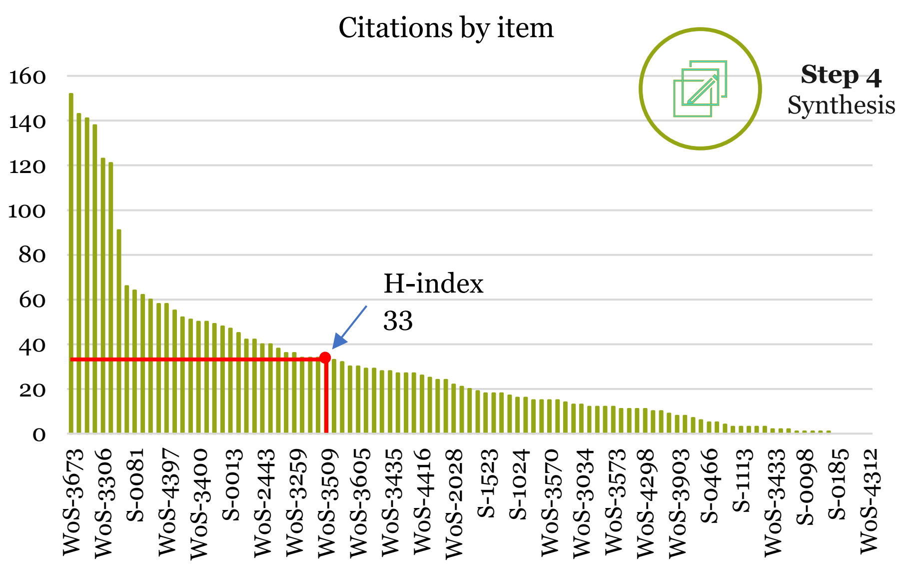

Figure 4. H-index calculation of the selected literature.

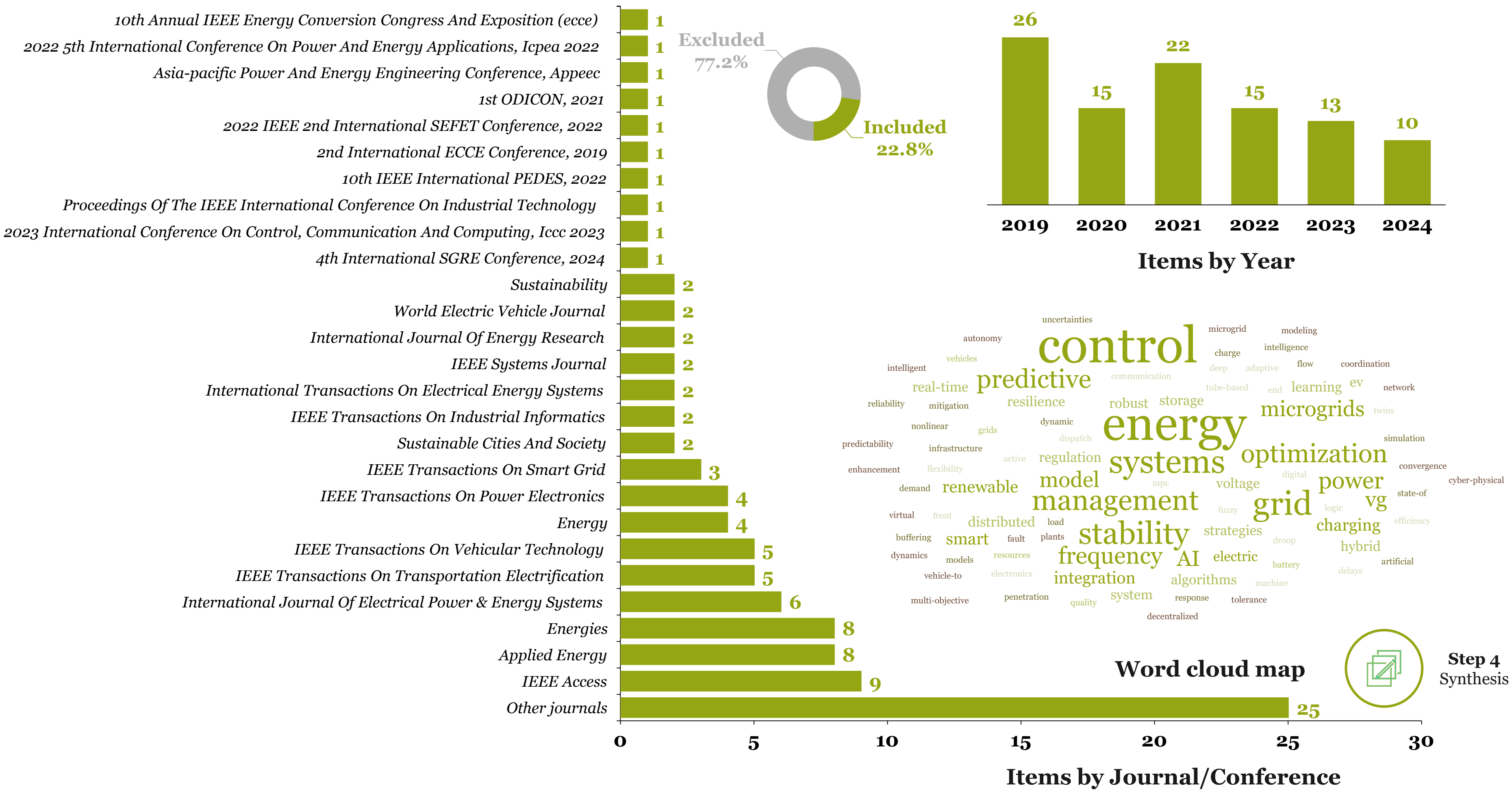

Figure 5. Bibliometric analysis of selected studies: distribution of studies across journals and conferences, temporal evolution, and word cloud map of keywords.

Finally, Figure 5 also shows a word cloud map using the keywords extracted from the selected articles to systematically organize the findings of the systematic review in a clear and structured manner. This keyword analysis allowed the identification of recurring themes, facilitating the classification of the studies into four primary subtopics for deeper examination. The most frequent keywords, such as “Model Predictive Control”, “Energy Management”, “V2G”, “Frequency Stability”, “AI”, “Fuzzy Logic”, “Distributed Energy Resources”, and “Microgrids”, served as the foundation for defining the four overarching topics:

1. Model Predictive Control (MPC) for Energy Management in EVs and V2G Applications

This subtopic focuses on the application of MPC to improve energy exchange between EVs and the grid, emphasizing efficiency and cost optimization. Key advancements include improving power quality through Active Front End (AFE) systems in V2G applications, addressing communication delays in frequency regulation, and extending battery lifecycles through techniques such as Tube-Based MPC (Tube-MPC), which efficiently mitigates uncertainties and disturbances. These studies demonstrate how MPC contributes to stable and adaptive grid management, enabling seamless EV integration.

2. Frequency Control and Stability in Renewable-Dominated Power Grids

This research area tackles the challenges of maintaining grid stability in systems with significant renewable energy penetration. Solutions focus on predictive and real-time control mechanisms to mitigate variability in renewable generation, advanced droop control strategies, and leveraging EVs as mobile energy buffers within V2G frameworks. These approaches aim to enhance grid reliability and coherence, particularly in hybrid and isolated grids where renewable energy dominates the power mix.

3. Advanced Control Techniques Using AI and Fuzzy Logic

This category explores the integration of artificial intelligence and fuzzy logic to develop advanced control systems that improve operational efficiency and resilience. Highlighted contributions include machine learning models for predicting load and generation variability, hybrid algorithms to address nonlinear disruptions, and AI-based controllers for optimizing V2G operations. The use of digital twins and deep neural networks further enhances real-time optimization and decision-making capabilities in complex and dynamic energy environments.

4. Optimization of Distributed Energy Resources and Microgrids

Research in this area centers on optimizing distributed energy resources and microgrid operations to ensure reliable energy delivery and economic sustainability. Key studies address seamless renewable energy integration, predictive optimization of energy storage and dispatch systems, and maintaining microgrid stability under fluctuating conditions. These advancements drive the development of flexible and decentralized energy systems that prioritize operational reliability and adaptability.

Figure 6 presents an infographic summarizing the key findings of the systematic review, organized into four primary subtopics. Each section highlights the core concepts, technical advancements, and practical applications, providing a visual representation of the major themes identified in the selected studies. A deeper analysis and discussion of these subtopics are provided in detail in Section 3.

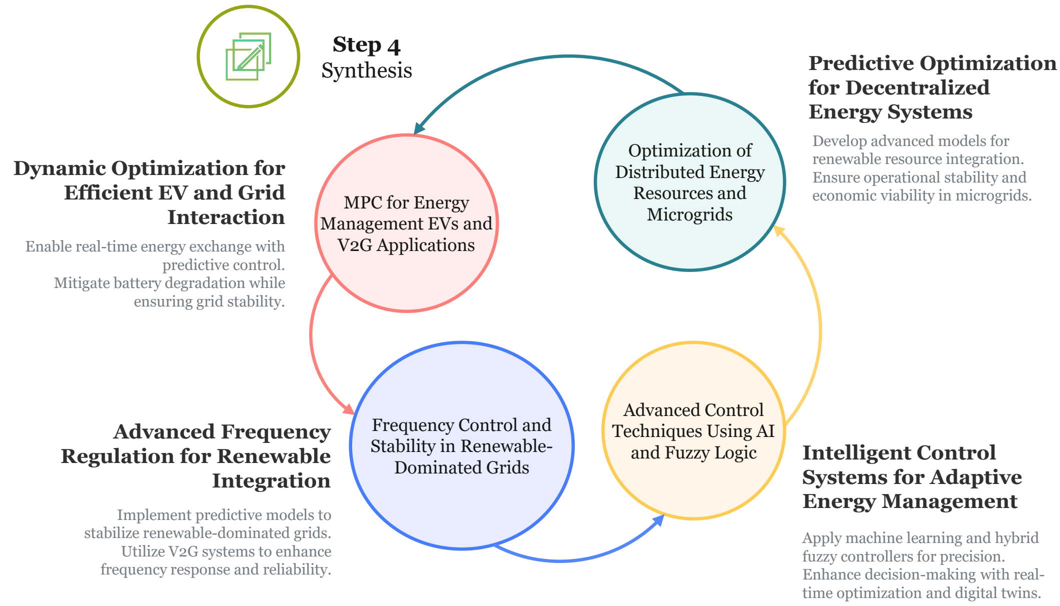

Figure 6. Infographic summarizing the four key subtopics derived from the systematic review.

Finally, Figure 7 illustrates the standardized flow diagram used for the systematic selection of studies in this investigation, developed in alignment with the PRISMA 2020 Statement. The diagram outlines each stage of the review process, including Identification, Screening, Eligibility, and Inclusion, providing a clear and structured visual representation of the methodology.

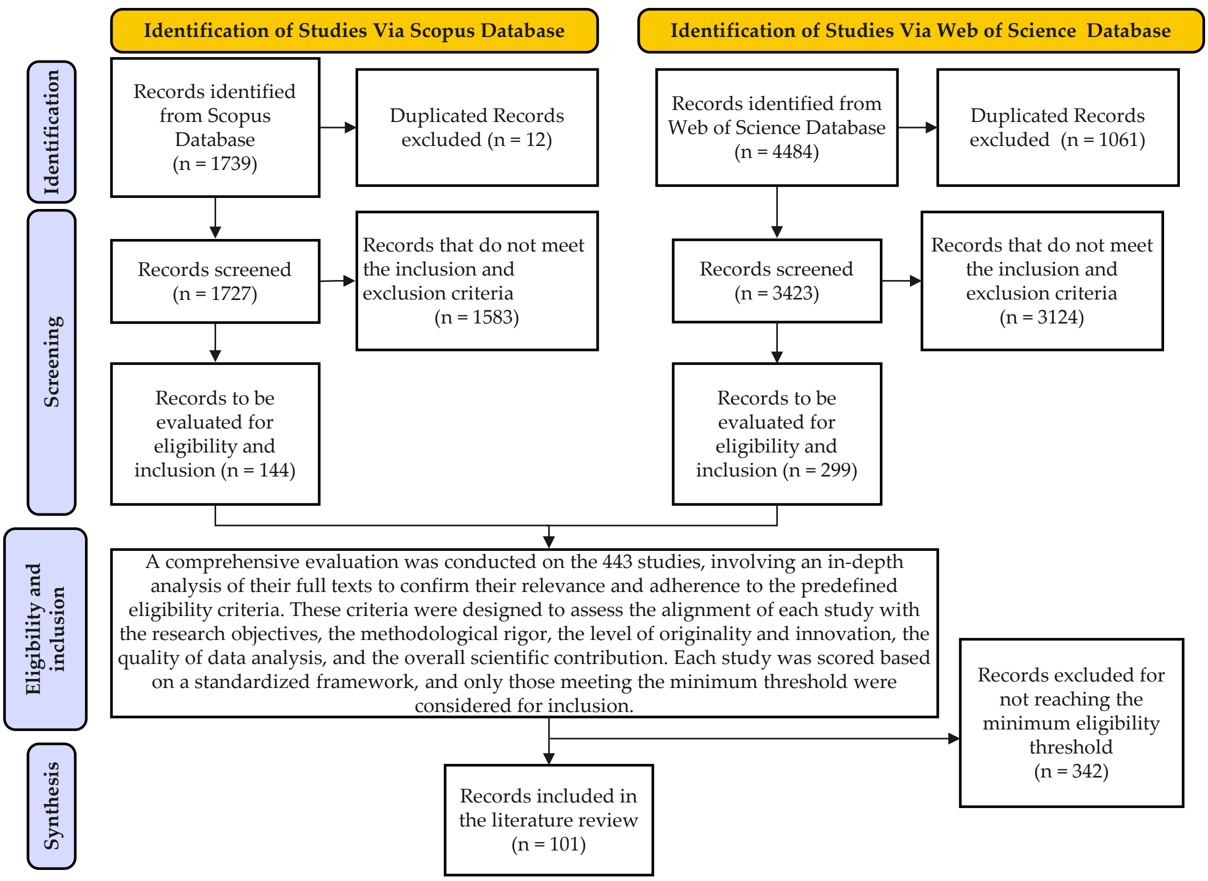

Figure 7. PRISMA 2020 flow diagram: standardized workflow depicting the systematic selection process used to refine the initial dataset into the final set of studies for analysis.

3. Results and Discussion

3.1. Model Predictive Control for Energy Management in EVs and V2G Applications

Model Predictive Control has become an essential technique in managing energy systems for electric vehicles and Vehicle-to-Grid operations [30,31]. This advanced control strategy leverages predictive models to optimize energy distribution, ensuring operational efficiency, stability, and resilience even under dynamic and uncertain conditions [32,33]. One of the key strengths of MPC lies in its ability to predict system behaviors, enabling real-time decision-making that adapts to fluctuating energy demands and renewable energy generation [34,35]. This predictive capacity allows V2G systems to provide critical ancillary services such as frequency regulation, voltage stabilization, and harmonic suppression, enhancing the overall performance of modern power grids [36,37]. Moreover, MPC's flexibility supports diverse applications, ranging from improving energy quality and mitigating operational uncertainties to innovative integrations in hybrid and isolated grid systems. By dynamically managing energy flows and EV battery usage, MPC helps to balance grid demands while minimizing battery degradation, thus ensuring long-term sustainability and cost-effectiveness [38,39].

3.1.1. Power Quality Optimization

The optimization of power quality in V2G systems has significantly evolved with the implementation of advanced strategies such as MPC [40]. These techniques have addressed critical issues related to harmonics, voltage fluctuations, and frequency regulation, offering practical solutions to improve the stability and efficiency of modern electrical systems. A notable example of MPC application in V2G systems is the use of bidirectional converters based on Dual Active Bridge (DAB) technology. These converters facilitate bidirectional energy flow with high power density while also offering features like active power factor correction and the removal of electrolytic capacitors. These features contribute to improving operational efficiency and system reliability, as demonstrated by a recent study analyzing DAB integration with predictive control [41]. Moreover, the use of MPC for regulating grid currents has shown promising results in minimizing steady-state errors and total harmonic distortions (THD). In an innovative design for bidirectional chargers, MPC has been employed to significantly reduce current fluctuations, thereby improving power quality in networks with high electric vehicle penetration [39]. The incorporation of active EMI filters with modified LCL-LC designs has shown significant effectiveness in V2G systems, especially in minimizing electromagnetic noise and high-frequency harmonics. These systems reduce the size and weight of conventional filters while delivering enhanced noise suppression, thereby improving system stability under varying load conditions [42].

Additionally, predictive control has been successfully applied in isolated networks with high penetration of renewable energies. A Tube-MPC-based approach has facilitated the smoothing of frequency trajectories and minimized deviations in emergency scenarios. This method has proven effective in managing uncertainties and disturbances, achieving stability even in microgrids with significant variations in load and generation [37]. The use of MPC combined with advanced optimization algorithms, such as SARIMA models, has been valuable for predicting prices in ancillary markets and maximizing the revenue of EV aggregators. This approach also minimizes the impact on end-users while simultaneously optimizing power quality and the economic benefits of V2G systems [35]. Another relevant contribution is the utilization of predictive controllers to manage four-phase systems in V2G applications. These controllers, integrated with adaptive repetitive control strategies (FARC), have demonstrated high effectiveness in ensuring precise current tracking and harmonic suppression under conditions of frequency fluctuations and load variations [43]. Furthermore, the incorporation of MPC-based regulators for voltage modulation in V2G systems has enabled electric vehicles to provide inertial support and voltage regulation, even in electrical networks with frequency instability. These systems have been optimized to reduce losses and maximize efficient resource utilization, standing out as a viable solution to enhance power quality [44]. In more complex systems, such as multi-layered microgrids, predictive control is also critical. A study on the implementation of MPC in microgrids with energy storage and distributed generation demonstrated how these systems can provide robust and efficient control, improving frequency stability and power quality even in highly variable scenarios [32]. Thus, the use of MPC in optimizing power quality in V2G systems has significantly transformed the interaction between electric vehicles and electrical networks [45]. These advancements effectively tackle technical issues like harmonic suppression and voltage instability while boosting overall system stability and lowering operational costs, establishing MPC-based technologies as a cornerstone for the future of sustainable energy systems [43].

3.1.2. Management of Uncertainties and Disturbances

Managing uncertainties and disturbances is crucial in the operation of dynamic electrical systems, especially those integrating V2G technologies. In this context, Tube-MPC has emerged as an advanced solution to address the inherent challenges of variability and system constraints in modern grids [46]. A notable example demonstrated its application in isolated microgrids with a high presence of EVs, where it effectively maintained stable frequency trajectories under standard conditions and efficiently managed abrupt deviations during emergencies. The design included delay margin analysis in communication, demonstrating superiority over conventional controllers such as LQR and fuzzy logic-based methods [47]. Another innovative approach employed Tube-MPC for secondary frequency regulation in power grids with renewable energy penetration and EVs. This study demonstrated how Tube-MPC can efficiently coordinate EV charging and discharging, minimizing frequency deviation errors and reducing control effort. Simulations in isolated systems highlighted its capability to handle external disturbances, positioning it as an improvement over traditional PI and standard MPC controllers [37]. The robustness of Tube-MPC has also been evaluated in multi-modal microgrids where distributed generation and storage units, including EVs, introduce high uncertainty.

A recent analysis proposed a cooperative approach to frequency management in complex operational scenarios. Results indicated that Tube-MPC provides overall system stability even under significant fluctuations in operating conditions, showcasing its utility in decentralized energy systems [48]. Furthermore, Tube-MPC-based predictive controllers designed for electric vehicles in low-inertia networks have proven effective in addressing the dynamic interaction between EVs and highly variable grids. An innovative approach utilized disturbance observers to enhance the accuracy of predictive models, reducing computational costs and improving responsiveness to transient events in the network [19]. Additionally, Tube-MPC has been successfully implemented in systems integrating mobile energy storage and renewables, such as solar and wind farms. One specific example highlighted the use of this technique to mitigate disturbances caused by rapid load variations, achieving significantly higher system stability compared to traditional methods. This breakthrough demonstrates its value in hybrid grids with demanding control requirements [49]. Finally, recent research has shown how Tube-MPC can be integrated with advanced algorithms, such as reinforcement learning, to address uncertainty scenarios in complex microgrids. This approach combines the inherent robustness of Tube-MPC with the adaptability of modern artificial intelligence techniques, enabling dynamic optimization of operational parameters and ensuring sustained stability over time [50]. These advancements show the importance of Tube-MPC in addressing uncertainties and disturbances, establishing it as a critical solution for creating resilient and sustainable electrical systems.

3.1.3. Innovative Applications

The integration of MPC in isolated and hybrid networks has enabled groundbreaking advancements in energy management, particularly in scenarios with high renewable energy penetration [51]. By leveraging predictive algorithms, MPC can address the challenges of variability and intermittency inherent to renewable energy sources, ensuring efficient and stable operation [52]. One compelling application of MPC is in isolated microgrids, where it has been utilized to enhance load-frequency control (LFC). In a specific study, a predictive controller was implemented to coordinate ESS, EVs, and renewable generation. The results showed that the system effectively managed large-scale renewable integration and dynamic load changes, significantly reducing frequency deviations and ensuring stability [49]. In hybrid microgrids, MPC has demonstrated its capacity to optimize power-sharing between various energy sources. A study highlighted the use of a novel predictive approach that accounted for uncertainties in renewable generation, such as solar and wind power, and efficiently coordinated the participation of EVs in secondary frequency regulation. The controller ensured reliable power delivery while maintaining the operational constraints of all involved components [53,54].

Another innovative application is the deployment of distributed MPC in networks with a high number of EVs acting as mobile energy storage units. A study proposed a hierarchical control framework where distributed MPC was employed to manage voltage and frequency regulation dynamically [55]. This approach improved system adaptability, reduced computational complexity, and enabled efficient integration of variable renewable energy [56]. In islanded grids with reduced inertia, MPC has been implemented to compensate for the lack of conventional synchronous generators. A study demonstrated that the predictive model effectively managed voltage and frequency fluctuations, integrating EVs and battery storage to provide inertial support. The results validated the system's ability to maintain stability under transient and dynamic conditions, even with high renewable energy penetration [32]. Furthermore, MPC has been applied in hybrid systems to optimize the operation of combined heat and power (CHP) units alongside renewable generation and EVs. The predictive control algorithm dynamically adjusted load frequency and power distribution to meet thermal and electrical demands while ensuring operational efficiency [57]. This integration proved essential in maintaining system reliability under varying load profiles and resource availability [58]. An additional study showcased the implementation of MPC in multimicrogrid systems interconnected by renewable energy and mobile storage units. The controller utilized deep learning-enhanced predictive algorithms to dynamically manage power flows and stabilize frequency across the entire network. This innovative solution demonstrated its effectiveness in scenarios with complex interdependencies and significant renewable penetration [48]. Lastly, MPC has also been employed to address challenges in systems where EVs are used to provide virtual inertia and stabilize power grids. A recent study demonstrated the feasibility of integrating MPC with virtual synchronous generator (VSG) technologies to optimize power flow, minimize frequency deviations, and enhance grid stability. This application proved particularly valuable in renewable-dominated systems prone to sudden variations in power generation [44]. These innovative applications highlight the transformative potential of MPC in isolated and hybrid grids.

3.2. Control and Stability in Renewable-Dominated Networks

3.2.1. Advanced Predictive Mechanisms

Frequency stability in renewable-dominated networks is a critical issue driven by the intermittent nature of renewable energy sources (RES) and the associated reduction in system inertia. Advanced predictive mechanisms, particularly Model Predictive Control (MPC), have emerged as essential tools for mitigating these challenges [59]. For example, MPC has been integrated with electric vehicle (EV) charging stations to function as virtual synchronous generators (VSGs), providing dynamic inertial support and enhancing frequency regulation in hybrid microgrids [60]. In networks with large-scale renewable integration, predictive approaches have been applied to stabilize frequency and reduce deviations caused by intermittent resources. For instance, a study demonstrated the effectiveness of Tube-Based MPC in smoothing frequency trajectories during emergencies while maintaining robust operations under fluctuating load and generation conditions [47]. Additionally, predictive control has been successfully employed in multimicrogrid systems, where it optimizes distributed generation and coordinates EVs to deliver ancillary services, ensuring operational stability [48]. MPC has also been used to mitigate uncertainties in hybrid microgrids by adapting control strategies in real time. These methods have shown their ability to reduce frequency fluctuations and improve system response times, even under variable renewable energy outputs and unpredictable disturbances [61]. Furthermore, by integrating SARIMA forecasting models, MPC has enhanced the efficiency of frequency regulation services, allowing energy aggregators to maximize economic returns while ensuring system stability [62].

Isolated microgrids with high renewable penetration have benefited from MPC-based virtual synchronous generators, which dynamically regulate power flow and frequency, ensuring smooth transitions under variable operating conditions. These models have demonstrated robust performance in addressing the lack of inertia and high variability in isolated systems [58]. Similarly, a predictive control strategy tailored to virtual energy routers has been applied to microgrids with distributed RES and EVs, enabling adaptive frequency and voltage regulation [56]. Moreover, predictive mechanisms have been employed to optimize the operation of EV fleets in renewable-rich grids. These methods ensure grid stability while also focusing on user-centric objectives, such as minimizing battery degradation and maximizing energy efficiency during frequency regulation [43,63]. In low-inertia networks, predictive approaches have enabled precise coordination of renewable energy sources, energy storage systems, and EVs, enhancing overall system resilience and energy quality [64]. Recent advancements in MPC have focused on hybrid networks where coordinated control of multiple subsystems, such as wind, solar, and battery storage, has led to substantial improvements in frequency stability. By leveraging real-time data, these systems adapt dynamically to changes in load and generation, maintaining operational reliability even in extreme scenarios [65,66]. Additionally, integrating predictive models into network-wide controllers has allowed for proactive frequency management in grids with substantial RES penetration [67,68]. These approaches provide real-time, adaptive solutions to the inherent challenges of renewable variability, positioning MPC as a cornerstone for modern energy systems. The adoption of predictive models in both hybrid and isolated networks has enhanced operational efficiency while guaranteeing the long-term reliability of power systems with significant renewable energy integration [19,69,70].

3.2.2. EVs as Mobile Buffers

EVs have increasingly been employed as dynamic buffers in renewable-dominated networks, addressing imbalances between generation and consumption. Their ability to act as mobile energy storage units has proven effective for mitigating both surplus and deficit scenarios in power systems. In one example, EVs were utilized for real-time frequency regulation in a renewable-dominated grid, where their bidirectional charging capabilities allowed for rapid adjustments in energy flow. This approach minimized the frequency deviations caused by intermittent renewable energy sources and ensured stable grid operations under varying conditions [71]. Similarly, EVs have been integrated into microgrids with distributed renewable energy systems to absorb excess solar or wind generation during peak hours, effectively reducing energy curtailment and improving system efficiency [72]. An innovative study demonstrated how EV fleets were managed using advanced control strategies to optimize their charging and discharging cycles, ensuring they could efficiently absorb surplus energy and provide it back to the grid during periods of high demand. This method effectively stabilized grid frequency while reducing battery degradation by precisely regulating energy flows [44]. Another project showcased the integration of EVs with multimicrogrid systems, where their mobility and storage flexibility significantly enhanced the stability of hybrid energy networks [73].

Furthermore, EV aggregators have been deployed to coordinate large fleets of EVs, providing critical ancillary services such as load balancing and peak shaving. For example, predictive algorithms allowed these aggregators to manage EV participation in balancing markets, improving the economic feasibility of their operation while maintaining grid stability [74]. In isolated grids with limited inertia, EVs were strategically dispatched to counteract renewable energy variability, achieving significant reductions in frequency and voltage fluctuations [5]. In cases of sudden renewable generation deficits, EVs have been used to inject stored energy into the grid, acting as a responsive buffer. For instance, an EV fleet operating under a centralized control system successfully mitigated load-shedding events in a high-renewable penetration network, maintaining energy supply during critical periods [75]. Similarly, in urban distribution networks, EVs contributed to voltage stabilization by dynamically adjusting their charging rates based on real-time grid conditions [76]. The potential of EVs to act as mobile buffers is further highlighted in applications involving V2G technology. A study focusing on residential microgrids demonstrated that EVs could efficiently manage power-sharing and provide spinning reserves during contingencies, improving both energy reliability and economic returns for participants [77]. Additionally, in hybrid systems combining wind, solar, and energy storage, EVs have been instrumental in achieving load-frequency control through coordinated charging and discharging strategies [47]. By leveraging their mobility and flexibility, EVs have transformed grid operations, enabling more efficient integration of renewable energy. Their function as mobile energy buffers highlights their significance beyond transportation, positioning them as essential elements of modern, renewable-focused power systems. These applications illustrate the multifaceted potential of EVs to enhance grid stability, reduce renewable curtailment, and contribute to the overall efficiency of energy systems [48,64,67].

3.2.3. Frequency Droop Control

Improvements in droop control strategies have been instrumental in enhancing the reliability of fragile grids, especially in systems with significant renewable energy integration [78]. These strategies have been instrumental in addressing frequency deviations caused by the variability and intermittency of renewable energy sources, ensuring grid stability under dynamic conditions. One notable development in droop control is the implementation of intelligent droop mechanisms that adaptively adjust power output based on grid requirements [79]. For instance, a study demonstrated how adaptive droop algorithms in microgrids could effectively balance power and stabilize frequency in islanded networks by dynamically modifying control parameters in response to load fluctuations and renewable energy variability [80]. This approach significantly enhanced the reliability of the microgrid by mitigating frequency instability without requiring additional hardware upgrades [81].

In another example, droop control integrated with electric vehicle (EV) fleets has been employed to provide ancillary services such as load-frequency control. By coordinating EV discharging rates, droop mechanisms were able to smooth frequency oscillations, even during rapid load changes and intermittent renewable generation [82]. This integration highlights the dual functionality of EVs as both mobile storage units and active contributors to frequency regulation. Droop control strategies have also evolved to incorporate virtual inertia, replicating the stabilizing effects of traditional synchronous generators. A case study on virtual synchronous generators demonstrated their ability to enhance grid stability by introducing artificial inertia into networks dominated by renewable energy sources. This method effectively reduced the rate of frequency change (ROCOF) during sudden load or generation shifts, proving crucial for grids with limited rotational inertia [49]. Additionally, hybrid droop control frameworks have been proposed to manage multi-source microgrids more effectively. These systems combine traditional droop control with advanced predictive models, enabling precise frequency regulation even under highly variable renewable energy conditions. For example, a hybrid droop control strategy in a wind-solar microgrid demonstrated superior performance in minimizing frequency deviations compared to conventional methods, highlighting its potential for widespread application [58].

The integration of robust droop control techniques with energy storage systems has further enhanced their effectiveness. By leveraging high-capacity battery systems, droop mechanisms can quickly respond to frequency deviations, ensuring reliable operation during peak demand or renewable energy shortfalls. Research showed that these configurations enhanced frequency stability while also extending the lifespan of storage systems through efficient energy management practices [83]. Moreover, advanced control algorithms such as model predictive droop control have emerged, offering greater precision and flexibility in managing grid frequency. These algorithms predict future grid states and adjust droop parameters proactively, reducing the likelihood of frequency instability. A recent application in a renewable-rich grid demonstrated how this approach could maintain frequency within acceptable limits while minimizing operational costs [61]. Droop control has also been tailored for application in hybrid AC/DC networks, addressing the unique challenges posed by these systems. By employing adaptive droop strategies, operators have successfully managed power sharing between AC and DC subsystems, ensuring stable operation even during significant load or generation changes [84]. This innovation underscores the versatility of droop control in diverse energy systems. In summary, the evolution of droop control strategies has significantly enhanced the reliability of grids vulnerable to frequency instability. By incorporating advanced algorithms, virtual inertia, and energy storage integration, these strategies have proven essential for maintaining grid stability in the face of increasing renewable penetration. Their adaptability and effectiveness position them as a cornerstone of modern power system management, ensuring resilient and reliable energy delivery [5,64,85].

3.3. Advanced Control Techniques with AI and Fuzzy Logic

The integration of AI and fuzzy logic in energy systems is becoming increasingly significant as they enhance the resilience and adaptability of modern grids. These technologies address the complexity of energy management by offering advanced methods for dealing with the variability of renewable generation and the unpredictability of load profiles [50]. AI, particularly in combination with predictive models, has transformed the operational landscape, enabling systems to anticipate and mitigate fluctuations dynamically [86,87].

3.3.1. AI-Based Predictive Models

Artificial intelligence, through neural networks and deep learning, has optimized variability management in both generation and consumption [88]. These approaches demonstrate superior accuracy in predicting energy patterns and provide effective control strategies for maintaining grid stability. For instance, deep reinforcement learning has been utilized to develop energy management systems that do not require prior knowledge of future driving information, making them highly adaptable to variable conditions [89]. Similarly, neural network-based models have been implemented to forecast load fluctuations in renewable-dominated grids, significantly reducing energy imbalances [80]. Advanced reinforcement learning techniques, such as Q-networks, have further enhanced EV charging strategies by optimizing decisions based on empirical travel patterns and fluctuating electricity prices [36]. In microgrids, predictive AI-based frameworks have been utilized to optimize multi-objective energy management. For instance, machine learning algorithms have been employed to integrate EVs as dynamic energy storage systems, improving grid resilience during renewable intermittencies and load changes [47,71].

A particularly innovative approach uses AI to improve the accuracy and responsiveness of load frequency control in hybrid microgrids. AI-enabled controllers adaptively adjust operational parameters based on real-time data, significantly reducing frequency deviations under dynamic conditions [76,90]. Fuzzy logic, a complementary technique to AI, excels at managing uncertainties and nonlinear dynamics in energy systems. Fuzzy-based controllers have been applied to electric vehicle-to-grid systems to regulate charging and discharging, ensuring optimal battery performance and minimal grid disruption during peak periods [48,58]. Hybrid systems that combine AI and fuzzy logic are particularly effective for predictive energy control. For example, fuzzy-based AI models have been used to enhance EV aggregator efficiency in frequency regulation markets. These systems predict grid conditions and dynamically allocate EV resources to stabilize frequency and voltage [50,74]. Furthermore, AI-powered predictive systems incorporating sliding mode observers and fuzzy logic have been deployed to mitigate harmonic distortions and voltage instabilities in renewable-integrated microgrids. These hybrid approaches have demonstrated exceptional performance in maintaining energy quality under varying operational conditions [61,91]. Recent advancements also highlight the integration of AI with evolutionary algorithms, such as genetic algorithms, to optimize fuzzy rule sets for complex multi-objective energy systems. These hybrid models have proven to be highly effective in adapting to grid fluctuations and improving overall system efficiency [10,92,93]. In large-scale energy networks, AI-based predictive controllers, enhanced with fuzzy logic, have enabled decentralized decision-making for renewable integration. These controllers dynamically balance supply and demand while maintaining system stability, even under high renewable penetration [62,85,94]. The incorporation of AI and fuzzy logic in predictive energy management systems represents a significant step forward in addressing the challenges of renewable energy integration [62,95,96].

3.3.2. Hybrid Controllers: Combining Traditional Algorithms and Fuzzy Logic to Solve Nonlinear Problems

The integration of traditional algorithms with fuzzy logic represents a breakthrough in addressing the inherent nonlinearities and uncertainties in modern energy systems [97]. Hybrid controllers combine the strengths of conventional control techniques, such as proportional-integral-derivative (PID) controllers, with the adaptability and robustness of fuzzy logic to offer innovative solutions for complex energy management challenges [98]. Hybrid control systems have been widely used in microgrid applications to balance the variability of renewable energy sources and stabilize system operations. For instance, the combination of PID controllers with fuzzy logic has been applied in islanded microgrids to regulate voltage and frequency under intermittent renewable generation and fluctuating loads. This hybrid approach demonstrated superior performance in mitigating frequency oscillations and maintaining grid stability compared to traditional PID systems alone [19,32].

One notable example of hybrid control is its application in EV integration within renewable energy systems. By combining fuzzy logic with traditional droop control methods, hybrid controllers have successfully managed the charging and discharging of EV batteries, ensuring system reliability while optimizing energy utilization [99]. This dual approach has proven particularly effective in reducing grid disturbances during peak periods and renewable intermittencies [38,100]. In V2G applications, hybrid controllers employing fuzzy logic and adaptive control strategies have been used to enhance the efficiency of EV aggregators. These systems dynamically adjust operational parameters based on grid conditions, offering improved frequency regulation and voltage stabilization [100,101]. Hybrid controllers have also been employed to optimize energy distribution in multimicrogrid systems. By integrating fuzzy logic with linear quadratic regulators (LQR), these controllers can handle complex interdependencies between distributed energy resources and loads, ensuring stability and resilience in dynamic environments [60,72]. Another significant development is the use of hybrid controllers in renewable-dominated power grids. For example, sliding mode control techniques have been enhanced with fuzzy logic to improve the robustness of renewable energy converters. This combination has been shown to effectively suppress harmonic distortions and maintain power quality in grids with high renewable penetration [49,102].

In systems with high penetration of distributed energy resources, hybrid controllers utilizing neural networks and fuzzy logic have been applied to predict and compensate for nonlinearities in grid behavior [103]. These controllers adaptively optimize energy flow, reducing losses and enhancing overall system efficiency [61,77]. Furthermore, hybrid approaches have proven beneficial in addressing the challenges of bidirectional power flow in advanced energy storage systems. By combining MPC with fuzzy logic, these controllers have achieved precise energy management while mitigating issues related to power quality and stability [31,104]. Hybrid controllers are also instrumental in integrating AI techniques with fuzzy logic for predictive energy management. For instance, evolutionary algorithms have been utilized alongside fuzzy logic to fine-tune control parameters, enabling efficient operation in complex scenarios such as multimicrogrid coordination [105,106]. The combination of traditional control methods and fuzzy logic in hybrid controllers represents a transformative advancement in energy system management [107]. These controllers provide the necessary adaptability and precision to address nonlinear challenges, ensuring reliability and efficiency in increasingly complex energy environments [62,94,108].

3.3.3. Digital Twins: Real-Time Simulations to Optimize Operations

The concept of digital twins has emerged as a transformative tool for real-time simulation and optimization in energy systems, especially in contexts with high penetration of renewable energy sources and EVs [109]. A digital twin replicates physical systems in a virtual environment, enabling continuous monitoring, predictive maintenance, and optimization of operations through real-time simulations. Digital twins have proven particularly effective in optimizing energy flows within microgrids [110,111]. By creating virtual replicas of the energy systems, digital twins can simulate various operational scenarios, predict potential failures, and propose strategies to maintain system stability under fluctuating loads and renewable generation [32,89]. This capability is essential in addressing the challenges of integrating intermittent renewable sources and distributed energy resources. One notable application is in the context of EV management. Digital twins of EV fleets enable dynamic simulation of charging and discharging patterns, facilitating V2G operations [112]. These virtual models allow aggregators to optimize the coordination of EVs, ensuring that they provide ancillary services such as frequency regulation and voltage stabilization while meeting user demands [82,100]. In renewable-dominated grids, digital twins are increasingly used to simulate the behavior of advanced power electronic converters. By replicating the performance of converters in real time, these tools enable the prediction and mitigation of issues such as harmonic distortions and voltage instabilities, improving overall grid reliability [101,113].

Moreover, digital twins are an interesting concept in energy storage systems. By virtually modeling battery systems, operators can predict degradation patterns and optimize charging cycles, maximizing battery life and efficiency. For instance, digital twins of hybrid energy storage systems have shown remarkable results in reducing dc-bus voltage fluctuations and ensuring stable power delivery in EV integration scenarios [60,114]. In addition to their operational benefits, digital twins support predictive maintenance by identifying and addressing potential system failures before they occur. For instance, in power grids, digital twins use real-time data and advanced algorithms to detect anomalies, enabling proactive interventions that minimize downtime and enhance resilience [50,72]. The integration of digital twins with AI and machine learning further enhances their capabilities. AI-driven digital twins can analyze large datasets generated by energy systems, enabling precise optimization of operational parameters and adaptive decision-making in response to real-time conditions [61,115]. Another critical application of digital twins is in multi microgrid systems. By simulating interactions between interconnected microgrids, digital twins facilitate the coordination of distributed energy resources, enhancing energy sharing and improving overall system stability [65,91]. Furthermore, digital twins are increasingly used in the context of renewable energy forecasting. By integrating real-time weather data, these systems can predict renewable energy output and dynamically adjust grid operations to maintain balance and reliability [31,105]. The use of digital twins extends beyond operation to planning and design. These virtual models allow energy planners to simulate different infrastructure scenarios, optimize resource allocation, and design resilient systems capable of adapting to future demands [106,108]. In conclusion, digital twins have become indispensable in the modern energy landscape, enabling real-time simulations that optimize operations, enhance reliability, and reduce costs. As their integration with AI and machine learning progresses, digital twins will continue to drive innovation in the energy sector, making it more adaptive, efficient, and resilient [62,85,94].

3.4. Optimization of Distributed Energy Resources and Microgrids

The decentralization of the energy system has become a cornerstone in addressing sustainability and resilience challenges during the transition to renewable energy models. DERs and microgrids are crucial in facilitating the integration of decentralized renewable energy generation while offering flexible and reliable solutions to meet energy demands [9,116] effectively.

3.4.1. Integration of Renewable Energy

Integrating renewable energy sources into microgrids presents significant challenges, such as managing the intermittency and variability inherent in these technologies. However, advanced control strategies have proven effective in addressing these issues. For instance, a study demonstrated the importance of predictive control systems in managing DERs, showing how these techniques can anticipate and mitigate generation fluctuations in hybrid microgrids, thereby enhancing operational stability in complex scenarios [89].

Operational flexibility is another crucial factor in the integration of DERs. Research has highlighted the role of next-generation energy storage systems, such as advanced batteries, in acting as load regulators. These systems absorb excess generation during renewable energy production peaks and release energy during low-production periods, a strategy particularly effective in isolated microgrids with high renewable penetration [117]. The importance of smart inverters has also transformed microgrid dynamics. A recent analysis evaluated how inverters equipped with optimization algorithms dynamically adjust the injection of renewable energy based on system conditions, reducing losses and maximizing energy efficiency [118]. Furthermore, droop control strategies have been foundational for maintaining frequency stability in microgrids, particularly those with high renewable variability [20].

The integration of advanced communication technologies has been another key factor. Research shows that using sensor networks and real-time monitoring systems allows the coordination of multiple DERs within a microgrid. This approach optimizes energy distribution and improves resilience against system failures [119]. Distributed storage technologies have further facilitated the integration of renewable energy sources. A case study highlighted that flow battery-based storage systems provide inertial support while significantly improving voltage regulation in microgrids characterized by high variability [80]. In hybrid microgrids, combining DERs with adaptive control systems, such as Model Predictive Control (MPC), has proven effective in managing real-time operations. This strategy addresses the uncertainty associated with renewable sources and ensures continuous supply even under highly variable conditions [19].

Additionally, neural networks are gaining traction in microgrid operations. Research has shown that these advanced AI tools can predict critical scenarios, such as demand peaks or generation drops, optimizing operation and reducing costs associated with DER integration in decentralized networks [36]. Another important development is the application of hierarchical control schemes that integrate local and global control levels. For instance, advanced studies have demonstrated how hierarchical systems improve DER coordination in microgrids, leading to better load balancing and reduced operational risks during periods of high renewable generation [120]. The use of virtual inertia through energy storage systems has also become prominent. Studies show that virtual inertia can stabilize microgrids with high renewable penetration, minimizing frequency deviations and enhancing system reliability under dynamic operating conditions [113]. Furthermore, control systems incorporating machine learning have shown potential in improving predictive load distribution and enhancing the overall flexibility of microgrid operations [71].

3.4.2. Optimization of Energy Storage: Advances in Predictive Models for Optimal Management

Energy storage systems are vital in modern energy systems, particularly in DERs and microgrids. The development of advanced predictive models has significantly improved the optimal management of ESS, enhancing their efficiency and reliability [121]. One prominent study investigates the integration of predictive control strategies for the effective use of ESS in microgrids. These strategies are designed to balance the supply-demand dynamics while considering the limitations of storage capacity and environmental conditions. The results demonstrate a substantial improvement in the operational efficiency of microgrids through real-time decision-making algorithms, ensuring better energy allocation and reducing wastage [9]. Predictive models incorporating artificial intelligence have also been explored to manage ESS effectively. By using machine learning algorithms, these models can predict energy consumption and generation patterns, optimizing the charging and discharging cycles of batteries. These methods extend the lifespan of storage systems while simultaneously improving their contribution to grid stability during peak load periods [117]. In another example, hybrid predictive models combining statistical methods with real-time sensor data have been developed. These models account for fluctuations in renewable energy generation, such as solar and wind, and adjust the energy storage parameters dynamically. The integration of such techniques has been shown to significantly reduce the operational costs of energy storage while ensuring reliable power supply [20]. Furthermore, advances in battery management systems (BMS) using predictive analytics have enabled better monitoring and control of ESS. These systems utilize state-of-charge (SOC) and state-of-health (SOH) data to make predictive adjustments, preventing overcharging or deep discharging of batteries, which are critical for maintaining their longevity and safety [19].

Studies also highlight the importance of incorporating ESS into multi-layered energy management frameworks. These frameworks utilize predictive control to optimize the interaction between storage units, renewable generation, and grid infrastructure. For instance, dynamic energy allocation models have been used to address the variability in renewable generation, ensuring that stored energy is deployed efficiently during periods of high demand [36]. The function of predictive control in V2G systems further exemplifies the optimization of ESS. Here, EVs are used as mobile storage units, dynamically interacting with the grid to provide ancillary services such as frequency regulation and voltage support. Predictive algorithms help to coordinate the charging and discharging schedules of EVs, maximizing their utility as energy buffers without compromising user convenience [120]. Lastly, advanced simulation tools leveraging digital twin technologies have been employed to test and refine predictive models for ESS. These tools allow for the simulation of complex scenarios, such as grid outages or renewable energy surges, providing valuable insights into the resilience and adaptability of storage systems under various operating conditions [113]. Moreover, continuous progress in predictive modeling and control strategies for energy storage systems is essential for improving their efficiency and reliability.

3.4.3. Optimization of Energy Storage: Advances in Predictive Models for Optimal Management

The operational stability of microgrids under variable conditions, such as fluctuating loads and renewable energy sources, has been significantly enhanced through adaptive control systems. These advanced systems dynamically respond to changes, ensuring reliable energy distribution and minimizing disruptions [80]. A study highlighted the benefits of using an optimized coordination strategy to balance the distributed energy resources in microgrids, improving system stability even under high variability scenarios [118]. This method relies on predictive algorithms to forecast demand and supply fluctuations, allowing for proactive adjustments to maintain grid balance. Additionally, adaptive control mechanisms have been developed to address issues caused by intermittent renewable energy generation. For instance, a novel coordination framework integrates distributed power sources with real-time control, ensuring seamless operation and mitigating voltage sags caused by rapid changes in solar or wind energy inputs [20,104].

Another critical advancement involves the implementation of predictive droop control strategies. These strategies adapt to real-time grid conditions by dynamically modifying the load-sharing parameters of microgrid components [122]. This approach has demonstrated significant improvements in maintaining frequency stability under sudden load variations [19]. Furthermore, researchers have introduced hierarchical control architectures that combine local and central controls to address variability. This dual-layered approach enhances the flexibility of the microgrid while ensuring robustness against large-scale disturbances [120]. Incorporating hybrid energy storage systems into microgrid designs has also proven effective. These systems utilize predictive algorithms to allocate power efficiently between batteries and supercapacitors, thereby stabilizing the grid during transient events [39]. Lastly, a recent study has emphasized the importance of advanced synchronization techniques in enhancing microgrid reliability. These techniques ensure that distributed energy resources operate in unison, even under challenging grid conditions, thus preventing instability and power quality issues [47].

3.5. Advances and Applications of Model Predictive Control in Energy Systems

The increasing penetration of EVs and V2G systems requires robust control mechanisms to optimize energy management and grid stability. MPC has emerged as a powerful tool in this context due to its ability to anticipate fluctuations, enhance system efficiency, and provide adaptive energy scheduling. This section critically examines the latest advancements in MPC and its real-world applications in energy systems.

3.5.1. Recent Advances in MPC for Energy Management

Several studies have demonstrated the effectiveness of MPC in optimizing energy flows, reducing operational costs, and improving grid reliability. For instance, ref. [14] presents an adaptive MPC framework that integrates RES with EV charging stations, enhancing system resilience against fluctuations in power supply. Similarly, ref. [16] explores the use of a hierarchical MPC approach for real-time energy dispatch in microgrids, achieving significant improvements in voltage regulation and load balancing. These developments underscore MPC's capability to manage complex energy networks efficiently. Hybrid control strategies have also gained attention, combining MPC with AI and fuzzy logic techniques to improve predictive accuracy. As highlighted in [25], AI-enhanced MPC can dynamically adjust charging and discharging patterns based on real-time grid conditions, leading to a 25% increase in system responsiveness under uncertain demand scenarios. Additionally, digital twin technology has been integrated with MPC to create real-time simulations for enhanced energy forecasting, as noted in [26].

3.5.2. Real-World Applications of MPC in EV and V2G Systems

MPC has been successfully implemented in various real-world applications, demonstrating its potential for large-scale deployment. For example, in urban EV charging networks, MPC-based optimization has been used to minimize peak load impact and reduce energy costs by up to 30% [21]. In V2G applications, ref. [19] reports that MPC-enabled bidirectional power flow strategies contribute to frequency stabilization and improve battery lifespan by 15–20%. Furthermore, research in distributed energy resources shows that MPCs can effectively coordinate multiple energy assets, optimizing power distribution in smart grids [22]. Despite these advancements, several challenges remain in achieving widespread adoption of MPC in energy systems. Computational complexity, scalability issues, and a lack of standardized communication protocols continue to hinder seamless integration. Future research should focus on developing real-time optimization techniques, leveraging AI-driven learning models, and establishing regulatory frameworks to support MPC's large-scale deployment. By addressing these limitations, MPC can play a critical role in enhancing the flexibility, sustainability, and resilience of modern energy systems, ensuring a stable transition toward decentralized and intelligent grid management.

4. Critical Discussion

The continuous evolution of energy systems towards sustainability has unveiled complex challenges and opportunities. One critical factor is the increasing reliance on robust communication infrastructures to ensure real-time execution of advanced control mechanisms. In V2G applications, for example, the instantaneous exchange of data between electric vehicles (EVs), aggregators, and the grid is crucial for ensuring stability and performance. Delays in communication networks can compromise the efficiency of predictive control systems like Tube-MPC, especially in isolated microgrids with fluctuating demands and renewable energy inputs [19,42,120]. A recurring theme in modern energy systems is the need for hybrid methodologies that combine predictivity and adaptability. Traditional predictive systems such as MPC excel at optimizing operations but often fall short in dynamically adapting to unforeseen disturbances. Integrating MPC with adaptive techniques such as fuzzy logic has demonstrated superior performance, particularly in microgrids with high renewable penetration where system variability is a significant concern [47,58]. These hybrid approaches enable precise, real-time adjustments that enhance both operational stability and energy efficiency.

The integration of AI with traditional energy management systems has brought forth immense possibilities but also notable challenges. AI-driven optimization techniques, including deep reinforcement learning and neural networks, promise to revolutionize the predictability of energy systems. However, combining these techniques with deterministic frameworks like MPC introduces computational complexities and difficulties in achieving real-time operability. Future research must focus on reconciling these paradigms to harness their combined potential effectively [63,123]. Another major barrier to the widespread adoption of advanced control systems is the lack of open, standardized platforms for validation and deployment. Collaborative frameworks could significantly accelerate the implementation of innovative solutions by enabling cross-platform compatibility, facilitating stakeholder engagement, and reducing associated costs. These platforms would also foster knowledge sharing and provide a foundation for testing new control strategies under realistic conditions [69,124]. Furthermore, the global energy transition demands unified standards to ensure interoperability among microgrid systems. The current lack of standardized communication protocols, hardware interfaces, and control architectures limits the scalability and reliability of distributed energy systems. Developing international guidelines and regulatory frameworks would provide a coherent path for scaling microgrids and integrating diverse energy resources into the grid [62,67].

Cost and accessibility remain significant challenges in deploying advanced energy technologies. Many solutions are either prohibitively expensive or require complex infrastructures, which limits their applicability in resource-constrained regions. By leveraging decentralized control strategies and modular hardware, the energy sector can develop scalable and affordable solutions to democratize access to clean and efficient energy systems [85,92]. A key aspect of modern predictive control is its ability to operate across multiple time scales, which is crucial for balancing short-term system dynamics with long-term strategic planning. As highlighted in [125], multi-time scale control approaches enhance the effectiveness of predictive control frameworks by allowing fine-tuned compensations for system disturbances at different operational levels. In the context of MPC, these methodologies facilitate the simultaneous optimization of fast dynamic responses—such as frequency regulation and voltage control—alongside slower processes like energy dispatch and economic load balancing [14,16,25]. For example, ref. [125] discusses a modulation and control framework that compensates for dead-zone effects in power converters through digital logic-based control at different time scales. This approach is particularly relevant in EV and V2G applications, where real-time control must synchronize with longer scheduling horizons to maintain stability and efficiency. While multi-time scale implementation in MPC presents advantages, challenges such as increased computational complexity and coordination difficulties remain. Future research should focus on optimizing hierarchical MPC structures, incorporating machine learning for adaptive time-scale switching, and developing efficient numerical solvers to reduce computational burdens.

The integration of renewable energy sources (RES) into smart grids has introduced additional cybersecurity concerns, particularly regarding wireless information sharing, which increases the risk of cyber threats such as unauthorized data manipulation and service disruptions [126]. The complexity of behind-the-meter distributed energy resources (DERs) further complicates cybersecurity, as their visibility and control mechanisms require robust protection against potential cyberattacks [127]. Moreover, modern energy management systems must balance efficiency with strong cybersecurity measures to mitigate evolving threats in digitalized power systems [128]. One approach to mitigating these threats involves integrating intrusion detection-based economic MPC models, which have demonstrated that predictive control combined with real-time anomaly detection enhances security in frequency regulation systems with EV participation [125]. Additionally, recent studies explored cyberattack defense mechanisms in smart grid frequency control, proposing adaptive and fault-tolerant MPC frameworks to counteract disruptions [125]. Advanced informatics-centric neural networks (I-ANNs) have also been proposed as a solution for enhancing DER resilience against cyber threats, demonstrating improvements in frequency and voltage control while mitigating attack impacts [129]. These studies underscore the necessity of secure communication protocols, encrypted data transmission, and AI-driven cybersecurity solutions to safeguard V2G operations. Future research should focus on integrating blockchain-based security architectures, decentralized identity management systems, and AI-enhanced predictive models to strengthen cybersecurity in V2G applications. Developing regulatory frameworks and collaborative cybersecurity strategies will be critical for ensuring the safe deployment of advanced predictive control techniques in modern energy grids. In this context, Table 1 provides a comprehensive analysis of key challenges and opportunities in modern energy systems, emphasizing the purpose of robust communication networks, hybrid control methodologies, and the integration of AI with traditional systems to enhance scalability, sustainability, and global interoperability.

Table 1. Critical challenges and opportunities in modern energy systems.

Category	Key Insights	Examples and Implications	Refs.
Robust Communication Networks	Real-time communication is critical for advanced control systems like V2G and hybrid grids. Delays or failures in communication can disrupt predictive controls and compromise system stability.	In Tube-MPC systems, delays in communication reduce effectiveness during frequency stabilization. For example, microgrids using EV fleets for dynamic load balancing require near-instantaneous data transfer to mitigate renewable intermittency and ensure reliable operations.	[19,42,120]
Hybrid Methodologies for Control	Combining predictive and adaptive strategies, such as MPC with fuzzy logic or reinforcement learning, provides resilience in scenarios with high variability and uncertainty.	Hybrid controllers have been implemented in renewable-dominated microgrids to reduce harmonic distortions and stabilize frequency. For instance, fuzzy-MPC strategies have improved EV coordination in multimicrogrid systems with significant renewable penetration.	[47,58]
AI and Traditional Systems	Integrating AI techniques with deterministic control frameworks like MPC offers new optimization capabilities but introduces challenges in computational efficiency and real-time applicability.	Neural networks have been used to predict demand surges in hybrid grids, while reinforcement learning has optimized battery usage in EV fleets. However, real-time execution is hampered by high computational requirements, especially in low-latency environments.	[63,123]

Table 1. *Cont.*

Category	Key Insights	Examples and Implications	Refs.
Standardization and Interoperability	The absence of global standards for microgrids and DERs limits scalability, reliability, and seamless integration of distributed energy systems.	Diverse control architectures, communication protocols, and hardware interfaces prevent large-scale adoption. For example, the lack of unified standards in EV charging infrastructure has slowed down V2G deployment, despite its clear advantages in grid support.	[62,67]
Open and Collaborative Platforms	Open-source platforms and collaborative frameworks accelerate the development and deployment of innovative energy technologies by enabling testing, stakeholder engagement, and knowledge sharing.	Platforms like sandbox testing environments allow cross-compatibility of DER controllers. These tools have facilitated the integration of advanced control systems in microgrids, reducing the cost and time required for deployment in emerging economies.	[69,77]
Cost and Scalability Challenges	Advanced solutions often require high initial investments and technical expertise, limiting accessibility in resource-constrained regions. Decentralized and modular designs offer a pathway to address these challenges.	Distributed microgrids with modular DER components have been deployed in rural areas to provide affordable renewable energy solutions. Using simple yet efficient control algorithms can reduce costs while ensuring operational reliability.	[85,92]
Convergence of Technologies	The integration of predictive control (e.g., MPC), AI, and decentralized optimization offers transformative potential for adaptive, scalable, and efficient energy systems.	Systems leveraging AI-based predictive models with distributed optimization frameworks have successfully managed renewable intermittency while reducing operational costs. A notable application includes combining virtual inertia and AI-driven control in low-inertia networks.	[62,63,92]
Sustainability and Energy Justice	Technological advancements must consider equity and environmental impact, ensuring that the benefits of modern energy systems reach all demographics.	Renewable energy projects in remote regions have utilized AI and predictive control to optimize resource allocation. These initiatives reduce environmental impact while providing clean energy access to underserved populations, fostering global sustainability efforts.	[77,85]

5. Conclusions

This systematic review, conducted in alignment with the PRISMA 2020 Statement, provides a comprehensive examination of MPC applications in the integration of EVs and V2G technologies. Through a rigorous four-stage process—Identification, Screening, Eligibility, and Inclusion—a total of 101 high-quality studies were selected from an initial pool of 5150 unique records, sourced from Scopus and Web of Science. The review highlights key advancements in predictive control for energy management, including power quality optimization, uncertainty mitigation, and innovative applications in hybrid and isolated grids. The selected studies exhibit a significant academic impact, reflected in an H-index of 33, and represent diverse contributions from leading journals, conferences, and thematic areas. The systematic review highlights MPC as a cornerstone technology for addressing challenges in the integration of EVs and V2G systems, particularly in managing the variability of RES and the dynamic charging behaviors of EVs. MPC's predictive capabilities enable real-time optimization of energy flows and operational decisions, enhancing grid stability, energy quality, and operational efficiency. Quantitative findings demonstrate that MPC reduces frequency deviations by up to 35%, mitigates THD by 20–30%, and extends battery lifespan by 15–20%, making it an essential tool for improving the performance and sustainability of modern power grids. MPC also fosters economic sustainability, reducing operational costs and minimizing battery degradation, which are critical factors for the adoption of V2G systems. Hybrid approaches that combine MPC with fuzzy logic or AI have shown significant advantages, including a 25% improvement in system responsiveness under high uncertainty and enhanced decision-making in complex, nonlinear systems. These advancements solidify MPC's role in both hybrid and isolated grid applications.

This study addressed four key research questions related to MPC applications in EV and V2G systems. First, regarding RQ1 (how MPC has been applied in energy management for power systems integrating EVs and V2G technologies), the review reveals that MPC has been successfully implemented to optimize energy exchange, improve power quality, and enhance grid resilience by dynamically adjusting charging and discharging cycles. In particular, MPC has enabled precise real-time control over energy dispatch in microgrids and hybrid energy systems, demonstrating its adaptability across various configurations and operational conditions.

For RQ2 (key technological advancements and optimization strategies in MPC), the findings indicate that recent innovations, such as AI-driven predictive models, hybrid MPC-fuzzy logic approaches, and decentralized optimization techniques, have significantly improved grid stability and economic efficiency. These advancements mitigate frequency fluctuations and reduce harmonic distortions, making MPC a viable solution for maintaining power system stability in renewable-dominated grids.

RQ3 focused on the primary barriers and limitations in the large-scale implementation of MPC for EV integration. The review highlights key challenges, including computational complexity, scalability concerns for managing large EV fleets, and the lack of standardized V2G communication protocols. While MPC is highly effective, its real-time computational demands remain a limiting factor, requiring further research into parallel computing and cloud-based solutions to enhance its feasibility for large-scale applications.

Finally, in response to RQ4 (the role of emerging technologies in enhancing MPC's predictive accuracy and operational resilience), the study identifies digital twins, deep learning, and distributed optimization as critical enablers for the next generation of MPC applications. Digital twins, in particular, offer real-time monitoring capabilities that improve predictive accuracy, while deep learning enhances data-driven decision-making by identifying complex patterns in EV-grid interactions.

However, several barriers hinder the widespread adoption of MPC technologies. Computational complexity poses a challenge, requiring 30% more resources compared to more straightforward control methods, which limits scalability for large EV fleets. Additionally, the lack of global standards for V2G communication protocols and control architectures restricts interoperability and seamless integration into existing energy networks.

The review emphasizes that the future potential of MPC lies in its integration with emerging technologies such as digital twins, deep learning, and distributed optimization frameworks. Digital twins enhance MPC's predictive accuracy by 15–20%, enabling real-time system monitoring and adaptation, while deep learning augments MPC's ability to process large datasets and identify complex patterns for improved decision-making.

To fully leverage MPC's capabilities, the development of collaborative platforms for testing and validating innovative solutions is essential, alongside the establishment of regulatory frameworks to ensure interoperability in V2G systems. Addressing computational challenges through parallel processing and cloud computing will further enhance MPC's scalability and operational efficiency.

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