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Systematic Review

A Systematic Review on the Integration of Artificial Intelligence into Energy Management Systems for Electric Vehicles: Recent Advances and Future Perspectives

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Abstract: This systematic review paper examines the current integration of artificial intelligence into energy management systems for electric vehicles. Using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology, 46 highly relevant articles were systematically identified from extensive literature research. Recent advancements in artificial intelligence, including machine learning, deep learning, and genetic algorithms, have been analyzed for their impact on improving electric vehicle performance, energy efficiency, and range. This study highlights significant advancements in energy management optimization, route planning, energy demand forecasting, and real-time adaptation to driving conditions through advanced control algorithms. Additionally, this paper explores artificial intelligence's role in diagnosing faults, predictive maintenance of electric propulsion systems and batteries, and personalized driving experiences based on driver preferences and environmental factors. Furthermore, the integration of artificial intelligence into addressing security and cybersecurity threats in electric vehicles' energy management systems is discussed. The findings underscore artificial intelligence's potential to foster innovation and efficiency in sustainable mobility, emphasizing the need for further research to overcome current challenges and optimize practical applications.

Keywords: artificial intelligence; energy management systems; electric vehicles; optimization techniques; battery management systems; renewable energy integration; smart grids; systematic literature review

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1. Introduction

The advancement towards electric vehicles (EVs) is undeniable in the current landscape of human mobility. However, for this transition to be optimal, efficient and advanced energy management systems (EMSs) are essential. EMSs play a critical role in managing the energy flow within EVs, ensuring that energy consumption is optimized and that vehicles operate at peak efficiency. They are responsible for monitoring and controlling various components, such as batteries and propulsion systems, to maximize performance while minimizing energy waste [1]. The necessity for efficient and advanced EMSs in EVs arises from several factors. Firstly, EVs require precise energy management to optimize battery usage, extend driving range, and enhance vehicle longevity. Effective EMSs ensure that batteries are charged and discharged optimally, preventing premature degradation and extending their lifespans [2]. Secondly, advanced EMSs incorporate real-time data analysis and predictive algorithms to adjust energy use based on driving conditions and driver behavior, thereby improving energy efficiency and autonomy [3–8].

Moreover, as EVs integrate more renewable energy sources and become key components of smart grids, EMSs must facilitate seamless interaction between the vehicle and the grid. This includes vehicle-to-grid (V2G) capabilities, where EVs can feed energy back into the grid during peak demand periods, enhancing grid stability and efficiency [9–11]. Integrating artificial intelligence (AI) into EMSs further enhances their capabilities, allowing for advanced features such as predictive maintenance, fault diagnosis, and personalized driving experiences. AI-driven EMSs can predict energy demand, optimize route planning, and adapt to changing environmental conditions, thereby improving EVs' overall efficiency and performance [2,9–11].

The review of EMS strategies for EVs, including those powered by hydrogen fuel cells, batteries, and hybrid energy storage systems, underscores the importance of advancing AI-based algorithms and intelligent control systems. Studies such as [12,13] indicate that hybrid energy storage systems, combining batteries and supercapacitors, offer promising solutions to key challenges like autonomy, performance, and battery lifespan. Moreover, research on energy microgrids and the integration of EVs highlights how AI advancements can enhance demand management and optimize energy production and consumption, as observed in [3,5]. These studies emphasize the need for adaptive and efficient EMSs to maximize available resources and dynamically respond to changing environmental conditions and power demand. Additionally, the application of machine learning and reinforcement learning (RL) algorithms in optimizing EMSs, as mentioned in [7,8], presents an exciting opportunity to improve operational efficiency and reduce energy costs in connected EV environments and distributed energy systems.

In a context where the transition to EVs is crucial for sustainability, efficient energy management becomes a determining factor. Although progress has been made in integrating AI into these systems, challenges persist in adapting algorithms to variable driving conditions and real-time optimization. This research aims to address these gaps identified in the current literature, exploring how AI can enhance the efficiency and autonomy of EVs. An interdisciplinary and collaborative approach between academia and industry is proposed to validate and implement practical solutions. The goal is to contribute to developing more advanced EMSs, thereby facilitating a more effective transition to electric and sustainable mobility.

The integration of AI into EMSs for EVs is a rapidly developing field, as evidenced by numerous recent studies. A comprehensive literature review reveals a series of studies that address this topic from different perspectives. Firstly, there has been extensive research on using AI-based algorithms and control systems to optimize the performance of specific vehicles, such as hydrogen fuel cell electric vehicles [1]. Additionally, AI techniques applied to battery management systems (BMSs) in EVs have been explored, addressing monitoring, battery state estimation, and cell balancing [14]. Another relevant aspect is edge computing, which allows vehicles to make intelligent decisions quickly [15].

EMSs have also been studied in microgrids, where the goal is to optimize energy production and consumption, including integrating EVs and AI techniques [16]. Furthermore, the role of AI in thermal management and the performance of lithium-ion batteries in EVs has been investigated [17]. The transformation towards connected, autonomous, and shared vehicles also drives the use of AI in the automotive sector [9]. Energy management strategies for fuel cell vehicles have also been reviewed [2]. Mechanical energy harvesting in traffic environments and its application in intelligent transportation systems have also been studied [18]. The management of braking energy in EVs has been examined [10]. These studies highlight the importance of developing practical algorithms, addressing research gaps, overcoming technical challenges, and leveraging the opportunities offered by AI to improve the efficiency and sustainability of electric mobility [13].

Research in the field of EMSs for EVs covers a wide range of topics, from developing integrated electronic control units (ECUs) to integrating emerging technologies such as blockchain and machine learning in smart grids. A recurring theme is the importance of optimizing EMSs to improve the efficiency and sustainability of EVs. A crucial aspect in this context is the development of integrated ECUs for Internet of Things (IoT)-enabled EVs [19]. The combination of blockchain and machine learning techniques in smart grids offers solutions for P2P energy trading and distributed energy management. However, challenges such as scalability and energy consumption of blockchain persist [20]. Supercapacitors (SCs) have also gained attention because of their high power density and durability, which are promising energy storage technologies [21]. Integrating EVs into smart grids also requires the development of appropriate communication technologies to ensure network reliability and consistency [22]. Optimizing EMS schemes for EV applications is crucial to improving battery efficiency, lifespan, and safety [11]. Smart charging is key to integrating plug-in electric vehicles into distribution grids, improving the system's technical and economic efficiency [23]. Hybrid architectures with advanced control strategies are being developed in the maritime sector to reduce fuel consumption and emissions [24].

Additionally, the use of RL in the energy management of multi-energy source vehicles and hybrid energy management strategies for EVs has been investigated [12,13]. Research continues to advance with proposals such as EMSs based on adaptive neuro-fuzzy inference systems (ANFISs) and multi-set learning algorithms for dual EVs, as well as EMSs based on deep reinforcement learning (DRL) and Markov Action Learning to optimize the energy management of hybrid EVs [3–8]. Collectively, these studies represent an ongoing effort to improve the efficiency and sustainability of electric mobility by applying advanced energy management technologies.

A comprehensive literature review on the integration of AI into EMSs for EVs reveals a wide variety of studies similar to those presented in this paper. However, upon closer examination, several areas still clearly need additional research [1,2]. One significant gap is the adaptation of EMS algorithms to dynamic driving conditions. Although advanced algorithms have been developed, significant challenges remain in optimizing energy management in real time, which could affect the performance and efficiency of EVs [25]. Studies [1,2,17] partially address this topic. Another important gap lies in the practical validation of proposed solutions. Closer collaboration between academia and industry is essential to implement and validate these solutions in real-world environments, ensuring their effectiveness and long-term viability.

With the transition to electric mobility, it is crucial to adapt EMSs to specifically address EVs' unique challenges and needs, including optimizing autonomy, efficiency, and charging processes. Studies [2,9,10] address this topic but do not compare the different deficiencies of each technology and do not analyze autonomy with actual values. By addressing these identified gaps, the proposed research will significantly contribute to advancing and developing more advanced and effective EMSs for EVs, thereby facilitating a more effective transition to electric and sustainable mobility.

Based on the points above and to fill the remaining gaps, this article comprehensively reviews the integration of AI into EMSs for EVs with the specific objectives of (1) analyzing the latest advancements in AI techniques, such as machine learning, deep learning, and optimization based on genetic algorithms, and their application in improving EVs' performance, energy efficiency, and range; (2) discussing how advanced control algorithms optimize energy management, from route optimization to energy demand prediction and real-time adaptation to driving conditions; (3) addressing the role of AI in fault diagnosis and predictive maintenance of electric propulsion systems and batteries; (4) examining how AI can personalize the driving experience and contribute to the detection and prevention of security and cybersecurity threats in EV EMSs. The literature review process detailed in this article employs the preferred reporting items for systematic reviews and meta-analyses (PRISMA) method to guarantee a transparent, reproducible, and methodologically robust approach. This method is essential for systematically identifying, selecting, and critically appraising relevant research, thereby enhancing the reliability and validity of this review's findings.

2. Literature Review Methodology

2.1. Study Selection Criteria

The bibliographic resources for this literature review were sourced from the following prestigious databases: Scopus, IEEE Xplore, and MDPI. These databases were selected because of their extensive coverage of high-quality research articles, ensuring a comprehensive, transparent, and objective review.

Scopus is renowned for its rigorous content selection policies and broad coverage across various disciplines, providing high-quality, peer-reviewed material. Its advanced analysis tools and bibliometric indicators further enhanced the credibility and depth of our review. IEEE Xplore is a leading source for electrical engineering and related fields, offering access to high-impact and frequently cited publications, thus ensuring the inclusion of the latest advancements and most relevant studies. MDPI, as a fully open-access platform, ensured that our review incorporated peer-reviewed research accessible to a wide audience, promoting inclusivity and broad dissemination of knowledge.

These databases offer a robust and diverse collection of relevant literature, capturing a broad spectrum of high-quality studies. By focusing on these well-regarded sources, we ensured that our review provided a comprehensive and reliable overview of the field, aligned with the highest standards of academic research.

To capture the relevant literature effectively, the search terms used across the Scopus, IEEE Xplore, and MDPI databases were derived from the preliminary literature analysis presented in the Introduction of this article. The specific search terms employed were the following: "artificial intelligence" AND "energy management systems" AND "electric vehicles". The inclusion and exclusion criteria designed for this research are summarized below.

2.1.1. Inclusion Criteria

The inclusion criteria for this review encompassed the following:

- **Peer-reviewed articles:** Only articles that underwent rigorous peer review were included to ensure the credibility and reliability of the findings.
- **Publications from the last 10 years (2014–2024):** This period was selected as the most appropriate for mapping knowledge in this study's thematic area. The justification for choosing this timeframe stems from the significant advancements and increasing interest in integrating AI into EMSs for EVs during this period. As highlighted in the preliminary research and Introduction, the past decade saw rapid developments in AI techniques, such as machine learning, deep learning, and genetic algorithms, which have significantly impacted EV performance, energy efficiency, and range. This period allowed for capturing both the evolution of these technologies and the most recent advancements.
- **Studies focusing on the application of AI in EMSs specifically for EVs:** This criterion ensured the relevance of the articles to the core research question.
- **Research that includes experimental results, case studies, simulations, or real-world implementations:** This criterion ensured that the studies provided practical insights and evidence of the effectiveness of AI techniques in EMSs for EVs.
- **Articles written in English:** This criterion maintained consistency and accessibility in the analysis.

2.1.2. Exclusion Criteria

The exclusion criteria included:

- **Conference and review papers:** These were excluded to focus on original research articles that provide detailed methodologies and experimental results.
- **Non-peer-reviewed articles, editorials, commentaries, and opinion pieces:** These types of publications were excluded to maintain a preference for primary sources and to ensure the rigor and credibility of the works included in this review.
- **Publications older than 10 years:** Older publications were excluded to keep this review focused on recent advancements.
- **Studies not directly related to EMSs or EVs:** This criterion maintained the relevance of this literature review.
- **Articles not available in full text:** This criterion ensured that all reviewed articles could be thoroughly analyzed.

- **Duplicate studies or those with insufficient methodological details:** This criterion avoided redundancy and ensured methodological rigor.

These inclusion and exclusion criteria were established to ensure that this literature review comprehensively addressed the most relevant and high-quality research on AI integration into EMSs for EVs. This study aims to capture the latest advancements and practical applications in this rapidly evolving area by focusing on recent, peer-reviewed articles that provide detailed methodologies and experimental results. This approach aligns with the objectives of this research, which are to explore the current state of AI technologies in EMSs for EVs, identify key trends, and highlight innovative solutions that enhance performance, energy efficiency, and vehicle range.

2.2. Literature Search Process

To capture the relevant literature effectively, the following search terms and query strings were utilized across the Scopus, IEEE Xplore, and MDPI databases. These search strategies ensured comprehensive coverage of the relevant research topics.

The review process detailed in this article adheres to the guidelines set forth by the preferred reporting items for systematic reviews and meta-analyses (PRISMA) 2020 statement [26]. This approach is critical for ensuring a transparent, reproducible, and methodologically sound review. The PRISMA guidelines provide a comprehensive framework for systematically identifying, selecting, and critically appraising relevant research, thereby bolstering the reliability and validity of our findings. By following PRISMA's structured checklist and flow diagrams, we guaranteed a rigorous review process that included detailed reporting of search strategies, selection criteria, and synthesis methods. This meticulous documentation enhanced this review's clarity and transparency, thus facilitating replication and updates. Furthermore, by employing PRISMA, we addressed common biases and improved the quality and completeness of reporting in systematic reviews. The literature systematic review protocol designed for this study is registered in the Open Science Framework (OSF) and can be found at https://doi.org/10.17605/OSF.IO/FHXCP. More details about the design and execution of this methodology are provided in Figure 1 and Section 2.3.

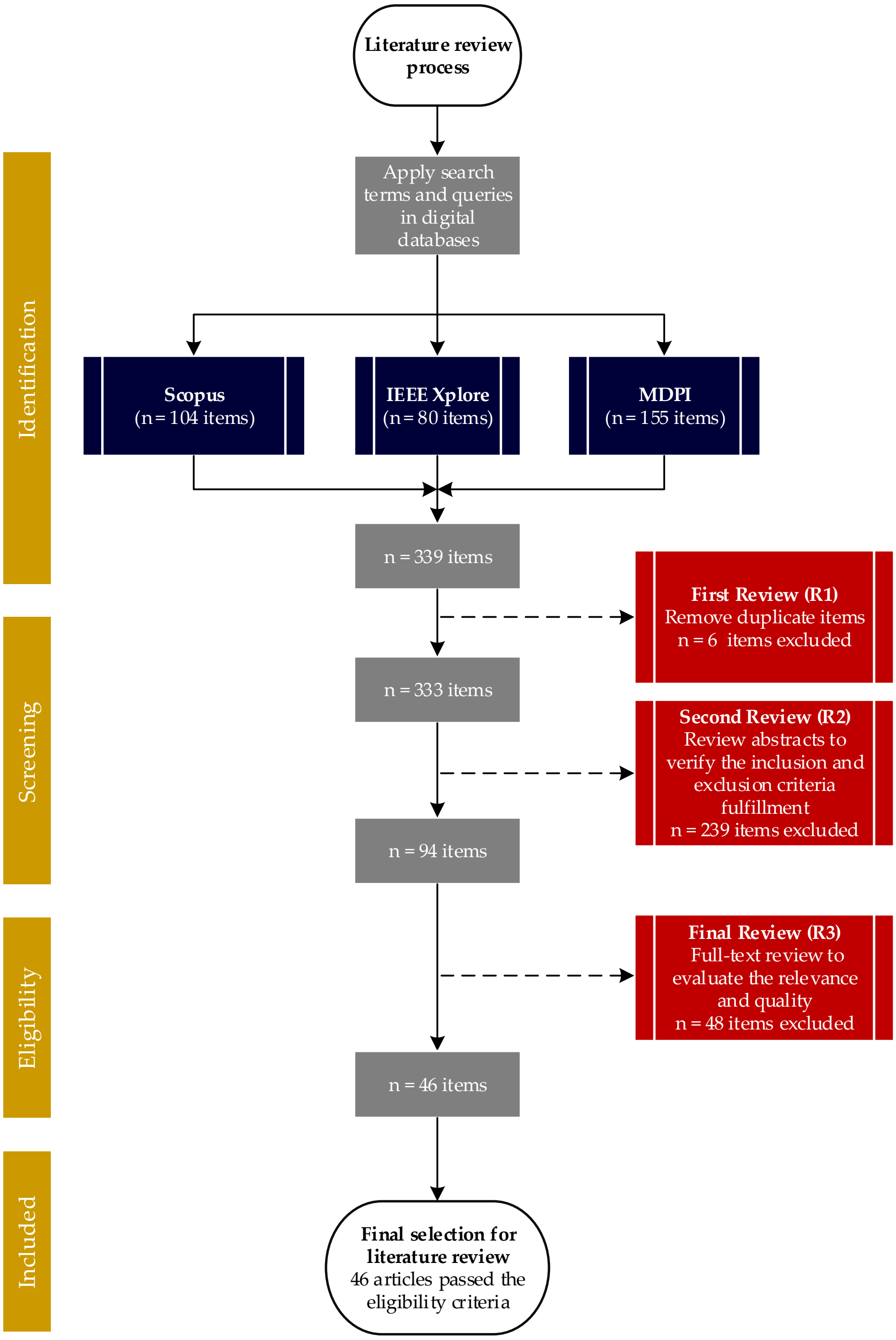


Figure 1. Diagram illustrating the steps of the literature review process.

2.3. *Selection of Studies and Eligibility*

Figure 1 illustrates a flowchart of the literature review process. The figure shows that the review process began with applying the search terms and queries in Table 1. This initial search yielded 339 items: 104 from Scopus, 80 from IEEE Xplore, and 155 from MDPI. With these raw results, the authors assigned the following coding system to the items to facilitate subsequent bibliometric processing: articles from Scopus were coded as S-XX, those from IEEE Xplore as IEEE-XX, and those from MDPI as MDPI-XX.

Table 1. Search terms and queries utilized for this literature review.

Database	Query String
Scopus	(TITLE-ABS-KEY ("Artificial Intelligence") AND TITLE-ABS-KEY ("EMS") AND ALL ("EVs")) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English"))
IEEEXplore	("Full Text & Metadata":"Artificial Intelligence") AND ("Full Text & Metadata":"Energy Management Systems") AND ("All Metadata":"EVs") Article type: Journals Year range: 2014–2024
MDPI	Search text: "Artificial Intelligence", Search Type: Full Text Logical operator: AND, Search text: "Energy Management Systems", Search Type: Full Text Logical operator: AND, Search text: "EVs", Search Type: All fields. Article type: Article Year range: 2014–2024

The first review stage (R1) involved the removal of duplicate items. During this stage, only six duplicate documents were identified and withdrawn. A preliminary bibliometric analysis is presented here to give the reader a global perspective of the literature review results. Figure 2 shows the distribution of the 333 preselected works across different digital databases, revealing a predominance in MDPI, which accounts for 47% of the total. Scopus follows with 29%, and IEEE Xplore is slightly below with 24%. This distribution highlights MDPI's strong positioning in recent years in the research topic addressed in this study, likely because of its extensive focus on cutting-edge technologies and interdisciplinary research. Additionally, Figure 2 presents the historical record of the number of publications per year. The trend line indicates a steady increase in publications over time, with a noticeable dip in 2020, likely due to the COVID-19 pandemic, which impacted research activities across various technological fields. Despite this temporary setback, the trend demonstrates a robust upward trajectory, suggesting continued growth in the number of publications through 2024, evidenced by the high number of publications recorded by mid-year.

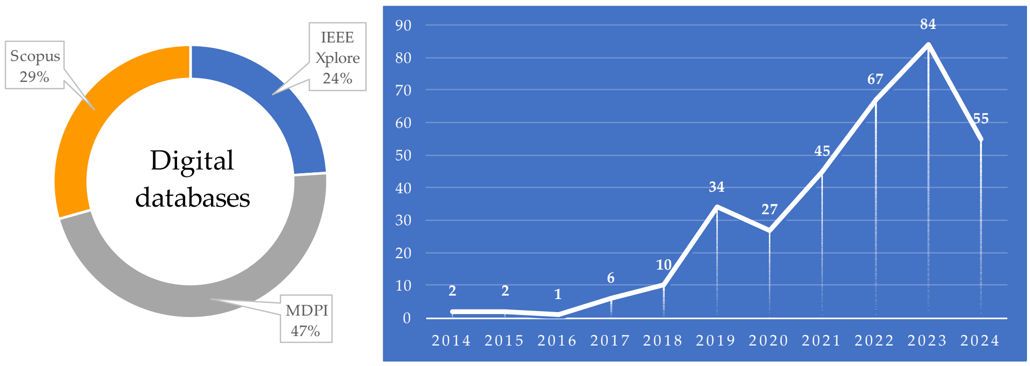


Figure 2. Breakdown of articles by digital database and publication year (R1 stage).

Following the bibliometric analysis, the second review stage (R2) involved evaluating the remaining works to ensure they met the predefined inclusion and exclusion criteria outlined in Sections 2.1.1 and 2.1.2 by examining the titles and abstracts. Two independent reviewers thoroughly assessed all articles to minimize bias, independently verifying each for potential bias to ensure objectivity and mitigate subjective influence. Importantly, no automation tools were used in this process. There was no missing or unclear information in the analyzed studies, eliminating the need for additional assumptions regarding the data.

This rigorous screening process reduced the pool to 94 qualifying works out of the initial 333, as shown in Figure 3. For the bibliometric analysis, we utilized tools such as MS Excel (Microsoft Office Professional Plus 2019) and Zotero (Version 6.0.36), free online resources like freewordcloudgenerator.com, URL: https://www.freewordcloudgenerator.com/ (accessed on

11 August 2024), and custom Python routines designed and implemented by the authors to facilitate the metadata collection, organization, and systematization. Figure 3 also presents the distribution of the 94 articles resulting from the R2 review stage by journal. The distribution highlights that a significant portion of the articles, approximately 13%, were published in the journal *Energies*, indicating its prominence in EMSs and EVs. Similarly, *IEEE Access* also features prominently, accounting for around 10% of the total articles. This reflects the journal's focus on high-impact, broad-scope research in electrical and electronic engineering. With six articles, *IEEE Transactions on Transportation Electrification* underscores its specialized focus on transportation electrification that is directly relevant to integrating AI into EV EMSs. Both *Sensors* and *Sustainability* contributed five articles each, highlighting the multidisciplinary nature of research in this field, encompassing sensor technology and sustainable practices.

Journals like *Energy* and *Applied Sciences* each contributed three articles, indicating their role in broader energy research and applied scientific studies. Specialized journals such as *Electric Power Components and Systems*, *Electronics*, and *Transportation Engineering* each contributed two articles, showcasing focused research areas that intersect with the main topic of this study. Lastly, *Applied Energy* contributed one article, while a significant portion (44 out of 94) were published in various other journals. This wide distribution across numerous journals emphasizes the diverse interests and interdisciplinary approach required to advance AI integration into EMSs for EVs.

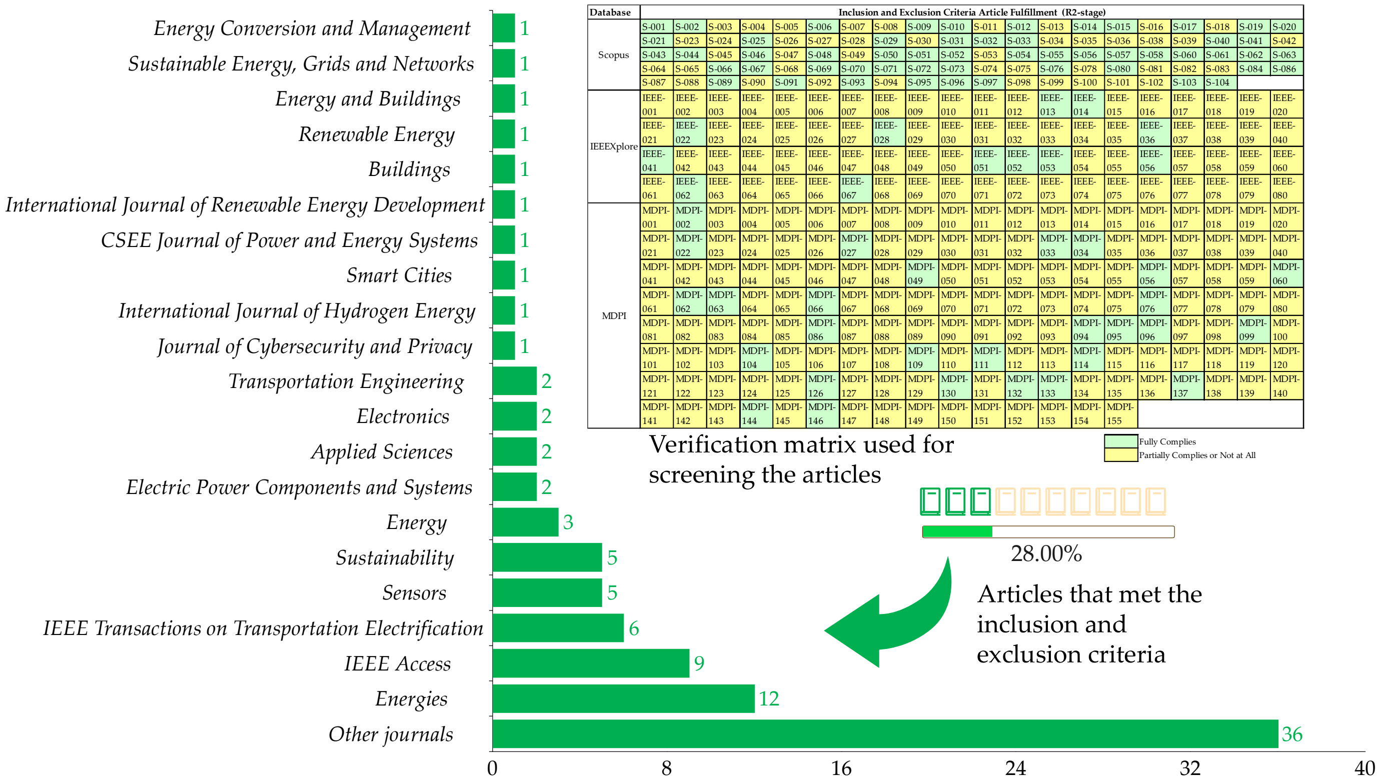


Figure 3. Summary of the screening process of this literature review (R2 stage).

The third review step (R3) involved conducting a comprehensive full-text review of each work to determine the relevance of the topics concerning the identified terms and the main focus of this research. For this purpose, the research team defined a series of criteria to evaluate each of the 94 items using a five-level Likert scale for the evaluation metrics. The Likert scale, rather than a binary rating system, was chosen to capture the nuanced and multifaceted nature of each study's contribution and relevance. A binary scale would have oversimplified the evaluation process, potentially overlooking significant qualitative differences among studies that a more granular scale can capture.

The evaluation criteria and metrics are provided in Table 2 below. Each criterion is rated on a scale from 1 to 5, where 1 indicates poor quality or relevance and 5 indicates excellent quality or relevance.

The suggested minimum score for inclusion in the review process was 35. This score ensured that articles comprehensively address the integration of AI in EMSs for EVs, demonstrating high methodological rigor, experimental validation, novelty, clarity, technical depth, reproducibility, data quality, practical applicability, and impact on the field. A score of 35, which is 70% of the maximum possible score (50), guaranteed that the articles included were of very high quality and relevance. This threshold ensured a balance among rigor, relevance, and practical applicability, allowing only the most pertinent and robust studies to be considered in this systematic review. Increasing the minimum score to 35 ensured a higher standard of excellence, enhancing the overall quality and reliability of the review.

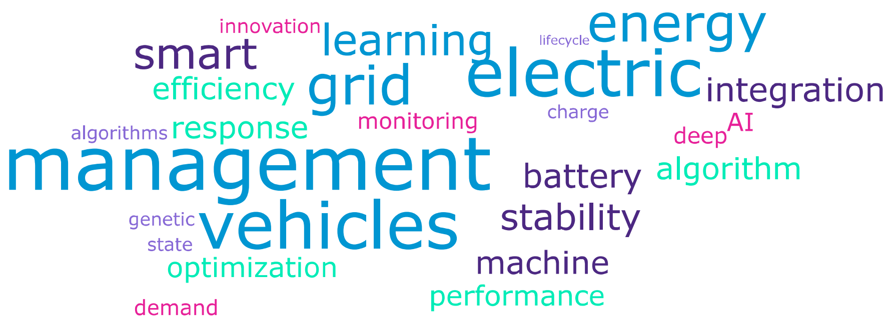
Figure 4a shows the final scores achieved by each item at this stage. Based on the results, 46 articles met the predefined minimum threshold; therefore, the remaining articles were discarded. To facilitate the reader's comprehension, the research team considered it convenient to group the main themes addressed by each article into broad study topics. The keywords from the 46 articles were extracted to generate a word cloud map to aid this clustering process. This method helped identify the frequency of terms used across the selected literature. The result, shown in Figure 4b, reveals that the most prevalent keywords are AI, EV energy management, optimization techniques, BMS, renewable energy integration, and smart grids.

Table 2. Criteria and metrics for full-text evaluation (R3 stage).

Criterion	Description and Evaluation Metrics
Relevance to AI in EMSs for EVs	How well the study addresses the integration of AI techniques in energy management systems for EVs (1: peripheral, 2: somewhat, 3: relevant, 4: highly relevant, 5: central focus).
Methodological rigor	The robustness and appropriateness of the research methodology employed in the study (1: needs improvement, 2: fair, 3: good, 4: very good, 5: excellent).
Experimental validation	The extent to which the study includes experimental results, simulations, case studies, or real-world implementations (1: none, 2: limited, 3: moderate, 4: extensive, 5: comprehensive).
Novelty and contribution	The originality and significance of the study's contributions to the field (1: minor, 2: low, 3: moderate, 4: significant, 5: groundbreaking).
Clarity and completeness	The clarity of writing and the completeness of the information provided in the study (1: needs improvement, 2: fair, 3: good, 4: very good, 5: excellent).
Technical depth	The level of technical detail and depth in the study (1: introductory, 2: basic, 3: adequate, 4: detailed, 5: highly detailed).
Reproducibility	The extent to which the study provides enough detail to allow for replication of the results (1: none, 2: limited, 3: moderate, 4: extensive, 5: comprehensive).
Data quality and integrity	The quality and integrity of the data presented in the study (1: poor, 2: fair, 3: good, 4: very good, 5: excellent).
Practical applicability	The potential for practical application of the study's findings in real-world scenarios (1: none, 2: low, 3: moderate, 4: high, 5: very high).
Impact on field	The potential impact of the study's findings on AI in energy management for EVs (1: minor, 2: low, 3: moderate, 4: significant, 5: groundbreaking).

ID	Relevance to AI in EMS for EVs	Methodological Rigor	Experimental Validation	Novelty and Contribution	Clarity and Completeness	Technical Depth	Reproducibility	Data Quality and Integrity	Practical Applicability	Impact on Field	Total
S-009	5	4	4	3	4	4	4	3	4	4	39
S-032	5	4	4	4	4	4	4	4	3	3	39
MDPI-096	5	4	4	4	3	4	3	4	4	4	39
S-029	5	3	3	4	4	4	4	4	3	3	37
S-040	4	4	4	3	4	3	3	4	4	4	37
S-060	5	4	4	4	3	3	3	4	4	3	37
S-069	5	4	4	4	3	3	3	4	4	3	37
MDPI-133	4	4	3	4	4	4	3	4	3	4	37
S-010	4	4	3	4	4	3	3	4	4	3	36
S-050	4	4	4	3	3	4	3	4	4	3	36
S-055	5	4	4	3	3	3	3	4	3	4	36
S-058	5	4	4	3	3	3	3	4	4	3	36
S-062	5	4	3	4	3	3	3	4	3	4	36
S-071	4	4	4	4	3	4	3	4	3	3	36
S-093	5	3	3	4	3	3	3	4	4	4	36
IEEE-013	4	4	3	4	3	3	3	4	4	4	36
MDPI-076	4	4	3	4	3	3	3	4	4	4	36
MDPI-111	4	4	4	4	3	3	3	4	3	4	36
MDPI-130	4	4	4	4	4	3	3	4	3	3	36
MDPI-146	4	4	3	4	4	4	4	3	3	3	36
S-006	5	4	4	4	3	3	3	3	3	3	35
S-012	4	4	4	4	3	3	3	3	4	3	35
S-017	4	4	3	4	4	3	3	3	3	4	35
S-025	4	4	4	4	3	4	3	3	3	3	35
S-031	4	4	4	4	3	3	3	3	4	3	35
S-033	5	4	3	3	3	3	3	4	4	3	35
S-046	4	3	4	4	3	3	3	4	4	3	35
S-048	5	3	3	4	3	3	3	4	4	3	35
S-054	5	4	3	3	3	3	3	4	3	4	35
S-061	5	4	3	3	3	3	3	4	3	4	35
S-067	5	4	4	3	3	3	3	4	3	3	35
S-086	5	4	3	4	3	3	3	4	3	3	35
S-104	5	4	4	4	3	3	3	3	3	3	35
IEEE-022	5	4	4	3	3	3	3	3	3	4	35
IEEE-028	4	4	4	3	3	3	3	4	4	3	35
IEEE-062	4	4	4	4	3	3	3	3	4	3	35
MDPI-027	4	4	4	4	3	3	3	3	4	3	35
MDPI-034	4	4	4	4	3	3	3	3	4	3	35
MDPI-060	4	4	4	4	3	3	3	4	3	3	35
MDPI-086	4	3	4	4	4	3	3	4	3	3	35
MDPI-095	4	4	4	4	3	3	3	4	3	3	35
MDPI-099	5	4	3	4	3	3	3	4	3	3	35
MDPI-104	4	4	4	3	3	3	3	4	3	4	35
MDPI-114	4	4	4	4	3	3	3	4	3	3	35
MDPI-137	4	4	3	3	4	3	3	3	4	4	35
MDPI-144	4	4	3	4	3	3	3	4	4	3	35
S-001	4	4	4	3	3	3	3	3	4	3	34
S-002	5	3	3	4	3	3	3	4	3	3	34
S-015	4	4	4	4	3	3	3	3	3	3	34
S-019	5	4	3	4	3	3	3	3	3	3	34
S-020	5	4	3	3	3	3	3	3	4	3	34
S-041	4	4	4	4	3	3	3	3	3	3	34
S-044	5	4	3	3	3	3	3	4	3	3	34
S-051	4	4	3	4	3	3	3	4	3	3	34
S-052	4	4	3	4	3	3	3	4	3	3	34
S-063	4	4	4	3	3	3	3	3	4	3	34
S-070	5	4	3	3	3	3	3	3	4	3	34
S-073	5	4	4	3	3	3	3	3	3	3	34
S-080	4	3	3	4	3	3	3	4	4	3	34
S-089	5	3	4	4	3	3	3	3	3	3	34
S-091	5	4	4	3	3	3	3	3	3	3	34
S-095	5	4	3	3	3	3	3	4	3	3	34
S-096	5	4	4	3	3	3	3	3	3	3	34
IEEE-036	5	4	3	3	3	3	3	4	3	3	34
IEEE-053	4	4	3	4	3	3	3	4	3	3	34
IEEE-056	4	4	3	4	3	3	3	4	3	3	34
MDPI-022	4	4	3	4	3	3	3	4	3	3	34
MDPI-033	4	4	4	3	3	3	3	4	3	3	34
MDPI-056	4	4	3	4	3	3	3	3	4	3	34
MDPI-062	4	4	3	4	3	3	3	4	3	3	34
MDPI-066	4	4	3	3	3	3	3	4	3	4	34
MDPI-094	4	4	4	3	3	3	3	4	3	3	34
MDPI-126	5	4	3	4	3	3	3	3	3	3	34
MDPI-132	4	4	3	4	3	3	3	4	3	3	34
S-014	4	4	4	3	3	3	3	3	3	3	33
S-043	4	4	3	4	3	3	3	3	3	3	33
S-057	4	4	3	3	3	3	3	3	3	4	33
S-072	4	4	3	4	3	3	3	3	3	3	33
S-097	4	4	3	3	3	3	3	4	3	3	33
S-103	4	4	3	4	3	3	3	3	3	3	33
IEEE-014	5	4	3	3	3	3	3	3	3	3	33
IEEE-041	5	4	3	3	3	3	3	3	3	3	33
IEEE-051	4	4	3	3	3	3	3	4	3	3	33
IEEE-067	4	4	3	4	3	3	3	3	3	3	33
MDPI-002	4	3	4	4	3	3	3	3	3	3	33
MDPI-049	4	4	3	3	3	3	3	4	3	3	33
MDPI-063	4	4	3	3	3	3	3	4	3	3	33
MDPI-109	4	3	3	4	4	3	3	3	3	3	33
S-056	5	3	3	3	3	3	3	3	3	3	32
S-066	4	3	3	3	3	3	3	4	3	3	32
S-076	5	3	3	3	3	3	3	3	3	3	32
S-084	4	4	3	3	3	3	3	3	3	3	32
IEEE-052	4	3	3	4	3	3	3	3	3	3	32
S-021	4	3	3	3	3	3	3	3	3	3	31

(a)



(b)

Figure 4. Graphical summary of the eligibility process (R3 stage) of this literature review: (**a**) eligibility matrix and (**b**) word cloud map of keywords from the selected articles.

Based on this identification, the synthesis process of the selected works focused on the following five specific topics:

- **Artificial Intelligence in EV Energy Management**: This topic encompasses articles that apply AI techniques such as machine learning, deep learning, and genetic algorithms in the EMSs of EVs. These studies explore how AI can optimize energy consumption, predict energy demand, and enhance the overall efficiency of EV operations.
- **Optimization Techniques in Energy Management Systems**: Articles under this topic discuss various optimization algorithms and techniques designed to enhance the efficiency and performance of EMSs in EVs. These include traditional optimization methods and advanced algorithms tailored to improve EVs' operational efficiency and energy utilization.
- **Battery Management Systems:** This category includes articles on the management, monitoring, and optimization of battery systems in EVs. Key areas of focus within this topic are estimating the state of charge (SoC), lifecycle management of batteries, and

strategies to ensure the longevity and reliability of battery systems through advanced monitoring and control techniques.

- **Renewable Energy Integration**: Articles exploring integrating renewable energy sources, such as solar and wind power, into the EMSs of EVs fall under this topic. These studies examine how renewable energy can be efficiently harnessed and managed to support the sustainable operation of EVs, thus contributing to a greener and more sustainable energy landscape.
- **Smart Grids and Electric Vehicles**: This topic covers articles examining the interaction between smart grids and EVs. Key areas of interest include grid stability, demand response strategies, and the impact of EV integration on smart grid infrastructure. These studies investigate how EVs can be integrated into smart grids to enhance grid efficiency, stability, and resilience and the potential benefits and challenges.

By categorizing the selected literature into these five overarching topics, the research team aimed to provide a clear and structured synthesis of the current state of the research. Table 3 shows the relationship of each selected item within the five identified topic groups.

Finally, overall bibliographic information of the selected studies for this literature review is provided in Appendix A.

Table 3. Categorization of selected items within the identified topic groups.

N°	Item ID	Ref.	AI in EV Energy Management	Optimization Techniques in EMS	BMS	Renewable Energy Integration	Smart Grids and EVs	N°	Item ID	Ref.	AI in EV Energy Management	Optimization Techniques in EMS	BMS	Renewable Energy Integration	Smart Grids and EVs
1	S-009	[27]	✓	✓				24	S-025	[28]	✓				
2	S-032	[29]	✓	✓		✓		25	S-031	[30]	✓			✓	
3	MDPI-096	[31]	✓					26	S-033	[32]	✓				
4	S-029	[33]	✓	✓			✓	27	S-046	[34]	✓	✓			
5	S-040	[35]	✓	✓		✓		28	S-048	[36]	✓	✓			
6	S-060	[37]	✓	✓				29	S-054	[38]	✓	✓			
7	S-069	[39]	✓	✓			✓	30	S-061	[40]	✓	✓		✓	
8	MDPI-133	[41]	✓			✓	✓	31	S-067	[42]	✓				
9	S-010	[25]	✓	✓			✓	32	S-086	[43]	✓				✓
10	S-050	[44]	✓	✓			✓	33	S-104	[45]	✓		✓		
11	S-055	[46]	✓	✓	✓			34	IEEE-022	[47]	✓	✓			
12	S-058	[48]	✓	✓				35	IEEE-028	[49]	✓	✓			
13	S-062	[50]	✓	✓			✓	36	IEEE-062	[51]	✓				
14	S-071	[52]	✓	✓				37	MDPI-027	[53]	✓			✓	✓
15	S-093	[54]	✓					38	MDPI-034	[55]	✓				✓
16	IEEE-013	[56]	✓	✓				39	MDPI-060	[57]	✓	✓			
17	MDPI-076	[58]	✓		✓	✓		40	MDPI-086	[59]	✓	✓		✓	✓
18	MDPI-111	[60]	✓				✓	41	MDPI-095	[61]	✓	✓			
19	MDPI-130	[62]	✓			✓		42	MDPI-099	[43]	✓				✓
20	MDPI-146	[63]	✓	✓	✓	✓	✓	43	MDPI-104	[64]	✓	✓			✓
21	S-006	[65]	✓	✓				44	MDPI-114	[66]	✓	✓	✓	✓	
22	S-012	[67]	✓	✓		✓	✓	45	MDPI-137	[68]	✓	✓			✓
23	S-017	[69]	✓	✓		✓		46	MDPI-144	[70]	✓	✓		✓	✓

3. Descriptive Analysis of the Literature

This section presents a detailed analysis of the reviewed studies, organized into the following five main topics: AI in EV energy management, optimization techniques in EMS, BMS renewable energy integration, and smart grids and EVs. Two independent reviewers meticulously evaluated the selected studies to ensure the integrity of and reduce the risk of bias in our synthesis. This independent review process helped maintain objectivity and enhanced the credibility of the findings. Each topic was divided into three subsections as follows: description, current state, trends, and future challenges, providing a comprehensive view of the advancements, current applications, and pending challenges in each area. By systematically categorizing and analyzing the studies, we aimed to offer a robust synthesis that highlights the key developments and identifies gaps in the existing literature.

3.1. Artificial Intelligence in EV Energy Management

3.1.1. Description

AI is pivotal in optimizing energy management for EVs, utilizing advanced machine learning algorithms, neural networks, and optimization techniques [27,31]. These technologies are essential for enhancing EV performance, energy efficiency, and range through sophisticated control algorithms. Techniques such as RL are particularly effective in real-time energy management, offering near-optimal solutions even in dynamic driving conditions [27,29]. AI applications extend to fault diagnosis and predictive maintenance of electric propulsion systems and batteries, ensuring higher reliability and extended battery life [46]. This capability is crucial for maintaining EV performance and user safety. Moreover, AI enables personalized driving experiences tailored to driver preferences and environmental conditions [35,39]. In cybersecurity, AI is instrumental in detecting and mitigating security threats within EV-EMS, safeguarding against potential vulnerabilities. The integration of AI into these domains highlights its potential to drive innovation and efficiency in sustainable mobility solutions [33].

3.1.2. Current State and Recent Advances

In the energy management of EVs, advances driven by AI are noteworthy [48,52]. Reinforcement learning (RL) has been particularly effective in optimizing energy consumption and route planning. For instance, ref. [27] proposes a Q-learning-based system for hybrid powertrains, emphasizing the need for precise agent and environment design to achieve near-optimal real-time solutions. Additionally, hybrid algorithms combining actual data and simulations, as seen in [29], enhance energy consumption efficiency in hybrid electric vehicles (HEVs) through advanced deep learning (DL) and RL techniques. In fuel cell electric buses, ref. [37] applies DRL to optimize energy management, reducing consumption and improving operational efficiency under diverse conditions. Strategies like TD3 in [35] optimize energy resources in residential settings, thus reducing costs. Moreover, algorithms such as deep q-network and double deep q-network in [44] enhance energy efficiency by optimizing device scheduling amidst dynamic environments.

An AI and IoT-based adaptive system can optimize energy efficiency and extend the EV range by up to 2.5% through DL algorithms [50]. Strategies combining heuristic knowledge with DRLA enhance the efficiency of hybrid electric vehicles, competing with traditional techniques like dynamic programming [54]. In microgrids, techniques such as artificial neural networks and RL optimize the economic dispatch of energy and integration of renewable resources [41,56]. A genetic optimization algorithm also manages energy storage in residential systems with solar panels and batteries, minimizing costs and maximizing self-consumption [63]. Technologies like DL are integrated into microgrid systems to improve energy efficiency and demand management [67]. Prediction models for photovoltaic solar energy integrated with EV charging platforms are also being explored to achieve sustainable energy transition and carbon neutrality [62]. These advancements demonstrate AI's potential to transform energy management, enhancing operational efficiency and promoting sustainability [34].

3.1.3. Industrial Adoption

Implementing AI in fleet management systems and autonomous vehicles is revolutionizing energy efficiency [58]. Strategies such as DRL, fuzzy logic control, and AI-based EMSs are optimizing consumption and operational stability. AI uses internal pricing mechanisms in households to optimize energy trading among distributed resources [28]. In renewable energy microgrids, AI systems ensure optimal energy flow and stability [30]. Furthermore, predictive models based on AI, such as deep neural networks and transfer learning, are crucial for predicting torque demand in electric and hybrid vehicles [32,42]. These models enhance vehicle efficiency and promote sustainable energy use.

In hydrogen fuel cell vehicles, AI-based optimization efficiently manages energy resources, minimizing environmental impacts and costs [36]. While it is true that the use of green hydrogen, which is produced through renewable energy sources, results in zero emissions during vehicle operation, there are still several environmental impacts associated with the lifecycle of hydrogen production, transportation, and storage. The production of hydrogen, particularly when not derived from renewable sources, can lead to significant environmental impacts. For instance, hydrogen production through natural gas reforming, a common method, results in carbon emissions unless carbon capture and storage technologies are employed. Moreover, the transportation and storage of hydrogen involve energy-intensive processes that can contribute to environmental footprints. Furthermore, in hydrogen fuel cell vehicles, efficient water management within the fuel cell is crucial to maintaining optimal performance [36].

The proton exchange membrane (PEM) fuel cells used in these vehicles require precise control of water balance to avoid issues such as water flooding or membrane drying. Water flooding occurs when excess water obstructs the gas diffusion layer, reducing fuel cell efficiency, while membrane drying can lead to cell degradation. AI-based optimization can enhance the management of these complex liquid water characteristics, ensuring efficient operation and extending the life of the fuel cells [36]. Algorithms such as Q-Learning can improve energy management in hybrid electric vehicles (HEVs) by adapting to changing conditions and optimizing energy flow [38]. Additionally, peer-to-peer platforms in smart homes utilize AI to distribute energy efficiently among prosumers, integrating photovoltaic systems and EVs [40]. Model predictive control (MPC) systems enhanced with machine learning can manage EV charging infrastructures, optimizing energy distribution in urban environments [45]. This adoption of AI drives operational efficiency and promotes sustainable energy practices, marking a step towards a smarter and more conscientious energy future.

3.1.4. Trends and Future Challenges

Advanced energy management increasingly uses real-time data and predictive analytics to enhance decision-making. This is evident in implementing systems like deep deterministic policy gradient (DDPG) integrated with ANFIS to optimize energy efficiency and state-of-charge for plug-in hybrid vehicles [51]. Furthermore, integrating AI-based smart EMSs into smart grids improves automation and interoperability, using embedded devices and IoT communication protocols to optimize consumption and renewable energy generation [53]. In the realm of electricity consumption and demand management, prototypes of energy meters based on current sensors with real-time and frequency-domain analysis are being developed, utilizing edge and cloud analytics for demand-side management (DSM) [55]. Moreover, expert home energy management systems integrate voice assistants with IoT platforms, enhancing user efficiency and comfort through multi-objective optimization and process automation [57,59,61].

The advancement towards smart grids and AI implementation is transforming energy markets towards greater operational efficiency and sustainability [64,66]. However, challenges such as cybersecurity in smart grids, ongoing optimization of prediction algorithms, and load management for EVs and renewable energy systems persist [68,70]. Addressing these challenges will enhance the reliability and efficiency of grids and facilitate the transition to cleaner and more sustainable energy sources.

The rise in EV usage has heightened the need for efficient electric load management, particularly to mitigate adverse impacts on the electrical grid [60]. ML-based charging management systems, such as long short-term memory recurrent neural networks (LSTM), k-nearest neighbors, random forests, support vector machines (SVMs), and decision trees, have proven effective in optimizing EV charging [45,60]. These systems reduce costs and voltage fluctuations and enhance electrical system stability [47]. Furthermore, energy management in autonomous residential microgrids benefits from advanced home EMSs based on AI [65]. Algorithms like the African Vultures optimization algorithm have been shown to reduce operational costs and improve the lifespan of energy storage systems, which are crucial for managing random EV charging. Digitization and the application of emerging technologies such as digital twins and multi-agent systems are revolutionizing energy efficiency in smart cities [69]. These technologies enable dynamic optimization of complex energy systems, including renewable energy integration and demand management, essential for resilience against extreme weather events [43,69].

Intelligent transformer management and the integration of AI-based EMSs are crucial for preventing grid failures and optimizing power flow in substations [43]. Hybrid AI models, such as combining SVM and linear regression algorithms, are used for real-time monitoring and maintenance planning, improving operational efficiency. Moreover, advances in large-scale EV charging management systems, driven by machine learning techniques and MPC, are transforming EV charging infrastructure. These systems significantly reduce phase imbalances and energy losses, which are crucial for mitigating impacts on low-voltage networks [45].

Figure 5 provides a summary of the key findings in the synthesis of the literature on artificial intelligence in EV energy management.

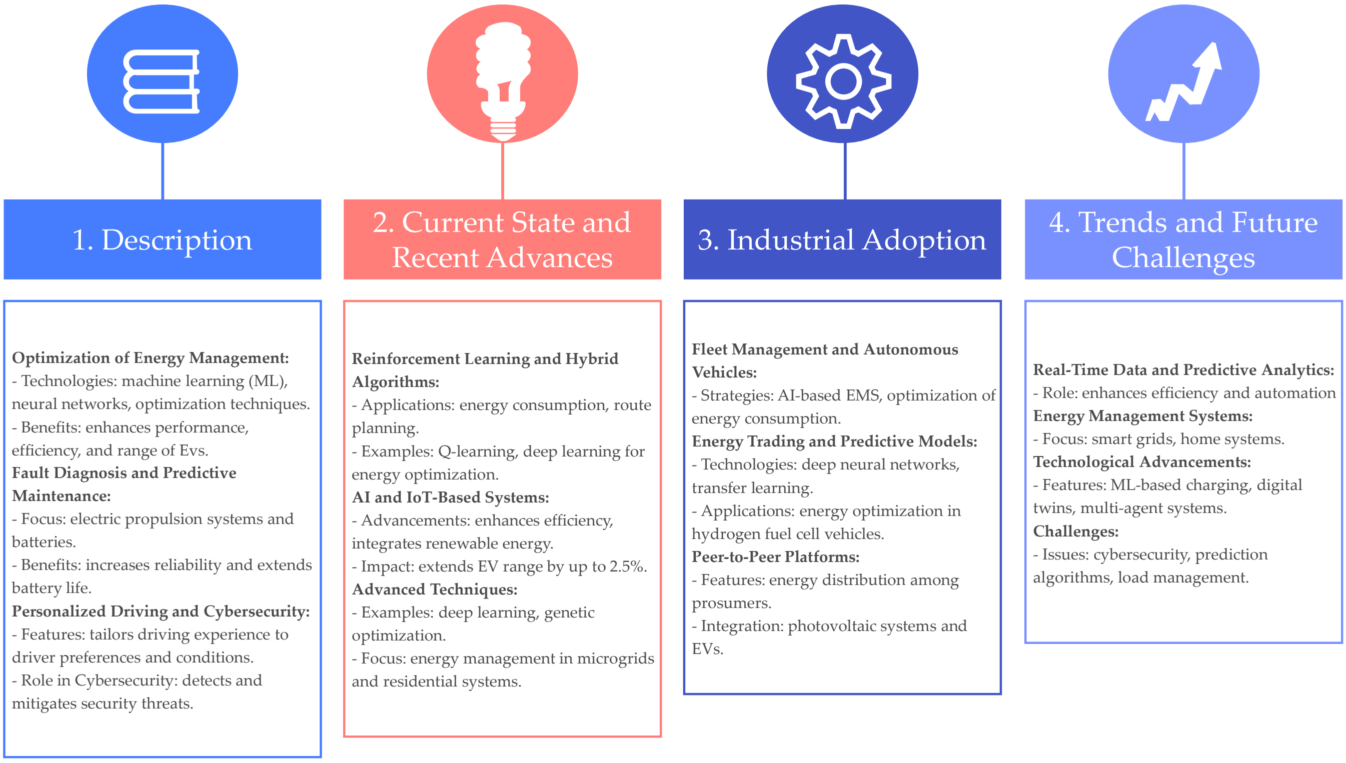


Figure 5. Literature review on artificial intelligence in EV energy management.

3.2. Optimization Techniques in EMSs

3.2.1. Description

Optimization techniques in EMSs encompass a variety of methodologies aimed at enhancing efficiency and reducing operational costs across diverse applications. These techniques leverage mathematical, heuristic, and metaheuristic approaches to address complex energy distribution and consumption challenges. Recent advancements highlight the integration of AI and machine learning (ML) paradigms, such as RL, DRL, and data-driven algorithms, into EMS frameworks [25,35,46,48,50,54]. RL methods, including Q-learning and twin delayed DDPG (TD3), have demonstrated efficacy in optimizing power allocation and energy flow in HEVs and fuel cell hybrid electric buses (FCHEBs). These algorithms adapt dynamically to real-world conditions, achieving near-optimal performance under varying operational scenarios.

Additionally, combining AI techniques with blockchain technology has facilitated the development of decentralized energy trading platforms, enhancing grid stability and optimizing power transactions in microgrid environments. Such platforms integrate smart contracts and distributed ledger technologies to ensure secure and transparent energy transactions. Moreover, the application of AI in smart home EMSs has revolutionized residential energy consumption by optimizing the use of distributed energy resources (DERs) and responding to real-time demand fluctuations [25,39,50]. These systems employ predictive analytics and adaptive control strategies to minimize costs and maximize energy efficiency, contributing to sustainable energy practices.

3.2.2. Current State

Recent innovations in EMSs highlight significant advancements driven by AI and machine learning (ML). For instance, integrating DL algorithms such as bidirectional long short-term memory (Bi-LSTM) with optimization techniques has revolutionized the management of home microgrids. As described in [42], this approach optimizes the scheduling of battery energy storage systems (BESSs) to minimize daily electricity costs under time-of-use pricing while also considering the operational constraints of renewable resources and household appliances. Similarly, advancements in digital twin technologies, detailed in [69], have enabled real-time monitoring and optimization of energy systems in smart cities, enhancing the efficiency and resilience of photovoltaic (PV) systems, heat pumps, and multi-energy storage solutions.

Real-world applications illustrate successful implementations across diverse energy management contexts. For instance, the application of backpropagation neural networks in hybrid energy recognition and management systems, discussed in [34], demonstrates high accuracy in identifying and managing various energy inputs, including photovoltaic and piezoelectric energy sources. Moreover, machine learning-based online MPC, as detailed in [45], has been pivotal in managing large-scale EV charging infrastructures. This approach leverages ML predictions to mitigate EV charging impacts on the grid, significantly reducing peak demand and enhancing voltage stability.

The impact of these innovations extends beyond technical advancements to tangible benefits in industry practices. In the context of hydrogen fuel cell vehicles, AI-driven EMSs, as reviewed in [36], optimize vehicle-to-everything (V2X) interactions, enhancing energy efficiency and sustainability. Furthermore, studies such as [64] explore the application of DRL in home EMSs, illustrating their effectiveness in dynamically optimizing energy consumption and costs through demand response strategies.

3.2.3. Trends and Future Challenges

Current trends in EMSs underscore a shift towards more adaptive and real-time approaches. These advancements leverage cutting-edge technologies such as AI, machine learning (ML), and digital twins to enhance operational efficiency and responsiveness [67]. For instance, AI-driven predictive models integrated with DL algorithms are increasingly used to optimize energy distribution and scheduling in microgrid systems [69]. Similarly, digital twin technologies enable dynamic modeling and simulation for proactive energy management, particularly in smart city infrastructures. These trends reflect a broader movement towards agile EMS solutions capable of swiftly adapting to changing energy demands and environmental conditions.

Despite these technological strides, the practical implementation of advanced EMS solutions faces significant challenges. One key obstacle is the inherent complexity of integrating diverse technologies and optimizing their performance across various operational contexts [34,38]. Customizing EMS solutions to meet specific environmental and user requirements demands extensive data integration, computational resources, and interdisciplinary expertise. Moreover, ensuring the interoperability and cybersecurity of interconnected energy systems remains critical [68]. Robust protocols and standards are essential to mitigate cybersecurity risks and ensure the reliable operation of smart grid infrastructures. Furthermore, scaling these solutions across different scales—from individual homes to large industrial complexes—poses additional logistical and regulatory challenges [40,49].

Figure 6 summarizes the key findings from the literature synthesis on optimization techniques in EMSs. This figure highlights the various optimization algorithms and methodologies identified in the reviewed articles, showcasing their applications and contributions to enhancing the efficiency and performance of EMSs in electric vehicles. The summarized findings illustrate the advancements in optimization techniques and their impact on the overall effectiveness of energy management in EVs.

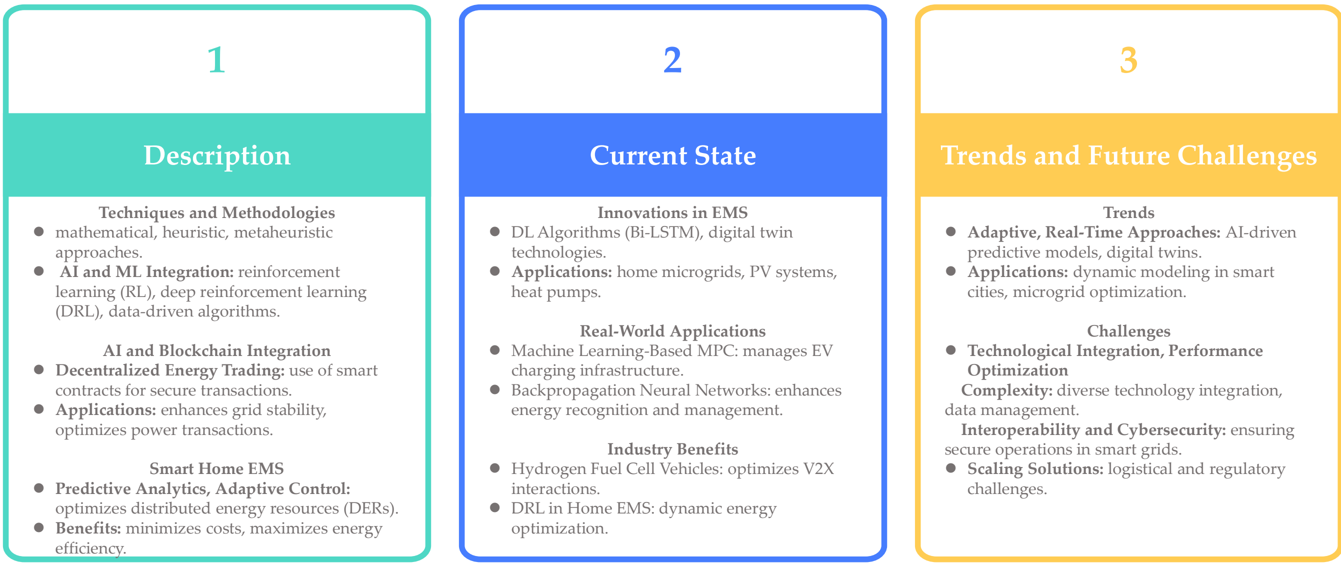


Figure 6. Literature synthesis on optimization techniques in EMSs.

3.3. Battery Management Systems

3.3.1. Description

BMSs are essential components in EVs and renewable energy systems, tasked with monitoring, controlling, and protecting battery packs to ensure their efficiency, longevity, and safety [45,46,58,63,66]. These systems integrate sophisticated electronics and software algorithms to oversee critical parameters such as SoC, SoH, and temperature, optimizing battery performance and preventing operational failures. Accurately measuring these parameters simultaneously can be challenging, and non-destructive testing technologies are often preferred. Recent advancements in this field include methods for joint estimation of SOC and temperature using ultrasonic reflection waves. A study [71] presents a novel approach where a piezoelectric transducer is affixed to the battery surface to enable ultrasonic-electric transduction. This method allows for the transmission and reflection of ultrasonic signals, providing accurate estimates of SOC and temperature with root mean square errors of 7.42% and 0.40 °C, respectively. Additionally, innovations in energy management strategies have highlighted the importance of degradation adaptive approaches that focus on the current SoH to enhance durability and prevent degradation. As a current example, in [72], an innovative technique is proposed to adapt the energy management process to the real-time state of the powertrain, achieving an optimal balance between energy economy and long-term durability.

3.3.2. Current State

Recent advancements in BMS technology have focused on enhancing monitoring precision and control accuracy. This includes implementing advanced diagnostic techniques and predictive algorithms [58]. For instance, artificial neural networks (ANNs) combined with adaptive strategies like the maximum correntropy criterion (MCC) have improved SoC estimation accuracy by considering higher-order statistical moments, thereby mitigating the impact of outliers in battery data. Similarly, intelligent prediction algorithms integrated into BMSs for microgrids utilize machine learning models such as LSTM networks to forecast energy production and optimize power management. Despite technological strides, challenges persist in mitigating battery degradation and managing thermal dynamics [46,63]. Maintaining optimal SoC without compromising battery lifespan and managing heat dissipation during high-demand scenarios remain critical areas of research and development.

3.3.3. Trends and Future Challenges

Future trends in BMSs point towards developing smarter systems capable of more accurate diagnostics and predictive capabilities [46]. Integrating AI technologies, including fuzzy logic and convolutional neural networks (CNNs), aims to enhance real-time decision-making and adaptive control strategies. These advancements are crucial for optimizing battery performance across environmental and operational conditions. Overcoming current limitations in battery technology, such as cycle life and temperature, remains a primary challenge for BMSs [66]. Effective energy management strategies are crucial for optimizing battery performance and lifespan. Reference [63] highlights the importance of advanced energy management strategies in hybrid systems to ensure continuous power supply. Reference [66] discusses intelligent algorithms for managing power flows and optimizing the SOC. By leveraging machine learning techniques, AI-based algorithms significantly improve battery health prediction, charging cycle optimization, and overheating prevention. For instance, LSTM networks enhance the accuracy and reliability of SOC forecasting. AI-driven control strategies use real-time data to keep batteries within safe temperature ranges, preventing thermal degradation [66]. Future advancements in AI, including reinforcement learning and advanced neural networks, promise further improvements in battery life and performance, contributing to the efficiency, reliability, and sustainability of electric vehicle battery systems [63,66].

3.3.4. Advantages and Shortcomings of AI Technologies in BMSs for EVs

The integration of AI into BMSs for electric vehicles offers numerous advantages. One of the main benefits is the optimization of battery performance. AI enables real-time optimization of energy use, improving efficiency and reducing waste. Algorithms such as ANNs and LSTM networks have shown significant improvements in SoC estimation accuracy [58]. Additionally, AI facilitates predictive diagnostics, allowing for the anticipation of battery failures and enabling preventive maintenance, thus avoiding unexpected breakdowns [58]. Another important advantage is the extension of battery life. Thermal management through AI helps control battery temperature, mitigating the risk of overheating and prolonging cell lifespan [63]. Furthermore, optimizing battery usage through AI reduces degradation, maintaining optimal performance for longer periods [63]. Real-time adaptation is another significant benefit. AI adapts battery management to changing driving and environmental conditions, optimizing energy use based on traffic, weather, and driver preferences [45,46]. Additionally, AI facilitates the integration of renewable energy sources, adjusting energy consumption according to the availability of solar or wind energy [55].

3.3.5. Shortcomings and Challenges of Applying AI in BMSs for EVs

Despite the numerous advantages, the application of AI in BMSs for electric vehicles also presents several shortcomings and challenges. One of the main shortcomings is the complexity of implementation. Adapting AI algorithms to real-world driving conditions remains a significant challenge, as simulations and theoretical models do not always accurately reflect real-world conditions [63,66]. Moreover, advanced AI algorithms require considerable processing power and data storage capacity, which can be costly and difficult to implement in real-time energy management systems [37,42]. Another important shortcoming is the lack of empirical validation. Many studies rely on simulations and lack testing in real-world scenarios, limiting the practical validation of proposed solutions [61]. Collaboration between academia and industry is crucial to implement and validate solutions in real environments, ensuring their effectiveness and long-term viability [46]. Interoperability and cybersecurity issues also represent significant challenges. Integrating various BMSs, IoT devices, and communication protocols requires seamless interoperability, which is challenging because of the lack of unified standards [66]. Additionally, energy management systems' increasing digitalization and connectivity make them vulnerable to cyberattacks. It is essential to develop robust cybersecurity protocols to protect these systems [46].

Figure 7 presents a summary of the key insights from the literature synthesis on battery management systems (BMSs). This figure showcases the strategies and technologies identified in the reviewed articles, highlighting their role in enhancing battery performance, longevity, and efficiency. The summarized findings underscore the advancements in BMSs and their critical impact on improving the overall effectiveness of energy management in electric vehicles.

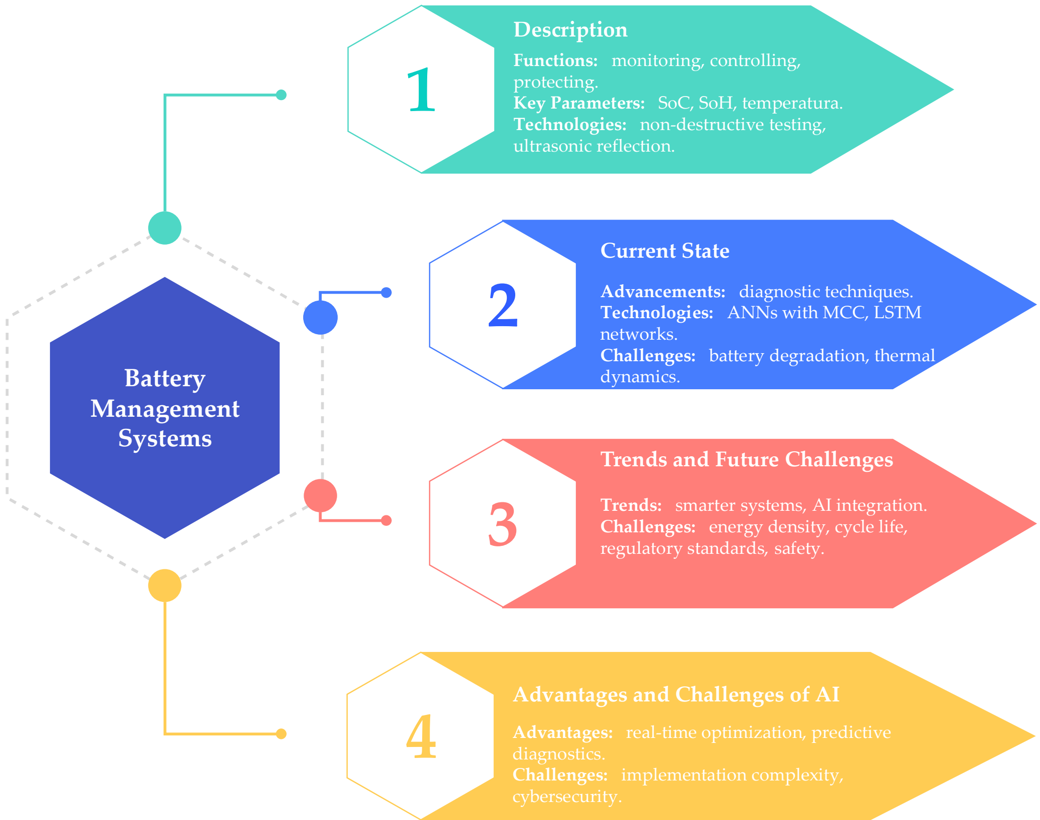


Figure 7. Key insights from the literature synthesis on battery management systems.

3.4. *Renewable Energy Integration*

3.4.1. Description

Renewable energy integration involves seamlessly integrating sustainable energy sources, such as solar and wind power, into the existing electrical grid and the EMSs of EVs. This process aims to enhance overall energy efficiency, reduce reliance on fossil fuels, and mitigate environmental impacts [41].

3.4.2. Current State, Projects, and Impact

Renewable energy integration is progressing through several noteworthy developments and initiatives. Across various sectors, significant projects are underway that combine EV technologies with renewable energy sources. These initiatives aim to reduce carbon footprints and demonstrate the synergy between transportation and energy sectors in achieving broader sustainability goals [62]. For instance, studies highlight the potential for effectively integrating predictive analytics and machine learning in managing energy consumption and distribution [35]. The integration of renewable energy is reshaping the energy market landscape. It promotes the adoption of cleaner technologies, enhances energy independence, and supports sustainable economic growth. This transition is crucial for reducing greenhouse gas emissions and advancing environmental stewardship.

3.4.3. Trends and Future Challenges

Recent trends and ongoing challenges in renewable energy integration are multifaceted. Hybrid renewable energy projects, which combine solar PV with wind turbines or other sources, are increasingly popular. These projects optimize energy production by leveraging the complementary characteristics of different renewable sources, thereby enhancing system reliability and performance [66]. Moreover, advancements in AI and machine learning facilitate more precise predictions of renewable energy generation, enabling better grid integration strategies [69]. Despite these technological advancements, significant challenges persist, particularly related to the algorithms used in renewable energy integration. One of the primary challenges is managing the intermittency of renewable sources, which remains a critical issue for grid stability [30]. AI algorithms must accurately predict energy supply and demand to maintain balance, but the variability in renewables like wind and solar can complicate this task.

Effective integration with existing infrastructure also requires robust energy storage solutions and adaptive management systems capable of responding to variable renewable outputs [53,63]. The complexity of developing algorithms that can seamlessly integrate diverse energy sources and adapt to fluctuating conditions poses a significant challenge. For instance, algorithms must account for the stochastic nature of renewable generation and optimize the dispatch of stored energy in real time. Another algorithmic challenge is the need for scalability and efficiency in handling large datasets from various sensors and devices within the grid. As the grid incorporates more renewable energy sources, the volume of data increases, necessitating more sophisticated data processing and decision-making algorithms. Ensuring these algorithms can operate efficiently without excessive computational resources is crucial [69].

Furthermore, integrating renewable energy with the market poses challenges related to pricing and incentives. Algorithms must dynamically adjust energy prices and manage transactions in a way that incentivizes renewable energy use while ensuring economic feasibility. This comprehensive literature review underscores the dynamic evolution of renewable energy integration, emphasizing ongoing efforts and advancements in technology, policy, and market dynamics [35,41,53,62,63,66,69]. These insights inform current practices and set the stage for future research and innovation to achieve a sustainable and resilient energy future. Addressing the algorithmic challenges associated with renewable energy integration is crucial to realizing the full potential of these technologies and achieving a stable, efficient, and sustainable energy system.

An overview of the key findings related to integrating renewable energy sources in the literature is provided in Figure 8. This figure details the approaches and technologies identified in the reviewed studies, emphasizing their role in incorporating renewable energy into energy management systems. The findings highlight significant advancements in integrating renewable sources, such as solar and wind power, and their impact on enhancing the sustainability and efficiency of electric vehicles' energy management systems.

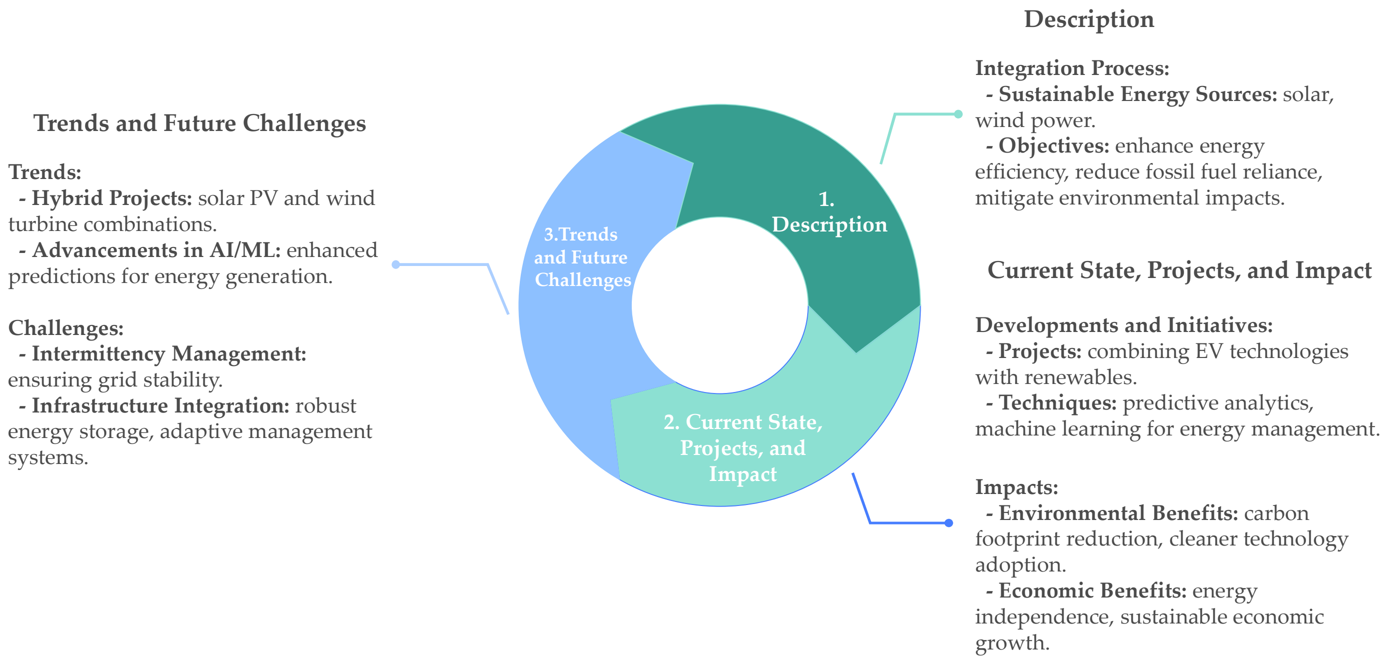


Figure 8. Key findings related to integrating renewable energy sources.

3.5. Smart Grids and EVs

3.5.1. Description

Smart grids represent a pivotal advancement in EMSs, particularly in optimizing EVs' charging and discharging cycles. This integration not only enhances the overall efficiency of the electrical grid but also supports the seamless incorporation of renewable energy sources [33]. Key technologies driving these advancements include AI, blockchain, and the Internet of Things (IoT), which collectively enable sophisticated energy management strategies [39,41].

AI algorithms embedded within smart grid frameworks enable real-time optimization of EV charging schedules based on fluctuating energy supply and demand dynamics [50,60]. By leveraging predictive analytics and machine learning, these systems ensure the optimal use of renewable energy resources while minimizing operational costs and grid congestion [50]. Moreover, the bidirectional capabilities facilitated by IoT devices allow EVs to not only consume energy but also contribute back to the grid during peak demand periods—a concept known as vehicle-to-grid (V2G) interaction. This bidirectional flow enhances grid stability and reliability, making EVs integral components of a sustainable and resilient energy infrastructure.

3.5.2. Current State and Implementations

Significant innovations in communication and control technologies have propelled recent advancements in energy management within smart grids. These developments enhance energy distribution, consumption efficiency, and flexibility across diverse grid environments. Technologies such as advanced metering infrastructure (AMI) and AI are crucial in optimizing grid operations, enabling real-time adjustments based on demand fluctuations and supply variations. AI-driven predictive models, like bidirectional Bi-LSTM, are increasingly integrated into EMSs, facilitating precise energy distribution and scheduling in microgrid environments [50].

Moreover, integrating edge and fog computing techniques has revolutionized the implementation of smart grid solutions. These techniques enhance local processing capabilities and reduce reliance on centralized cloud services, improving system reliability and response times [53]. The deployment of smart autonomous devices, capable of real-time analysis and decision-making at the network edge, exemplifies this trend [55].

Cities and regions worldwide actively implement smart grid technologies to bolster sustainability and energy efficiency. For instance, integrating distributed energy resources (DERs) and energy storage systems (ESSs) in urban settings exemplifies a proactive approach to grid modernization. These implementations leverage smart sensors and IoT-based communication protocols to optimize energy consumption and reduce environmental impact [43]. In addition, adopting incentive mechanisms within smart grids incentivizes consumer participation in demand-side management (DSM) activities. This includes leveraging game theory and blockchain technologies to optimize energy distribution during peak periods and promote using renewable energy sources (RESs) [59]. Such initiatives enhance grid reliability and contribute significantly to carbon emission reduction efforts.

3.5.3. Trends and Future Challenges

The evolution of smart grids is increasingly characterized by decentralization and participatory energy management strategies. Cities and regions are moving towards integrating distributed energy resources (DERs), energy storage systems (ESSs), and EV charging stations into their grid infrastructures [43]. This shift facilitates a more adaptive and resilient grid architecture that manages fluctuating power flows and enhances overall reliability. Furthermore, advancements in AI and ML are driving innovations in grid management, enabling predictive maintenance and optimal energy distribution [70]. These technologies empower local communities to engage in energy generation and consumption decisions actively, fostering a more sustainable energy ecosystem.

Despite the promising advancements, smart grids face significant challenges that must be addressed for widespread adoption and efficiency. One of the foremost challenges is cybersecurity. The increased digital connectivity in smart grids makes them susceptible to cyberattacks, posing risks to grid stability and consumer data security [68]. Ensuring robust cybersecurity measures, including AI-enhanced threat detection and mitigation strategies, is crucial to safeguarding grid operations and maintaining public trust.

Another critical challenge is interoperability. Integrating diverse EMSs, IoT devices, and communication protocols requires seamless interoperability to ensure efficient grid operations [53]. Standardization efforts are essential to enable compatibility and interoperability across various grid components and technologies, enhancing system resilience and scalability. Moreover, substantial investments in infrastructure are required to support the transition towards smarter grids. Upgrading existing grid infrastructure to accommodate DERs, ESSs, and advanced metering systems entails significant costs [64]. Addressing these investment needs while ensuring affordability and equitable access to smart grid benefits remains a key challenge for policymakers and utilities.

In summary, while the trends towards decentralized, participatory grids powered by AI and ML show immense promise for energy sustainability and efficiency, addressing cybersecurity, interoperability issues, and infrastructure investments is critical for realizing the full potential of smart grid technologies in the future. Decentralized grids enhance security by distributing control across multiple nodes, which reduces vulnerability to single points of failure often targeted in cyberattacks. AI and ML algorithms further bolster this security by providing real-time monitoring and anomaly detection, allowing for quick identification and response to potential threats. These technologies can dynamically adjust security measures, making them more adaptive to emerging threats and ensuring robust protection of grid infrastructure. Interoperability remains a challenge as well, requiring standardized communication protocols and seamless integration of diverse energy management systems and IoT devices. AI can aid in overcoming these challenges by optimizing data exchange and ensuring compatibility across different platforms and technologies. Significant infrastructure investments are needed to support the widespread adoption of smart grids, including upgrading existing systems to accommodate distributed energy resources and advanced metering technologies. Ensuring these investments are made effectively will be crucial in achieving a secure, efficient, and resilient energy future where smart grid technologies can thrive.

Figure 9 encapsulates the comprehensive findings on the integration of smart grids and electric vehicles (EVs) from this literature review.

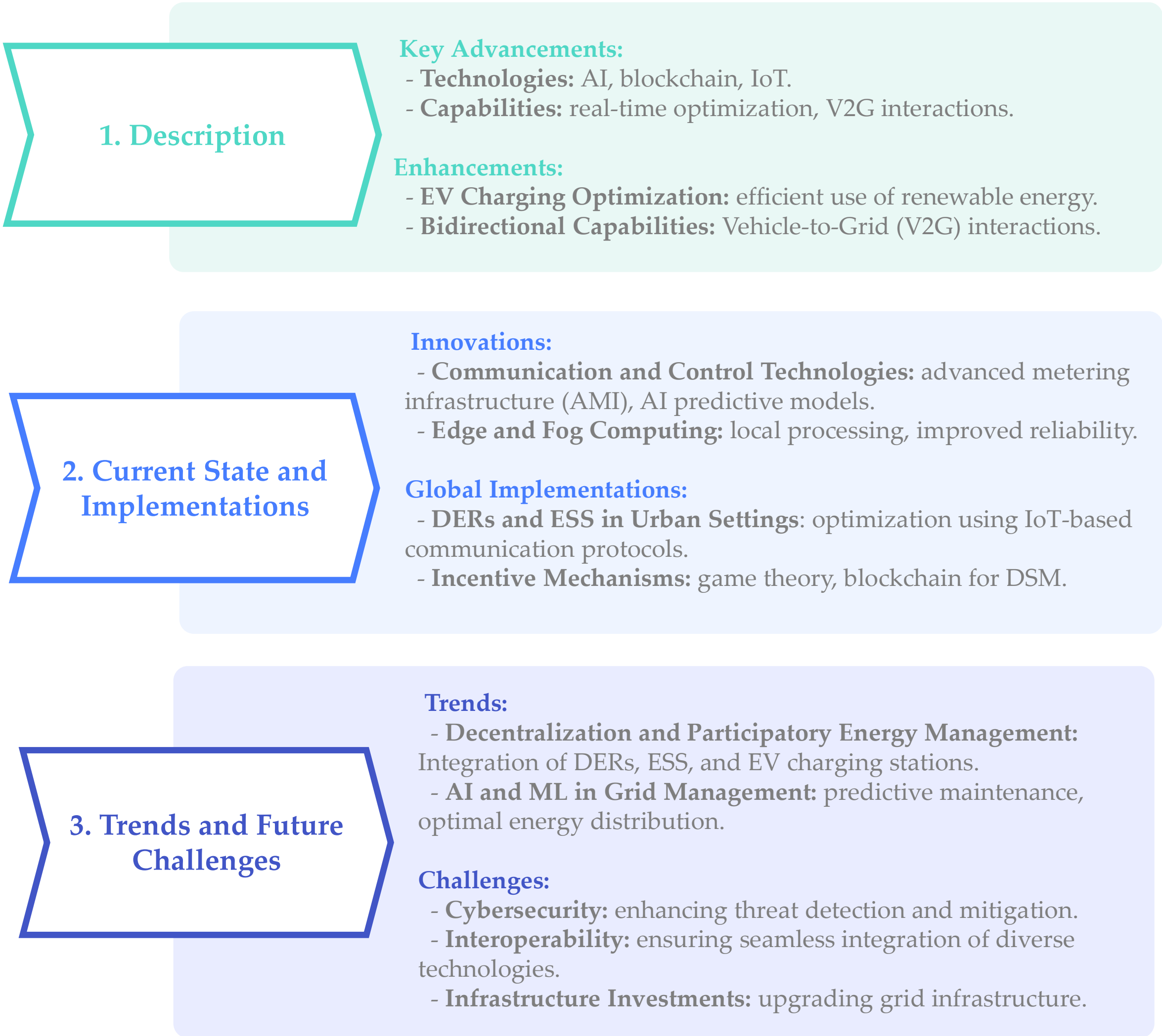


Figure 9. Comprehensive findings on the integration of smart grids and electric vehicles (EVs) from this literature review.

4. Discussion

Based on the findings synthesized in the previous section of this systematic literature review report, integrating artificial intelligence into energy management systems for electric vehicles reveals substantial advancements and potential for optimizing EV performance, energy efficiency, and range. The application of AI techniques, including machine learning (ML), deep learning (DL), and reinforcement learning (RL), has demonstrated significant improvements in real-time energy management, fault diagnosis, predictive maintenance, and cybersecurity. The general interpretation of these results aligns with the broader evidence that AI is pivotal in addressing EVs' dynamic and complex energy demands, offering near-optimal solutions under varying operational conditions. For instance, studies utilizing Q-learning and hybrid algorithms illustrate AI's capability to enhance energy consumption efficiency in hybrid electric vehicles and fuel-cell electric buses, achieving improved operational efficiency and reduced energy costs.

However, several limitations of the evidence included in this review warrant discussion. The variability in algorithm adaptation to real-time driving conditions remains a critical challenge, impacting the practical application of these AI techniques. Furthermore, the reviewed studies often lack comprehensive real-world validation, primarily relying on simulations and theoretical models. This gap highlights the necessity for closer collaboration between academia and industry to implement and test these AI-driven solutions in actual EV environments, ensuring their effectiveness and long-term viability.

The review process itself also has limitations, particularly in the selection criteria and scope. While ensuring high-quality evidence, excluding conference papers and non-peer-reviewed articles may have omitted relevant findings from emerging research. Additionally, the focus on publications from the last ten years may exclude foundational studies that could provide valuable insights into the evolution of AI in EMSs for EVs. These methodological choices, while aimed at maintaining rigor and relevance, inherently limit the breadth of this review.

The implications of these results for practice, policy, and future research are profound. Practically, the integration of AI into EMSs can revolutionize fleet management, enhance renewable energy integration, and improve the overall sustainability of EV operations. Policymakers should consider supporting the development and implementation of AI-driven EMS technologies, promoting standards that facilitate interoperability and data sharing between different systems and platforms. For future research, there is a clear need for interdisciplinary approaches that combine AI, energy management, and automotive engineering to address the identified gaps. Specifically, research should focus on developing adaptive algorithms capable of real-time optimization in diverse driving conditions, validating AI techniques through extensive field trials, and exploring the socio-economic impacts of widespread AI adoption in EVs.

5. Conclusions

This systematic review comprehensively examined the integration of artificial intelligence (AI) into energy management systems (EMSs) for electric vehicles (EVs) using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology. We identified 46 relevant articles highlighting the significant advancements and practical applications of AI, focusing on machine learning (ML), deep learning (DL), and genetic algorithms. The findings reveal that AI integration into EMSs offers numerous advantages. Optimized energy management is achieved through AI's ability to provide precise real-time optimization, enhancing energy efficiency and vehicle range. Advanced AI techniques enable effective route planning and energy consumption adjustments, considering traffic and environmental conditions. Fault diagnosis and predictive maintenance are significantly improved with AI, which allows for accurate predictions of battery health and energy needs, thereby reducing unexpected failures and extending the lifespan of critical components.

AI also plays a crucial role in renewable energy integration, promoting sustainable energy practices by enhancing the prediction and management of renewable energy sources. This integration supports energy independence and contributes to environmental sustainability by enabling better forecasting and utilization of renewable energy. However, this study also identifies several challenges that must be addressed for the widespread adoption of AI-enhanced EMSs. Cybersecurity is a primary concern as increased connectivity exposes EMSs to potential cyberattacks. Implementing robust cybersecurity measures, including AI-driven threat detection and mitigation strategies, safeguards data and maintains grid stability. Interoperability poses another challenge, requiring the seamless integration of diverse EMSs, IoT devices, and communication protocols. Establishing standardized protocols is crucial to ensure efficient communication across different systems and enhance the functionality of AI-enhanced EMSs. Infrastructure investments are critical to supporting the transition towards AI-integrated EMSs. Upgrading existing grid infrastructures to accommodate distributed energy resources, advanced metering systems, and smart grids is vital to achieving reliability and efficiency. Addressing these infrastructure needs while ensuring equitable access to benefits remains a key challenge for policymakers and utilities.

Finally, AI integration into EMSs for EVs holds transformative potential to enhance performance, efficiency, and sustainability. Future research should focus on developing advanced AI models adaptable to diverse driving conditions, improving cybersecurity measures, and exploring innovative optimization techniques. These efforts will be instrumental in creating more robust and adaptive AI applications in EMSs, paving the way for a sustainable and efficient future in electric mobility. Enhanced interdisciplinary collaboration between academia and industry will be essential to validate and implement these solutions in real-world environments, ensuring their effectiveness and long-term viability.

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

Appendix A

Overall Information of the Selected Studies for This Literature Review

All the bibliographic information for the 94 articles resulting from stage R2 and the 46 articles that passed the eligibility criteria in stage R3 can be downloaded from the following GitHub URL: https://github.com/dannyochoa87/WEVJ-MDPI-001.git (accessed on 11 August 2024).

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